Quantifying and Characterizing Near-Port Populations in the Conterminous United States

National Results Using High-Resolution Population Data from EPA's EnviroAtlas



Quantifying and Characterizing Near-Port Populations in the Conterminous United States

National Results Using High-Resolution Population Data from EPA's EnviroAtlas

Transportation and Climate Division Office of Transportation and Air Quality U.S. Environmental Protection Agency

NOTICE

This technical report does not necessarily represent final EPA decisions or positions. It is intended to present technical analysis of issues using data that are currently available. The purpose in the release of such reports is to facilitate the exchange of technical information and to inform the public of technical developments.



EPA-420-R-24-021 December 2024

Executive Summary

Marine ports are critical for commerce and economic growth, and they play a significant role in the goods movement supply chain. However, port-related activity often contributes to air pollution emissions from a variety of diesel-powered mobile sources that operate in port areas such as trucks, locomotives, cargo handling equipment, harbor craft, and ocean-going vessels. These sources can have important impacts on local and distant air pollution, including fine particulate matter, nitrogen oxides, air toxics, which are associated with increased risk of adverse health outcomes among those who are exposed, as well as carbon dioxide emissions. Communities near ports may be exposed to harmful local emissions related to port activity and may benefit from efforts to make ports cleaner. However, the number of people living near ports and the demographics of these populations remains poorly defined, in part due to the complex and numerous ways to describe a port and port operations. In this study, we identified populations near ports in a more sophisticated manner than traditional proximity analyses by leveraging a 2010 high-resolution population dataset of the conterminous United States (CONUS, the lower 48 states and the District of Columbia) and port geometries from two different Federal agencies. We also characterized the sociodemographic attributes of these near-port populations to identify potential disproportionalities in community demographics that may be indicative of potential environmental justice (EJ) concerns for near-port populations.

Depending on the port boundaries used, at least 16.1M or 31.1M people live within 5000m of major ports in the conterminous U.S.

A total of 123 major ports in the conterminous United States were investigated in this study based on their inclusion in the U.S. Army Corps of Engineers (ACE) 2017 Principal Ports list of the top 150 ports by tonnage throughput and their representation in two different Federal datasets: the EPA's National Emissions Inventory (NEI) and ACE's Master Docks Plus. By overlapping 2010 population data with either the NEI or ACE port geometries, we estimated that 16.1 or 31.1 million individuals live within 5000m (~3.1 mi.) of ports included in this study. We also estimated that 2.6 or 4.7 million individuals live within 1000m (~0.6 mi.). We caution that these values likely underestimate the total number of people impacted by port operations, as the precise numbers presented in this study are highly dependent on the port geometry used, the set of ports included, and the distance used to define 'near port'.

Near-port populations have higher shares of sociodemographically vulnerable groups than comparison populations.

We also assessed the sociodemographic characteristics of these near-port populations based on variables that are widely used across published EJ tools and represent a wide range of vulnerabilities. Using two different comparison groups, we identified several vulnerable sociodemographic groups that are overrepresented in the near-port population. For the racial and ethnic groups quantified, there were higher percentages of Hispanic, Non-Hispanic Black, Non-Hispanic Asian, and people of color in the near-port populations as compared to neighboring populations and the general population of CONUS. We also detected disproportionalities among near-port populations for several socioeconomic factors,

including the percentages of individuals living below twice the poverty level, renters, individuals living in areas of persistent poverty, adults with less than a high school education, households in linguistic isolation, and households living below a Quality of Life income threshold. The differences in sociodemographic characteristics between the near-port populations and their comparison groups were surprisingly consistent using either the NEI or ACE port geometries. This consistency increases confidence in the overall takeaway that certain sociodemographically vulnerable groups are overrepresented in proximity to major ports in CONUS.

These national near-port demographic disproportionalities are not driven by just a few ports, but instead point to broader trends around ports.

We also conducted a supplemental analysis in which we subset the 123 ports included in this study into the top 10 ports by tonnage and the remaining 113 ports. The purpose of this supplemental analysis was to understand whether the sociodemographic patterns observed in the primary analysis were driven solely by the busiest ports by tonnage, which also aligned with major metro areas. Further, we sought to understand if there were meaningfully different disproportionalities or sociodemographic characteristics surrounding the top 10 busiest ports, which may also contribute the most emissions related to port activity. In general, the national results were supported by the supplemental analysis, with some nuances depending on the port geometry or comparison group that was used. Further, we found that the populations living within 5000m of the top 10 ports accounted for 30-40% of the total near-port population around all 123 major ports that were included in this study. Therefore, actions taken to lower emissions at these top 10 ports with the largest tonnage throughput may have an outsized impact on the nation's near-port population.

A key challenge of this work is the complexity of mapping and defining port operations geospatially.

Across the spectrum of port-related federal activities conducted by EPA, U.S. Department of Transportation (DOT), ACE, and others (including grants and programmatic work), there are varying definitions for a 'port' that come from statutory language or administrative requirements. In addition to there being multiple definitions of 'port' in use, there is also not a single authoritative source for the geospatial extent of U.S. ports or the extent over which vehicles and equipment serving a port may operate. This study navigates these complexities by using the best available data from two different agencies (ACE and EPA) for the same set of 123 ports and by making simplifying assumptions to capture nearby impacts of port activities. The total near-port population estimates from this study varied substantially depending on the port geometry used, which underscores the critical role of source geometry in proximity analyses.

Table of Contents

E>	cecutive Summary	. ii
	List of Figures	. v
	List of Tables	vi
	List of Acronyms & Abbreviations	vii
1.	Introduction	.1
2.	Methods and Approach	. 3
	2.1 Port Geospatial Data	. 3
	U.S. Army Corps of Engineers Master Docks Plus Shapefiles	. 4
	EPA Port Polygons from the National Emissions Inventory	. 5
	Port Inclusion Criteria	. 6
	2.2 Geodesic Buffers Around Port Geometry to Describe Near-Port Populations	. 8
	2.3 Higher Resolution Population Estimates	. 9
	2.4 Sociodemographic Variables	10
	2.5 Comparison Groups	13
	Conterminous United States	14
	Intra-County Comparison Group	14
	2.6 Developing a National Analysis	15
	2.7 Top 10 Ports Supplemental Analysis	16
3.	Results	18
	3.1 National Estimates of Near-Port Populations and Comparison Groups	18
	3.2 National Disproportionalities of Near-Port Populations	19
	Overrepresentation of People of Color in Near-Port Populations compared to Comparison Groups. 2	22
	Multiple Metrics of Income Point to Economic Disproportionalities between Near-Port Populations Comparison Groups	
	No detectable disproportionalities among vulnerable age groups in Near-Port Populations	27
	3.3 Top 10 Ports Supplemental Analysis Supports Conclusions of National Analysis	27
	Estimates of Near-Port Populations & Comparison Groups	27
	Disproportionalities of Near-Port Populations	32
4.	Discussion	37
	4.1 Summary of Results	37
	4.2 Differences between the EPA and ACE Shapefiles and Impact on Population Totals	38

Z	1.3	Other Study Limitations	40
5.	C	Conclusion	41
Wo	orks	s Cited	42
Ap	per	ndix	46
A	۹.	List of Ports Included in Study	46
E	3.	Summary of Geospatial Port Data Sources	47
C	2.	Summary of Port Definitions from Various Federal Agencies and Programs	48
	E	nvironmental Protection Agency	48
	ι	J.S. Department of Transportation	48
	ι	J.S. Army Corps of Engineers	51
0).	Additional Notes about the Dasymetric Model	51
E		Data Processing	52
F		Supplemental Figures	53
C	3.	Alternative Comparison Groups Considered	56
	Ν	Neighboring Block Groups	56
	R	Rural-Urban Continuum Codes	57
	В	Balance of State Population	57
ŀ	١.	Authors and Acknowledgements	57

