IEc

Assessing the Mortality Burden of Air Pollution in Lima-Callao

Final Report | May 14, 2021

prepared for:

U.S. Environmental Protection Agency

prepared by:

Industrial Economics, Incorporated

2067 Massachusetts Avenue

Cambridge, MA 02140

617/354-00074

INDUSTRIAL ECONOMICS, INCORPORATED

TABLE OF CONTENTS

ACKNOWLEDGEMENTS

CHAPTER 1 | INTRODUCTION
1.1 Background 1-1
1.2 Analytic Overview 1-2
1.2.1 Research Objectives 1-2
1.2.2 Analytic Steps 1-3
1.3 Report Organization 1-3

CHAPTER 2 | SCENARIO DEVELOPMENT

CHAPTER 3 | EMISSIONS ESTIMATION
3.1 Baseline Emissions Inventory 3-1
3.2 Accounting for Non-Compliance 3-3
3.3 Emissions Modeling Results 3-4

CHAPTER 4 | AIR QUALITY DATA AND MODELING
4.1 Air Quality Surfaces 4-1
4.1.1 Monitor Surfaces 4-1
4.1.2 Satellite Surfaces 4-3
4.1.3 Summary of Air Quality Surfaces 4-3
4.2 Air Quality Modeling 4-5

CHAPTER 5 | MORTALITY BURDEN ESTIMATION AND VALUATION
5.1 Overview of Approach 5-1
5.2 Data Inputs 5-2
5.2.1 Population 5-2
5.2.2 Baseline Mortality Incidence 5-2
5.2.3 Health Impacts Functions 5-2
5.2.4 Valuation 5-4

CHAPTER 6 | RESULTS
6.1 Total $PM_{2.5}$ Attributable Mortality Burden 6-1
6.2 Transport Attributable $PM_{2.5}$ Mortality Burden 6-2
6.3 $PM_{2.5}$ Mortality Burden from Non-Compliant Vehicles 6-3

CHAPTER 7 | SUMMARY OF FINDINGS
7.1 Summary of Findings 7-1
7.2 Uncertainties 7-2
7.3 Next Steps 7-3

REFERENCES

APPENDICES
Appendix A | Supplemental Emissions Estimation Results
Appendix B | Satellite Measurements and Processing
Appendix C | Health Impact Estimation
Appendix D | District-Level Results

ACKNOWLEDGEMENTS

This report was prepared by Industrial Economics, Incorporated (IEc) for the U.S. Environmental Protection Agency (USEPA) Office of Air Quality Planning and Standards (OAQPS), under USEPA contract EP-D-14-032 as part of EPA's Megacities Partnership program in Lima, Peru. Consistent with the Megacities Partnership approach to air quality management, this project was a collaborative effort between USEPA, IEc, and local partners at the Peruvian Ministry of Environment (MINAM). In particular, IEc acknowledges critical support from Luis Antonio Ibañez Guerrero, Katyuska Barja Paredes, and Guisselle Castillo Coila of MINAM, who provided key data sets, valuable local institutional knowledge, and helpful advice. We also thank USEPA staff including the Lima Megacities Project Manager Paul Almodóvar as well as a Richard Baldauf, Ali Kamal, and Ken Davidson for their input on the analysis and helpful feedback on earlier drafts of this report.

CHAPTER 1 | INTRODUCTION

The United States Environmental Protection Agency (USEPA) and the Ministry of the Environment of Peru (MINAM) are collaborating under the USEPA Megacities Partnership to:

- Strengthen air quality management in the Lima-Callao region through policy development, community outreach, and stakeholder engagement;
- Support air quality monitoring initiatives; and
- Build technical capacity in Lima-Callao for scientific and economic analyses and communication planning in support of air quality management plan (AQMP) development.

This report presents results from assessments of the current overall mortality burden attributable to concentrations of fine particulate matter ($PM_{2.5}$) in the region. In addition to estimating total $PM_{2.5}$-attributable health burden with respect to premature deaths, we employ emissions inventories and reduced-form air quality modeling techniques to analyze the burden attributable to concentrations of $PM_{2.5}$ associated with emissions from on-road motor vehicles. We further evaluate the burden of a subset of these vehicles—those out of compliance with currently established emissions limits—and highlight the potential benefits associated with increased enforcement and expanded vehicle inspections and maintenance (I&M) programs.

1.1 BACKGROUND

The Lima-Callao metropolitan region is home to approximately 10 million people, nearly one-third of Peru's total population. This large and growing population is exposed to significant air pollutant concentrations due to emissions from sources such as motor vehicles. These exposures can be exacerbated by Lima-Callao's meteorological conditions, primarily the Humboldt ocean current and the Andes Mountains to the east. The Humboldt ocean current carries cold water north from the tip of South America, which lowers atmospheric temperatures and prevents the formation of rain clouds (Thiel et al. 2007). The Humboldt ocean current is also responsible for persistent fog in Lima-Callao. The fog, combined with the obstruction of warmer and more humid air masses from the Amazon, by the Andes, results in frequent air inversions in Lima-Callao. These air inversions trap ambient pollutants at the surface level, causing pollutants to accumulate rather than disperse via coastal winds. As a result, Lima-Callao is ranked among the most polluted cities in Latin America by the World Health Organization (WHO, 2016).

Transportation sources are responsible for much of the region's air pollution. Despite comprising one-third of the country's population, Lima-Callao is home to roughly two-thirds of Peru's vehicle fleet. In addition to the size of the vehicle fleet, its age plays a significant role in resulting air pollution (MINAM, 2018). According to surveys of registered vehicles from 2016-2019, approximately 34 percent of the on-road vehicles in Lima-Callao are greater than 15 years old. These older vehicles tend to have poor fuel economy and lack the emissions controls required of new vehicles. Based on emissions tests, MINAM partners note that many vehicles are non-compliant with national emissions standards; however, empirical estimates of non-compliance rates are currently limited.

To address emissions from the transportation sector, the Government of Peru has passed several laws and regulations concerning emissions standards and vehicle inspection requirements. For example, in 2008, Peru established the National System of Technical Vehicle Inspection, which is responsible for inspecting and testing vehicles for safety and compliance with emissions standards. More recently, Peru adopted the Euro 4 vehicle emissions standards for all new vehicles and is considering implementing Euro 6 standards. Because of the slow rate of turnover in the vehicle fleet—as shown by the prevalence of old vehicles in circulation—additional measures may be needed to address the sector's emissions. In this report, we provide insight into the potential magnitude of these on-road vehicle emissions and associated adverse health outcomes.

1.2 ANALYTIC OVERVIEW

In this section, we summarize our analytic approach to estimating the mortality burden associated with $PM_{2.5}$ concentrations in Lima-Callao. We first define our research objectives and then outline the analytic steps we follow in the remainder of the report.

1.2.1 RESEARCH OBJECTIVES

In close consultation with MINAM and USEPA, we developed three research objectives addressed in this report. First, we aim to quantify and value the premature deaths associated with overall ambient $PM_{2.5}$ concentrations in Lima-Callao. Second, we aim to quantify and value the premature deaths associated with emissions from Lima-Callao's on-road vehicles, to better understand how vehicles contribute to the overall burden of premature deaths. Third, we aim to quantify and value the premature deaths associated with emissions from non-compliant vehicles in the Lima-Callao on-road vehicle fleet, to help MINAM understand the potential health gains from focusing on the non-compliance issue. For each research objective, we consider annual impacts using data that best characterize recent conditions for air quality, population, baseline health, and other relevant data. In Chapter 7, we highlight additional areas of future research that could complement this report. We hope that the analytical framework IEc applied in this analysis will serve as a useful guide for addressing these research topics, including estimating the benefits of specific transportation emissions control measures.

1.2.2 ANALYTIC STEPS

Our methodology is comprised of five key steps:

- **Step 1: Scenario development.** Define the research objectives and the spatial and temporal scale of our analyses. Specify conditions under a “business-as-usual” or “baseline” scenario and under a “regulatory” scenario in which the proposed regulation is implemented. Based on these scenario definitions, develop baseline and regulatory air quality surfaces.
- **Step 2: Emissions estimation.** Develop or obtain emissions inventories for the transportation sector. Develop estimate of the fraction of non-compliant vehicles. Estimate the excess emissions associated with non-compliant vehicles in the Lima-Callao fleet. (Note: this step is not needed for assessing the total $PM_{2.5}$-attributable mortality burden.)
- **Step 3: Air quality modeling.** Obtain and process air quality data, such as satellite-based estimates and data from air quality monitors to characterize baseline conditions in Lima-Callao. Use air quality modeling methods to estimate the impact of vehicle emissions on ambient $PM_{2.5}$ concentrations.
- **Step 4: Health impact estimation.** Quantify premature deaths associated with $PM_{2.5}$ concentrations using BenMAP-CE and relevant datasets, including population, air quality, baseline mortality incidence, and concentration-response relationships from the epidemiological literature.
- **Step 5: Valuation.** Apply economic valuation estimates to quantified mortality values to characterize the $PM_{2.5}$-attributable mortality burden in monetary terms.

These steps are described in greater detail throughout the report.

1.3 REPORT ORGANIZATION

The remainder of this report is organized as follows:

- In Chapter 2, we briefly summarize our scenario development efforts, including defining baseline and regulatory air quality conditions needed for estimating $PM_{2.5}$-attributable mortality burden.
- In Chapter 3 we detail our methods for quantifying emissions from the on-road vehicle fleet, including accounting for empirically-derived estimates of non-compliance with emissions standards.
- In Chapter 4, we summarize available air quality data in Lima-Callao and methods for estimating changes in air quality stemming from emissions changes.
- In Chapter 5, we describe our methods for conducting health impact estimation and valuation using USEPA’s BenMAP-CE tool, including summaries of key data inputs such as population, baseline mortality incidence, health impact functions, and valuation estimates.

- In Chapter 6, we present the results of our health burden analyses, including an all-$PM_{2.5}$ mortality estimate, a transportation-attributable $PM_{2.5}$ mortality estimate, and an estimate associated with excess $PM_{2.5}$ mortality resulting from non-compliant vehicle emissions.
- In Chapter 7, we discuss the findings of this research and notable data and methodological limitations. We then provide recommendations for next steps to build upon this collaborative research effort.
- In Appendices A-D, we provide supplemental methods discussions and results beyond the primary estimates provided in the main text.

CHAPTER 2 | SCENARIO DEVELOPMENT

In this chapter, we define the scenarios assessed in the remainder of the report to estimate the number of premature deaths attributable to $PM_{2.5}$ concentrations in Lima-Callao. As described in Chapter 1, a key element of scenario development involves defining temporal and geographic scope. First, we focus on estimating *recent* mortality burden associated with ambient $PM_{2.5}$. Therefore, we employ datasets that best characterize conditions in recent years, including air quality, population, and baseline mortality incidence.[1] Second, we consider emissions, air quality, and associated health impacts in the Lima-Callao region. We work to employ spatially resolved datasets and report results at fine geographic resolutions (e.g., districts) where data allow.[2] Pollutant emissions, air quality, and health impacts outside of Lima-Callao are not considered in our analysis.

For regulatory benefit-cost analysis, we typically define *business-as-usual* and *regulatory* scenarios. In a forward-looking analysis of a proposed regulation, the *business-as-usual* scenario reflects conditions as they are now (or are expected to be in the future) without the proposed emissions control measures in place. The *regulatory* scenario reflects expected conditions now or in the future if the proposed regulation is implemented. In the context of burden analyses—the focus of this report—we similarly define *baseline* and *control* scenarios. The baseline scenario reflects observed, recent $PM_{2.5}$ concentrations in the region. The control scenarios are hypothetical representations of what recent $PM_{2.5}$ concentrations would be absent contributions from some or all emissions sources. While our baseline scenario is the same across our three analyses, the control scenario differs for each run. These scenarios are summarized in Exhibit 2-1. Importantly, air quality is the only data input that varies across baseline and control scenarios.

[1] Our estimates do not account for any effects of the COVID-19 pandemic. To the extent that the virus has affected air quality, population, and baseline death rates in Lima-Callao, these impacts are not quantified in our analysis.

[2] In Peru, administrative divisions are geographically resolved, from largest to smallest, into regions, provinces, and districts. Lima and Callao are the names of both a province and a district within a province. This analysis encompasses the Lima and Callao provinces, which are comparable to US states. The districts analyzed are comparable to US counties and range in size from 1 to 2,800 km².

EXHIBIT 2-1. DEFINING AIR QUALITY SCENARIOS

ANALYSIS	BASELINE AIR QUALITY	CONTROL AIR QUALITY
Total $PM_{2.5}$ burden	Recent characterization of observed $PM_{2.5}$ concentrations	$PM_{2.5}$ concentrations set to 0 $\mu g/m^3$
Transportation sector $PM_{2.5}$ burden		Observed $PM_{2.5}$ concentrations *minus transportation sector contributions*
Non-compliant vehicles $PM_{2.5}$ burden		Observed $PM_{2.5}$ concentrations *minus contributions from non-compliant vehicles*[3]

By comparing the estimated health impacts between baseline and control air quality conditions, we can attribute the mortality burden to various sources. For example, by comparing recent $PM_{2.5}$ concentrations with a hypothetical scenario where we reduce $PM_{2.5}$ concentrations by the transportation sector's contribution, we can quantify the mortality burden associated with the sector as a whole. In the following chapters, we explain how we estimate the contributions of transportation sources—and non-compliant vehicle emissions alone—to ambient $PM_{2.5}$ concentrations.

[3] We do not remove all $PM_{2.5}$-relevant emissions associated with non-compliant vehicles. Rather, we only assess the emissions in excess of comparable vehicles compliant with vehicle emissions standards.

CHAPTER 3 | EMISSIONS ESTIMATION

In this chapter, we explain our data sources and methods for characterizing emissions from the transportation sector in Lima-Callao. While MINAM possesses a comprehensive emissions inventory for on-road vehicles, the inventory assumes that vehicles emit at fixed emissions rates representing "compliant" rates for a given vehicle class (e.g., bus, passenger vehicle), fuel type (e.g., gasoline, diesel), and emissions class (e.g., Euro 2, Euro 6). Yet, inspection data from the Urban Transport Management Office (UTMO) of the Municipality of Lima indicates a significant fraction of the vehicle fleet is out of compliance. This may be due to several factors including the potential tampering of emission control devices, the age of the vehicle fleet, and driving cycles in Lima-Callao. Therefore, the inventory likely underestimates emissions from the vehicle fleet. Although the true rate of non-compliance is not known, it is expected to be significant based on recent data collected by the UTMO. We used these estimates to update the emissions inventory to account for observed rates of non-compliant emissions in the region so that it better reflects the true rate of emissions.

3.1 BASELINE EMISSIONS INVENTORY

The calculations in this section detail IEc's implementation of the MINAM transportation sector emissions inventory model. This model generates annual emissions estimates based on the size and composition of the region's on-road vehicle fleet. The model summarizes emissions in tons per year for seven pollutants: $PM_{2.5}$, NO_X, CO, total hydrocarbon, black carbon, SO_2 and CO_2. Estimates were derived for each combination of vehicle type, emissions class, and fuel type (e.g., Euro 2 diesel automobiles). Additional detail on these vehicle characteristics is summarized in Exhibit 3-1.

