CALIFORNIA STATE UNIVERSITY, NORTHridge

DIESEL TRUCKS:
HEALTH RISK AND ENVIRONMENTAL EQUITY

A thesis submitted in partial fulfillment of the requirements
For the degree of Master of Arts
in Geography

By

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ABSTRACT

DIESEL TRUCKS:
HEALTH RISK AND ENVIRONMENTAL EQUITY

By

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Master of Arts in Geography

This study examines the excess cancer risk (ECR) posed by cargo truck diesel particulate matter (DPM) in Los Angeles, California and whether or not related environmental inequities are occurring. While previous research has widely shown evidence of environmental injustices in Los Angeles, this study delves deeper into the issue of environmental inequity by specifically identifying pollution-related health risks. This study includes the use of USEPA’s AERMOD program to model ECR levels around major L.A. port-adjacent freeways. The modeled data is used in conjunction with 2010 U.S. Census data to perform an environmental equity analysis of race and median household income. Results show high levels of excess cancer risk, in some cases exceeding a level of 500 per million, with overall levels extending far into populated neighborhoods. This study does not show evidence of environmental inequity regarding median household income. However, some evidence of environmental inequity is apparent in regard to race, with white population decreasing in accordance with levels of ECR, and the opposite correlation apparent for minority races.
Chapter 1 Introduction

1.1 The Problem

It is well known that air pollution is a major cause of a plethora of negative health effects. In particular, there is evidence of a causal relationship between air pollution and lung cancer. This has proven to be the case even when smoking, age, and other variables are taken into consideration (Hemminki and Pershagen, 1994). This is especially alarming considering that in many cases air pollution is something to which an entire population is exposed.

One common pollutant, diesel exhaust, is a complex mix of chemicals that is cause for epidemiological concern (Kagawa, 2002; CARB, 2008). The California Air Resources Board (CARB) estimates that diesel particulate matter (DPM) is responsible for approximately 3,500 premature deaths and thousands of hospital admissions every year in California. The inhalation of DPM is proven to cause a wide range of health effects including masculinization of fetuses during pregnancy (Watanabe and Kurita, 2001), decreased lung function in children (Brunekreef et al., 1997) as well as asthma and other respiratory and allergic diseases (Pandya et al., 2002; CARB, 2008). Moreover, as is the case with general air pollution, studies show that DPM is carcinogenic with epidemiological evidence pointing toward lung cancer as an effect of DPM inhalation (CARB, 2008). The link between DPM and lung cancer risk is apparent in trucking industry workers, who are exposed to high concentrations of DPM for long periods of time (Garshick et al., 2008). A meta-analysis reveals this causal relationship based on a
cohort of studies that also show an increased excess cancer risk based on length of exposure (Bhatia et al., 1998).

One probable source of significant amounts of diesel emissions is the traffic associated with business at the Port of Los Angeles (POLA) and the Port of Long Beach (POLB). These large ports are the entry point for nearly half of all cargo containers entering the United States (Wu et al., 2009). As a result of transporting the vast quantity of cargo containers, freeways leading out of the ports are heavily trafficked by heavy-duty diesel trucks (HHDTs). These trucks, classified as having three or more axles, emit large amounts of pollution into the surrounding air. Seeing as the POLA and POLB are in an urban area, many lives may potentially be affected by the pollution and its associated health effects.

While exposure to carcinogenic pollution would be a problem for any population, what is particularly disturbing is the past evidence that minorities and disadvantaged communities are often unfairly exposed to public health concerns, including (though not limited to) air pollution (United Church of Christ, 1987; Bowen et al., 1995; Perlin et al., 1995; Boone et al., 2009). Research and actions associated with environmental inequalities are termed as the environmental justice movement. According to the United States Environmental Protection Agency (2012):

Environmental Justice is the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies… The environmental justice movement was started by
individuals, primarily people of color, who sought to address the inequity of environmental protection in their communities. Grounded in the struggles of the 1960's Civil Rights Movement, this movement sounded the alarm about the public health dangers for their families, their communities and themselves.

Past environmental equity and justice studies have identified many disparities, particularly in the distribution of hazards (Stretsky and Lynch, 1999; Buzzelli et al., 2003; Morello-Frosch and Jesdale, 2006; Chakraborty, 2009; Su et al., 2009). Most notable and abundant are studies about proximity of populations to point sources of pollution such as toxic waste sites or landfills (Mantaay, 2002).

1.2 Research Question and Hypothesis

This study seeks to add to the existing environmental justice literature with some data and methodologies that are seldom-applied in conjunction with one another. Specifically, this study looks at disparity based on estimated health risk in relation to HHDT emissions in Los Angeles. Potential disparity is evaluated based on health risks from pollution from HHDT traffic on major thoroughfares surrounding the POLA and POLB. Using variables such as truck counts from these freeways, meteorological data, unit risk value as defined by the CARB, and elevation datasets, an atmospheric dispersion model is employed to find the areas where residents are projected to be most at risk for developing cancer by inhalation of DPM.

Next, to evaluate environmental inequity existence in this area, isopleths generated by the model are used along with U.S. Census data to perform an analysis
using GIS. This study determines whether a disparity exists by making a simple comparison of the proportions of populations in areas exposed to various degrees of excess cancer risk to each other and to the population of Los Angeles County as a whole. The populations examined are ethnicities classified by the U.S. Census Bureau. It is also determined whether there is a disparity in median family income of those exposed to the levels of cancer risk.

This study adds to the previous pollution-related environmental justice literature in several ways. While the vast majority of the previous literature relies on simple proximity analysis, this study is one of the few to use more detailed methodology by the employment of a dispersion model. Moreover, this study attempts to close the gap between pollution levels and populations exposed by examining projected cancer risk levels. Using refined methodology such as modeling and estimating cancer risk adds credibility to the environmental justice movement as a whole, as well the potential of leading to further research or improved policy decisions in the future.

This report is outlined as follows. Chapter 2 is a review of the existing literature on the subject of diesel exhaust, air dispersion modeling, and environmental justice. Chapter 3 is a description of data and methods. Results are outlined in Chapter 4, and a discussion of the results follows in Chapter 5. Finally, Chapter 6 is a conclusion to this study.
Chapter 2 Literature Review

2.1 Environmental Justice: In the Beginning

The environmental justice movement was born out of the Civil Rights movement of the 1960s (Bowen and Wells, 2002). However, it wasn’t until the late 1980’s and early 1990’s that concerns became more widespread (Maantay, 2002). This sudden awareness stemmed from a groundbreaking study by the United Church of Christ (1987). The major findings of this study were that racial minorities were disproportionately burdened by the location of hazardous waste facilities in the United States. In the years after the release of this study, local minority communities as well as a range of progressive coalitions began to oppose racial injustices involving the placement of hazardous wastes and other pollutants.

Boone et al. (2009) described the early environmental equity studies as being primarily statistical, focusing on the distribution of toxic facilities in relation to minority communities. Most of these early environmental equity studies were quantitative in nature, examining proximity to point sources of pollution with occasional studies touching on rudimentary ways of evaluating actual exposure levels.

The environmental hazards in many of the early studies are toxic sites such as hazardous waste treatment, storage, and disposal facilities (TSDFs), USEPA Superfund sites, and especially those listed in the US EPA’s Toxic Release Inventory (TRI) (Maantay, 2002). The use of these datasets poses a methodological dilemma in that often times they are incomplete or inaccurate (Bolin et al., 2000). Furthermore, site lists such
as these are often broad in scope and make it difficult to pinpoint the specific exposures to potential risks.

Another issue apparent in many of the early studies is the use of large geographic units (Maantay, 2002). Some studies (Bowen et al., 1995; Perlin et al., 1995) used demographic data at the county level in their evaluations. This left room to grow in the environmental justice literature in the form of more detailed studies, focusing in on smaller areas and using smaller geographic units.