List of Figures

FIGURE 1. MAP OF BOSTON, MA WITH PORT GEOMETRIES FROM ACE (RED POINTS) AND EPA (YELLOW POLYGONS)
FIGURE 2. MAP OF 123 PORTS FEATURED IN STUDY. EACH UNIQUE PORT GEOMETRY HAS BEEN PRESENTED AS A SINGLE POINT FOR
SIMPLIFICATION OF VIEWING PORT LOCATIONS USED IN THIS STUDY ACROSS THE CONTERMINOUS U.S7
FIGURE 3. SCHEMATIC OF HOW THE SUBSET OF PORTS WAS SELECTED FOR THIS STUDY. A FULL LIST OF THE 123 PORTS USED IN THIS STUDY
IS SHOWN IN TABLE A-1. LIST OF PORTS INCLUDED IN STUDY (N=123).
FIGURE 4. ILLUSTRATION OF THE DASYMETRIC MODEL USING A CENSUS BLOCK NEAR SACRAMENTO, CA WITH A CEMETERY, AND
RESIDENTIAL HOUSING ALONG THE EASTERN BORDER. THE ENVIROATLAS DASYMETRIC METHOD ALLOCATES ZERO POPULATION TO
THE CEMETERY AND DENSER POPULATION ALONG THE EASTERN BORDER. ADAPTED FROM FIGURE 6 WITHIN BAYNES ET AL., 2022.10
FIGURE 5. SCHEMATIC TO ILLUSTRATE INTRA-COUNTY COMPARISON GROUP. FOR SIMPLICITY TO ILLUSTRATE THE APPROACH THAT WAS
used to define the Intra-County Comparison Groups, block groups are shown as square polygons, and port buffers
ARE SHOWN AS CIRCLES. IN REALITY, THE BLOCK GROUPS, COUNTY BOUNDARIES, AND PORT BUFFERS THESE ARE IRREGULARLY SHAPED
POLYGONS
FIGURE 6. MAP OF THE TOP 10 PORTS FEATURED IN SUPPLEMENTAL ANALYSIS (AS DARK TRIANGLES) AND REMAINING 113 PORTS (LIGHT
blue circles) by tonnage in this study. Each unique port geometry has been presented as a single icon for
SIMPLIFICATION OF VIEWING PORT LOCATIONS USED IN THIS STUDY ACROSS THE CONTERMINOUS U.S
FIGURE 7. THE RELATIVE SHARE OF TONNAGE BY PORTS CONTRIBUTING \geq 1% RELATIVE SHARE, AMONG THE 123 PORTS FEATURED IN THIS
STUDY, BASED ON ACE PRINCIPAL PORT DATA FROM 2010-2019

FIGURE 8. COMPARISON OF THE PERCENTAGE OF PEOPLE OF COLOR BETWEEN NEAR-PORT POPULATIONS AND COMPARISON GROUPS FOR
123 PORTS INCLUDED IN THE PRIMARY ANALYSIS
FIGURE 9. PYRAMID PLOT OF THE PERCENTAGE OF THE POPULATION BELONGING TO SELECTED RACIAL AND ETHNIC GROUPS BY NEAR-PORT
POPULATIONS AND COMPARISON GROUPS
FIGURE 10. COMPARISON OF PERCENTAGE OF THE POPULATION LIVING BELOW TWICE THE POVERTY THRESHOLD BETWEEN NEAR-PORT
POPULATIONS AND COMPARISON GROUPS FOR 123 PORTS INCLUDED IN THE PRIMARY ANALYSIS.
FIGURE 11. COMPARISON OF MEDIAN HOUSEHOLD INCOME BETWEEN NEAR-PORT POPULATIONS AND COMPARISON GROUPS FOR 123
PORTS INCLUDED IN THE PRIMARY ANALYSIS
FIGURE 12. PYRAMID PLOT OF THE PERCENTAGE OF THE POPULATION BELONGING TO SELECTED SOCIOECONOMIC GROUPS BY NEAR-PORT
POPULATIONS AND COMPARISON GROUPS
FIGURE 13. COMPARISON OF QUALITY OF LIFE INDEX, EQUAL TO THE PERCENTAGE OF THE POPULATION LIVING BELOW THE QUALITY OF
LIFE INCOME THRESHOLD, BETWEEN NEAR-PORT POPULATIONS AND COMPARISON GROUPS FOR 123 PORTS INCLUDED IN THE
PRIMARY ANALYSIS
FIGURE 14. COMPARISON OF VERY NEAR PORT, NEAR PORT, AND INTRA-COUNTY COMPARISON GROUP POPULATIONS FOR THE
SUPPLEMENTAL ANALYSIS
FIGURE 15. COMPARISONS BY RACE/ETHNICITY BETWEEN NEAR-PORT POPULATIONS AND COMPARISON GROUPS FOR THE 123, TOP 10,
AND REMAINING 113 PORTS. THE DIFFERENCE IN PERCENTAGE BY RACE/ETHNICITY BETWEEN THE NEAR-PORT POPULATIONS AND
COMPARISON GROUP IS PRINTED NEXT TO EACH BAR; BARS WITH POSITIVE VALUES INDICATE A HIGHER PERCENTAGE OF THAT
DEMOGRAPHIC GROUP IN THE NEAR-PORT POPULATIONS THAN THE COMPARISON GROUP, WHILE NEGATIVE VALUES INDICATE A
HIGHER PERCENTAGE IN THE COMPARISON GROUP. ONLY DEMOGRAPHIC CHARACTERISTICS WITH DIFFERENCES IN PERCENTAGE
GREATER THAN 1% PT. IN THE PRIMARY ANALYSIS ARE SHOWN
FIGURE 16. COMPARISONS BY POVERTY-RELATED FACTORS BETWEEN NEAR-PORT POPULATIONS AND COMPARISON GROUPS FOR THE 123,
TOP 10, AND REMAINING 113 PORTS. THE DIFFERENCE IN PERCENTAGE BETWEEN THE NEAR-PORT POPULATION AND COMPARISON
GROUP IS PRINTED NEXT TO EACH BAR; BARS WITH POSITIVE VALUES INDICATE A HIGHER PERCENTAGE OF THAT GROUP IN THE NEAR-
PORT POPULATION THAN THE COMPARISON GROUP, WHILE NEGATIVE VALUES INDICATE A HIGHER PERCENTAGE IN THE COMPARISON
GROUP. ONLY SOCIOECONOMIC CHARACTERISTICS WITH DIFFERENCES IN PERCENTAGE GREATER THAN 1% pt. in the primary
ANALYSIS ARE SHOWN
FIGURE 17. COMPARISONS BY OTHER SOCIOECONOMIC BETWEEN NEAR-PORT POPULATIONS AND COMPARISON GROUPS FOR THE 123, TOP
10, AND REMAINING 113 PORTS. THE DIFFERENCE IN PERCENTAGE BETWEEN THE NEAR-PORT POPULATION AND COMPARISON
GROUP IS PRINTED NEXT TO EACH BAR; BARS WITH POSITIVE VALUES INDICATE A HIGHER PERCENTAGE OF THAT GROUP IN THE NEAR-
PORT POPULATION THAN THE COMPARISON GROUP, WHILE NEGATIVE VALUES INDICATE A HIGHER PERCENTAGE IN THE COMPARISON
GROUP. ONLY DEMOGRAPHIC CHARACTERISTICS WITH DIFFERENCES IN PERCENTAGE GREATER THAN 1% pt. in the primary
ANALYSIS ARE SHOWN
FIGURE 18. COMPARISON OF MEDIAN HOUSEHOLD INCOME BETWEEN NEAR PORT POPULATIONS AND COMPARISON GROUPS FOR THE TOP
10 PORTS
FIGURE 19. COMPARISON OF QUALITY OF LIFE INDEX, EQUAL TO THE PERCENTAGE OF THE POPULATION LIVING BELOW THE QUALITY OF
Life income threshold, between near port populations and comparison groups for the top 10 ports 37
FIGURE 20. MAP COMPARING THE DIFFERENCES BETWEEN THE EPA (LEFT) AND ACE (RIGHT) PORT GEOMETRIES AND THE RESULTING
IMPACT ON DIFFERENCES IN THE EXTENT OF BLOCK GROUPS IN NEAR PORT POPULATIONS (SHOWN IN LIGHT BLUE) AND THE EXTENT
OF THE INTRA-COUNTY COMPARISON GROUPS (SHOWN IN PEACH) USING CHICAGO AS AN EXAMPLE. NOTE BLOCK GROUPS WITH
ZERO POPULATION ARE INCLUDED IN THE FIGURE ABOVE
FIGURE 21. VISUALIZATION OF THE NUMBER OF NEAR-PORT BLOCK GROUPS CAPTURED BY THE ACE PORT GEOMETRIES, THE EPA PORT
GEOMETRIES, OR BOTH

List of Tables

TABLE 1. TABLE OF THE VARIABLES THAT WERE OF INTEREST IN THIS STUDY BY DEMOGRAPHIC CATEGORY AND DATA SOURCE.