EXHIBIT 3-1. TRANSPORTATION EMISSIONS INVENTORY DATA ELEMENTS

VARIABLE	VALUES
Fuel type	Diesel, high octane gasoline, low octane gasoline, liquified petroleum, natural gas
Emissions class	Pre-Euro, Euro 2, Euro 3, Euro 4
Vehicle type	Automobile, station wagon, pick-up truck, rural truck, panel truck, omnibus, heavy-duty truck, tow truck, motorcycle

To generate emissions estimates for each vehicle group, the model utilizes information on vehicle counts, average distance driven per year, and emissions factors to calculate annual emissions estimates. First, we multiplied vehicle category counts by the fraction of vehicles with each fuel type to estimate vehicle counts by fuel type and category.[4,5] Next, we multiplied vehicle counts by average annual distance for each fuel type and vehicle category to estimate total annual distance driven for all vehicles by fuel type and category.[6] We then multiplied the total annual distances by the percentage of vehicles in each Euro level, specific to fuel type and vehicle category, to determine total annual distance by fuel type, vehicle category and Euro emissions level.[7] Finally, we applied emissions factors to total distance estimates. Emissions factors reflect the rate of emissions per unit of distance traveled (e.g., 0.05 grams of $PM_{2.5}$ emitted per kilometer traveled). These steps result in 180 emissions estimates (all combinations of nine vehicle categories, five fuel types, and four Euro levels). Example calculations with hypothetical values are illustrated in Exhibit 3-2.

EXHIBIT 3-2. ILLUSTRATIVE EMISSIONS ESTIMATION CALCULATIONS

STEP	EXAMPLE
1	100,000 automobiles * 30% diesel fuel use = 30,000 diesel automobiles
2	30,000 diesel automobiles * 10,000 km avg. distance = 300,000,000 km traveled by diesel automobiles
3	300,000,000 km * 10% Euro 4 = 30,000,000 km traveled by Euro 4 diesel automobiles
4	30,000,000 km * 0.05 g $PM_{2.5}$/km = 1,500,000 g = 1.5 tons $PM_{2.5}$ emitted annually by Euro 4 diesel automobiles

[4] Estimates of vehicle category counts are derived from a sum of the Peruvian National Statistical System (INEI) vehicle registry from 2011 to 2016. See https://www.inei.gob.pe/media/MenuRecursivo/publicaciones_digitales/Est/Lib1483/cap20/ind20.htm

[5] Estimates of the share of vehicles with each fuel type are from the 2012 MINAM National Inventory of Greenhouse Gases. See http://infocarbono.minam.gob.pe/annios-inventarios-nacionales-gei/ingei-2012/

[6] Average annual distances are provided by the Climate Change Planning Project. See http://planccperu.org/wp-content/uploads/2016/05/informe_final.pdf. These data are supplemented by information on total distance per year for diesel and gas vehicles within the automobile category in Lima from MINAM, in cooperation with the CALAC+ and GIZ projects.

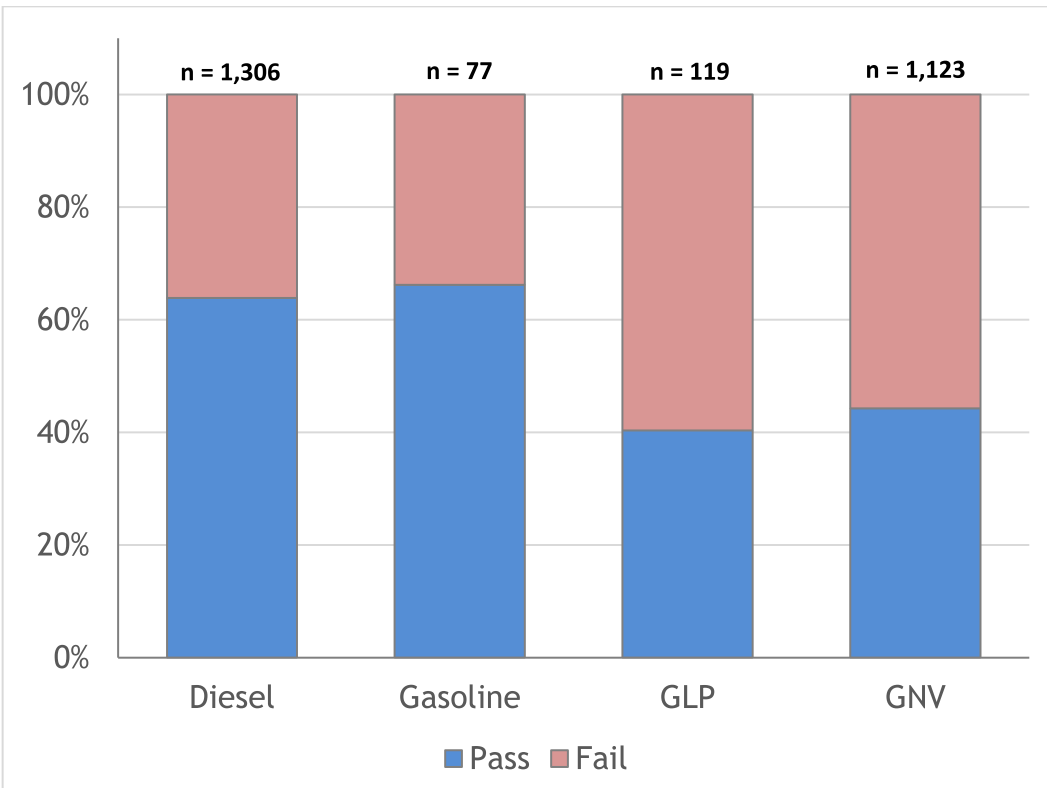
[7] The portion of the Lima vehicle fleet within each Euro-level are provided by a Nationally Appropriate Mitigation Action (NAMA) Support Project report. See http://www.transferproject.org/projects/transfer-partner-countries/peru/. Vehicles 15 years or older are classified as emitting at the Pre-Euro level, vehicles between the ages of 15 and 12 years are classified as Euro 2, vehicles between the ages of 11 and one years are classified as Euro 3, and vehicles less than 1 year old are classified as Euro 4.

In the example above, Euro 4 diesel automobiles are estimated to emit 1.5 tons of $PM_{2.5}$ annually. These estimates would be compiled with the emissions from the 179 other vehicle type, fuel type, emissions class combinations to yield total transportation sector emissions in the region. As noted above, the inventory implicitly assumed perfect compliance in its application of emissions factors – vehicles cannot emit above (or below) the rates established by each Euro class. In the section below, we explain how we adapted these values to account for non-compliance in the vehicle fleet.

3.2 ACCOUNTING FOR NON-COMPLIANCE

Empirical evidence demonstrates that many on-road vehicles in Lima-Callao do not comply with emissions limits established by MINAM. In a 2017 analysis of 2,625 vehicles in Lima-Callao conducted by the UTMO, roughly half of vehicles tested as out of compliance with emissions limits.[8] Compliance rates, depicted in Exhibit 3-3, varied by vehicle fuel type.

EXHIBIT 3-3. COMPLIANCE RATES BY FUEL TYPE



Notes: GLP = liquified petroleum, GNV = natural gas, n = sample size.

[8] For diesel vehicles, compliance is determined using an opacity standard and for gasoline, natural gas and liquefied petroleum compliance is based on combined CO, CO_2, and HC standards.

Compliance rates were found to range from 40 percent for liquified petroleum vehicles to 66 percent for gasoline vehicles. We used these data to adjust the emissions inventory estimates to account for emissions rates that likely exceed those quantified in the model's emissions factors. For each fuel type, we divided total annual distances (by vehicle category, fuel type and emissions class) into compliant and non-compliant designations. For compliant vehicles, we applied the conventional emissions factors associated with the vehicle category, fuel type, and emissions class. Non-compliant vehicles, however, were assumed to emit at higher rates (i.e., more pollution per kilometer driven). Given uncertainty in the true emissions rates of non-compliant vehicles, we estimated a lower- and upper-bound emissions estimate using alternative assumptions: [9]

- **Lower bound emissions estimate:** Non-compliant vehicles were assumed to emit at one emissions standard older than previously assigned. For example, a non-compliant Euro 4 vehicle was assumed to emit at a rate consistent with Euro 3 emissions factors.
- **Upper bound emissions estimate:** All non-compliant vehicles were assumed to emit at the Pre-Euro level.

Notably, IEc only adjusted emissions for $PM_{2.5}$ and NO_X, i.e., the precursors of ambient $PM_{2.5}$ to account for non-compliance. We were unable to adjust for SO_2 emissions as the data were not broken out by Euro-level. However, it is reasonable to assume that compliant and non-compliant vehicles emit comparable SO_2 per kilometer traveled (for a given fuel type and vehicle type) as SO_2 emissions are a function of distance traveled and sulfur content in fuel—not emissions class.

We summed the non-compliant and compliant emissions for each vehicle category and Euro-level to determine annual emission estimates of $PM_{2.5}$ and NO_X for each fuel type. Finally, IEc summed across fuel type to determine estimates of total annual $PM_{2.5}$ and NO_X emissions.

3.3 EMISSIONS MODELING RESULTS

The results of emissions inventory model are summarized in Exhibit 3-4.

[9] In estimating non-compliance rates, we assumed a random sampling of vehicles and accuracy of the inspection testing method by the UTMO. We explored our assumption that non-compliance corresponded to older Euro standards of emissions using the following sensitivity analysis. IEc assessed the distributions of opacity inspection measurements for diesel vehicles and the distributions of CO measurements for gasoline, natural gas and liquified petroleum vehicles. The percent increase in opacity for compliant to non-compliant diesel vehicles was comparable to the percent increase in $PM_{2.5}$ emissions for changing from the Euro 4-2 level to the Pre-Euro level. Therefore, IEc determined that accounting for non-compliant vehicles in the inventory model by scaling diesel emissions factors by opacity would likely not change the result significantly. Additionally, the percent increase in CO for compliant to non-compliant gasoline, natural gas and liquified petroleum vehicles was orders of magnitude higher than the percent increase in $PM_{2.5}$ emissions for changing from the Euro 4-2 level to the Pre-Euro level. IEc determined that scaling gasoline, natural gas and liquified petroleum emissions factors by CO measurements to account for non-compliance would not be appropriate.

EXHIBIT 3-4. 2018 VEHICLE EMISSIONS ESTIMATES FOR $PM_{2.5}$, NO_X, AND SO_2

SCENARIO		TOTAL VEHICLE EMISSIONS (TONS/YEAR)		
		$PM_{2.5}$	NO_X	SO_2
Full Compliance		4,092	164,038	21,908
Non-Compliance Adjusted	Upper Bound	5,176	203,564	21,908
	Lower Bound	4,297	175,097	21,908

Implementing the MINAM emissions model assuming perfect compliance results in estimates of $PM_{2.5}$ emissions of 4,092 tons per year, NO_X emissions of 164,038 tons per year, and SO_2 emissions of 21,908 tons per year. We found that accounting for non-compliance resulted in a 5 to 26 percent increase in $PM_{2.5}$ emissions and a 6 to 24 percent increase in NO_X emissions (Exhibits 3-5 and 3-6). SO_2 emissions were not adjusted and therefore do not vary between the full compliance and non-compliance adjusted scenarios. Appendix A provides greater detail on these estimates, including the share of emissions by vehicle fuel type.

EXHIBIT 3-5. ESTIMATED PRIMARY $PM_{2.5}$ EMISSIONS, 2018

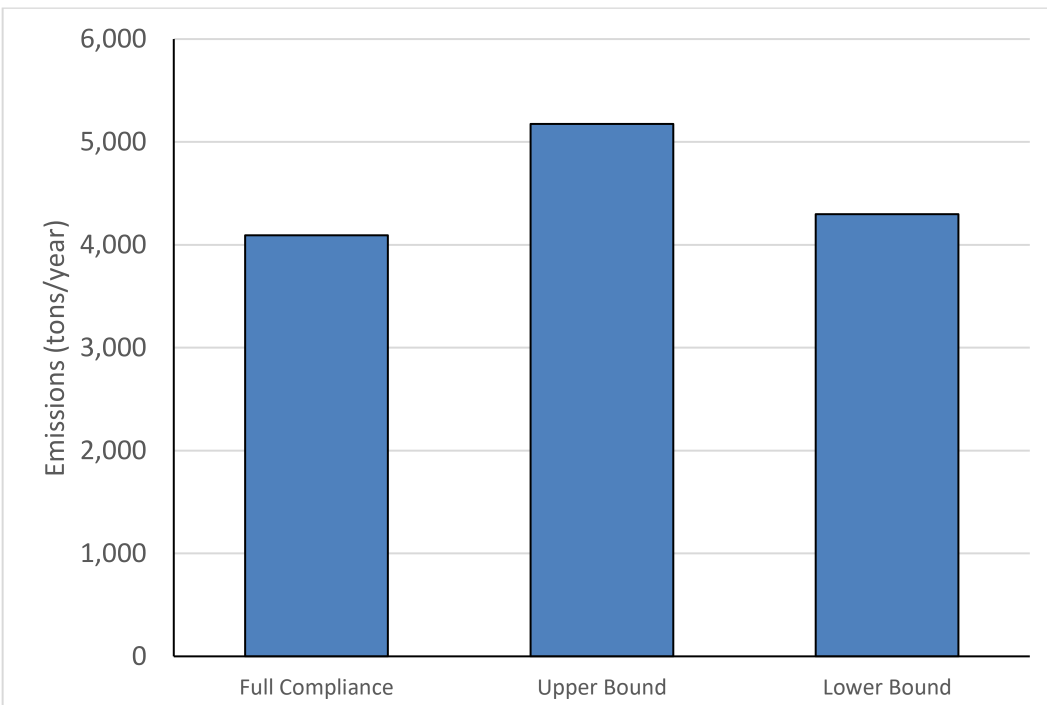
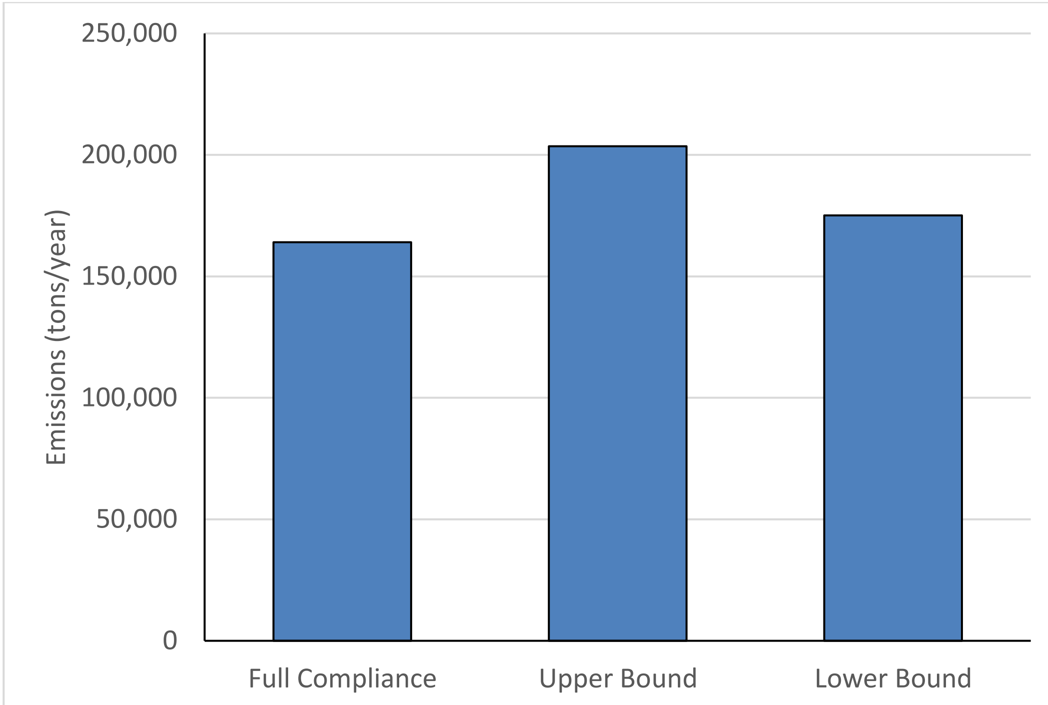


EXHIBIT 3-6. ESTIMATED NO_X EMISSIONS, 2018



CHAPTER 4 | AIR QUALITY DATA AND MODELING

In this chapter, we describe our approach to characterizing recent $PM_{2.5}$ concentrations in Lima-Callao. First, we describe available air quality monitor data and satellite-derived PM data in the region, as well as our approaches to fuse these data sources. Second, we outline our approach to estimating the contribution of transportation sources to ambient $PM_{2.5}$ concentrations based on the emissions data described in the previous chapter.