Still, many of these studies revealed preliminary implications about the placement of hazardous facilities, as the majority of early studies of this nature found that there was in fact some kind of disproportionate burden based on the geographic location of hazardous facilities in relation to race and/or wealth. Some of these studies from the 1990’s are as follows.

One study by Bowen et al. (1995) examined issues of environmental equity at the county level in Ohio as well as at the census tract level in Cuyahoga County, Ohio. They used data about sites listed in the EPA’s TRI, using an index to find not only the raw pounds produced by listed facilities but also the associated toxicity. They used these data to find whether there was a correlation between minority races and low income levels and high levels of toxicity. When looking at minority population and low income levels against exposure to toxicity, they found that there was a positive correlation in Ohio at the county scale, and a negative correlation when examining the smaller census units in Cuyahoga County. Based on these findings, the authors concluded that there was a need for further research including the use of dynamic models and further investigation into theories of urban structure and its role in environmental equity issues.
Another study by Perlin et al. (1995) also used an emission index for TRI data in conjunction with 1990 U.S. Census data to evaluate environmental equity; in this case at the county level for the entire United States. They used an emission index approach in order to calculate and compare the distribution of exposure versus race and income. They also compared race groups’ exposure values against each other. The findings were that there was a positive correlation between minority races (blacks, Asian/Pacific Islanders, other races, and Hispanics) and areas with high emission rates. In the case of income level, this study found that environmental inequity was not taking place, as income level was higher in areas with more TRI facilities. The authors speculated that these incongruous findings may be due in part to using data aggregated at the county level.

Pollock and Vittas (1995) also used TRI facilities in their environmental equity inquiry. This study, however, examined demographic data at a smaller scale, focusing on census block group data in the state of Florida. The researchers used estimated potential exposure as a function of [log(Miles)]; their reasoning being that changes in distance closer to a source are generally more drastic in terms of exposure than changes in distance farther away from the source. The authors found environmental inequity to be occurring on the basis of race and income when correlated to the natural log of the distance to the TRI facilities. In particular, findings showed low income white population generally living farther away from TRI facilities than low-income Hispanics, with low-income African Americans living the closest to facilities.

In yet another Florida study, Stretsky and Lynch (1999) found there to be environmental inequity taking place at the census tract level in Hillsborough County.
This study added to the previous environmental equity literature by using hazard data besides the usual TRI facilities. The data used in this study was of accidental chemical releases (ACR) as reported to the US EPA’s Accidental Reporting Information Program. After using several statistical methods to relate the tract centroids and their corresponding demographic data to the ACR facilities, the authors found there to be inequity occurring in regard to race and income. This was especially apparent in a bivariate analysis, where findings showed that the percentage of African Americans and/or low-income population in a census tract relates inversely to the distance from ACRs. Similar findings were revealed in a multivariate analysis with controls for urbanization, population density, and facility location.

Pastor et al. (2001) analyzed environmental equity based on proximity to TSDF sites by using buffers to identify impacted census tracts in Los Angeles County. They compared demographic data from the U.S. Census in tracts assumed to be affected by TSDFs and tracts not affected. Using GIS and geocoded locations of TSDF sites, the authors analyzed data for tracts falling within one-quarter mile and one-mile buffers. This study also examined changes in the statistics over time in an attempt to find out whether injustices are occurring due to disproportionate facility siting or disproportionate minority move-in. The authors found that disproportionate siting was occurring more often than disproportionate minority move-in, and that disproportionate siting was especially prevalent in neighborhoods in the process of racial transition.
2.2 Expanding the Research

With the vast majority of preliminary environmental equity studies showing evidence of racial or economic disparities, researchers built on this by becoming more vigorous in their methodological considerations as well as exploring disparities in regards to more specific risks or burdens. Some studies also expand on the initial research by attempting to answer the question of why environmental inequities occur (Boone and Modarres, 1999; Pulido, 2000; Boone et al., 2009). Examples of studies showing innovative additions to the research are as follows.

Buzzelli et al. (2003) expanded on the previous literature by using more sophisticated data to research environmental equity based on estimated air pollution levels in Hamilton, Canada. They used data about total suspended particulates (TSP) gathered from a network of monitoring stations operated in 1985, 1990, and 1995 and demographic data from 1986, 1991, and 1996. They used kriging to estimate the pollution distribution. After using regression models to analyze the pollution data in conjunction with the demographic data at the census tract scale, the authors found that injustices were occurring when examining variables such as education and unemployment. By looking at temporal changes, they also interpreted that injustices persisted but lessened over the period of 1985-1996, except in the case of dwelling value, which consistently correlated inversely to TSP levels.

Morello-Frosch and Jesdale (2006) expanded even further by evaluating environmental equity based on estimated cancer risks due to air pollution in metropolitan areas of the United States. They used modeled pollution concentration estimates from the U.S. EPA’s National Air Toxics Assessment and the pollutants’ associated potencies to
estimate cancer risk. They used this data and U.S. Census race/ethnicity data at the tract level to perform several statistical tests to assess whether environmental inequities were occurring in 309 metropolitan areas. The findings were that highly racially segregated metropolitan areas are more likely to be exposed to cancer risks associated with ambient air toxics.

In an attempt to more accurately summarize racial-ethnic and socioeconomic inequalities from cumulative environmental burdens, Su et al. (2009) created an index which they applied to Los Angeles County. The index was created to assess environmental equity in terms of exposure to pollutants considered prevalent in the area, such as NO2 (nitrogen dioxide) and PM2.5 (particulate matter less than 2.5 µm). They used demographic data from the 2000 U.S. Census at the tract level. Upon implementation of the index, the authors found patterns indicating that communities with higher percentages of low-income and minority residents were exposed to more pollution.

Some environmental justice studies have also expanded on the previous research by investigating the motives behind inequities. Researchers have used historical analyses in attempts to address the question of whether polluting facilities are placed in existing minority communities, or whether minority move-in is responsible for inequities. However, as exemplified by the following studies, the mechanisms leading to environmental injustices are often complex.

One study found environmental injustices occurring in Baltimore, Maryland based on the distribution of public parks (Boone et al., 2009). While it was found that African-Americans have more parks within walking distance, it was also found that they had access to less acreage of parks than the white population, and that the parks in
neighborhoods with a predominantly black population are more congested. Boone et al. expanded on the existing literature by investigating why the injustices revealed were taking place. By examining historical data, the authors found evidence explaining high black population percentage in the urban areas of Baltimore due to segregation ordinances, racial covenants, and other mechanisms that in turn created black segregation to areas with insufficient park space. The black population therefore inherited existing park space within the city, resulting in closer, smaller parks with more congestion whereas white/middle-class flight to the more spread-out suburbs resulted in higher distance to parks with much less congestion.

Boone (1999) also examined the issue of why environmental injustices were occurring in the industrial area of Commerce, CA. In areas where manufacturers were emitting high levels of toxic chemicals, Boone found minority populations to be disproportionately exposed. He determined that these inequities were largely due to zoning decisions made in the 1920s and 1930s which lent to heavy industrialization of Commerce. The reasoning behind these zoning decisions was found to be very complex, and likely due to a number of factors such as accessibility and land availability. While the area was already home to a large minority population, Boone could not find definitive evidence that this was the prime motive behind the industrial facility siting.

In another case study of Los Angeles, Pulido (2000) also delved deeper into the history and causes of environmental disparities. Pulido investigated the issue of environmental racism and its history in the area. She discussed the prevalence of white privilege and the motives and ease of suburbanization, particularly for middle-class whites. This trend was encouraged by a complex combination of factors including
advertising, governmental mechanisms, and the movement of mainly white-employed companies, especially those in the defense industry, to the outskirts of the city. Pulido established that, after 150 years of racism, the city remains highly segregated, with Latinos in particular disproportionately burdened by pollution.

2.3 Environmental Equity of Transportation

It is apparent that most environmental equity studies in the past have dealt with some type of environmental hazard, with many studies focusing particularly on air pollution. Oftentimes the data used in these studies concerns pollution from a point source or more general monitored pollution levels. There have also been a handful of studies evaluating equity regarding exposure to pollution from a mobile source, such as automobile traffic or other modes of transportation.