 12

TABLE 2. SUMMARY OF 2010 POPULATIONS WITHIN VERY NEAR AND NEAR PORT POPULATION AND COMPARISON GROUPS BY PORT	-
GEOMETRY (ACE OR EPA).	19
TABLE 3. NATIONAL ESTIMATES OF NEAR-PORT POPULATIONS BY BUFFER DISTANCE FROM PORT AND PORT GEOMETRY (ACE OR EPA	A).
	19
TABLE 4. SUMMARY OF DIFFERENCES IN PERCENTAGE OF SOCIODEMOGRAPHIC GROUPS BETWEEN VERY NEAR PORT POPULATIONS AN	ND
Comparison Groups (within 1000m)	20
TABLE 5. SUMMARY OF DIFFERENCES IN PERCENTAGE OF SOCIODEMOGRAPHIC GROUPS BETWEEN NEAR PORT POPULATIONS AND	
Сомраrison Groups (within 5000м)	21
TABLE 6. SOCIODEMOGRAPHIC CHARACTERISTICS OF VERY NEAR PORT POPULATIONS (WITHIN 1000m)	30
TABLE 7. SOCIODEMOGRAPHIC CHARACTERISTICS OF NEAR PORT POPULATIONS (WITHIN 5000M)	31

List of Acronyms & Abbreviations

ANALYTICAL TOOLS INTERFACE FOR LANDSCAPE ASSESSMENTS	ATtILA
Conterminous United States	CONUS
Environmental Justice	EJ
NATIONAL EMISSIONS INVENTORY	NEI
Non-Hispanic	NH
Office of Research and Development	ORD
OFFICE OF TRANSPORTATION AND AIR QUALITY	OTAQ
Rural-Urban Continuum Codes	RUCC
U.S. ARMY CORPS OF ENGINEERS	ACE
U.S. DEPARTMENT OF TRANSPORTATION	DOT
U.S. ENVIRONMENTAL PROTECTION AGENCY	EPA

1. Introduction

Marine, coastal, river, and Great Lake ports are vital to the Nation's economy, serving as pivotal links in local, regional, and global supply chains. Ports rely on a variety of vessels, vehicles, and other mobile equipment to move passengers and cargo to and from shore and onto the next link in the supply chain. The mobile equipment serving ports, including trucks, locomotives, cargo handling equipment, and vessels, are typically diesel-powered. Consequently, port-related activity often contributes to air pollution emissions and can have important impacts on local air pollution, including fine particulate matter, nitrogen oxides, air toxics, and carbon dioxide, in addition to impacts farther downwind.¹ These and other air pollutants are associated with increased risk of adverse health outcomes. Research indicates that people living in close proximity to mobile sources and those who are exposed to higher concentrations of mobile source- and traffic-related air pollution have higher rates of adverse health outcomes, including asthma onset and acute respiratory infections in children, adverse birth outcomes (e.g., small for gestational age, childhood leukemia, asthma onset and lung cancer in adults, and premature death.^{2,3,4,5,6,7} Moreover, many studies have found that air pollution, including from mobile sources, is higher in areas where people of color and low-income populations represent a higher fraction

¹ For more information about ports emissions, see U.S. EPA Ports Initiative (2022) <u>Port and Goods Movement</u> <u>Emission Inventories</u>

 ² Laden, F., Hart, J., Smith, T., Davis, M., & Garshick, E. (2007). Cause-specific mortality in the unionized U.S. trucking industry. Environmental Health Perspectives, 115(8), 1192-1196. doi: <u>10.1289/ehp.10027</u>
 ³ Peters, A., von Klot, S., Heier, M., Trentinaglia, I., Hormann, A., Wichmann, H., & Lowel, H. (2004). Exposure to traffic and the onset of myocardial infarction. New England Journal of Medicine, 351(17), 1721-1730. doi:

^{10.1056/}NEJMoa040203

⁴ Zanobetti, A., Stone, P., Spelzer, F., Schwartz, J., Coull, B., Suh, H., Nearling, B.D., Mittleman, M.A., Verrier, R.L., & Gold, D. (2009). T-wave alternans, air pollution and traffic in high-risk subjects. American Journal of Cardiology, 104(5), 665-670. doi: <u>10.1016/j.amjcard.2009.04.046</u>

⁵ Adar, S., Adamkiewicz, G., Gold, D., Schwartz, J., Coull, B., & Suh, H. (2007). Ambient and microenvironmental particles and exhaled nitric oxide before and after a group bus trip. Environmental Health Perspectives, 115(4), 507-512. doi: <u>10.1289/ehp.9386</u>

⁶ Boogaard, H., Patton, A., Atkinson, R., Brook, J., Chang, H., Crouse, D., Fussell, J.C., Hoek, G., Hoffmann, B., Kappeler, R., Kutlar Joss, M., Ondras, M., Sagiv, S.K., Samoli, E., Shaikh, R., Smargiassi, A., Szpiro, A.A., Van Vliet, E.D.S., Vienneau, D., Weuve, J., Lurmann, F.W., Forastiere, F. (2022). Long-term exposure to traffic-related air pollution and selected health outcomes: A systematic review and meta-analysis. Environment International, 164, 107262. doi: <u>10.1016/j.envint.2022.107262</u>

⁷ Boothe, VL.; Boehmer, T.K.; Wendel, A.M.; Yip, F.Y. (2014) Residential traffic exposure and childhood leukemia: a systematic review and meta-analysis. Am J Prev Med 46: 413–422. doi: <u>10.1016/j.amepre.2013.11.004</u>

of the population compared against the general population.^{8,9,10,11,12,13,14,15} Given the volume of mobile source activity at ports, there is a need to quantify and characterize populations that may be affected by emissions at port facilities.

The primary objective of this study is to meet this need by answering three questions:

- 1. How many people live in close proximity to major U.S. port operations and their associated mobile sources of air pollution?
- 2. What are the racial, ethnic, age, and socioeconomic characteristics of people living in close proximity to major U.S. port operations?
- 3. Are there disproportionalities between people who live near U.S. ports compared to those who do not with respect to their sociodemographic characteristics?

To answer these questions, we have conducted a near-port proximity analysis. Proximity analyses are a common approach used by the EPA to estimate the size of a potentially affected community and screen for potential environmental justice (EJ) concerns.^{16,17} Proximity analyses use distance from a source as a proxy for risk or exposure when actual observations or models of risk or exposure are not readily available. Therefore, we do not quantify risk from or exposure to port-related diesel activity or air pollution in this study. To use distance from a source as a proxy for risk or exposure, proximity analyses have two underlying assumptions: 1) those within a specified distance of the source experience different conditions than those beyond that distance and 2) the underlying data appropriately represent the source. In this study, we addressed these assumptions by exploring how different distances and port geometries used to define 'near-port' impacted our results.

⁸ Rowangould, G. M. (2013). A census of the near-roadway population: public health and environmental justice considerations. Transportation Research Part D: Transport and Environment, 25, 59-67. doi: <u>10.1016/j.trd.2013.08.003</u>

⁹ Marshall, J. D. (2008). Environmental inequality: Air Pollution exposures in California's South Coast Air Basin. Atmospheric Environment, 42(21), 5499-5503. doi: <u>10.1016/j.atmosenv.2008.02.005</u>.