4.1 AIR QUALITY SURFACES

Several data sources provide estimates of ambient $PM_{2.5}$ concentrations in Lima-Callao. We describe these air quality surfaces below and weigh the relative benefits and limitations of each data source.

4.1.1 MONITOR SURFACES

Monitor data in Lima-Callao were provided by MINAM covering a range of pollutants ($PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, and CO) and temporal scales. Pollutant concentrations were summarized at hourly, daily, monthly, and annual timesteps since 2000.[10] The monitors analyzed are owned and operated by two separate agencies: Ministry of Health (MINSA) and the National Meteorology and Hydrology Service of Peru (SENAMHI).

To best depict the air quality in the Lima-Callao metropolitan area, including "hot spots" of concern to MINAM (e.g., localized high pollutant concentrations in Callao), we used hourly $PM_{2.5}$ measures from 10 monitors in 2019 and supplemented these values with daily $PM_{2.5}$ measures from two active samplers in the Callao district.[11,12] We combined the measures into a single dataset by converting hourly $PM_{2.5}$ concentrations to daily averages for each 24-hour period.[13]

Exhibit 4-1 maps these air quality monitor stations in Lima-Callao. Since monitor data provides concentrations at a fixed location, we used the Voronoi Neighborhood Averaging (VNA) method in BenMAP-CE to interpolate $PM_{2.5}$ concentrations at a 1km x

[10] Some pollutants and metrics are only available in select years.

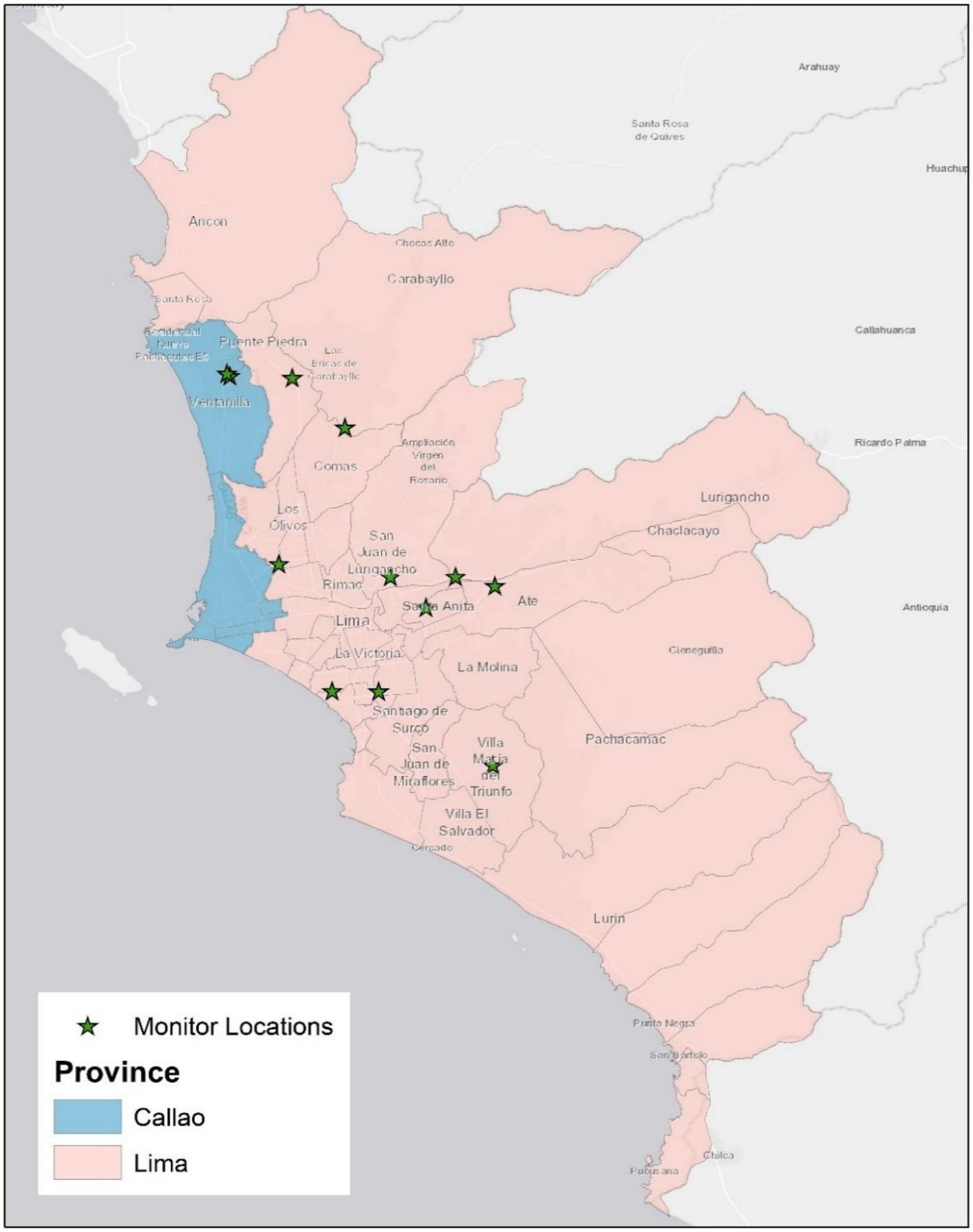
[11] Daily monitoring data in Callao are only available for approximately one week of each month in 2019 from the Environmental Assessment and Enforcement Agency (OEFA).

[12] Additional monitors provide data in earlier years (e.g., 27 in 2016), but these data risk reflecting older air quality levels and distributions.

[13] After converting the hourly data to daily averages, we excluded eight outlier daily values for three monitors.

1km grid (not pictured). The VNA method calculates an inverse-distance weighted average for each grid cell from the monitors surrounding the grid's center.[14]

EXHIBIT4-1. AVAILABLE AIR QUALITY MONITORING STATIONS IN LIMA-CALLAO (2019)



[14] See Appendix B in the BenMAP-CE user manual for a detailed discussion of VNA methods: https://www.epa.gov/sites/production/files/2015-04/documents/benmap-ce_user_manual_march_2015.pdf

4.1.2 SATELLITE SURFACES

In areas lacking monitor coverage, satellite data can be useful for estimating ambient surface concentrations of $PM_{2.5}$. In areas with robust monitoring networks, those data are likely to best represent ground-level ambient concentrations (assuming appropriate quality control procedures are followed); however, satellite data still play an important role by filling gaps between monitored locations and providing information on the spatial distribution of $PM_{2.5}$ at finer resolutions. Lima-Callao has an established network of monitors; however, coverage is more limited in outer districts. Therefore, we leveraged two satellite-based estimates for the Lima-Callao metropolitan area: an estimated surface from van Donkelaar et al. (2016) and an estimated surface from Shaddick et al. (2017). The van Donkelaar surfaces provide annual estimates of $PM_{2.5}$ at 0.01° resolution (1km x 1km) for 1998-2016 and the Shaddick surfaces provide annual estimates of $PM_{2.5}$ at 0.1° (10km x 10km) resolution for 2014 and 2016.

The van Donkelaar et al. (2016) and Shaddick et al. (2017) surfaces combined information from satellites, model simulations and ground-level monitors. Their methods are explained in further detail in Appendix B. Notably, both surfaces incorporate monitor data from the WHO Global Ambient Air Quality Database, which contains only one monitor with a directly measured estimate for $PM_{2.5}$ for Lima-Callao.[15] As such, while the surfaces may provide insight into the spatial distribution of air pollution, the magnitude of $PM_{2.5}$ concentrations may not accurately reflect real-world conditions (as measured by monitors).

Therefore, IEc performed additional local calibration of the van Donkelaar and Shaddick surfaces for 2016 using data from twelve SENAMHI and MINSA monitoring stations. Satellite surface calibration was broken into four steps: (1) calculating annual $PM_{2.5}$ averages at the monitor locations, (2) calculating the ratio between monitor and satellite annual $PM_{2.5}$ averages, (3) spatially interpolating the ratios to create a calibration surface, and (4) multiplying the calibration surface against the satellite surface to create a locally calibrated air quality surface. These steps, implemented in ArcMap version 10.4.1 using the Spatial Analyst package, are explained in greater detail in Appendix B.

4.1.3 SUMMARY OF AIR QUALITY SURFACES

Exhibit 4-2 displays the three final surfaces used to assess the mortality burden of ambient $PM_{2.5}$ in Lima-Callao. Exhibit 4-2 (a) shows 2019 monitor data interpolated to a 1km x 1km grid. The 2019 monitor surface had an average daily $PM_{2.5}$ concentration of 33.0 $\mu g/m^3$, with a minimum and maximum observed concentration of 16.2 $\mu g/m^3$ and 46.9 $\mu g/m^3$, respectively. Exhibit 4-2 (b) is the 10km x 10km 2016 Shaddick model surface, locally calibrated using monitor data (see Appendix B). The Shaddick model surface had an annual average $PM_{2.5}$ concentration of 21.4 $\mu g/m^3$, with a minimum and

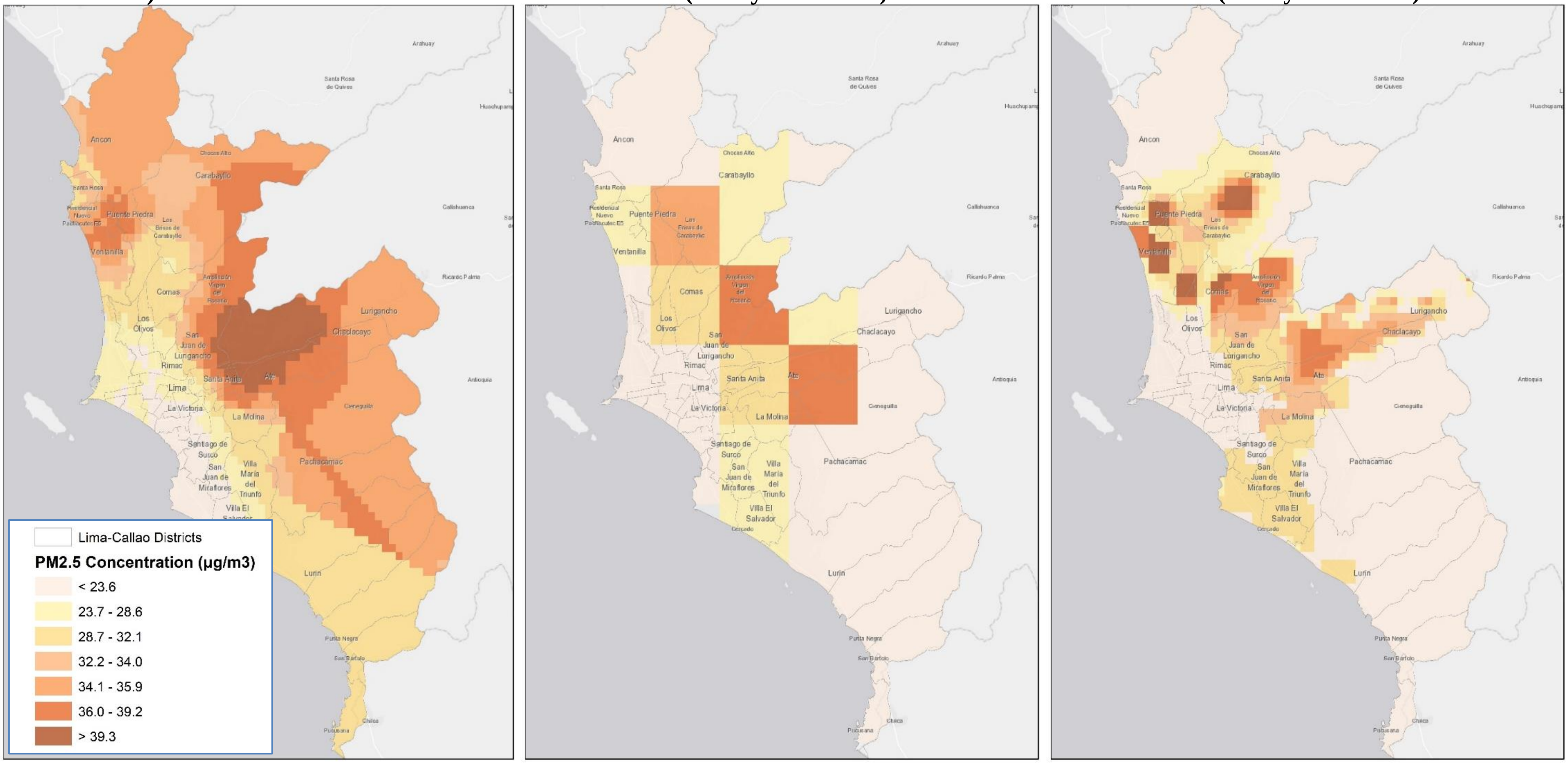
[15] World Health Organization. *WHO Global Ambient Air Quality Database (Update 2018)*; WHO: Geneva, 2018: https://www.who.int/airpollution/data/cities/en/

EXHIBIT 4-2. AIR QUALITY SURFACES[16]

a) 2019 Monitors

b) 2016 Shaddick Model (locally calibrated)

c) 2016 Van Donkelaar Model (locally calibrated)



[16] There are numerous ways one could interpolate between monitors to develop an air quality surface. Exhibit 4-2a was developed using the BenMAP-CE default interpolation procedure, Voronoi Neighborhood Averaging (VNA). The VNA interpolation method may or may not accurately reflect ground-level conditions in Lima-Callao.

maximum observed concentration of 11.8 μg/m^3 and 36.4 μg/m^3, respectively. Lastly, Exhibit 4-2 (c) is the 1km x 1km van Donkelaar model surface, calibrated using monitor data (see Appendix B). The van Donkelaar model surface had an annual average $PM_{2.5}$ concentration of 21.6 μg/m^3, with a minimum and maximum observed concentration of 10.5 μg/m^3 and 53.5 μg/m^3, respectively.