Wier et al. (2009) described a collaborative effort between several organizations looking at traffic-related health risks in San Francisco, California and the burdens placed on neighborhood residents. A wide array of methods were implemented including dispersion modeling, community surveys, noise modeling, and an analysis of U.S. Census data. Results showed that traffic-related burdens were resulting in a social disparity.

In another study, Chakraborty (2009) focused on modeled health risks from automobile traffic in Tampa Bay, Florida. Chakraborty used a Gaussian dispersion model to estimate cancer risk in the area. The results of this analysis were then used with 2000 U.S. Census data at the tract level to estimate disparity based on several variables. Results of this study indicate that minority races and neighborhoods with high population and low home ownership are more likely to be at risk of cancer and respiratory ailments.
due to traffic-related pollution. In addition to racial inequity, this study’s findings expanded on previous research by showing injustices to be further compounded by the fact that neighborhoods most affected by traffic-related pollution were home to fewer automobile owners.

In 2001, the American Lung Association expressed the need for more research concerning environmental injustices relating to mobile source emissions. While the aforementioned studies begin to do so, further research on the subject is still possible in terms of improved methodology, research on the pollution resulting from different modes of transportation, study of injustices related to more specific health concerns, and/or varied study locations.

2.4 Transportation of Goods in Los Angeles

Southern California is well-known to be an area developed largely around the use of the automobile. This includes the use of HHDTs for the movement of goods. Several studies illustrate the polluting impact of goods movement in the region around the POLA and POLB.

In one study, Wu et al. (2009) examined exposures to PM$_{2.5}$ and elemental carbon (EC) due to traffic around the ports. They used a dispersion model and found that local traffic contributed significantly to the overall levels of these pollutants in surrounding neighborhoods. The authors found annual average PM$_{2.5}$ and EC exposures due to local traffic to be 3.8 $\mu$g/m$^3$ and 0.4 $\mu$g/m$^3$, respectively. They estimated local traffic to be responsible for approximately 22-24% of total PM$_{2.5}$ concentrations and 30-40% of total EC concentrations in the area. They based these estimates on PM$_{2.5}$ and EC
measurements taken in the area between 1994-2005 and ranging from 15.9-17.4 \( \mu g/m^3 \) for \( PM_{2.5} \) and 1.0-1.33 \( \mu g/m^3 \) for EC.

In another study, Kozawa et al. (2009) assessed traffic emissions around the POLA and POLB by taking measurements from a mobile platform in the form of an electric vehicle. They found that diesel-related pollutants were highly elevated within 150 m of major traffic thoroughfares and especially so in areas downwind of the roads. They noted that wind direction and wind speed are “dominant drivers” in the extent of impact zones, with exposure levels several-fold higher in downwind areas than the ambient levels predicted in upwind locations. This was especially the case with the I-710 freeway during summer months, and particularly in the morning hours, when winds were more southerly and easterly compared to the rest of the year.

These studies shed light on the severity of the pollution situation around the ports. The ill effects of goods movement in Los Angeles are bound to lead to negative health effects in the surrounding communities. It is possible that the residents of these Southern California communities are facing environmental injustices as has been proven in so many other cases.

### 2.5 Gaps in the Literature

While there is already extensive research in the subject of environmental equity and environmental justice, there is still room to explore further. This study aims to do so in several key ways.
First, this study adds to the existing research in environmental equity regarding transportation-related pollutants. While a few studies of this kind have been done, this branch of environmental equity research is still in its youth.

Second, this study utilizes a dispersion model to generate data about projected excess cancer risk. Basing racial and socio-economic equity analysis on this data adds to the existing environmental equity research, much of which relies on some form of proximity analysis as methodology.

Finally, what makes this study truly unique is the study area. It has already been proven that port-related traffic around the POLA and POLB results in significant emissions that can be detected in surrounding neighborhoods. However, to the author’s knowledge, no study has looked at this area in terms of environmental equity relating to projected cancer risks from diesel emissions. This study takes this extra step, adding to the environmental equity literature and the environmental justice movement as a whole.
Chapter 3 Data and Methodology

The first step in this study includes the use of an air dispersion model to assess health risk related to DPM from port-related traffic. An air dispersion model uses a grid of receptor points to calculate the concentration of pollutants in the atmosphere over a given period of time. Though models provide a simulation, the even dispersion of receptor points provides a consistent prediction of concentrations over space that is not usually possible to measure using sampling or other methods.

The second part of this study is an analysis of the population exposed to DPM. This analysis includes examination of race and median family income within the modeled exposure areas.

3.1 Study Area

In this study, air dispersion model is used to estimate long-term air concentrations of DPM from diesel trucks around portions of freeways and major highways adjacent to the POLA and POLB. The general area examined in this study is represented in Figure 3.1.

Port-related activities are responsible for significant amounts of air pollution in the Los Angeles area, particularly in the form of DPM. Some of the most severe sources include diesel engine-powered ocean-going ships, harbor craft, cargo handling equipment, trucks, and locomotives (CARB, 2005). One study estimated in-port activities to be responsible for about 21 percent of total regional DPM emissions in the
South Coast Air Basin, with areas bordering the ports to have cancer risk levels exceeding 500 per million (CARB, 2006).

This study includes modeling of truck emissions around these ports because they support a high volume of container traffic. In fact, the POLA moves more containers than any other port in the nation, and has thus been coined “America’s Port.” Located adjacent to the POLA, the POLB is the second busiest port in the United States and handles nearly 1 in 5 loaded containers moving through all U.S. ports. When combined, the POLA and POLB rank number six in the world regarding container volume. Though some of this containerized cargo is transported via rail or air, much is transported by truck, with some roads averaging more than 25,000 trucks per day (SCAG, 2012).

The specific freeways and highways that this study examines have been chosen based on proximity to the ports as well as availability of HHDT traffic counts obtained from Caltrans. The freeway segments included in the modeling are the I-110 and I-710 freeways between the POLA and POLB and the I-405 as well as portions of the I-405, SR-1, SR-47 and SR-103 running between the two aforementioned freeways. These road segments are depicted in Figure 3.2.

Communities adjacent to these freeways include San Pedro, Carson, West Side, Wilmington, and Long Beach. According to the Los Angeles Times’ “Mapping L.A.” project (2009), the demographics of these communities vary widely. The population of Wilmington, for example, is not particularly diverse, and overwhelmingly Latino at 86.6%. The median income of Wilmington is low compared to the county as a whole. Being right next to the ports, Wilmington has a lower population density than is usual for the city of Los Angeles.
Carson, on the other hand, north of Wilmington, is much more diverse and much more densely populated. Still, only 12% White with Asian, Black/African American, and Latino populations at much higher percentages. Median income in this area is much higher at about $70,000 per year. Though further from the ports, Carson still surrounds freeways that act as major thoroughfares for port-related goods movement that could affect the population.

In general, the racial makeup of port-adjacent communities is much more diverse than in the county as a whole, with the percentage of black people within port-adjacent communities is high when compared to the county. Median income within these communities also shows a wide variance. The diversity within this area could lend itself to a possibility of disparity in regards to pollution exposure.
Figure 3.1: Study Area
Figure 3.2: Modeled Road Segments
3.2 Air Dispersion Model

The modeling program used in this study is USEPA’s AERMOD (version 11103). AERMOD is an acronym for the American Meteorological Society/Environmental Protection Agency Regulatory Model Improvement Committee’s Dispersion Model. AERMOD is the USEPA preferred air dispersion model for determining air impacts within 50 kilometers of air pollution emission sources (USEPA, 2005). AERMOD contains the algorithms necessary to model air concentrations from a wide range of emission source types, including ground-based area sources such as the Long Beach area freeways.