¹⁰ Mohai, P., Pellow, D., & Roberts, J. T. (2009). Environmental Justice. Annual Review of Environment and Resources, 34, 405-430. doi: <u>10.1146/annurev-environ-082508-094348</u>.

¹¹ Jbaily, A., Zhou, X., Liu, J., Lee, T.-H., Kamareddine, L., Verguet, S., & Dominici, F. (2022). Air pollution exposure disparities across US population and income groups. Nature, 601(7892), 228-233. doi: 10.1038/s41586-021-04190-y.

¹² Collins, T. W., & Grineski, S. (2022). Racial/Ethnic Disparities in Short-Term PM2.5 Air Pollution Exposures in the United States. Environmental Health Perspectives, 130(8). doi: <u>10.1289/EHP11479</u>

¹³ Weaver, G.M., & Gauderman, W.J. (2018). Traffic-Related Pollutants: Exposure and Health Effects Among Hispanic Children. American Journal of Epidemiology, 187(1), 45-52. doi: <u>10.1093/aje/kwx223</u>.

¹⁴ Tessum, C. W., Paolella, D. A., Chambliss, S. E., Apte, J. S., Hill, J. D., & Marshall, J. D. (2021). PM2.5 polluters disproportionately and systemically affect people of color in the United States. Science Advances, 7(18). doi: <u>10.1126/sciadv.abf4491</u>

¹⁵ Valencia, A., Serre, M., & Arunachalam, S. (2023). A hyperlocal hybrid data fusion near-road PM2.5 and NO2 annual risk and environmental justice assessment across the United States. PLOS ONE. doi: <u>10.1371/journal.pone.0286406</u>

¹⁶ U.S. EPA (2016), "Technical Guidance for Assessing Environmental Justice in Regulatory Analysis"

¹⁷ U.S. EPA (2023), "DRAFT <u>Technical Guidance for Assessing Environmental Justice in Regulatory Analysis</u>"

There is no single, united definition of what a port is¹⁸, nor does the port-related activity end at the port's gate. Vessel anchorage areas may be miles downriver or offshore from a port; dray trucks may use local roads to reach nearby warehouses or queue to enter the gate; and locomotives may haul cargo to and from nearby railyards. Typically, studies examining near-port populations have either relied on a patchwork of representative point locations to describe ports or have focused on a small sample of ports. For example, Greenburg (2021) used a combination of port names, coordinates, and aerial photography to develop point locations for 50 ports across the U.S., and analyzed the population within 2, 5, and 10 miles (~3.2, ~8.0, and ~16.1km) of the centroids of these points. ¹⁹ Rosenbaum et al. (2011) analyzed health risk disparities of near-port communities but did not expound on how the 43 harbor areas in the study were defined geospatially.²⁰ Several Federal agencies have developed geospatial representations of ports in pursuit of mission-specific purposes; however, the use of these geospatial data in near-port studies is limited. One notable exception is Gillingham and Huang (2022), who used coordinates of 27 coastal ports sourced from the U.S. Army Corps of Engineers (ACE) as part of their study on racial disparities in the health effects from air pollution at ports.²¹

We emphasize that the plurality of ways to define ports as described above is an important challenge of conducting a near-port proximity analysis, and there is a need for more unified port geometries or on-the-ground efforts to corroborate our findings in the future. Nevertheless, this study is a first effort to quantify and characterize the near-port population in the U.S., and we have conducted a robust analysis that leverages a uniquely high-resolution population data set and port geometries from two different Federal agencies. Using this approach, we generated a range of near-port population estimates that are likely to underestimate the total number of people living near port operations. Furthermore, we were able to characterize the near-port population and, using two comparison groups, identify several vulnerable sociodemographic groups that are overrepresented in the near-port population.

2. Methods and Approach

2.1 Port Geospatial Data

This study required high quality geospatial representations of ports due to the nature of proximity analyses, which use distance to a source as a proxy for potential risk or exposure from primary

¹⁸ There is no single, government-wide definition for what constitutes a port, and various federal agencies have defined ports differently depending on their mission. For purposes of this analysis, we define a port as "places alongside navigable water with facilities for the loading and unloading of passengers and/or cargo from ships, ferries, and other vessels". This is consistent with the definition in the EPA Ports Initiative Primer for Ports and recent Diesel Emission Reduction Act Grant program requests for applications (see <u>EPA Ports Primer: Glossary</u> and 2021 <u>DERA RFA I. B.7.b.2</u>). For additional definitions of 'port' used by Federal programs, see Appendix C. ¹⁹ Greenburg, M. R. (2021). Ports and Environmental Justice in the United States: An Exploratory Statistical Analysis. Risk Analysis, 41(11). doi:<u>10.1111/risa.13697</u>

 ²⁰ Rosenbaum, A., Hartley, S., & Holder, C. (2011). Analysis of Diesel Particulate Matter Health Risk Disparities in Selected US Harbor Areas. American Journal of Public Health, 101(S1), S217-S223. doi:<u>10.2105/AJPH.2011.300190</u>
 ²¹ Gillingham, K., & Huang, P. (2021). Racial Disparities in the Health Effects from Air Pollution: Evidence from Ports. National Bureau of Economic Research. doi:10.3386/w29108

air pollutants. However, as there is not a single, unified geospatial dataset for all U.S. ports, we used shapefiles published by two different federal agencies: U.S. EPA (EPA) and U.S. Army Corps of Engineers (ACE). These distinct shapefiles describe ports geospatially as a series of polygons (in the case of EPA) or as a series of point locations (in the case of ACE). As **Figure 1** illustrates, these two datasets represent port locations very differently from one another in pursuit of each agency's specific mission and are not official designations of any port authority's jurisdiction or a terminal operator's area of control. Proximity analyses depend on the geospatial representation of the source of interest. Our choice to use these two port geometries offers an opportunity to demonstrate the implications of source geometries on the results of proximity analyses. For the purposes of this study, we assume that these shapefiles may approximate areas where port operations and associated mobile source emissions may occur, including port-related emissions from vessels, cargo-handling equipment, locomotive, and some dray truck operations. However, neither port geometry is expected to perfectly capture the extent of port operations or all ports in the U.S. Therefore, we emphasize that the resulting near-port populations are likely underestimations of the total number of people potentially impacted by port operations and that our results should be corroborated with on-the-ground experience.

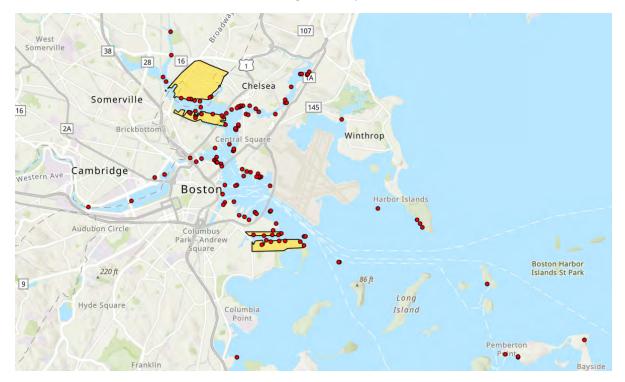


Figure 1. Map of Boston, MA with port geometries from ACE (red points) and EPA (yellow polygons).

U.S. Army Corps of Engineers Master Docks Plus Shapefiles

U.S. Army Corps of Engineers (ACE) Institute of Water Resources maintains the database Master Docks Plus²², which provides geospatial data for over 40,000 port and waterway facilities along coastal,

²² U.S. Army Corps of Engineers Navigation and Civil Works Decision Support Center, Waterborne Commerce Statistics Center. "Master Docks Plus". Accessed May 2019. <u>https://www.iwr.usace.army.mil/About/Technical-Centers/WCSC-Waterborne-Commerce-Statistics-Center-2/WCSC-Navigation-Facilities/</u>

Great Lakes, and inland ports across the U.S. This dataset covers a significant geographic extent using latitude and longitude coordinates and is widely used across various federal agencies.