4.2 AIR QUALITY MODELING

In the previous section, we presented data sources and methods used to characterize recent concentrations of $PM_{2.5}$ in the Lima-Callao region. The resulting air quality surfaces are used to assess the mortality burden associated with all sources of $PM_{2.5}$. To assess the transport-attributable mortality burden, we needed a means of quantifying the effect of transportation emissions on ambient $PM_{2.5}$ concentrations. We employed a reduced-form air quality modeling technique employed in past studies commissioned by MINAM: emissions concentration factors (FECs, from the Spanish *factor emisión-concentración*). The FECs used in this report were developed for vehicle emissions in the Valparaiso region of Chile.[17] While FECs exist for Lima, they are not specific to the transportation sector. After consultation with MINAM, we elected to use the Valparaiso FECs, as this coastal and mountainous region may be similar to the Lima-Callao Metropolitan area in important meteorological and topographical respects. FECs are modeled by the following equation:

$$FEC_i^t = \left(\frac{\delta C_i^t}{\delta E^t}\right)^{-1} \approx \frac{E_i^t}{C^t}$$

where FEC_i^t is the emission-concentration factor in zone *i* for year *t* in tons/(μg/m^3), C_i^t is the ambient concentration of $PM_{2.5}$ in zone *i* for year *t* in μg/m^3, and E_i^t is pollutant emissions in zone *i* for year *t* in tons. Pollutant-specific FECs for vehicle emissions are shown in Exhibit 4-3.

EXHIBIT 4-3. POLLUTANT-SPECIFIC EMISSION-CONCENTRATION FACTORS (FEC)

POLLUTANT	FEC (TON/YEAR PER μg/m^3)
$PM_{2.5}$	1,148.106
SO_2	15,220.700
NO_x	18,867.925

[17] GreenLab, 2011: https://silo.tips/download/estudio-co-beneficios-de-la-mitigacion-de-gei

We estimated the total contribution to ambient concentrations from primary $PM_{2.5}$ from NO_X, SO_2 and $PM_{2.5}$ vehicle emissions according to the following equation:

$$C_p = \left(\frac{1}{FEC_p}\right) * E_p,$$

where *C* is the contribution to ambient $PM_{2.5}$ concentrations of pollutant *p*, FEC_p is the emission-concentration factor for pollutant *p*, and E_p are the primary emissions for pollutant *p*. We estimated contributions to ambient $PM_{2.5}$ concentrations for the full compliance, non-compliance upper bound, and non-compliance lower bound scenarios. Finally, we isolated the contribution of non-compliant emissions by subtracting the full compliance total emissions from the non-compliant vehicle emissions, such that:

$$C_{nc} = C_{nc\_adjusted} - C_{full}$$

where C_{nc} are non-compliant emissions, $C_{nc\_adjusted}$ are total vehicle emissions adjusted for non-compliance, and C_{full} are total vehicle emissions assuming full compliance. This estimated non-compliant emissions rather than the total emissions of non-compliant vehicles. Specifically, a non-compliant vehicle has a portion of emissions that are compliant (i.e. would have still been emitted if they met standards) and a portion of emissions that are in exceedance of the standard. To address the mortality burden of non-compliance, we determined the contribution of only the excess emissions. Results of FEC calculations are shown in Exhibit 4-4.

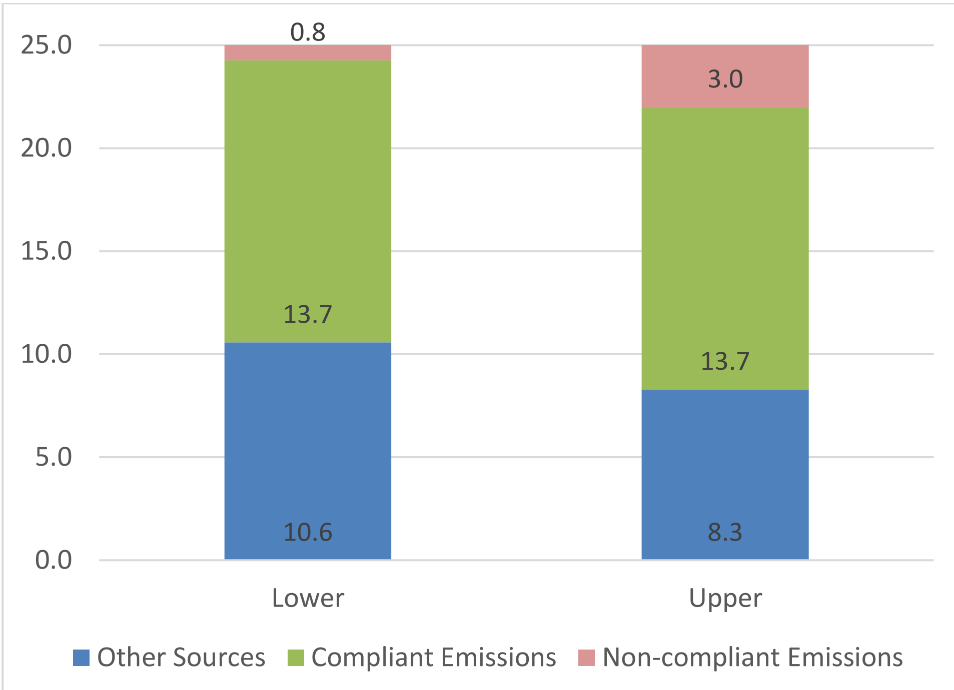
EXHIBIT 4-4. TRANSPORTATION AND NON-COMPLIANT VEHICLE EMISSION CONTRIBUTIONS TO AMBIENT $PM_{2.5}$ CONCENTRATIONS

SCENARIO		CONTRIBUTION OF VEHICLE EMISSIONS TO AMBIENT $PM_{2.5}$ CONCENTRATIONS (µg/m^3)				CONTRIBUTION OF NON-COMPLIANT EMISSIONS
		$PM_{2.5}$	NO_X	SO_2	TOTAL	
Full Compliance		3.56	8.69	1.44	13.70	N/A
Non-Compliance Adjusted	Upper Bound	4.51	10.79	1.44	16.74	3.04
	Lower Bound	3.74	9.28	1.44	14.46	0.76

Exhibit 4-5 shows the relative contributions of the transport sector (compliant and non-compliant emissions) and other sources to ambient concentrations of $PM_{2.5}$. We estimated the contribution of other sources, both anthropogenic and non-anthropogenic, by subtracting the total vehicle contribution to ambient $PM_{2.5}$ concentrations from the 2016 annual average of ambient $PM_{2.5}$ concentrations in Lima-Callao[18].

The annual average $PM_{2.5}$ concentration for 2016 was 25.0 µg/m^3. Vehicle emissions contribute between 67 and 58 percent (upper and lower bounds) of ambient $PM_{2.5}$ concentrations and non-compliant emissions contribute between 12 and 3 percent (upper and lower bounds).

EXHIBIT 4-5. CONTRIBUTIONS OF TRANSPORT SECTOR AND OTHER SOURCES TO 2016 AVERAGE $PM_{2.5}$ CONCENTRATIONS



We note that the $PM_{2.5}$ contributions displayed in Exhibit 4-5 reflect *mean* effects in the region. While this analysis evaluates transportation emissions impacts and contributions to air pollution at the regional and district level, research has shown that air pollution can be significantly higher within a short distance of large roadways and other transportation facilities, especially within the first 150-300 meters, compared with district-level air pollution concentrations (Karner et al., 2010). Individuals living, working and going to school within this short distance of roadways have increased risks for adverse health effects, including premature mortality (Health Effects Institute 2010). As a result, relying on district-level air quality analyses may underestimate the impacts of transportation sources on the overall mortality burden to the population of Lima-Callao.

[18] The annual average was estimated in BenMAP-CE using 2016 monitor data and is population- and spatially-weighted. The other sources category is expected to include both anthropogenic and non-anthropogenic sources of emissions.

CHAPTER 5 | MORTALITY BURDEN ESTIMATION AND VALUATION

In this chapter, we detail our methods for assessing the mortality burden associated with $PM_{2.5}$ concentrations in Lima-Callao. In total, we performed three health benefits analyses:

1. The total mortality burden of current $PM_{2.5}$ concentrations in Lima-Callao;
2. The contribution of transportation emissions to the total mortality burden; and
3. The contribution of non-compliant vehicle emissions to the total mortality burden.

For these analyses, we used the USEPA's Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE) version 1.5.2.0, an open-source program that quantifies and values the adverse health effects associated with changes in pollutant concentrations. The remainder of this chapter provides an overview of our approach, including our data sources for key inputs such as population, baseline incidence rates, and concentration-response functions from the epidemiological literature. Finally, we provide an overview of our valuation approach.

5.1 OVERVIEW OF APPROACH

We used BenMAP-CE to estimate the impact of $PM_{2.5}$ concentrations on premature mortality by assessing the difference in the risk of those endpoints under the baseline and control scenarios presented in Chapter 2. BenMAP-CE relies on health impact functions to quantify the change in incidence of adverse health impacts stemming from changes in ambient pollutant concentrations:

$$\Delta y = y_o \cdot \left(1 - e^{-\beta \cdot \Delta PM}\right) \cdot Pop$$

where Δy is the change in the incidence of the adverse health effect, y_o is the baseline incidence rate for the health effect, beta (β) is a coefficient derived from a relative risk (RR) estimate associated with a change in exposure (i.e., pollutant concentration) as expressed in concentration-response functions, ΔPM is the change in concentrations of fine particulate matter, and *Pop* is the exposed population.[19]

[19] Based upon the functional form of the underlying concentration-response function, the functional form of the health impact function may differ. ΔPM may also be replaced by concentrations of other pollutants (e.g., ozone) or conditions (e.g., temperature).

5.2 DATA INPUTS

We drew upon multiple data sources to parameterize and implement the generic health impact function presented above. These data sources are described below.

5.2.1 POPULATION

MINAM provided district-level population data from the Peruvian National Statistical System (INEI) for the period 2005 to 2015, as well as national projected population data from 1950 through 2070 in five-year increments. Both population datasets include age stratification into five-year age bins. To account for population growth since 2015 (the most recent year with district-level population estimates), we projected the 2015 district-level population to the year 2020 by applying age-specific national growth rates. Finally, we formatted these data for use in BenMAP-CE.

5.2.2 BASELINE MORTALITY INCIDENCE

To characterize baseline rates of death, we processed data from the Peruvian Ministry of Health (MINSA) National Center for Epidemiology, Prevention and Control of Disease (CNEPCE). These data include counts for a range of mortality and morbidity endpoints from 1986 through 2016. Available mortality data are reported by district, gender, and five-year age increments. For this analysis, we focused on the mortality incidence for the following endpoints: Ischemic Heart Disease (IHD), Acute Lower Respiratory Infection (LRI), Chronic-Obstructive Pulmonary Disease (COPD), Lung Cancer, Cerebrovascular Disease, and Natural Causes (hereafter referred to as Non-Communicable Diseases (NCD) plus LRI). These endpoints were selected to match the health impact functions described in the following section.

Prior to use in BenMAP-CE, we converted mortality count data to incidence rates (cases per person per year). First, we formatted the mortality data to align with the level of aggregation in the population dataset (year, district, endpoint, and age group). We then divided the counts by the district- and age-specific population for corresponding years. To minimize variability across years, we estimated incidence rates for a five-year period (2011 to 2015). In some cases, we aggregated incidence rates from various causes to align with the endpoint definitions in the health impact functions (described below). For example, Tapia et al. (2020) reflects respiratory and circulatory mortality.

5.2.3 HEALTH IMPACT FUNCTIONS

As described above, health impact functions provide the quantitative framework to estimate changes in health outcomes resulting from changes in pollutant concentrations, incorporating data on population and baseline incidence. These functions are derived from concentration-response relationships published in epidemiological research, which provide insight into the strength of a pollutant's effect on health. For example, a study may suggest that for every 10 $\mu g/m^3$ change in $PM_{2.5}$, we can expect baseline mortality incidence to change by 6 percent. Exhibit 5-1 summarizes our selected health impact functions for assessing mortality burden.

EXHIBIT 5-1. BENMAP-CE HEALTH IMPACT FUNCTIONS

AUTHOR	MORTALITY ENDPOINT GROUP	AGES
Burnett et al. (2018)	Non-communicable diseases plus lower respiratory infection (NCD + LRI)	25-99
	Cerebrovascular disease	25-99
	Chronic obstructive pulmonary disease (COPD)	25-99
	Ischemic heart disease (IHD)	25-99
	Lung cancer	25-99
	Lower respiratory infection (LRI)	25-99
Tapia et al. (2020)	All respiratory and circulatory	0-99

Two epidemiological studies provide the concentration-response relationships summarized in Exhibit 5-1. First, we utilized the Global Exposure Mortality Model (GEMM) health impact functions pre-loaded into BenMAP-CE. The GEMM is a family of functions developed by Burnett et al. (2018) to estimate the global burden of disease attributable to $PM_{2.5}$ exposure over the entire global exposure range. The GEMM consists of risk functions for six mortality endpoints: NCD + LRI, Cerebrovascular Disease, COPD, IHD, Lung Cancer, and LRI.[20] Notably, the GEMM is a meta-analytic function developed based on high-quality $PM_{2.5}$ studies conducted globally. Additionally, the functions are non-linear. That is, the strength of the effect of $PM_{2.5}$ on premature deaths depends upon the observed $PM_{2.5}$ concentrations. In general, the functions suggest that the marginal effect of $PM_{2.5}$ lessens at higher concentrations.

Second, we utilized Tapia et al. (2020) estimates of $PM_{2.5}$-attributable respiratory and circulatory mortality.[21] While these estimates are specific to Lima, Peru, the study

[20] While age-specific GEMM functions are presented in Burnett et al. (2018), we leverage the all-ages (25-99) functions to capture population-wide effects. Similarly, Burnett et al. (2018) provide estimates with and without a Chinese male cohort included in their meta-analysis. We leverage the GEMM functions with the Chinese male cohort because these estimates are, in part, informed by higher $PM_{2.5}$ exposure levels experienced by the Chinese cohort. These higher concentrations may be relevant to air quality conditions in Lima-Callao.

[21] We identified the Tapia et al. (2020) study by conducting a literature review for $PM_{2.5}$ epidemiological studies local to Lima-Callao, Peru, or South America using a broad keyword search in Google Scholar and PubMed. We identified 17 potentially relevant papers and abstracts, then narrowed this list to three potential candidates for health impact calculation in BenMAP-CE: Hansel et al. (2018), Tapia et al. (2019) and Tapia et al. (2020). The three studies were selected due to their relevant respiratory and cardiovascular endpoints. Hansel et al. (2018) provided functions that relate $PM_{2.5}$ exposure to asthma morbidity, including uncontrolled asthma, adverse asthma-related quality of life, health care utilization and missed school days. Tapia et al. (2019) provided functions that relate $PM_{2.5}$ exposure with cardiorespiratory emergency room visits and Tapia et al. (2020) provided functions that relate $PM_{2.5}$ exposure with cardiorespiratory mortality. We did not apply the other functions identified as they are for morbidity endpoints and this report focuses solely on the mortality health burden.

assesses mortality associated with short-term $PM_{2.5}$ exposures. As such, we expect the study to understate the total impacts of $PM_{2.5}$ due to strong empirical evidence that much of the pollutant's effect is associated with its long-term exposure.