3.3 Model Inputs

The AERMOD air dispersion model requires a lengthy list of input values. Key inputs to this dispersion model include local geography, air emission rates of the released pollutant, source parameters (how and where the material is released to the air), receptors (locations where the offsite DPM concentrations are calculated), and meteorological data (which determines how and where the material is dispersed in the air). Each of these inputs is discussed below.

3.3.1 Geographical Inputs

A primary step in the air dispersion modeling analysis is to establish a coordinate system for identifying the geographical location of emission sources and receptors. These geographical locations are used to determine local characteristics (such as land use and elevation), as well as to find source to receptor distances and relationships.
Road source emissions are treated as area sources in AERMOD. In this study, the Universal Transverse Mercator (UTM) NAD83 zone 11 coordinate system is used for identifying the easting (x) and northing (y) coordinates of the modeled source areas and receptors. Using ESRI’s ArcGIS geographic information system (ArcMap v. 10), the source and receptor locations are obtained from aerial imagery in NAD83 UTM coordinates. A map of the source areas is available in Figure 3.3.
Figure 3.3: Modeled Area Sources
3.3.2 Emission Rates and Source Parameters

Since the freeways are considered area sources, the modeling in this study includes a series of AREAPOLY sources in AERMOD. The AREAPOLY source type is ideally suited to modeling irregularly shaped polygons, such as segments along freeways and other roads (USEPA 2004).

For each freeway AREAPOLY source, the following AERMOD inputs are required:

- A source identifier number or name;
- Source Location X (Easting) coordinate (UTM Zone 11, NAD83);
- Source Location Y (Northing) coordinate (UTM Zone 11, NAD83);
- Source base elevation (meters above sea level);
- Emission flux \( \text{g}/(\text{s-m}^2) \);
- Release height of the area source (meters);
- Number of polygon vertices;
- X and Y coordinates for each polygon vertex (UTM Zone 11, NAD83);
- Initial vertical dispersion of the area source plume (meters).

A source identifier is applied to each AREAPOLY source, and the centroid for each area is found using ArcGIS. USEPA’s AERMAP program (version 09040) is used to extract elevation data for each centroid, using 1/3rd arc-second resolution National Elevation Dataset (NED) data (USEPA, 2004). A map of the centroids for each source and their respective elevations are available in Figure 3.4.
Figure 3.4: Source Centroids and Elevations
A release height of 2.0 meters is applied and a vertical dimension of the plume equal to 4.0 meters. From this vertical dimension an initial vertical plume dispersion input is calculated to be 1.86 meters \((\text{SZINIT} = 4.0 \text{ meters}/2.15)\) (USEPA 2004). Each of the AREAPOLY sources has four vertices.

The EMFAC 2007 model is used to calculate DPM \((\text{PM}_{10})\) emissions for road segments identified by Caltrans traffic count locations. Emissions are calculated at a vehicle speed of 55 miles per hour. For HHDTs in the area around the ports, EMFAC 2007 calculates a DPM emission rate of 0.651 grams per mile \((\text{g/mile})\), per vehicle. This value is used in combination with the Caltrans truck counts, the lengths of the road segments, and the percentage of trucks using diesel fuel to find the total DPM for the road segments. The Caltrans data is the most recent available, which is from 2009. Since freeway segments are treated as area sources, the total segment DPM is in units of grams per second, per square meter \((\text{g}/(\text{s-m}^2))\). Table 3.1 shows these values.
Table 3.1: Total Road Segment DPM Calculations

| Road Area                  | Total Segment Length (m) | HDT 55 mph DPM EF (g/mi) | HDT 55 mph DPM EF (g/m) | Segment Total DPM/Vehicle (g) | Number of HDT Vehicles/day | Average Number of Vehicles/hr | % Diesel Trucks | Total Segment DPM (g/day) | Total Segment DPM (g/s) | Segment Area (m²) | Total Segment DPM (g/(s·m²)) |
|----------------------------|--------------------------|---------------------------|-------------------------|-------------------------------|-----------------------------|-----------------------------|---------------------------|---------------------|---------------------|---------------------|------------------------|------------------------|
| 710: start to Hwy 1        | 2490                     | 0.617                     | 3.83E-04                | 9.55E-01                      | 13934                       | 581                         | 95.80%                    | 1.27E+04            | 1.47E-01           | 1.28E+05            | 1.150E-06              |
| 710: Hwy to 405            | 4025                     | 0.617                     | 3.83E-04                | 1.34E+00                      | 17081                       | 712                         | 95.80%                    | 2.35E+04            | 2.92E-01           | 1.70E+05            | 1.717E-06              |
| 110: 47 to 1               | 5000                     | 0.617                     | 3.83E-04                | 1.92E+00                      | 2936                        | 122                         | 95.80%                    | 5.39E+03            | 6.24E-02           | 2.21E+05            | 2.82E-07               |
| 110: Hwy to 228th St.      | 3334                     | 0.617                     | 3.83E-04                | 1.28E+00                      | 5687                        | 237                         | 95.80%                    | 6.90E+03            | 8.06E-02           | 1.46E+05            | 5.51E-07               |
| 110: 228th St. to 405      | 4212                     | 0.617                     | 3.83E-04                | 1.61E+00                      | 6282                        | 262                         | 95.80%                    | 9.72E+03            | 1.12E-01           | 2.02E+05            | 5.56E-07               |
| 405: 710 to 110            | 8690                     | 0.617                     | 3.83E-04                | 3.33E+00                      | 6155                        | 256                         | 95.80%                    | 1.90E+04            | 2.27E-01           | 5.63E+05            | 4.04E-07               |
| 1: 103 to 110              | 5313                     | 0.617                     | 3.83E-04                | 2.94E+00                      | 3053                        | 127                         | 95.80%                    | 5.96E+03            | 6.90E-02           | 1.53E+05            | 4.52E-07               |
| 1: 710 to 103              | 1565                     | 0.617                     | 3.83E-04                | 6.00E+01                      | 4990                        | 208                         | 95.80%                    | 2.87E+03            | 3.32E-02           | 5.34E+04            | 6.22E-07               |
| 47: 110 to Harbor          | 928                      | 0.617                     | 3.83E-04                | 3.56E+01                      | 3907                        | 163                         | 95.80%                    | 1.33E+03            | 1.54E-02           | 2.02E+04            | 7.62E-07               |
| 47: Harbor to Helm Lift Bridge | 5856                  | 0.617                     | 3.83E-04                | 2.25E+00                      | 5594                        | 233                         | 95.80%                    | 1.20E+04            | 1.39E-01           | 1.87E+05            | 7.44E-07               |
| 103: Helm Lift Bridge to end | 4260                 | 0.617                     | 3.83E-04                | 1.63E+00                      | 7597                        | 317                         | 95.80%                    | 1.19E+04            | 1.38E-01           | 1.29E+05            | 1.07E-06               |

3.3.3. Receptors

Modeled source and receptor locations require terrain elevation data, in meters above sea level. Terrain elevation data for these locations are obtained using NED data for the area encompassing the modeled freeways and receptors. A total of 6552 receptors are modeled in the easting range of 377,000 and 391,200 meters and in the northing range of 3,732,000 and 3,750,000 meters. The receptors are spaced 200 meters apart and extend approximately three kilometers in each direction from the outermost roadways of
concern. This area is an ideal choice as it encompasses levels of significant cancer risk as are necessary for the population analysis portion of this study. For each receptor, terrain elevations are extracted from the NED files using USEPA’s AERMAP program (version 09040) with 1/3rd arc-second resolution (USEPA, 2004).