For this study, we used a May 2019 query of Master Docks Plus, featuring 41,697 distinct waterway facilities. The extract was filtered to isolate only dock facilities, which we assumed represent points where vessels come to land, and thus represent areas where goods or people move from water to shore. All other facility types, such as locks, dams, mile point markers, and virtual docks, were removed from the dataset, as they were considered to not be immediately part of the goods movement activity occurring at ports. To focus on 'active' docks, we only included those associated with ports for which 'Service Terminated' was not equal to 'Yes'. The final dataset included 15,320 active dock locations associated with 834 distinct port IDs. These docks were represented geospatially as points, with latitude and longitude coordinate data and port IDs, five-digit alphanumeric strings unique to each port in the database The port IDs associated with dock coordinates were used to help match these coordinates to the same ports in the EPA shapefiles.

EPA Port Polygons from the National Emissions Inventory

For this study, we used a composite of the 2011 and 2014 port shapefiles used in the 2011 and 2014 National Emissions Inventories (NEI), totaling 534 polygons representing 404 ports in CONUS. These port shapefiles were first developed by Eastern Research Group under contract by EPA's Office of Air Quality Planning and Standards for the 2008 NEI; they were then updated for the 2011 and 2014 NEI publications and have not been updated since due to methodology changes.²³ The purpose of these shapefiles was to aid in the allocation of emissions from marine vessels to specific counties. The original shapefiles were developed using a variety of resources including GIS shapefiles provided directly from ports, maps or port descriptions from local port authorities, satellite imagery from tools such as Google Earth and street layers from StreetMap USA, and feedback from the U.S. Army Corps of Engineers.²⁴

The 2011 iteration of these shapefiles attempted to approximate landside boundaries of ports that reported Marine Engine Category 3 vessel activity. The demographics analysis team determined that these were the approximate areas where significant cargo handling equipment, rail, and drayage truck activity occurs, as well as the docking locations for vessels visiting the port. A total of 381 polygons representing 337 unique ports were included in the 2011 NEI. A subset of these (n=211 ports) were represented as circles with a quarter mile radius (n=217 circles).

The 2014 NEI took a different approach, replacing all landside and circular boundaries with simplified waterside boundaries. The goals of this effort were to generate a file that represented primary areas where vessel hoteling²⁵ and maneuvering activities were conducted and to simplify and

²³ The <u>2011 National Emissions Inventory</u> represents modeled emissions from 2011 and the <u>port shapefile</u> was published in August 2014. The <u>2014 National Emissions Inventory</u> represents modeled emissions from 2014 and the <u>port shapefile</u> was published in May 2017. The <u>2017 National Emissions Inventory</u>, published in April 2020, uses the same port shapefile as the 2014 National Emissions Inventory.

²⁴ Eastern Research Group, 2010. Project report: Documentation for the Commercial Marine Vessel Component of the National Emissions Inventory Methodology. Eastern Research Group No. 0245.02.302.001, March 30, 2010. Available via <u>2008 NEI Reference List</u> as "cmv_report4.pdf".

²⁵ Accurately capturing landside port boundaries was not the intent of the EPA NEI port shapefiles, but the 2011 dataset nevertheless contains some polygons stretching landside. The purpose of the NEI port shapefiles is to help allocate marine vessel emissions to specific counties for totalling emissions.

process the shapes so that they would be more suitable for modeling. The resulting shapefile used 914 polygons to represent 489 unique ports.

The composite shapefile used for this study was created by compiling ports represented by landside boundaries from NEI 2011 polygons and remaining ports represented by waterside boundaries from NEI 2014 polygons. Landside boundaries (NEI 2011) were considered preferable to waterside (NEI 2014) boundaries because nearby populations residing on land can be exposed to emissions from ports' landside operations – such as dray trucks and cargo handling equipment – in addition to marine vessel emissions. For the purposes of this study, the circular polygons included in the 2011 NEI were considered a lower-quality depiction than the specific shapes that were used for every port in 2014 and were removed in the composite file. Combining the two versions of NEI allowed for a larger number of port boundaries to be represented geospatially. The shapefile combining two versions of NEI contains 164 NEI 2011 landside polygons representing 126 ports and 480 NEI 2014 waterside polygons representing 363 ports.

Port Inclusion Criteria

This study focused on a subset of ports that are represented in both the EPA and ACE datasets and, to align with the population data used in this study (see Section 2.3: *Higher Resolution Population Estimates* section for more), fall within the conterminous U.S. (CONUS, the adjoining 48 states and the District of Columbia).²⁶ To further narrow the scope to ports that likely have the most diesel-related activity and therefore represent the greatest mobile source emissions and potential impact on air quality, this study only included ports with the highest tonnage levels, using the ACE 2017 Principal Ports list²⁷ to determine tonnage throughput. This approach, using port tonnage as a proxy for air quality impacts, has been previously described by Gillingham and Huang (2021).²⁸ Using these criteria, 123 ports were selected for inclusion in this study. A map of these ports is shown in **Figure 2**, a complete list of the 123 ports can be found in Table A-1, and a high-level schematic of how ports were selected is shown in **Figure 3**.

²⁶ Findings related to Alaska, Hawaii, Puerto Rico, and the U.S. Virgin Islands are currently outside of the scope of this research.

²⁷ Each year, ACE reports a list of the top 150 Principal Ports by tonnage throughput within port limits determined by ACE. The list of 2017 USACE Principal Ports can be found at:

https://usace.contentdm.oclc.org/digital/collection/p16021coll2/id/3114/rec/5. Because this analysis is limited to the contiguous United States, the 14 following 2017 ACE Principal Ports are not considered: Valdez, AK; Honolulu, HI; San Juan, PR; Barbers Point, Oahu, HI; Nikishka, AK; Kahului, Maui, HI; Anchorage, AK; Kivilina, AK; Hilo, HI; Kawaihae Harbor, HI; Nawiliwili, Kauai, HI; Unalaska Island, AK; Ponce, PR; Ketchikan, AK.

²⁸ Gillingham, K., & Huang, P. (2021). Racial Disparities in the Health Effects from Air Pollution: Evidence from Ports. 29108. Retrieved February 2023 from <u>https://ideas.repec.org/p/nbr/nberwo/29108.html</u>.

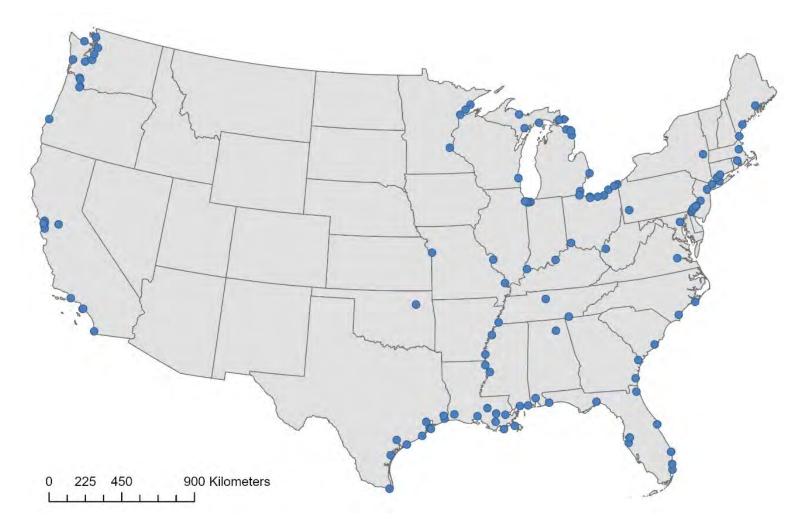


Figure 2. Map of 123 ports featured in study. Each unique port geometry has been presented as a single point for simplification of viewing port locations used in this study across the conterminous U.S.