5.2.4 VALUATION

Based on direction from MINAM, we valued mortality using a value per statistical life (VSL) estimate from Seminario de Marzi (2017). The VSL represents the contribution to national income per avoided death, referred to as human capital. This approach values mortality effects by considering the labor productivity of individuals and their future income. The authors synthesize estimates by age and sex using an eight percent discount rate. The resulting average value, $0.14 million (2017$), is applied to premature deaths to reflect the costs of $PM_{2.5}$-attributable mortality. As we note in the subsequent chapters, this estimate is associated with some uncertainty, and alternative valuation methodologies may result in different estimates. For example, MINAM's analysis of the Euro 6 standards included a range of estimates from $0.14 to $1.6 million (2017$).[22]

[22] An alternative to the human capital approach would be to use an estimate of willingness to pay (WTP) for mortality risk reductions, for example those provided by Robinson et al. (2018). The VSL represents individuals' WTP for incremental reductions in their annual risk of death and is generally understood to be a more comprehensive approach to valuing mortality risk reduction. Robinson et al. (2018) extrapolate a Peru-specific VSL of $1.21 million (2015$) from the OECD VSL base ($3 million) using the ratio of gross national income per capita between Peru and OECD countries. While we are unaware of any WTP studies conducted in Peru, the Robinson et al. provides methods and results for transferring VSL values to countries without primary estimates. The authors synthesize available estimates in other countries and transfer these values to Peru, among many other countries, by accounting for differences in per capita income, a key factor influencing WTP and VSL. We use the human capital approach based on direction from MINAM.

CHAPTER 6 | RESULTS

In this chapter, we present the results of our mortality burden analyses using the methods and data sources described in previous chapters. First, we present the quantified and valued mortality impacts associated with total $PM_{2.5}$ concentrations in Lima-Callao. Second, we present results specific to the transportation sector. Finally, we estimate the burden associated with excess emissions from non-compliant vehicles in the region. In Appendix D, we present these results stratified by Lima-Callao District.

6.1 TOTAL PM2.5 ATTRIBUTABLE MORTALITY BURDEN

We estimate that ambient $PM_{2.5}$ emissions in Lima-Callao result in over 10,000 deaths annually. These results, summarized in Exhibit 6-1, vary depending on the selected health impact function and baseline air quality surface. We highlight the GEMM NCD & LRI results as our preferred estimates. This HIF captures a broader range of air pollution attributable deaths relative to the five cause-specific (5 COD, i.e., cause-of-death) GEMM estimates and the local Tapia et al. (2020) results. Further, the Tapia et al. study only accounts for short-term exposure to $PM_{2.5}$ and ignores the substantial long-term mortality impacts of air pollution. Results are largely stable across air quality surfaces, with the greatest burden resulting from the 2019 monitor data (12,016 deaths) relative to the Shaddick and van Donkelaar surfaces (10,556 and 10,838, respectively). For the remainder of this report, we present the Shaddick surface and GEMM NCD & LRI results as our primary estimates. We highlight the Shaddick surface results because Shaddick contains more recent data and was generated using a WHO model which builds upon earlier van Donkelaar methods. The model estimates the spatially varying relationship between ground measurements of $PM_{2.5}$ and factors from the various air quality models (see Appendix B for details).

EXHIBIT 6-1. ESTIMATED $PM_{2.5}$ ATTRIBUTABLE MORTALITY BURDEN

CAUSE OF MORTALITY	PREMATURE DEATHS		
	MONITORS	SHADDICK	VAN DONKELAAR
GEMM: NCD + LRI	**12,016**	**10,556**	**10,838**
GEMM: 5 COD	**7,425**	**6,517**	**6,514**
Lower respiratory infection	4,022	3,538	3,531
Ischemic heart disease	1,486	1,321	1,338

CAUSE OF MORTALITY	PREMATURE DEATHS		
	MONITORS	SHADDICK	VAN DONKELAAR
Cerebrovascular disease	987	843	841
Lung Cancer	590	524	508
COPD	339	292	296
Tapia: Respiratory & circulatory (short-term exposure)	**1,486**	**1,245**	**1,272**

Total $PM_{2.5}$ attributable deaths, estimated at 10,556, represent the annual toll of air pollution in the region. To the extent that air quality, population, and baseline rates of death are relatively comparable over time, we expect that these adverse impacts are likely to occur each year. The costs associated with these deaths amount to $1.5 billion annually 2017$).[23] Notably, these costs are irrespective of source: both anthropogenic (e.g., industry, transportation) and non-anthropogenic (e.g., sea salt, crustal dust) sources contribute to the total ambient $PM_{2.5}$ concentrations in the region. In the following sections, we present the burden associated with transportation sources.

6.2 TRANSPORT ATTRIBUTABLE PM2.5 MORTALITY BURDEN

Emissions from on-road vehicles in Lima-Callao result in 5,150 to 6,200 premature deaths each year. These results are summarized in Exhibit 6-2 along with the associated economic costs. It is important to note that the contribution of vehicle emissions to ambient $PM_{2.5}$ assumes there is some level of non-compliance in meeting emissions standards (i.e. neither estimate represents 100 percent compliance with emissions standards). Additionally, the variance in vehicle emissions contribution is solely due to the variance in non-compliant vehicle emissions.

EXHIBIT 6-2. ESTIMATED $PM_{2.5}$ ATTRIBUTABLE ANNUAL MORTALITY BURDEN, TRANSPORTATION SECTOR

VEHICLE EMISSIONS CONTRIBUTION	ANNUAL $PM_{2.5}$ ATTRIBUTABLE DEATHS (SHADDICK)	ANNUAL ECONOMIC COSTS (2017$, MILLIONS)
Lower bound	5,150	$710
Upper bound	6,200	$860

[23] Using the range of VSL estimates in MINAM's Euro 6 analysis, the total monetized mortality burden in Peru may range from $1.5 billion (VSL = $0.14 million) to $16.9 billion (VSL = $1.61 million).

The estimated mortality burden for transportation sources amounts to over half of the total $PM_{2.5}$ mortality burden, reflecting the sector's outsized influence on air pollution in the region. The range in mortality estimates reflects uncertainty in the exact emissions rates of non-compliant vehicles. As summarized in Exhibit 6-2, the economic costs associated with transportation-attributable $PM_{2.5}$ concentrations are $710 to $860 million annually. As we describe in Appendix C, these estimates may understate the burden of transportation sources due to the non-linearity of the GEMM function. Additionally, as noted in Chapter 4, these results may not fully capture local-scale effects, including exposures to significant greater $PM_{2.5}$ concentrations on or near roadways.

6.3 PM2.5 MORTALITY BURDEN FROM NON-COMPLIANT VEHICLES

As discussed in Chapter 3, MINAM emissions measurements suggest roughly half of all on-road vehicles in Lima-Callao are out of compliance with emissions standards. We adjust emissions inventories accordingly and estimate the resulting air quality and health impacts. In total, we find that emissions from non-compliant vehicles in excess of emissions standards are responsible for 248 to 991 deaths annually. These results are presented in Exhibit 6-3. Excess emissions (i.e., above and beyond compliant emission levels) from non-compliant vehicles account for roughly 5 to 16 percent of the transportation mortality burden (comparing Exhibits 6-2 and 6-3).

EXHIBIT 6-3. ESTIMATED $PM_{2.5}$ ATTRIBUTABLE ANNUAL MORTALITY BURDEN, NON-COMPLIANT EMISSIONS

VEHICLE EMISSIONS CONTRIBUTION	ANNUAL $PM_{2.5}$ ATTRIBUTABLE DEATHS (SHADDICK)	ANNUAL ECONOMIC COSTS (2017$, MILLIONS)
Lower bound	248	$34
Upper bound	991	$140

As noted above, the range in mortality estimates reflects uncertainty in the exact emissions rates of non-compliant vehicles. The associated economic costs for non-compliant vehicle emissions amounts to $34 to $140 million annually. Policymakers may interpret these estimates as the potential annual benefits that may be achieved through regulatory measures that address the entirety of non-compliant emissions. That is, achieving perfect compliance with vehicle emissions standards would be expected to avoid 248 to 991 deaths annually, resulting in annual benefits of $34 to $140 million. While perfect compliance may be infeasible, the mortality burden associated with non-compliant vehicle emissions is sizeable—any policy that materially improves compliance will produce significant public health benefits in Lima-Callao.

CHAPTER 7 | DISCUSSION AND NEXT STEPS

In the previous chapters, we described our analytic approach and findings in detail. In this chapter, we summarize our findings and discuss their implications. We also suggest possible next steps for researchers and MINAM staff.

7.1 SUMMARY OF FINDINGS

Our mortality burden analyses provide evidence that $PM_{2.5}$ concentrations in the Lima-Callao region represent a substantial public health concern. Overall, ambient concentrations typically range from 11.8 to 36.4 μg/m^3 on an annual basis, with some "hot spots" likely to experience markedly higher pollution concentrations, particularly at shorter time and distance scales. These values exceed the WHO annual guideline of 10 μg/m^3. In total, we estimate that over 10,000 deaths each year result from $PM_{2.5}$ exposure in Lima-Callao. The economic costs of this loss amount to $1.5 billion USD annually.

The transportation sector represents a major contributor to ambient $PM_{2.5}$—and premature mortality—in the region. We expand upon the overall $PM_{2.5}$ burden analysis by more closely evaluating the mortality burden associated with $PM_{2.5}$ concentrations originating from on-road vehicles. We estimate that 14.5 to 16.7 μg/m^3 of ambient $PM_{2.5}$ concentrations (58 to 67 percent) result from on-road transportation emissions in the region. These emissions result in 5,150 to 6,200 premature deaths annually, equating to $710 to $860 million in economic costs.

Regulatory interventions in Lima-Callao may lessen the mortality burden associated with transportation emissions. We highlight the role that non-compliant vehicles play in regional emissions by adjusting available emissions inventories using recent MINAM estimates of non-compliance rates (roughly 3 to 12 percent) in the region. We find that 1 to 3 μg/m^3 in the region may be explained by emissions from this subset of vehicles. The wide range in estimates stems from uncertainty in quantifying emissions from these vehicles. Emissions from non-compliant vehicles in excess of federal vehicle emissions standards result in 250 to 990 premature deaths annually, equating to $34 to $140 million in economic costs. These costs may be reduced through regulatory measures, such as increased enforcement or enhanced I&M programs.

7.2 UNCERTAINTIES

The results presented in this report are accompanied by numerous sources of uncertainty, of which the net effect on our estimates is ambiguous. We attempt to catalogue the major sources of uncertainty in Exhibit 7-1.

EXHIBIT 7-1. KEY UNCERTAINTIES WITH BURDEN ANALYSES

POTENTIAL LIMITATION / SOURCE OF ERROR	DIRECTION OF POTENTIAL BIAS FOR ESTIMATED BURDEN
Health impacts associated with other pollutants are not quantified.	Underestimate. Epidemiological evidence supports a causal relationship between ozone exposure and mortality and morbidity effects. Quantifying and valuing these outcomes would increase the overall burden of air pollution in the region.
Morbidity effects are not quantified.	Underestimate. Epidemiological evidence supports a causal relationship between $PM_{2.5}$ exposure and numerous non-fatal respiratory and cardiovascular effects. Quantifying and valuing these outcomes would increase the overall burden.
Mortality burden for near-road populations.	Underestimate. Epidemiological evidence supports additional health effects to populations living very close to large roadways. Quantifying and valuing these outcomes would increase the overall burden of air pollution in the region.
Prevalence of non-compliant vehicles.	Unable to determine based on current information. Non-compliance rates are calculated based on a limited sample (n = 2,625) but may be lower or higher in the entire vehicle fleet.
Emissions rates for non-compliant vehicles.	Unable to determine based on current information. Non-compliance is determined based on tests that do not measure for NO_X or $PM_{2.5}$. Empirical estimates of the effects on these pollutants are not available. We provide two potential assumptions on the emissions from non-compliant vehicles; however, the true emissions may fall above or below these bounds.
Air quality modeling approach.	Unable to determine based on current information. Alternative air quality models may better characterize the magnitude and spatial distribution of $PM_{2.5}$ concentrations stemming from one ton of precursor emissions.
Concentration-response relationship between $PM_{2.5}$ and mortality.	Unable to determine based on current information. The GEMM function compiles results from many epidemiological studies, some of which find weaker or stronger $PM_{2.5}$-induced effects. We also do not have an estimate of long-term mortality impacts based on a locally conducted study; the only local study of mortality impacts only assessed those associated with short-term exposures, which will underestimate longer-term mortality impacts.
No cessation lag used for premature mortality.	Overestimate. If there is a time lag between $PM_{2.5}$ changes and premature mortality, then benefits occurring in the future should be discounted.
Valuation of mortality benefits.	Unable to determine based on current information. The human capital valuation approach is frequently thought to underestimate individual's true willingness to pay to reduce their risk of death. However, no primary studies have been conducted in Peru to estimate WTP for mortality risk reductions. MINAM's Euro 6 analysis includes several VSL estimates larger than the estimate employed in this analysis.

Addressing specific uncertainties, where possible, is an important next step MINAM staff and academic researchers. While the uncertainties presented in Exhibit 7-1 may be deemed acceptable for the types of analyses summarized in this report, addressing one or more of these limitations may be warranted for regulatory benefits analyses. We present our recommended topics for future research in the following section.

7.3 NEXT STEPS

As discussed above, our results are accompanied by data and methodological limitations, some of which may be addressed in future analyses by MINAM and academic researchers. We recommend several areas of focus for building upon the methods presented in this report:

- Pursue more advanced air quality modeling, such as leveraging photochemical air quality models previously employed in Lima-Callao (see Sánchez-Ccoyllo et al. 2016);
- Quantify and value morbidity effects (e.g., onset asthma and exacerbations, respiratory and cardiovascular hospitalizations and emergency room visits);
- Consider the impacts of transportation-attributable ozone formation and exposure;
- More closely evaluate near roadway exposures (i.e., health impacts resulting from exposure to elevated $PM_{2.5}$ and other pollutant concentrations near busy, polluted roads and highways).

In addition to addressing the methodological limitations outlined above, this report presents a framework that may be expanded to answer related research questions. First, the burden analyses conducted thus far may be adapted to assess the benefits of specific regulatory measures, such as increased enforcement for vehicle emissions standards and enhanced vehicle I&M programs. Second, the burden analyses may be expanded to assess the $PM_{2.5}$-attributable mortality burden stemming from other sources in Lima-Callao. For example, the results could be stratified further to highlight the mortality burden associated with specific sources within the transportation sector, such as buses or trucks. Additionally, this analysis could be expanded to assess the mortality burden attributed to $PM_{2.5}$ generated through energy production or chemicals manufacturing, which are two prominent industries within Lima-Callao (MINAM, 2018). Such results could also be expressed at the vehicle level. Understanding the average mortality burden resulting from one non-compliant vehicle, for example, may serve as a useful guide for policymakers in (1) identifying vehicle types for targeted emissions controls and (2) assessing whether emissions control costs would be justified based on the societal costs associated with each vehicle. In addition, evaluations could be made for implementing PM2.5 mitigation strategies to reduce concentrations at the community-level, such as street cleaning, low emission zones, and roadside barriers as part of expanding this work to assess near-road exposures. Additionally, this report presents a framework that could be expanded to include other sectors. Pending emissions data availability and compatibility with air quality models, this framework could be applied to other sources, such as industrial point sources.