### 3.3.4. Meteorological Data

One of the most important inputs to AERMOD is meteorological data. USEPA’s definition of preferred meteorological data includes the most recent five years of National Weather Service (NWS) data or at least one year of site-specific data. At the time of this study, this condition is satisfied using 2006 through 2010 Automated Surface Observing Station (ASOS) data collected at the most site-appropriate airport, or from using one year or more of site-specific data (if available). From Section 8.3.1.2 of the Guideline on Air Quality Models:

a. Five years of representative meteorological data should be used when estimating concentrations with an air quality model. Consecutive years from the most recent, readily available 5-year period are preferred. The meteorological data should be *adequately representative*, and may be site specific or from a nearby NWS station. Where professional judgment indicates NWS-collected ASOS (automated surface observing stations) data are inadequate [for cloud cover observations], the most recent 5 years of NWS data that are observer-based may be considered for use.
The use of 5 years of NWS meteorological data or at least 1 year of site specific data is required. If one year or more (including partial years), up to five years, of site specific data is available, these data are preferred for use in air quality analyses. Such data should have been subjected to quality assurance procedures as described in subsection 8.3.3.2. (USEPA, 2005).

In the AERMOD analyses, three years (2005 through 2007) of Long Beach site-specific meteorological data are used. This data was developed by the South Coast Air Quality Management District (SCAQMD). These are the preferred data to be used in AERMOD for modeling the Long Beach area. The SCAQMD developed the Long Beach meteorological data by using the USEPA AERMET program (SCAQMD, 2009). Required data inputs to AERMET are: surface meteorological data, twice-daily soundings of upper air data, and the micrometeorological parameters surface roughness, albedo, and Bowen ratio. AERMET creates the model-ready surface and profile data files required by AERMOD. A three-year wind rose of the AERMOD-ready meteorological data sets used in this study is shown in Figure 3.5.
Figure 3.5: Long Beach 3-year Wind Rose
3.3.5 AERMOD Input Control Options

The AERMOD model is run with the following control options:

- 3-year period average air concentrations
- Regulatory defaults
- Flagpole receptors
- Urban dispersion coefficients (URBANOPT)

An optional FLAGPOLE parameter specifies the height of receptors above local ground level. If not specified, a default value of 0.0 meters is assumed. In this case, a value of 1.5 meters is assumed, as this is the average measurement above ground of an adult nose or mouth, where DPM would be inhaled.

It is determined that Long Beach area freeway emission sources should be modeled with urban dispersion coefficients. This option is available as a way to account for increased dispersion due to an urban heat island effect. If not specified as urban, a rural classification is assumed. In most cases, an examination of land use and/or population density is sufficient in determining whether a study area is classified as urban. If more than 50% of the surrounding area is urban and developed, then an urban classification is supported. The urban option may also apply if the population density in the area is more than 750 people per square kilometer (USEPA, 2005). It is also recommended that all sources within an urban complex should be defined as urban, regardless of land use and population findings (USEPA, 2009). Since this study concerns
freeways that are within the Los Angeles/Long Beach/Santa Ana Metropolitan Statistical Area (MSA), the study area is automatically classified as urban.

The URBANOPT option requires a population estimate and an input surface roughness length. The AERMOD URBANOPT control option is used with urban population based on the 2010 Long Beach, CA city population (approximately 475,000) (USEPA, 2009). A default surface roughness of 1.0 meter is also specified. This is an average value calculated to be appropriately applied to most cities (USEPA 2004).

3.3.6 Output Options

Consistent with the long-term averages used to calculate cancer risks from air pollution exposures, the period output option is used in this study. This provides an output file with three-year average air concentrations, which corresponds with the three years of site-specific meteorological data described in section 3.3.4. This output file also provides the data necessary for preparing air concentration isopleths.

3.4 Population Analysis

To determine whether injustices are occurring, demographic data is examined from the U.S. Census in relation to the modeling results. Golden Software’s Surfer mapping software is utilized, with kriging gridding algorithms, to generate isopleths showing the areas with excess cancer risk of 100, 200, 300, 400, and 500 per million. These values are chosen for several reasons. First, the even increments of risk values are appropriate for further population analysis. The lowest risk value, 100 per million excess
cancer risk, extends away from the freeways a reasonable distance, without extending so far as to warrant questions of accuracy of the model.

The excess cancer risk areas are based on the cancer unit risk value for DPM as developed by the CARB (1998), which is 3.0E-04 (µg/m³)⁻¹. In essence, excess cancer risk is the product of the calculated DPM air concentration (in µg/m³) produced by the model and the aforementioned DPM unit risk value. This equates to DPM air concentrations of 0.33, 0.67, 1.00, 1.33, and 1.67 µg/m³ for the 100, 200, 300, 400, and 500 per million cancer risk zones, respectively. Isopleths depicting these cancer risk zones are generated in Surfer as shapefiles to be used in ArcGIS where the isopleths are analyzed in conjunction with the census data.

The population analysis begins with a calculation of the total population within each isopleth. The proportions of the population categorized by race for each risk isopleth are also calculated. Demographic data used in this study is 2010 U.S. Census Summary File 1 race data at the block level. This dataset includes population counts for seven race categories: white alone, black or African American alone, American Indian and Alaska native alone, Asian alone, native Hawaiian and other Pacific Islander alone, some other race alone, and two or more races.

Since the shapes of census units and the shapes of the isopleths do not conform to one another, a method called areal weighted interpolation is used to determine the population counts within the isopleths. In areal weighted interpolation, the data associated with the intersected units is recalculated based on the portion that lies inside the area of interest (Maantay, 2005). In doing this with census data, the assumption is made that data is evenly spread within the census units. Since this is probably not the
case, there will be some error in areal weighted interpolation, as it is a method of approximation. Goodchild and Lam (1980) found that this potential pitfall may be lessened in severity by using sample data consisting of the smallest units possible, which is the case in this study. After performing the interpolation for the race data, the proportion of each race is calculated for each of the isopleths so that they may be compared to each other as well as with the proportions for Los Angeles County as a whole.

In addition to race, median household income for each of the excess cancer risk isopleths is examined. The most recent U.S. Census data available at the time of this study is median household income from the 2010 American Community Survey 5-year estimates. This data is used at the smallest scale available, which in this case is at the census tract level. Once again, the census units and the isopleths do not conform to one another, so the census tracts are split so that they conform to the isopleths. After doing so, a weighted average is found for the median income for each of the excess cancer risk isopleths. The results for the isopleths are compared to one another as well as with the average median income for all of Los Angeles County.
Chapter 4 Results

4.1 Dispersion Modeling

The results of the modeling indicate that large areas are exposed to excess cancer risk from HHDT DPM. When cumulated, areas with 100, 200, 300, 400, and 500 per million excess cancer risk total 18.72 square miles. A list of the individual risk categories and their respective areas is available in Table 4.1.

Table 4.1: Excess Cancer Risk Areas

<table>
<thead>
<tr>
<th>Excess Cancer Risk</th>
<th>Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>100 per million</td>
<td>10.85 square miles</td>
</tr>
<tr>
<td>200 per million</td>
<td>3.44 square miles</td>
</tr>
<tr>
<td>300 per million</td>
<td>1.76 square miles</td>
</tr>
<tr>
<td>400 per million</td>
<td>0.86 square miles</td>
</tr>
<tr>
<td>500 per million</td>
<td>1.81 square miles</td>
</tr>
</tbody>
</table>

When layered on top of aerial imagery, the 100 per million excess cancer risk area looks to cover large portions of Long Beach and areas surrounding the roads including residential neighborhoods, as seen along with the other isopleths in Figure 4.1. In some areas the 100 per million risk area extends outward from the freeways three quarters of a mile or more.

On the other end of the spectrum, the 500 per million excess cancer risk areas are much smaller and mostly hug the freeways. One prominent characteristic of the 500 per million isopleths is a pattern of circles that follow the length of the freeway, particularly along Hwy 47 and Hwy 103. These are most likely due to slight variability in terrain.
The 500 per million risk areas seem to include some areas that might include residences, industrial facilities, or businesses. This is especially concerning in consideration of the significantly high risk level.
Figure 4.1: Excess Cancer Risk Isopleths
The other excess cancer risk areas of 200, 300, and 400 per million extend outward past the 500 per million areas, yet do not extend nearly as far as the 100 per million isopleths. Nevertheless, these isopleths represent a significant risk and cover populated areas.