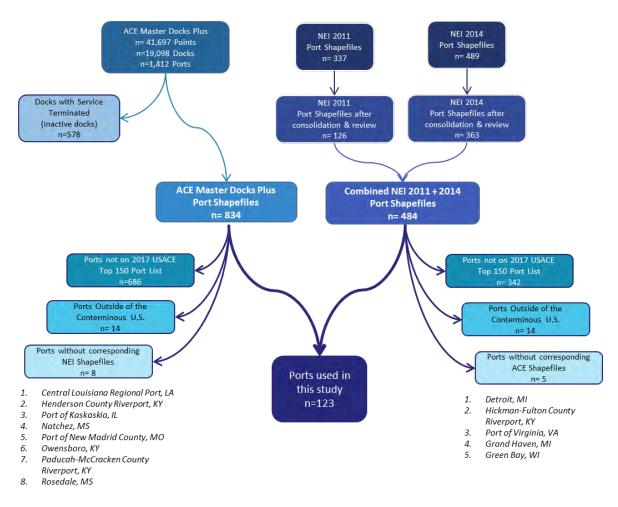


Figure 3. Schematic of how the subset of ports was selected for this study. A full list of the 123 ports used in this study is shown in Table A-1. List of ports included in study (n=123).

2.2 Geodesic Buffers Around Port Geometry to Describe Near-Port Populations

Port operations can occur over a much larger geographic area than just the immediate location where cargo and passengers are loaded and unloaded from vessel to the shore. On-water activities, including positioning of tug and pilot vessels, can happen well outside of a port's waterside boundary, while port-related cargo handling equipment, dray trucks, locomotives, and other port-related mobile sources can operate well beyond a port's official boundaries inland. As a result, emissions from ports often have a wide geographic range of impact on nearby air quality. For that reason, we developed buffers around the various ports' geometries; we estimated dasymetric population counts within geodesic²⁹ buffers drawn 1000m and 5000m from the port boundary, consistent with the smaller

²⁹ Geodesic buffers account for the shape of the earth when drawn on a map and are more accurate over large distances than Euclidean buffers. For more, see: <u>https://www.esri.com/news/arcuser/0111/geodesic.html</u>

vicinities used in recent near-port studies.^{30,31} The geodesic buffer of 5000m captures areas farther from the port's immediate vicinity that may still experience negative impacts from nearby port-related operations, including, but not limited to, worsened air quality. We considered expanding this near-port buffer to capture a larger area that may be impacted by air pollution from port operations. For example, Agrawal et al. estimated that emissions from ocean-going vessels operating at the San Pedro ports contributed 8.8% of the total PM_{2.5} emissions at a site nearly 10,000m away from the port.³² However, we ultimately decided to limit our buffer distances to 5000m to ensure that the results of this proximity analysis would provide an underestimation of the total population that is potentially impacted by primary port-related emissions, including hazardous air pollutants like CO, ultrafine particles, metals, elemental carbon (EC), NO, NOX, and VOCs that can have steeper near-source gradients than PM_{2.5}.³³. Furthermore, these areas may also experience other port-related impacts, such as noise and traffic. We also considered smaller buffers of 100m, 200m, and 500m, but primarily report the sociodemographic characteristics of the populations living within the 1000m and 5000m buffers, referred to as *Very Near Port* and *Near Port* populations, respectively.

2.3 Higher Resolution Population Estimates

Recognizing that people are not uniformly distributed geographically, we used the dasymetric³⁴ population dataset, developed and refined by EPA's Office of Research and Development (ORD), to improve population estimates. ORD's dasymetric population model intelligently allocates 2010 U.S. Census counts from 2010 Census boundaries in the lower 48 states and the District of Columbia of varying sizes and shapes to a standard 30x30-meter grid. ³⁵ This method identifies uninhabitable areas (e.g., open water, emergent wetlands, railroad lines, cemeteries, areas with a slope of more than 25%) and excludes populations from those areas, as illustrated in **Figure 4**. Within habitable landscape categories, more people are allocated to areas where populations are more likely to live (e.g., developed areas) and fewer people where they are less likely to live (e.g., forests) while maintaining Census block level population counts. These habitable areas vary in population density by the intensity of development. The intelligent dasymetric allocation of populations across a gridded area improves residential population estimates compared to assuming equal residential population distribution across irregularly shaped census geographies. The dasymetric model offers significant improvements compared to equal area near-port population estimates. Demographic variables (e.g., people of color, low income)

³⁰ Greenburg, M. R. (2021). Ports and Environmental Justice in the United States: An Exploratory Statistical Analysis. Risk Analysis, 41(11). doi:<u>10.1111/risa.13697</u>

³¹ Svendsen, E. R., Reynolds, S., Ogunsakin, O. A., Williams, E. M., Fraser-Rahim, H., Zhang, H., & Wilson, S. M. (2014). Assessment of Particulate Matter Levels in Vulnerable Communities in North Charleston, South Carolina prior to Port Expansion. Environmental Health Insights, 8, 5-14. doi: <u>10.4137/EHI.S12814</u>.

³²Agrawal, H., Eden, R., Zhang, X., Fine, P. M., Katzenstein, A., Miller, J. W., . . . Cocker, D. R. (2009). Primary Particulate Matter from Ocean-Going Engines in the Southern California Air Basin. Environmental Science & Technology, 43(14), 5398–5402. doi: <u>10.1021/es8035016</u>

³³ Karner, A.A.; Eisinger, D.S.; Niemeier, D.A. (2010). Near-roadway air quality: synthesizing the findings from realworld data. Environ Sci Technol 44: 5334–5344. Doi: <u>10.1021/es100008x</u>

 ³⁴ "Dasymetric" means "density measurement" and is derived from the Greek *dasýs* (dense) and *métro* (measure).
 ³⁵ Baynes, J., Neale, A., & Hultgren, T. (2022). Improving intelligent dasymetric mapping population density estimates at 30 m resolution for the conterminous United States by excluding uninhabited areas. Earth Syst Sci Data, 14(6), 2833–2849. doi: <u>10.5194/essd-14-2833-2022</u>

can be proportionally allocated from lower resolution Census geometries (e.g., tracts or block groups) to the dasymetric population counts.



Figure 4. Illustration of the dasymetric model using a census block near Sacramento, CA with a cemetery, and residential housing along the eastern border. The EnviroAtlas dasymetric method allocates zero population to the cemetery and denser population along the eastern border. Adapted from Figure 6 within Baynes et al., 2022.

The underlying population density raster³⁶ used for this analysis is available to the public via EPA's EnviroAtlas³⁷, a public resource of geospatial data and tools. The data may be accessed as a feature layer through the EnviroAtlas Interactive Map, and as downloadable raster file through the EnviroAtlas Data Downloads webpage. Since this analysis was conducted, ORD's dasymetric model has been updated to use 2020 U.S. Census decennial census counts and geometries and further expanded to include Alaska, Hawaii, and other U.S. territories. Future analyses may incorporate the updated dasymetric model.

2.4 Sociodemographic Variables

This study explored demographic and socioeconomic variables that are used widely across published EJ tools and represent a wide range of vulnerabilities. The list of sociodemographic variables included in this report is shown in Table 1. The list of demographic variables was generated after reviewing available data and key variables in leading EJ screening tools (e.g., EPA EJScreen, CalEnviroScreen, Climate and Economic Justice Screening Tool.) and speaking with EPA Office of Environmental Justice and External Civil Rights subject matter experts. Data are available for each of

³⁶ U.S. EPA. EnviroAtlas. Dasymetric Allocation of Population for the Conterminous United States, 2010. Retrieved: May 26, 2021, from https://www.epa.gov/enviroatlas/data-download

³⁷ Pickard, B. R., Daniel, J., Mehaffey, M., Jackson, L. E., & Neale, A. (2015). EnviroAtlas: A new geospatial tool to foster ecosystem services science and resource management. Ecosystem Services, 14, 45-55. doi: 10.1016/j.ecoser.2015.04.005.

these variables to identify vulnerable populations at the block group level nationwide. ³⁸ This suite of demographic metrics includes aspects of race, ethnicity, sex, age, language, and multiple metrics of economic status. While this analysis was not related to any regulatory effort, these demographic variables follow the first recommendation within the 2023 draft of the EPA's <u>Technical Guidance for</u> <u>Assessing Environmental Justice in Regulatory Analysis</u>: "When achievable, analysts should present information on estimated health and environmental risks, exposures, outcomes, benefits, or other relevant effects disaggregated by race, ethnicity, income, and other demographic categories."³⁹ Finally, the vintages of demographic data used reflect a broad period of time, from 2010-2019 and were the best available data at the time of analysis; many of these data sources have since been updated to reflect the 2020 Census.