Finally, we hope this report may serve as a conduit for continued technical capacity building for health benefits analysis. Similar analyses conducted under other Megacities efforts have been accompanied by workshops focused on the BenMAP-CE tool, best practices for conducting air pollution benefits analyses, and policy synthesis for advancing local air quality management efforts. We understand that MINAM is currently conducting a parallel analysis using the AirQ+ software. Comparing results and methods would serve to bolster the numbers presented in this report and to improve MINAM capabilities with each tool. Further, engaging additional MINAM staff and relevant stakeholders (e.g., academics, industry experts, municipalities) may serve to (1) disseminate the results more broadly and improve the usefulness of the report, and (2) enhance this study by incorporating alternative data sources and methods recommended by stakeholders.

REFERENCES

Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., et al. 2018. Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. Proceedings of the National Academy of Sciences. Vol. 115 (38): 9592-9597.

Hansel, N.N., Romero, K.M., Pollard, S.L., Bose, S., Psoter, K.J., J. Underhill, L., Johnson, C., Williams, D.A., Curriero, F.C., Breysse, P. and Koehler, K. 2019. Ambient air pollution and variation in multiple domains of asthma morbidity among Peruvian children. *Annals of the American Thoracic Society*, *16*(3), pp.348-355.

Health Effects Institute. 2010. *Traffic-Related Air Pollution: A Critical Review of the Literature on Emissions, Exposure, and Health Effects*. https://www.healtheffects.org/system/files/SR17TrafficReview.pdf

Karner, A., Eisinger, D., and Niemeier, D. 2010. Near-Roadway Air Quality: Synthesizing the Findings from Real-World Data. *Environmental Science and Technolology*, 44(14): 5334-44.

MINAM. 2018. Avance: Plan de Acción para el Mejoramiento de la Calidad del Aire de Lima-Callao; *Versión Preliminar: Diagnóstico de la Gestión de la Calidad Ambiental del Aire de Lima y Callao*.

Robinson, L.A., Hammitt, J.K., and O'Keefe, L. 2018. Valuing Mortality Risk Reductions in Global Benefit-Cost Analysis. Guidelines for Benefit-Cost Analysis Project Working Paper No. 7.

Sánchez-Ccoyllo, O.R., C.G. Ordoñez-Aquino, Á.G. Muñoz, A. Llacza, M.F. Andrade, Y. Liu, W. Reátegui-Romero, and G. Brasseur. 2018. Modeling Study of the Particulate Matter in Lima with the WRF-Chem Model: Case Study of April 2016. *International Journal of Applied Engineering Research*, 13(11): 10129-10141.

Shaddick, G., Thomas, M. L., Green, A., Brauer, M., van Donkelaar, A., Burnett, R., Chang, H.H., Cohen, A., Van Dingenen, R., Dora, C. and Gumy, S. 2018. Data integration model for air quality: a hierarchical approach to the global estimation of exposures to ambient air pollution. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 67(1), 231-253.

Tapia, V., Steenland, K., Sarnat, S. E., Vu, B., Liu, Y., Sánchez-Ccoyllo, O., Vasquez, V., and Gonzales, G. F. 2019. Time-series analysis of ambient PM 2.5 and cardiorespiratory emergency room visits in Lima, Peru during 2010–2016. *Journal of Exposure Science & Environmental Epidemiology*, 1-9.

Tapia, V., Steenland, K., Vu, B., Liu, Y., Vásquez, V., and Gonzales, G.F. 2020. $PM_{2.5}$ exposure on daily cardio-respiratory mortality in Lima, Peru, from 2010 to 2016. *Environmental Health*, 19(63). https://doi.org/10.1186/s12940-020-00618-6

Thiel, M., E.C. Macaya, E. Acuña, W.E. Arntz, H. Bastias, K. Brokordt, et al. 2007. The Humboldt Current System of Northern and Central Chile. Oceanography and Marine Biology 15: 195-344. https://www.researchgate.net/publication/210779714_The_Humboldt_Current_System_of_Northern_and_Central_Chile

Van Donkelaar, A., Martin, R. V., Brauer, M., Hsu, N. C., Kahn, R. A., Levy, R. C., Lyapustin, A., Sayer, A.M. and Winker, D. M. 2016. Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors. *Environmental science & technology*, *50*(7), 3762-3772.

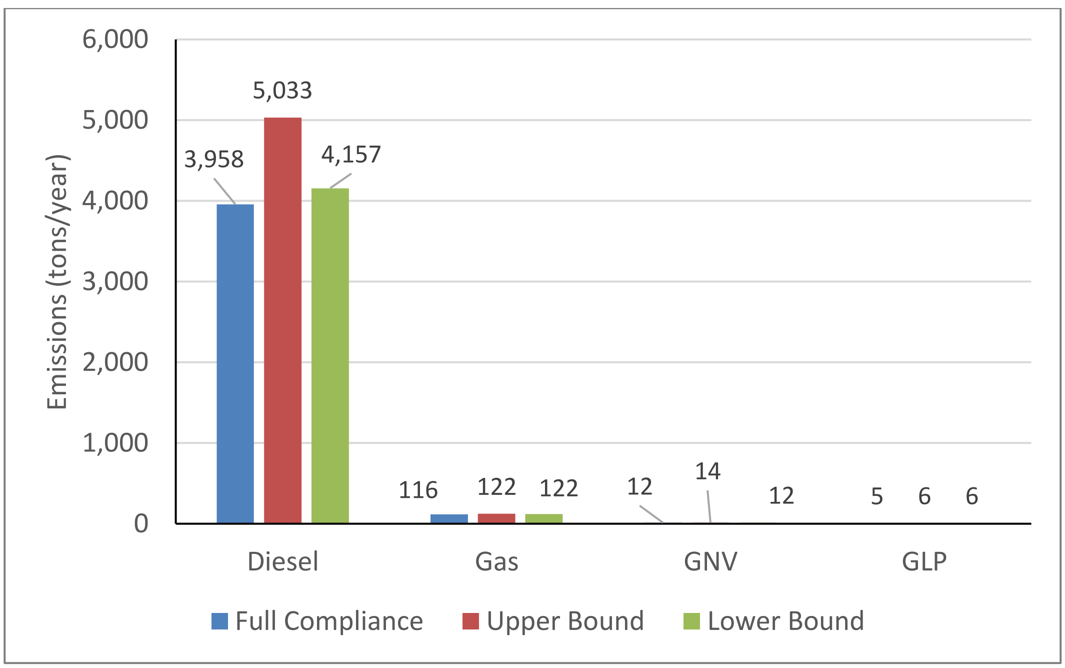
APPENDIX A | SUPPLEMENTAL EMISSIONS ESTIMATION RESULTS

In this section, we provide greater detail on estimated pollutant emissions from the transportation sector. In Chapter 3, we summarize emissions estimates by pollutant and compliance assumptions. Below, we further stratify these estimates to show the relative contributions by vehicle fuel type.

For $PM_{2.5}$ and NO_x, diesel emissions comprise the majority of total annual emissions (Exhibits A-1, A-2). We determined that high diesel emissions are not caused by a greater share of diesel vehicles in the fleet. Diesel vehicles make up less than 20 percent of the fleet, whereas gasoline vehicles made up greater than 70 percent. Instead, diesel vehicles make up large share (more than 85 percent) of high emitting vehicle types such as pick-up trucks, omnibuses, trucks, and tow trucks. In contrast, gasoline emissions are the largest contributor to SO_2 emissions, as seen in Exhibit A-3.

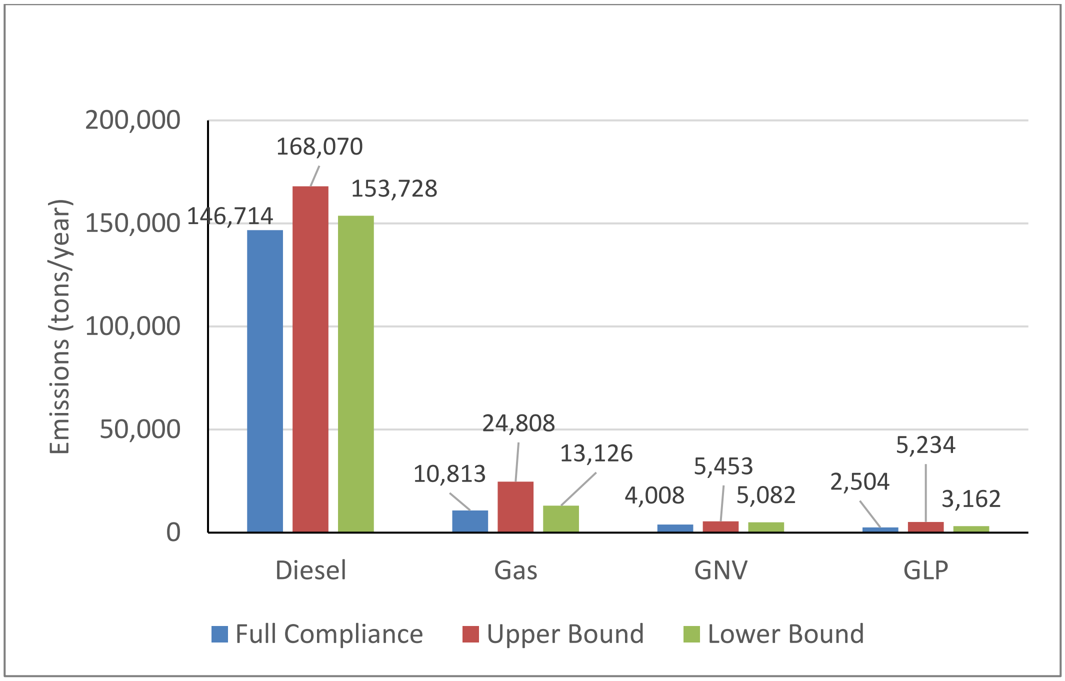
Notably, SO_2 emissions are assumed to vary with sulfur content in fuels and total fuel consumption. Emissions controls, and thus compliance status, are assumed to not affect SO_2 emissions in our model.

EXHIBIT A-1. 2018 $PM_{2.5}$ EMISSIONS BY FUEL TYPE



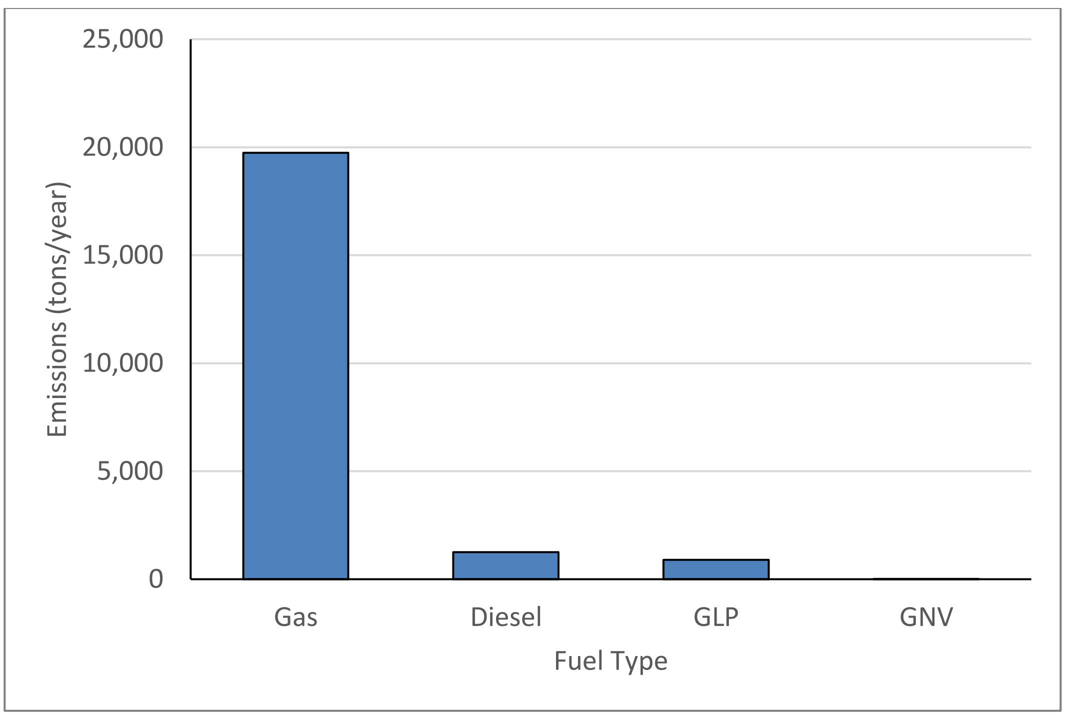
Notes: GLP = liquified petroleum, GNV = natural gas.

EXHIBIT A-2. 2018 NO_X EMISSIONS BY FUEL TYPE



Notes: GLP = liquified petroleum, GNV = natural gas.

EXHIBIT A-3. 2018 SO_2 EMISSIONS BY FUEL TYPE



Notes: GLP = liquified petroleum, GNV = natural gas.

APPENDIX B | SATELLITE MEASUREMENTS AND PROCESSING

In Chapter 4, we summarize available data sources characterizing air pollution in Lima-Callao, including both monitor and satellite data. In this Appendix, we provide greater detail on the satellite datasets and our methods for "ground-truthing" these datasets to more closely reflect monitor concentrations.

Van Donkelaar et al. (2016) combine information from satellites, model simulations and monitors. Satellites provide global measurements of aerosol optical depth (AOD). The van Donkelaar surfaces combine AOD retrievals from the NASA Moderate Resolution Imaging Spectroradiometer, Multi-angle Imaging SpectroRadiometer and the Sea-Viewing Wide Field-of-View Sensor. Next, model simulations from the GEOS-Chem chemical transport model are used to convert total column AOD to near-surface $PM_{2.5}$ concentrations. Finally, ground-based monitor measurements from the WHO Global Ambient Air Quality Database[24] are used with a GWR to predict and adjust for residual $PM_{2.5}$ bias in each grid cell from the initial satellite derived values.

The Shaddick et al. (2017) surfaces are the result of the Data Integration Model for Air Quality (DIMAQ) developed by the WHO Data Integration Task Force. This model integrates monitor measurements from the WHO Global Ambient Air Quality Database, satellite remote sensing, population estimates, topography, and measures of specific contributors of air pollution from chemical transport models. The same methods as van Donkelaar et al. (2016) are used to combine AOD from multiple satellites with GEOS-Chem chemical transport model simulations to produce estimates of near-surface $PM_{2.5}$ at 0.1° resolution. DIMAQ goes beyond the methods of van Donkelaar et al. (2016) by using a Bayesian model to estimate the spatially varying relationship between ground measurements of $PM_{2.5}$ and factors from the GEOS-Chem, TM5, and TM5-FASST chemical models that estimate air quality.

Our methods for locally calibrating the satellite surfaces are broken into four steps: (1) calculate annual $PM_{2.5}$ averages at the monitor locations, (2) calculate the ratio between 2019 monitor and 2016 satellite annual $PM_{2.5}$ averages, (3) spatially interpolate the ratios to create a calibration surface, and (4) multiply the calibration surface against the satellite surface to create a locally calibrated air quality surface.