The highest levels of modeled ECR exceed 1000 per million. However, these areas are very small and mostly located directly above the freeways and other non-populated areas, so they are not used in the following population analysis.

4.2 Population Analysis

Further analysis of the excess cancer risk areas reveals some interesting trends. The results are as follows.

4.2.1 Population Counts

To begin analyzing the population within the five isopleths, a basic count of the total population is calculated as well as basic counts for each of the seven race categories. The results of these calculations are listed in Table 4.2. The total population counts reveal that significant numbers of people live within even the smallest risk areas. Specifically, the total population counts are 5,189 in the 500 per million risk area, 2,283 in the 400 per million risk area, 6,671 in the 300 per million risk area, 17,181 in the 200 per million risk area, and 63,234 in the 100 per million risk area.
Table 4.2: Race Population Counts within Risk Isopleths

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>White</th>
<th>Black or African American</th>
<th>American Indian and Alaskan Native</th>
<th>Asian</th>
<th>Native Hawaiian and Other Pacific Islander</th>
<th>Some Other Race</th>
<th>Two or More Races</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>500 per Million</strong></td>
<td>5189</td>
<td>1479</td>
<td>746</td>
<td>32</td>
<td>1095</td>
<td>110</td>
<td>1499</td>
<td>228</td>
</tr>
<tr>
<td><strong>400 per Million</strong></td>
<td>2283</td>
<td>674</td>
<td>320</td>
<td>21</td>
<td>467</td>
<td>73</td>
<td>621</td>
<td>107</td>
</tr>
<tr>
<td><strong>300 per Million</strong></td>
<td>6671</td>
<td>2066</td>
<td>868</td>
<td>55</td>
<td>1625</td>
<td>152</td>
<td>1577</td>
<td>328</td>
</tr>
<tr>
<td><strong>200 per Million</strong></td>
<td>17181</td>
<td>5075</td>
<td>2051</td>
<td>111</td>
<td>4698</td>
<td>381</td>
<td>3992</td>
<td>873</td>
</tr>
<tr>
<td><strong>100 per Million</strong></td>
<td>63234</td>
<td>21001</td>
<td>7566</td>
<td>476</td>
<td>12366</td>
<td>984</td>
<td>17673</td>
<td>3168</td>
</tr>
</tbody>
</table>

4.2.2 Population Distribution

Figures 4.2-4.9 display the spatial distribution for the total population as well as for each of the race categories. It should be noted that the population counts for the races varies widely, as seen in Figure 4.10. It is apparent in Figure 4.2 that while population density is relatively low in blocks around the ports, the same cannot be said for blocks surrounding the freeways. There are many densely populated blocks well within the risk isopleths, particularly around the northern portion of the I-110, portions of I-405, and areas west of I-710. Figure 4.3 shows a similar population distribution for white population. Figure 4.4 reveals highest Black or African American population density in areas north of I-405, which are not within the risk isopleths. The densest population for this race category within the isopleths appears to be in blocks surrounding I-110 and southwest of the I-710 and I-405 interchange. Figure 4.5 shows that the blocks with highest American Indian and Alaska Native population counts seem to be dispersed
randomly, with several more highly-populated blocks within the isopleths nearest I-110 and west of I-710. In Figure 4.6, the Asian population is concentrated mainly in blocks surrounding and to the east of I-110 as well as west of I-710, including areas within the risk isopleths. Figure 4.7 shows Native Hawaiian and Other Pacific Islander populations distributed similarly to Asian populations. In Figure 4.8, Some Other Race population in this area appears to be most densely populated in clumps of blocks between the freeways and sometimes within the risk isopleths, surrounding I-110, west of the northern portion of I-710, east of I-710 but mostly out of the risk isopleths, and northeast of the freeways and out of the risk isopleths. Finally, in Figure 4.9 the Two or More Races population seems to be distributed fairly randomly, with some of the more densely populated blocks lying within the risk isopleths surrounding I-110, I-405, and west of I-710.
Figure 4.2: Total Population and Risk Isopleths
Figure 4.3: White Population and Risk Isopleths

<table>
<thead>
<tr>
<th>Excess Cancer Risk</th>
<th>White Population</th>
</tr>
</thead>
<tbody>
<tr>
<td>100 per million</td>
<td>0 - 25</td>
</tr>
<tr>
<td>200 per million</td>
<td>26 - 74</td>
</tr>
<tr>
<td>300 per million</td>
<td>75 - 159</td>
</tr>
<tr>
<td>400 per million</td>
<td>160 - 346</td>
</tr>
<tr>
<td>500 per million</td>
<td>347 - 844</td>
</tr>
</tbody>
</table>
Figure 4.4: Black or African American Population and Risk Isopleths
Figure 4.5: American Indian and Alaska Native Population and Risk Isopleths
Figure 4.6: Asian Population and Risk Isopleths
Figure 4.7: Native Hawaiian and Other Pacific Islander Population and Risk Isopleths

<table>
<thead>
<tr>
<th>Excess Cancer Risk</th>
<th>Native Hawaiian and Other Pacific Islander Population</th>
</tr>
</thead>
<tbody>
<tr>
<td>100 per million</td>
<td>0 - 3</td>
</tr>
<tr>
<td>200 per million</td>
<td>4 - 10</td>
</tr>
<tr>
<td>300 per million</td>
<td>11 - 23</td>
</tr>
<tr>
<td>400 per million</td>
<td>24 - 46</td>
</tr>
<tr>
<td>500 per million</td>
<td>47 - 86</td>
</tr>
</tbody>
</table>
Figure 4.8: Some Other Race Population and Risk Isopleths
Figure 4.9: Two or More Races Population and Risk Isopleths
4.2.3 Population Percentages

A table and graph displaying percentages of all seven race categories exposed to the excess cancer risk levels are available in Table 4.3 and Figure 4.10, respectively. In addition, Figures 4.11-4.17 reveal trends for each race category individually. These graphs show each race category’s percentage of the total population in relation to each risk isopleth. For comparison, statistics regarding all of Los Angeles County are also included.

Table 4.3: Race Percentages within Risk Isopleths

<table>
<thead>
<tr>
<th></th>
<th>White</th>
<th>Black or African American</th>
<th>American Indian and Alaskan Native</th>
<th>Asian</th>
<th>Native Hawaiian and Other Pacific Islander</th>
<th>Some Other Race</th>
<th>Two or More Races</th>
</tr>
</thead>
<tbody>
<tr>
<td>500 per Million</td>
<td>28.50%</td>
<td>14.38%</td>
<td>0.62%</td>
<td>21.10%</td>
<td>2.12%</td>
<td>28.89%</td>
<td>4.39%</td>
</tr>
<tr>
<td>400 per Million</td>
<td>29.52%</td>
<td>14.02%</td>
<td>0.92%</td>
<td>20.46%</td>
<td>3.20%</td>
<td>27.20%</td>
<td>4.69%</td>
</tr>
<tr>
<td>300 per Million</td>
<td>30.97%</td>
<td>13.01%</td>
<td>0.82%</td>
<td>24.36%</td>
<td>2.28%</td>
<td>23.64%</td>
<td>4.92%</td>
</tr>
<tr>
<td>200 per Million</td>
<td>29.54%</td>
<td>11.94%</td>
<td>0.65%</td>
<td>27.34%</td>
<td>2.22%</td>
<td>23.24%</td>
<td>5.08%</td>
</tr>
<tr>
<td>100 per Million</td>
<td>33.21%</td>
<td>11.97%</td>
<td>0.75%</td>
<td>19.56%</td>
<td>1.56%</td>
<td>27.95%</td>
<td>5.01%</td>
</tr>
<tr>
<td>All L.A. County</td>
<td>50.28%</td>
<td>8.73%</td>
<td>0.74%</td>
<td>13.72%</td>
<td>0.27%</td>
<td>21.80%</td>
<td>4.47%</td>
</tr>
</tbody>
</table>
Figure 4.10: Percentages of Races within Risk Isopleths and All Los Angeles County
Figure 4.11: White Population Percentages
Figure 4.12: Black or African American Population Percentages
Figure 4.13: American Indian and Alaskan Native Population Percentages
Figure 4.14: Asian Population Percentages
Figure 4.15: Native Hawaiian and Other Pacific Islander Population Percentages

![Bar chart showing the percentage of Native Hawaiian and Other Pacific Islander population in different Excess Cancer Risk Areas and All of Los Angeles County.](chart.png)
Figure 4.16: Some Other Race Population Percentages
White is the leading population in most of the risk areas, with the exception of the most severe cancer risk area and closest to the freeway at 500 per million, where the population identified as “some other race” shows slightly higher percentage. Compared to the demographics in Los Angeles County, the percentage of white population is much lower (around 30% in this area vs. 50% in Los Angeles County), while most non-white groups show slightly higher percentage. Notably, Asian population in the area is about 20-27% compared with 13.72% in L.A. County, and black/African Americans are about 12-14% of the population in the area, compared with 8.7% in L.A. County.