³⁸ For more on Census geographic hierarchies, terms, and geographic classifications, see U.S. Census's '<u>Understanding Geographic Identifiers (GEOIDs)</u>'

³⁹ U.S. EPA (2023), "DRAFT <u>Technical Guidance for Assessing Environmental Justice in Regulatory Analysis</u>", page 18

Category	Data Source	a Source Demographic Characteristics			
		People of Color (not Non-Hispanic White)			
		Non-Hispanic White			
		Non-Hispanic Black/African American			
	2010 Decennial Census	Hispanic/Latino			
Race/Ethnicity		Non-Hispanic American Indian/Alaska Native			
	census	Non-Hispanic Asian			
		Non-Hispanic Native Hawaiian/Pacific Islander			
		Non-Hispanic Two or More Races			
		Non-Hispanic Other Race			
	2014-2018 American Community Survey	Population in Households Below 2x Poverty Level ⁴⁰			
		Population in Households Below 1x Poverty Level			
		Population in Households Below 0.5x Poverty Level			
Income		Median Household Income			
Income	U.S. EPA EnviroAtlas (2017)	Households Below Quality of Life Income Threshold ⁴¹			
	U.S. DOT RAISE Persistent Poverty Tracts (FY2021)	Population in Persistent Poverty Area ⁴²			
	2010 Decennial Census	Population Less than 5 Years Old			
Ago		Population Less than 18 Years Old			
Age		Population 18-64 Years Old			
		Population Greater than 64 Years Old			
Language	2014-2018 American Community Survey	Households in Linguistic Isolation			
Educational Attainment	2014-2018 American Community Survey	Population 25 Years Old or Older with Less than a High School Education			
Hausing	2010 Decennial	Occupied Housing Units			
Housing	Census	Renter-Occupied Housing Units			

Table 1. Table of the variables that were of interest in this study by demographic category and data source.

For all variables, data were the latest available at the time that the geospatial analysis was conducted.

⁴⁰ The percentage of the population in households below twice, once, or half their poverty threshold comes from the ACS income-to-poverty ratio. This metric is calculated by comparing a family's income to a poverty threshold that is based on household size and number of children. For more, see <u>U.S. Census Poverty Glossary</u> and <u>Poverty Thresholds</u>.

⁴¹ Quality of Life Threshold Income refers to the regionally adjusted income where the basic needs of life are met, including food, shelter, health care, and leisure time. For more, see the <u>Threshold Income for Quality of Life</u>, <u>EnviroAtlas Data Fact Sheet</u> (July 2019)

⁴² Areas of Persistent Poverty, as defined by the Bipartisan Infrastructure Law (<u>Sec 21202, §6702</u>) are areas meeting at least one of the following criteria: 1) county with greater than or equal to 20% of the population living in poverty in the 1990 decennial census, the 2000 decennial census, and the most recent annual Small Area Income and Poverty Estimates as estimated by the Bureau of the Census; 2) any Census Tract with a poverty rate of at least 20 percent as measured by the 2014–2018 5-year data series available from the American Community Survey of the Bureau of the Census; 3) Any U.S. Territory.

The available resolution of Census data limits meaningful reporting of demographics at smaller distance intervals from a port. While the dasymetric model can report population counts at a 30x30meter resolution, the Census demographic data used in this study are at the block group level. The average block group found within 5000m of ports included in this study covered an area of 1.1 or 1.3 square miles (2.9 or 3.4 million square meters) using the ACE or EPA port geometries, respectively. The dasymetric population data are so highly spatially resolved, that there are over 3,300 dasymetric model grid cells within the average near-port block group; each of these grid cells would be allocated sociodemographic characteristics from the same block group for which Census data are available. At smaller buffer distances from a port, there are often few or no new block groups (and their associated demographics) captured by the next largest buffer. Comparing demographic characteristics for populations living within 100m or 200m from a port was not prioritized in this study since the underlying Census data used in both groups would be similar. Instead, we compared the demographics of populations within 1000m and 5000m of a port (*Very Near Port* and *Near Port*, respectively) against comparison groups that live further from a port, which are described in more detail in Section 2.5 below: *Comparison Groups*.

2.5 Comparison Groups

We followed EPA's Technical Guidance for Assessing Environmental Justice in Regulatory Analysis⁴³ to develop our comparison groups for this demographic analysis. This guidance document emphasizes the importance of defining the general population and appropriate comparison groups to meaningfully characterize the population of interest. These categorizations are used to estimate differentials between populations with potential EJ concerns and populations without those concerns. Specifically, we aimed to create comparison groups that are as similar as possible to near-port populations found within the geodesic buffers drawn around the 123 ports of interest but that are assumed to be far enough away from the port as to be unaffected by port-related mobile source emissions. Populations farther from a port may have demographic characteristics that differ from populations living closer to a major U.S. port; however, moving too far out in the comparison group may pull in different population dynamics unrelated to the major port. For example, many ports are colocated with major metropolitan areas, and we did not want to inadvertently compare urban areas to non-urban areas by drawing the near-port buffer too large. The EPA's technical guidance also suggests considering a variety of comparison groups to provide a more complete view of potential differences between population groupings. For this study, we used two comparison groups: the Intra-County Comparison Group and CONUS. Additional comparison groups considered for this study are noted in Appendix G of this report.

⁴³ U.S. EPA. "Technical Guidance for Assessing Environmental Justice in Regulatory Analysis" June 2016. <u>https://www.epa.gov/sites/default/files/2016-06/documents/ejtg 5 6 16 v5.1.pdf</u>

Conterminous United States

The first comparison group used in this study was the entire Conterminous United States (i.e., the lower 48 states and the District of Columbia), including near-port areas. This comparison group is considerably larger than the populations of interest and captures areas very far from the ports included in this study. This comparison group was used to broadly contextualize near-port and nationwide demographic patterns.

Intra-County Comparison Group

The Intra-County Comparison Group was intended to identify sociodemographic differences between near-port populations and those less affected by port activity more locally than CONUS. The Intra-County Comparison Group was developed by first identifying counties that contain any population within the 5000m buffer of any of the 123 ports included in this analysis. These are classified as port counties. Within these port counties, the block groups that intersect the 5000m buffer are classified as near-port block groups; the remaining block groups within the port counties comprise the Intra-County Comparison Group, as shown in **Figure 5**. Because ACE and EPA define port geometry differently and thus have differently sized and shaped 5000m buffers, unique Intra-County Comparison Groups were developed for the ACE and EPA datasets separately.

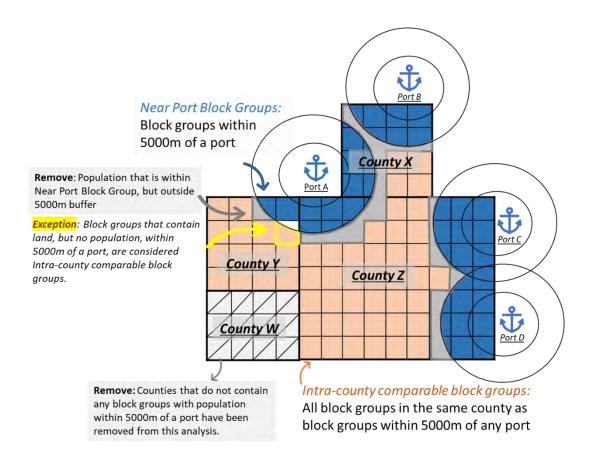


Figure 5. Schematic to illustrate Intra-County Comparison Group. For simplicity to illustrate the approach that was used to define the Intra-County Comparison Groups, block groups are shown as square polygons, and port buffers are shown as circles. In reality, the block groups, county boundaries, and port buffers these are irregularly shaped polygons.