First, we determine the annual average $PM_{2.5}$ concentration measured by monitors at each location. A 2016 $PM_{2.5}$ annual average is available for the ten stations in the SENAMHI

[24] World Health Organization. *WHO Global Ambient Air Quality Database (Update 2018)*; WHO: Geneva, 2018: https://www.who.int/airpollution/data/cities/en/

ground monitoring network. Station information is available in Exhibit 1. Additionally, we use an adjusted 2019 $PM_{2.5}$ annual average for two MINSA operated stations, "CA-VMP-1" and "CA-VMP-2" as these new stations show a hotspot, or area of higher concentrations, in Callao which is not captured by the SENAMHI monitor network. To include as many monitoring locations as possible, we adjust the 2019 $PM_{2.5}$ annual average at the Callao stations to 2016 concentrations using a ratio of 2016 to 2019 values. For numerator of the ratio, we use a distance-weighted average of the 2016 annual average from the two closest SENAMHI monitors. For the denominator of the ratio, we use the grid cell value at the Callao monitor locations of a 2019 annual average surface created using data from the ten SENAMHI monitors.

We then determine the annual average satellite surface $PM_{2.5}$ concentration at each location by creating a one kilometer buffer around each station and calculating an area-weighted average within the buffer zone.

Second, we calculate a calibration factor for each station, which is equal to the monitor annual average divided by the satellite annual average for each station. A calibration factor greater than one adjusts satellite data upwards and a factor less than one adjusts satellite data downwards. Third, we interpolate the calibration factors across the domain using a Kriging function to create a calibration surface (Exhibit B-1). Finally, we multiply the calibration surface against the original satellite surface to create a locally calibrated final surface.

EXHIBIT B-1. SHADDICK AND VAN DONKELAAR CALIBRATION SURFACES

b) 2016 Van Donkelaar Calibration **a) 2016 Shaddick Calibration**

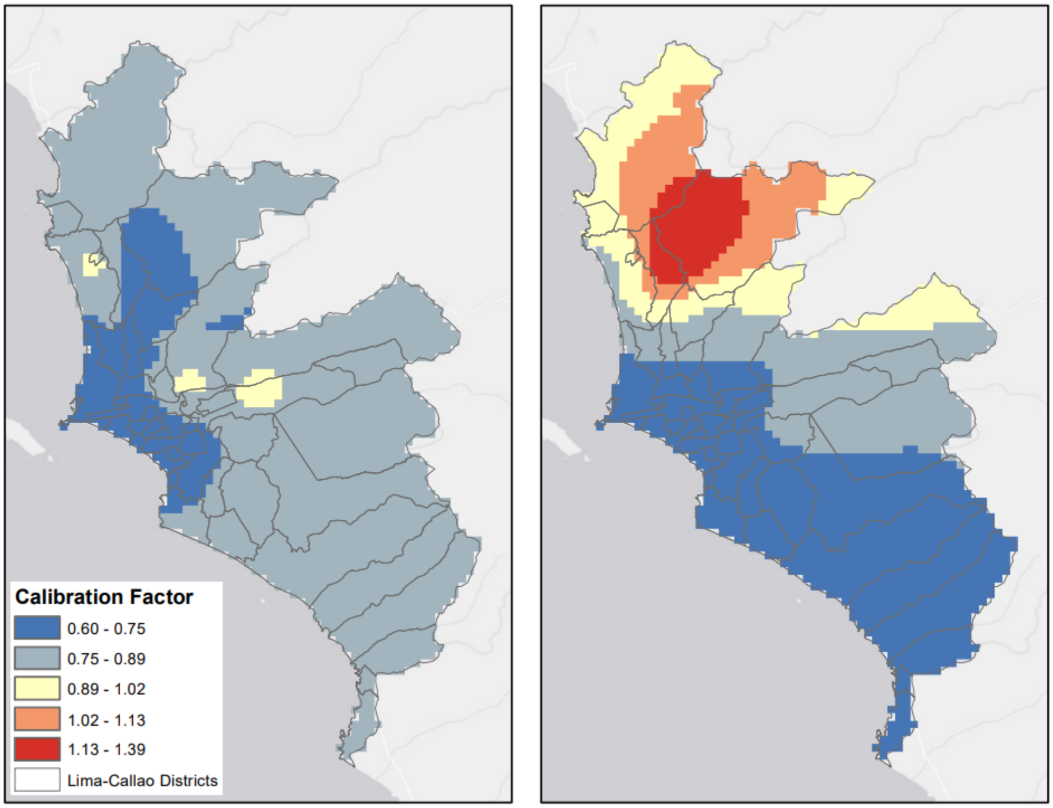
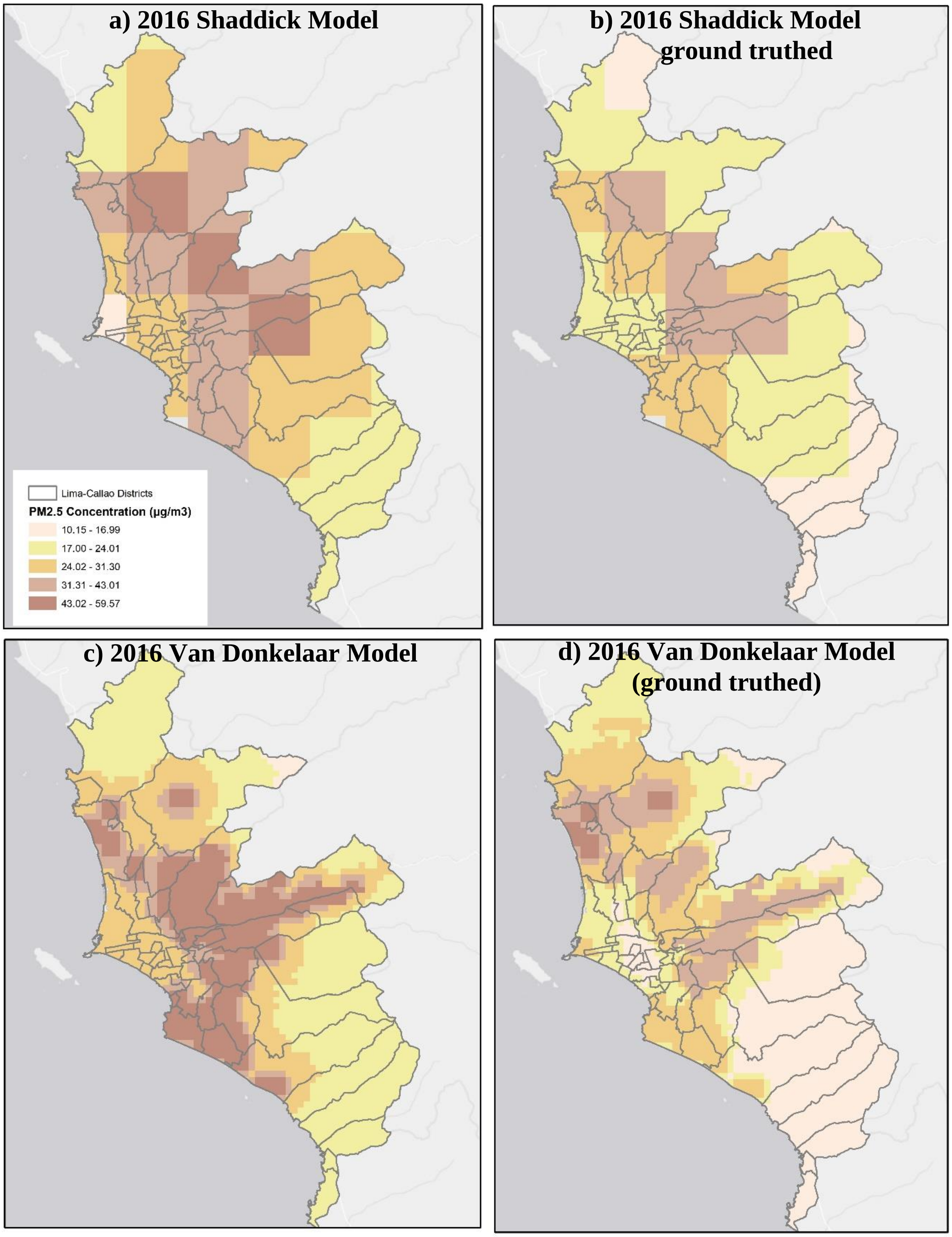


EXHIBIT B-2. SHADDICK AND VAN DONKELAAR AIR QUALITY SURFACES PRE- AND POST-CALIBRATION



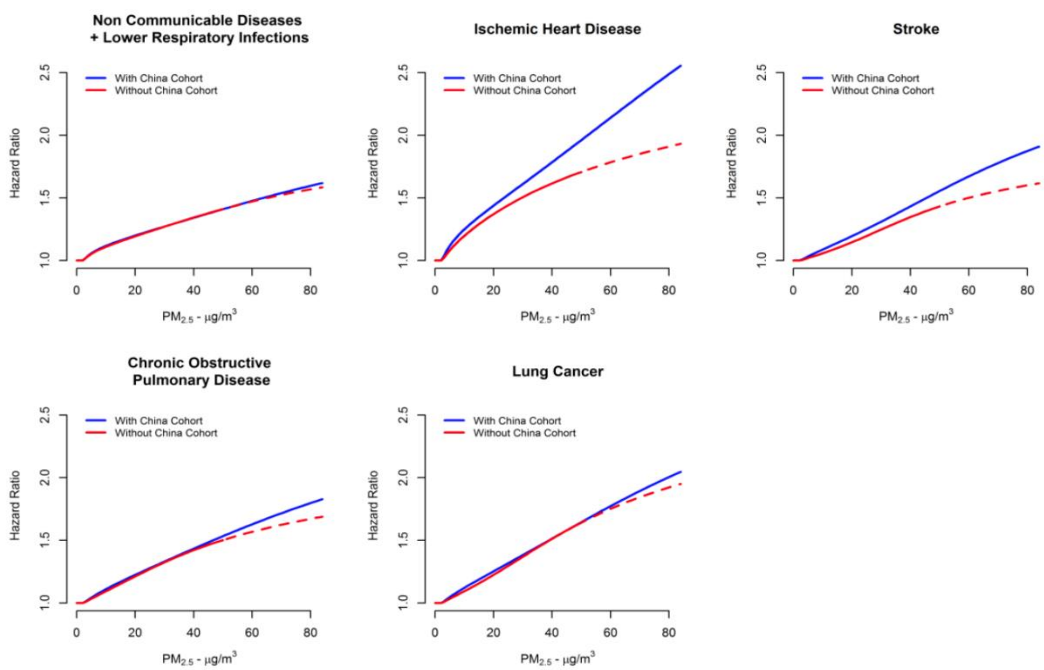
APPENDIX C | HEALTH IMPACT ESTIMATION

In this Appendix we discuss additional health impact results, as well as the implication of using a non-linear mortality function. This Appendix will include discussion of the GEMM functions, alternative transport contribution results, alternative non-compliant vehicle contribution results, and the health endpoints not discussed in Chapter 6.

GEMM NON-LINEARITY

As discussed in Section 5.2.3, we utilized six of the 83 non-linear GEMM functions pre-loaded into BenMAP-CE. It is important to note that these GEMM functions are non-linear with a decreasing marginal relationship between $PM_{2.5}$ concentration and the mortality hazard ratio (Exhibit C-1). Because we modeled mortality burden analyses by removing the transportation sector's contribution from the high end of $PM_{2.5}$ concentrations (i.e., "rolling back" baseline values), we may understate mortality burden due to the lower mortality response per unit change in $PM_{2.5}$ at these higher concentrations.

EXHIBIT C-1. BURNETT ET AL. (2018) FIGURE S6



s a sensitivity analysis, we calculated the contribution of transport emissions and non-compliant vehicle emissions to the total burden of $PM_{2.5}$ in Lima-Callao by calculating the mortality burden *as a percentage of total mortality burden based on the sector's contributions to ambient* $PM_{2.5}$ *concentrations.* That is, if the sector was responsible for 50 percent of ambient concentrations, we would apportion 50 percent of the total Lima-Callao mortality burden to this sector. Exhibits C-2 and C-3 compare the BenMAP-CE GEMM function results against a direct proportional analysis for the transport and non-compliant vehicle burden contributions. Overall, the GEMM functions may underestimate the contribution of the transport sector and non-compliant vehicles to the total burden of $PM_{2.5}$.

EXHIBIT C-2. TRANSPORT ATTRIBUTABLE $PM_{2.5}$ MORTALITY BURDEN

CAUSE OF MORTALITY	GEMM FUNCTION		DIRECT PROPORTIONAL CONTRIBUTION	
	LOWER	UPPER	LOWER	UPPER
GEMM: NCD + LRI	**5,150**	**6,200**	**6,097**	**7,057**
GEMM: 5 COD	**4,221**	**4,855**	**3,764**	**4,357**
Lower respiratory infection	2,522	2,855	2,044	2,365
Ischemic heart disease	680	814	763	883
Cerebrovascular disease	534	616	487	563
Lung Cancer	315	368	302	350
COPD	171	201	168	195

EXHIBIT C-3. NON-COMPLIANT VEHICLE ATTRIBUTABLE PM2.5 MORTALITY BURDEN

CAUSE OF MORTALITY	GEMM FUNCTION		DIRECT PROPORTIONAL CONTRIBUTION	
	LOWER	UPPER	LOWER	UPPER
GEMM: NCD + LRI	**248**	**991**	**322**	**1,281**
GEMM: 5 COD	**223**	**890**	**199**	**791**
Lower respiratory infection	135	541	108	429
Ischemic heart disease	33	133	40	160
Cerebrovascular disease	30	116	26	102
Lung Cancer	16	65	16	64
COPD	9	34	9	35

APPENDIX D | DISTRICT-LEVEL RESULTS

In this Appendix, we highlight the variability in mortality burden results across districts. The tables highlight the importance of the geographic resolution of the selected air quality model when viewing district level results. We compare our primary results (10km x 10km grid, Shaddick) with a finer scale surface (1km x 1km grid, van Donkelaar) and present an average effect across these models. Exhibits D-1 through D-5 provide the district level NCD + LRI mortality results for:

- Total mortality burden attributed to ambient $PM_{2.5}$: Exhibit C-1
- Transport sector mortality burden: Exhibits C-2 (lower bound) and C-3 (upper bound)
- Mortality burden of non-compliant emissions: Exhibits C-4 (lower bound) and C-5 (upper bound)

Overall, while the regional-level differences in mortality burden are negligible across surfaces, we observe notable differences at the district level. Such results may motivate air quality controls be focused in regions with significant mortality burden.