Upon first glance the population percentages for the cancer risk areas do not seem to vary dramatically, but the directions in which they fluctuate show some interesting...
trends. With the exception of a dip in population percentage at the 200 per million risk level, the white population proportion rises as the level of risk decreases, as can be seen in Figure 4.11. Specifically, white is about 28.5% of the population in the area with 500 per million ECR and its proportion within the population increases to 33.2% in the area with 100 per million ECR.

As seen in Figure 4.14 Asian percentage of the population follows a similar trend, generally rising as the level of risk decreases, with 21.10% closest to the freeways at the 500 per million risk level and 27.34% further from the freeways within the 200 per million ECR area. Exceptions are a very minor dip in percentage at the 400 per million risk level (from 21.10% within 500 per million ECR down to 20.46% within 400 per million ECR) and a more dramatic drop off at the 100 per million risk level, with population percentage of 19.56% Asian.

Figure 4.17 shows that the population of two or more races also increases in proportion slightly but steadily with a decrease in risk level, with the exception of a dip in percentage at the 100 per million ECR level. Specifically, the population percentage of two or more races is 4.39% within the most severe areas of 500 per million ECR, increasing to 4.69%, 4.92%, and 5.08% within the 400 per million, 300 per million, and 200 per million ECR areas respectively, and then dipping to 5.01% within the 100 per million ECR area.

In contrast, the “some other race” population shows a fairly dramatic decrease in proportion with a decrease in risk level, with the exception of a jump up at the 100 per million risk level (Figure 4.16). Its percentage in the population decreases from 28.9% in
the zone of 500 per million ECR to 23.2% in the 200 per million ECR zone, with a jump to 27.95% in the 100 per million ECR zone.

Though less dramatically so, the black population proportion also shows a decrease as the risk level decreases, with a very slight increase only at the 100 per million ECR level as seen in Figure 4.12. In the 500 per million ECR area the percentage of black population is 14.38% and drops with decreasing risk level to 11.94% within the 200 per million ECR zone.

As seen in Figure 4.15, the Native Hawaiian and other Pacific Islander race category also steadily though slightly decreases in coordination with the decreasing risk level. The exception is at the most severe risk level of 500 per million level ECR, where this race category proportion starts off lower than at most of the other risk levels at 2.12%. However, the population percentage increases to 3.20% at the 400 per million ECR level and then decreases in conjunction with decreasing risk to 1.56% at the 100 per million ECR level.

The proportion of American Indian and Alaska Native population in Figure 4.13 shows less regularity, starting with 0.62% of the total population within the 500 per million ECR zone. The population percentage increases to 0.92% at the 400 per million ECR level, then decreases to 0.82% and 0.65% within the 300 per million and 200 per million ECR zones respectively, seeming to show a coincidence of decreasing population percentage with decreasing level of risk. However, the percentage rises again at the 100 per million risk level, with 0.75% of the total population being American Indian and Alaska Native.
4.2.4 Median Household Income

The distribution of the median household income levels along with the risk isopleths are mapped in Figure 4.18. In general, the lowest income levels seem to occur right around the middle of the ports and in areas to the north that are mainly industrial. The higher income levels occur on the coast right around the ports as well as in select inland areas. These include a tract in the Bixby Knolls area northeast of the I-405/I-710 interchange and in several tracts around I-110.

It can be seen that no census tracts with the highest median family income grouping of $117,906-$242,935 fall within the ECR isopleths. Some tracts with the second-highest grouping of $76,980-$117-905 do fall within the isopleths, and even within the highest risk level of 500 per million ECR. This is especially the case near the coast and in areas around I-110 north of CA-1 and around the I-405/I-710 interchange. There are not any readily apparent trends regarding median household income in relation to the ECR isopleths when simply visually analyzing the data in Figure 4.18.
Figure 4.18: Median Household Income and Risk Isopleths
Further analysis of median household income within the ECR isopleths represented as weighted averages reveal some interesting trends, as can be seen in Table 4.4 and Figure 4.19.

Table 4.4: Median Household Income within Risk Isopleths and in All L.A. County

<table>
<thead>
<tr>
<th>Income</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>500 per Million ECR</td>
<td>$41,965</td>
</tr>
<tr>
<td>400 per Million ECR</td>
<td>$52,575</td>
</tr>
<tr>
<td>300 per Million ECR</td>
<td>$50,668</td>
</tr>
<tr>
<td>200 per Million ECR</td>
<td>$48,661</td>
</tr>
<tr>
<td>100 per Million ECR</td>
<td>$43,642</td>
</tr>
<tr>
<td>All L.A. County</td>
<td>$60,343</td>
</tr>
</tbody>
</table>

Figure 4.19: Median Household Income Graph
The median income in all of the risk level areas ranges from $41,965 to $52,575 and is less than that for all of Los Angeles County ($60,343) in every case. The 500 per million ECR area has a population with median household income of $41,965. The 400 per million ECR area shows a jump in income with a median household income of $52,575. Then the income drops with decreased ECR, with median household income of $50,668 at the 300 per million ECR level, $48,661 at the 200 per million ECR level, and $43,624 at the 100 per million level.

The findings of this study reveal significant health risks as well as some disparity regarding race groups exposed to DPM. The proportion of white population is much lower within my study area than in Los Angeles County in general, while other minority races such as Asian and Black or African American are higher. In addition, some race groups such as Black or African American are higher in proportion within the highest cancer risk zones, while others, such as White population, show the opposite. Median family income does not seem to show an expected lower income coinciding with higher risk, since with the exception of the highest risk level, income actually increases with higher cancer risk. Overall, however, median family income within this study area is lower than in Los Angeles County as a whole. The significance of these trends are discussed in the next chapter.
Chapter 5 Discussion and Conclusions

This study brings several issues to light. First, by modeling HHDT emissions from freeways adjacent to the POLA and POLB, it is apparent that the nearby communities are being exposed to a significant risk of cancer from pollution. By the use of GIS to analyze census data within specified risk zones based on the modeling, this study reveals evidence of racial disparities. The study area has higher percentages of minority races and lower percentages of white population than in all of Los Angeles County. In particular, black, some other race, and native Hawaiian/Pacific Islander populations have increasing percentages with increasing levels of ECR, with white and two or more race populations showing the opposite trend.

In this chapter, these findings are discussed in further detail. The limitations of this study and the potential for future research are also identified.

5.1 Excess Cancer Risk

The results of the modeling of HHDT DPM emissions from Los Angeles port-adjacent freeways indicate large areas exposed to concerning levels of pollution. The lowest-level impact zone represented in this study of 100 per million ECR covers large swaths of populated areas, affecting over 63,000 residents. This amounts to approximately six residents within the 100 per million risk zone alone predicted to develop cancer resulting from DPM emissions from the modeled freeways. To put this 100 per million level of ECR in perspective, this is ten times the California Proposition 65 (Safe Drinking Water and Toxic Enforcement Act of 1986) “significant risk” of 10 per
million, and one hundred times the 1 per million level at which the USEPA usually recommends taking action (USEPA, 1999).

Residents within the identified risk zones should be concerned about DPM exposure. While the risks described in this study are alarming, they are even more so when considering that this study only examines ECR regarding DPM from HHDTs on select freeways. There are many other sources of DPM near to and within the study area that were not accounted for in this study that most likely compound the cancer risk to area residents. Some other significant sources of DPM include idling trucks at the ports, cargo handling equipment, HHDT traffic on smaller area roadways, trains, and harbor craft (CARB, 2006).

5.2 Environmental Justice: Race

This study’s analysis of race within the ECR zones seems to support the notion that a disparity is occurring. This is especially evident when comparing the racial makeup of the population within all risk zones compared to the racial makeup of Los Angeles County as a whole. The population within the ECR zones is much more diverse than in all L.A. County, where white population is a majority with over 50% of the total, with other minority races each representing less than 25% of the total population. Within the ECR zones, white is still highest percentage of the population in four out of five cases, but by a much narrower margin, as it never exceeds 35% of the total. Percentage of minority races with the ECR zones, on the other hand, exceed their corresponding percentages for all of L.A. County in nearly all cases.
Evidence of racial disparity is also apparent when comparing the ECR risks against each other. The white and two or more race populations mostly decrease in percentage with higher risk level. Minority populations of black, some other race, and native Hawaiian/Pacific Islander populations show an opposite trend, with higher population percentages corresponding with higher risk levels. Asian and American Indian/Alaskan Native populations did not show any readily apparent trends when examining percentages within the ECR zones.

There are several possible explanations as to why these inequities are occurring. First, the area around the POLA and POLB has a history of being racially diverse, especially since the 1950’s. This is largely due to the white middle class moving outward to the suburbs, leaving poorer Latino, Asian, and black populations in the inner city and amongst more industrial activity (such as that which takes place around the ports) where there is likely to be more pollution (Pulido, 2000). Pulido described, “As whites moved outward, Chicanos, African Americans, Japanese Americans, Chinese Americans and the remnant Indian population were relegated to San Pedro, Watts, and the central city (including downtown and the east side).” This segregation was further enforced by mechanisms such as homeowners associations. Avila (1998) stated that the decentralization of the city after World War II also resulted in a decentralization of the economy, with aspects such as retail sales plundering downtown and rising rapidly in the suburbs. As time progressed, new immigrants would not be able to afford to live in the white suburbs, and would be forced to live in the less-expensive sections of town already largely occupied by minority races.
Ironically, Avila pointed out that the pollution-causing freeways themselves also acted as a catalyst, facilitating suburbanization. What’s more, he described the actual creation of the freeways as an injustice, as many were built through poor, non-white (particularly Chicano) neighborhoods, causing severe disruption to the communities. As to the “which came first” question applying to environmental justice cases, it seems in this case that the source of pollution was unfairly placed within existing minority communities, and that this disparity has possibly been exacerbated over time by suburbanization and results of environmental racism.

5.3 Environmental Justice: Income

The results of this study support the occurrence of a disparity when comparing income within my study area to income in all of Los Angeles County. The incomes within the modeled ECR zones range between $41,965 and $52,575. Even the high end of that range is significantly lower than the median of $60,343 for Los Angeles County.

However, when comparing the median incomes of the individual ECR zones against each other, there is not evidence of a disparity. While the lowest income level of $41,965 does occur within the highest risk zone, the second highest risk zone of 400 per million ECR sees the highest median income, and from there the income levels actually decrease with reduced risk. This correlation between median income and the 400, 300, 200, and 100 per million ECR zones is contrary to what is expected for there to be an occurrence of environmental injustice.

These results could be explained in part by the fact that the census data used in this study was aggregated to the census tract level. Perlin et al. (1995) discussed the
pitfalls of using aggregated data, and note that smaller units are likely to provide more accurate results. If income data aggregated at a smaller level had been available, it is possible that results may have shown a disparity.

Of course, another possibility is that there is actually not a disparity. The census tracts that bear the highest median household incomes are right along the coast, which in Southern California is nearly always considered a desirable place to reside, and further north around neighborhoods such as Bixby Knolls and Carson. These communities are located within a corridor of suburbs that sits between downtown Los Angeles and the coast. Some other communities adjacent to Bixby Knolls and Carson that sit in the same corridor are Torrance and Lakewood, which Pulido (2000) and Avila (1998) identified as some of the most prominent early suburbs inhabited by mainly middle-class white population. Perhaps these communities are still considered desirable for the same reasons the white middle-class flocked to them in the first place. They are far enough away from both downtown and the industrial activities near the ports to offer a pleasing family-friendly lifestyle, yet close enough to the conveniences of urban Los Angeles.

In another light, maybe those in the working middle class do not want to live far from freeways. Los Angeles commutes to and from work are notoriously treacherous. It is possible that those with occupations outside of their communities may actually view easy freeway access as an amenity.

5.4 Conclusions

This study adds to the previous research by furthering evidence of the occurrence of environmental inequity, particularly in the Los Angeles area. It is one of few
environmental justice studies to use the method of modeling to estimate exposures, especially in regard to freeway traffic and goods movement. This study also adds to previous modeling and environmental justice literature by the addition of calculating ECR, giving an actual estimate of health outcomes. Combining this methodology with analysis of race and income to examine environmental inequities is a new step in environmental justice research.

While this study gives a preliminary look at environmental justice issues relating to freeway pollution, it also leads to many opportunities for further research. One possibility could include an examination of environmental inequities resulting from pollution from traffic on smaller roads in the area or other sources of DPM. Further study could also delve deeper into the injustices revealed in this study. For example, perhaps more refined income data could be collected, or different population classifications such as ethnicities could be analyzed. Populations identifying as Hispanic, for instance, could lead to more insight to injustices in this study area. More statistical analyses such as a T test could be employed to assess whether injustices are occurring at a statistically significant level. A more detailed investigation into the history and motives of the environmental injustices revealed in this study could also offer useful insight as to the reason for disparities so that they can hopefully be amended and prevented in the future.

It should also be noted that the modeling performed in this study provides a predictive measurement of actual conditions. There is currently no direct measurement technique for DPM (CARB, 2006). While using a predictive model is the best method for analysis in this case, it does lend to potential uncertainty pertaining to DPM
concentrations. There is also some uncertainty associated with the cancer risk factor, which is also an estimate. Future research might include validation of the modeling results or new pollution analyses as improved monitoring and sampling methods or models are developed, or validation of the cancer risk estimates as health data becomes available.

Still, the results of this study suggest that, going forward, policy changes and mitigation ought to play an important role in improving the amount of pollution resulting from goods movement. There has already been some headway in reducing port-related pollution and the resulting health risks, such as the implementation of the San Pedro Bay Ports Clean Air Action Plan (CAAP), and more specifically the Clean Truck Program (CTP) of 2008. One of the aims of the CTP is to phase out older (pre-1989) diesel trucks, which generally spew more emissions than newer trucks. This is a step in the right direction, but the damage may already have been done for long-time residents, and there is still room for improvement. Newer diesel trucks may still emit harmful amounts of pollution, especially if the volume of trucks entering and exiting the ports continues to grow. Further improvements could include the use of alternative fuels, such as biodiesel (Weinhold, 2002). Though they look promising, there is still a need for more research as to the health effects of diesel fuel alternatives (Swanson et al., 2007).

The attention given to the issues surrounding diesel truck pollution and environmental injustices in the last couple decades is encouraging. This heightened awareness may result in further work toward cleaner air and a more just society. Regardless of demographics, we all deserve the right to clean air.
Sources


http://www.arb.ca.gov/toxics/dieseltac/de-fnds.htm (last accessed 20 November 2010).