EXHIBIT D-1. DISTRICT-LEVEL TOTAL $PM_{2.5}$ MORTALITY BURDEN

DISTRICT NAME	DISTRICT POPULATION (AGES 25-99)	SHADDICK	VAN DONKELAAR	AVERAGE	
		DEATHS	DEATHS	DEATHS	RATE PER 100,000
Overall	**6,815,428**	**10,556**	**10,838**	**10,697**	**157**
San Juan De Lurigancho	695,326	1,054	1,009	1,031	148
Comas	361,764	624	707	665	184
San Martin De Porres	488,004	606	654	630	129
Lima	207,527	538	646	592	285
Callao	304,221	535	503	519	171
Villa Maria Del Triunfo	294,591	504	397	451	153
Ate	394,943	370	512	441	112
Santiago De Surco	272,592	354	376	365	134
Carabayllo	189,698	472	247	360	190
Lurigancho	139,146	484	215	349	251
Villa El Salvador	291,540	256	370	313	107
Chorrillos	224,392	350	263	307	137
La Molina	132,567	382	228	305	230
Los Olivos	254,864	277	320	299	117
San Juan De Miraflores	272,025	211	381	296	109
Rimac	120,902	302	285	294	243
Ventanilla	271,339	315	254	285	105
La Victoria	125,163	225	314	270	216
Puente Piedra	210,135	242	289	266	127
Independencia	149,822	253	272	263	175
San Miguel	108,804	217	196	207	190
El Agustino	125,281	165	241	203	162
Miraflores	74,718	127	229	178	238
San Isidro	49,229	197	145	171	348
San Borja	94,488	130	190	160	170
Jesus Maria	61,365	108	174	141	230
Magdalena Vieja	63,935	116	157	136	213
Santa Anita	149,168	91	177	134	90
Breña	60,003	80	144	112	187
Cieneguilla	30,285	166	23	94	311
Magdalena Del Mar	45,329	84	100	92	203
Surquillo	72,492	61	116	89	122
Lince	42,557	69	108	88	208
Bellavista	59,552	66	97	81	137
Lurin	52,254	101	48	75	143

DISTRICT NAME	DISTRICT POPULATION (AGES 25-99)	SHADDICK	VAN DONKELAAR	AVERAGE	
		DEATHS	DEATHS	DEATHS	RATE PER 100,000
Pachacamac	76,225	94	51	73	96
San Luis	42,772	48	75	61	143
La Perla	49,511	33	79	56	113
Chaclacayo	31,232	33	78	55	176
Ancon	27,202	69	38	53	196
Barranco	24,956	38	57	48	191
Carmen De La Legua Reynoso	31,190	48	37	42	135
Santa Rosa	12,157	25	8	17	138
La Punta	3,131	8	8	8	249
Punta Hermosa	5,230	9	2	6	110
Pucusana	10,443	5	4	5	46
Mi Peru*	-	6	2	4	NA
Punta Negra	5,400	5	3	4	68
San Bartolo	4,845	2	3	3	54
Santa Maria Del Mar	1,113	1	1	1	109

*The Mi Peru district in Callao had zero population in our dataset. Because the Shaddick and van Donkelaar surfaces overlap the population grid (districts), BenMAP apportions incidence results from air quality grid cells into the overlapping districts (including Mi Peru).

EXHIBIT D-2. DISTRICT-LEVEL $PM_{2.5}$ MORTALITY BURDEN, TRANSPORTATION SECTOR (LOWER BOUND)

DISTRICT NAME	DISTRICT POPULATION (AGES 25-99)	SHADDICK	VAN DONKELAAR	AVERAGE	
		DEATHS	DEATHS	DEATHS	RATE PER 100,000
Overall	**6,815,428**	**5,150**	**5,195**	**5,173**	**76**
San Juan De Lurigancho	695,326	509	476	492	71
Comas	361,764	299	333	316	87
San Martin De Porres	488,004	296	314	305	63
Lima	207,527	265	318	292	141
Callao	304,221	287	248	267	88
Villa Maria Del Triunfo	294,591	242	188	215	73
Ate	394,943	178	242	210	53
Santiago De Surco	272,592	171	177	174	64
Carabayllo	189,698	227	117	172	91
Lurigancho	139,146	233	102	168	120
Villa El Salvador	291,540	123	173	148	51
Chorrillos	224,392	170	123	147	65
La Molina	132,567	183	107	145	109
Los Olivos	254,864	134	152	143	56
Rimac	120,902	149	135	142	117
San Juan De Miraflores	272,025	101	179	140	51
Ventanilla	271,339	153	120	136	50
La Victoria	125,163	111	153	132	105
Puente Piedra	210,135	116	136	126	60
Independencia	149,822	122	128	125	83
San Miguel	108,804	108	100	104	96
El Agustino	125,281	80	113	97	77
Miraflores	74,718	62	110	86	115
San Isidro	49,229	97	73	85	172
San Borja	94,488	63	91	77	82
Jesus Maria	61,365	53	88	71	115
Magdalena Vieja	63,935	57	80	68	107
Santa Anita	149,168	44	83	63	43
Breña	60,003	39	72	56	93
Magdalena Del Mar	45,329	41	51	46	102
Cieneguilla	30,285	80	11	46	151
Lince	42,557	34	54	44	104
Surquillo	72,492	30	56	43	59
Bellavista	59,552	35	49	42	70

DISTRICT NAME	DISTRICT POPULATION (AGES 25-99)	SHADDICK	VAN DONKELAAR	AVERAGE	
		DEATHS	DEATHS	DEATHS	RATE PER 100,000
Lurin	52,254	49	24	37	70
Pachacamac	76,225	46	26	36	47
San Luis	42,772	23	36	29	69
La Perla	49,511	18	40	29	59
Chaclacayo	31,232	16	37	26	84
Ancon	27,202	34	18	26	95
Barranco	24,956	19	27	23	91
Carmen De La Legua Reynoso	31,190	24	18	21	67
Santa Rosa	12,157	12	4	8	66
La Punta	3,131	4	4	4	134
Punta Hermosa	5,230	5	1	3	56
Pucusana	10,443	3	2	3	24
Mi Peru	-	3	1	2	NA
Punta Negra	5,400	2	1	2	36
San Bartolo	4,845	1	2	1	29
Santa Maria Del Mar	1,113	1	1	1	57
*The Mi Peru district in Callao had zero population in our dataset. Because the Shaddick and van Donkelaar surfaces overlap the population grid (districts), BenMAP apportions incidence results from air quality grid cells into the overlapping districts (including Mi Peru).					

EXHIBIT D-3. DISTRICT-LEVEL $PM_{2.5}$ MORTALITY BURDEN, TRANSPORTATION SECTOR (UPPER BOUND)

DISTRICT NAME	DISTRICT POPULATION (AGES 25-99)	SHADDICK	VAN DONKELAAR	AVERAGE	
		DEATHS	DEATHS	DEATHS	RATE PER 100,000
Overall	**6,815,428**	**6,200**	**6,238**	**6,219**	**91**
San Juan De Lurigancho	695,326	607	564	585	84
Comas	361,764	356	394	375	104
San Martin De Porres	488,004	358	381	369	76
Lima	207,527	323	387	355	171
Callao	304,221	355	302	329	108
Villa Maria Del Triunfo	294,591	290	224	257	87
Ate	394,943	211	287	249	63
Santiago De Surco	272,592	205	212	208	76
Carabayllo	189,698	270	140	205	108
Lurigancho	139,146	277	122	200	143
Villa El Salvador	291,540	147	206	177	61
Chorrillos	224,392	206	147	176	79
La Molina	132,567	218	127	173	130
Rimac	120,902	181	162	171	67
Los Olivos	254,864	160	183	171	142
San Juan De Miraflores	272,025	122	213	167	61
Ventanilla	271,339	184	142	163	60
La Victoria	125,163	135	186	160	128
Puente Piedra	210,135	138	161	150	71
Independencia	149,822	146	152	149	100
San Miguel	108,804	132	123	128	117
El Agustino	125,281	96	134	115	92
Miraflores	74,718	75	134	104	140
San Isidro	49,229	118	89	103	210
San Borja	94,488	76	110	93	98
Jesus Maria	61,365	65	108	86	141
Magdalena Vieja	63,935	69	98	84	131
Santa Anita	149,168	52	99	75	50
Breña	60,003	48	88	68	113
Magdalena Del Mar	45,329	50	63	57	125
Cieneguilla	30,285	95	13	54	180
Lince	42,557	41	67	54	127
Surquillo	72,492	36	68	52	72
Bellavista	59,552	43	60	51	86
Lurin	52,254	59	29	44	84

DISTRICT NAME	DISTRICT POPULATION (AGES 25-99)	SHADDICK	VAN DONKELAAR	AVERAGE	
		DEATHS	DEATHS	DEATHS	RATE PER 100,000
Pachacamac	76,225	55	32	43	57
La Perla	49,511	23	49	36	85
San Luis	42,772	28	43	35	72
Chaclacayo	31,232	19	44	31	101
Ancon	27,202	41	22	31	114
Barranco	24,956	23	32	27	109
Carmen De La Legua Reynoso	31,190	29	22	26	82
Santa Rosa	12,157	14	5	10	79
La Punta	3,131	6	5	5	166
Punta Hermosa	5,230	6	2	4	68
Pucusana	10,443	3	3	3	30
Mi Peru	-	4	1	2	NA
Punta Negra	5,400	3	2	2	44
San Bartolo	4,845	1	2	2	36
Santa Maria Del Mar	1,113	1	1	1	71

*The Mi Peru district in Callao had zero population in our dataset. Because the Shaddick and van Donkelaar surfaces overlap the population grid (districts), BenMAP apportions incidence results from air quality grid cells into the overlapping districts (including Mi Peru).

EXHIBIT D-4. DISTRICT-LEVEL $PM_{2.5}$ MORTALITY BURDEN, NON-COMPLIANT EMISSIONS (LOWER BOUND)

DISTRICT NAME	DISTRICT POPULATION (AGES 25-99)	SHADDICK	VAN DONKELAAR	AVERAGE	
		DEATHS	DEATHS	DEATHS	RATE PER 100,000
Overall	**6,815,428**	**248**	**250**	**249**	**4**
San Juan De Lurigancho	695,326	25	24	25	4
Comas	361,764	15	17	16	4
San Martin De Porres	488,004	14	15	14	3
Lima	207,527	12	15	13	6
Callao	304,221	13	11	12	4
Ate	394,943	9	12	10	4
Villa Maria Del Triunfo	294,591	12	9	10	3
Carabayllo	189,698	11	6	9	3
Santiago De Surco	272,592	8	9	8	4
Lurigancho	139,146	12	5	8	6
Villa El Salvador	291,540	6	9	7	3
La Molina	132,567	9	5	7	3
Chorrillos	224,392	8	6	7	5
Los Olivos	254,864	7	7	7	3
San Juan De Miraflores	272,025	5	9	7	6
Rimac	120,902	7	7	7	2
Ventanilla	271,339	7	6	7	2
Puente Piedra	210,135	6	7	6	5
Independencia	149,822	6	6	6	3
La Victoria	125,163	5	7	6	4
El Agustino	125,281	4	6	5	4
San Miguel	108,804	5	4	5	4
Miraflores	74,718	3	5	4	5
San Isidro	49,229	5	3	4	8
San Borja	94,488	3	4	4	4
Jesus Maria	61,365	2	4	3	5
Santa Anita	149,168	2	4	3	5
Magdalena Vieja	63,935	3	4	3	2
Breña	60,003	2	3	3	4
Cieneguilla	30,285	4	1	2	5
Magdalena Del Mar	45,329	2	2	2	7
Surquillo	72,492	1	3	2	5
Lince	42,557	2	2	2	3
Bellavista	59,552	2	2	2	3

DISTRICT NAME	DISTRICT POPULATION (AGES 25-99)	SHADDICK	VAN DONKELAAR	AVERAGE	
		DEATHS	DEATHS	DEATHS	RATE PER 100,000
Lurin	52,254	2	1	2	3
Pachacamac	76,225	2	1	2	2
San Luis	42,772	1	2	1	3
La Perla	49,511	1	2	1	3
Chaclacayo	31,232	1	2	1	4
Ancon	27,202	2	1	1	5
Barranco	24,956	1	1	1	4
Carmen De La Legua Reynoso	31,190	1	1	1	3
Santa Rosa	12,157	1	0	0	3
La Punta	3,131	0	0	0	6
Punta Hermosa	5,230	0	0	0	3
Pucusana	10,443	0	0	0	1
Mi Peru	-	0	0	0	NA
Punta Negra	5,400	0	0	0	2
San Bartolo	4,845	0	0	0	1
Santa Maria Del Mar	1,113	0	0	0	3

*The Mi Peru district in Callao had zero population in our dataset. Because the Shaddick and van Donkelaar surfaces overlap the population grid (districts), BenMAP apportions incidence results from air quality grid cells into the overlapping districts (including Mi Peru).

EXHIBIT D-5. DISTRICT-LEVEL $PM_{2.5}$ MORTALITY BURDEN, NON-COMPLIANT EMISSIONS (UPPER BOUND)

DISTRICT NAME	DISTRICT POPULATION (AGES 25-99)	SHADDICK	VAN DONKELAAR	AVERAGE	
		DEATHS	DEATHS	DEATHS	RATE PER 100,000
Overall	**6,815,428**	**991**	**1,003**	**997**	**15**
San Juan De Lurigancho	695,326	101	95	98	14
Comas	361,764	59	67	63	17
San Martin De Porres	488,004	56	59	58	12
Lima	207,527	49	59	54	26
Callao	304,221	51	46	48	16
Villa Maria Del Triunfo	294,591	47	37	42	14
Ate	394,943	36	48	42	11
Carabayllo	189,698	45	23	34	12
Santiago De Surco	272,592	33	35	34	18
Lurigancho	139,146	46	20	33	24
Villa El Salvador	291,540	24	34	29	10
La Molina	132,567	36	21	29	13
Chorrillos	224,392	32	24	28	21
Los Olivos	254,864	26	30	28	11
San Juan De Miraflores	272,025	20	36	28	23
Rimac	120,902	28	26	27	10
Ventanilla	271,339	29	24	27	10
Puente Piedra	210,135	23	28	25	20
Independencia	149,822	24	25	25	12
La Victoria	125,163	21	28	25	16
El Agustino	125,281	15	23	19	18
San Miguel	108,804	20	18	19	15
Miraflores	74,718	12	21	16	22
San Isidro	49,229	18	13	16	32
San Borja	94,488	12	17	15	16
Jesus Maria	61,365	10	16	13	21
Santa Anita	149,168	9	17	13	20
Magdalena Vieja	63,935	11	14	12	8
Breña	60,003	7	13	10	17
Cieneguilla	30,285	16	2	9	20
Magdalena Del Mar	45,329	8	9	8	28
Lince	42,557	6	10	8	19
Surquillo	72,492	6	10	8	11
Bellavista	59,552	6	9	8	13

DISTRICT NAME	DISTRICT POPULATION (AGES 25-99)	SHADDICK	VAN DONKELAAR	AVERAGE	
		DEATHS	DEATHS	DEATHS	RATE PER 100,000
Lurin	52,254	9	4	7	13
Pachacamac	76,225	9	5	7	9
San Luis	42,772	4	7	6	13
La Perla	49,511	3	7	5	10
Chaclacayo	31,232	3	7	5	16
Ancon	27,202	6	3	5	18
Barranco	24,956	3	5	4	18
Carmen De La Legua Reynoso	31,190	4	3	4	12
Santa Rosa	12,157	2	1	2	13
La Punta	3,131	1	1	1	24
Punta Hermosa	5,230	1	0	1	10
Pucusana	10,443	0	0	0	4
Mi Peru	-	1	0	0	NA
Punta Negra	5,400	0	0	0	6
San Bartolo	4,845	0	0	0	5
Santa Maria Del Mar	1,113	0	0	0	10

*The Mi Peru district in Callao had zero population in our dataset. Because the Shaddick and van Donkelaar surfaces overlap the population grid (districts), BenMAP apportions incidence results from air quality grid cells into the overlapping districts (including Mi Peru).