This comparison group allows for a subnational, regional, or subregional look into demographic dynamics relevant to areas containing busy ports. Across the U.S., there is a wide range of heterogeneity with respect to racial, ethnic, and economic demographics. Focusing on these smaller geographic subsets allows for more precise comparisons between near-port and non-near port populations and avoids confounding by factors that can influence demographics regionally, such as being coastal vs. non-coastal or urban vs. non-urban. Not accounting for regional and sub-regional differences can mask demographic or socioeconomic patterns among people who live near or far from a port. The Intra-County Comparison Group is similar to the population group of concern, but we assume that it is outside of the area more affected by port operations. Therefore, this comparison allows us to target the differences between near-port populations and those who are less impacted by port activity more precisely than a comparison against the general public.

2.6 Developing a National Analysis

In this study, we established a national estimate for the number of people living near ports, described the demographic characteristics of these near-port populations, and compared how their characteristics differ from those of the comparison groups described previously. Due to the significant differences between the EPA and ACE port geographies, this national analysis was conducted using both the EPA and ACE port geographies separately, resulting in two distinct analytical tracks and sets of national results.

For each buffer distance tested (100, 200, 500, 1000, and 5000m; see Section 2.2: *Geodesic Buffers Around Port Geometry to Describe Near-Port Populations*), we estimated the total near-port population by first dissolving the boundaries of all 123 ports' geodesic buffers into a single layer. This approach prevented double-counting of individuals who lived in proximity to more than one port. The dissolved buffer layer was then overlaid on the dasymetric population model to estimate the total population living within the specified distance of any of the 123 ports included in this study.

We leveraged block group-level sociodemographic data from Census and DOT (see Table 1) to characterize the near-port population. For each near-port block group, we allocated its sociodemographic composition to the population of the block group that fell within the near-port buffer, which could be less than its total population if the block group was bisected by the buffer. Using this approach, the near-port population was characterized under the assumption that sociodemographic percentages are uniform across a block group. After the Census and DOT data were allocated to the near-port population of each block group, the resulting subpopulations by sociodemographic group were summed. These totals represented the national near-port population broken down by sociodemographic characteristic.

For each of the near-port populations, median household income and the Quality of Life index were calculated using a dasymetric population-weighted average. This approach accounted for the population of each block group that fell within a near-port buffer, so that low-population block groups or those that were only partially overlapping with the near-port buffer would not skew the median household income or Quality of Life index for the entire near-port population. Similarly, the Quality of Life index and median household income of the Intra-County Comparison Group was calculated as the

population-weighted average of the relevant block groups. Direct comparisons were made across the near-port and comparison groups for these two variables.

The CONUS comparison group reflects the total population and combined sociodemographic features of all block groups within the lower 48 states and District of Columbia, including the near port populations. The Intra-County Comparison Group represents the total population and combined demographic features of all block groups that were within a port county but did not overlap a 5000m port buffer. For instances in which a block group was bisected by the 5000m buffer, the population that fell outside the geodesic buffer was not included in either the Intra-County Comparison Group or the near-port population.

After estimating the breakdown of the near-port population by sociodemographic characteristic using the approach described above, we compared it against those of the comparison groups. We identified a difference in proportion between the near-port and comparison group populations of greater than or equal to 1 percentage point as an indicator of disproportionate populations. This threshold of 1 percentage point was selected as an initial screening threshold for the variables included this study. A *post hoc* analysis found differences of less than 1% between variables that we would expect to be proportional between comparison groups, the share of males and females (**Figure A-4**).⁴⁴ Identifying disproportionalities between the near-port populations of both port geometries (ACE and EPA) and their comparison groups (CONUS and Intra-County) can be considered stronger evidence of a national EJ concern than identifying differences using just one comparison group or port geometry.

2.7 Top 10 Ports Supplemental Analysis

While the national analysis supports a general understanding of sociodemographic dynamics among near-port populations and their comparison groups, we also pursued a supplemental analysis to understand if the national results were being driven by a subset of the busiest ports as determined by tonnage. The results of this supplemental analysis also provide insight into how representative national disproportionalities are of typical near-port populations across the U.S. For this supplemental analysis, we replicated the approach described above for two subsets of the 123 ports included in the study. These subsets were the 10 ports that had the largest quantity of tonnage during 2010-2019 (a period that aligns with the demographic data featured in this study) and the remaining 113 ports. The 10 ports with the largest quantity of tonnage are listed below and shown in **Figure 6**.

- 1. Port of South Louisiana, LA
- 2. Houston Port Authority, TX
- 3. Port of New York and New Jersey, NY and NJ
- 4. Port of Beaumont, TX
- 5. Port of New Orleans, LA

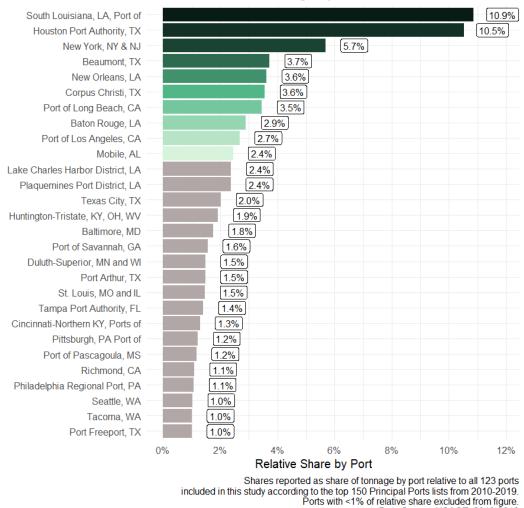
- 6. Port of Corpus Christi, TX
- 7. Port of Long Beach, CA
- 8. Port of Baton Rouge, LA
- 9. Port of Los Angeles, CA
- 10. Port of Mobile, AL

⁴⁴ Demographic proportions of male and female populations are not presented in the primary results of this work, as these were not among the sociodemographic variables that we considered for exploring vulnerable sociodemographic groups listed in **Table 1**.



Figure 6. Map of the top 10 ports featured in supplemental analysis (as dark triangles) and remaining 113 ports (light blue circles) by tonnage in this study. Each unique port geometry has been presented as a single icon for simplification of viewing port locations used in this study across the conterminous U.S.

From 2010 to 2019, these 10 ports accounted for 45.6% of all tonnage handled across the top 150 ports in the U.S. and 49.5% of all tonnage handled across the 123 ports in this study (**Figure 7**).



Relative Share of Tonnage by Port, 2010-2019

Data Source: USACE, 2010-2019

3. Results

3.1 National Estimates of Near-Port Populations and Comparison Groups

The national analysis indicates that 16.1M or 31.1M people live within 5000m of major ports in CONUS using the EPA or ACE port geometries, respectively (Table 2). These values correspond to 5% and 10% of the total CONUS population. Additionally, Table 2 summarizes the total size of the two comparison groups used in the study. The population of the Intra-County Comparison Group was over four times larger or over two times larger than the *Near Port* population for the EPA or ACE port geometries, respectively.

Figure 7. The relative share of tonnage by ports contributing \geq 1% relative share, among the 123 ports featured in this study, based on ACE Principal Port Data from 2010-2019.

		Very Near Port Population (within 1000m of any port in this study)	Near Port Population (within 5000m of any port in this study)	Intra-County Comparison Group	Conterminous United States
504 David	Total Population	2,618,779	16,124,914	70,241,778	306,563,500
EPA Port Geometry	Number of Block Groups	3,473	15,029	47,890	216,017
Geometry	Number of Counties	157	186	182	3,107
	Total Population	4,676,199	31,058,906	70,125,603	306,563,500
ACE Port Geometry	Number of Block Groups	6,328	27,621	46,915	216,017
Geometry	Number of Counties	203	243	241	3,107

Table 2. Summary of 2010 Populations within Very Near and Near Port Population and Comparison Groups by Port Geometry(ACE or EPA).

Table 3. National Estimates of Near-Port Populations by Buffer Distance from Port and Port Geometry (ACE or EPA).

Population living within indicated	Port Geometry		
distance of any port	ACE	EPA	
100m	24,473	448,940	
200m	123,354	629,820	
500m	1,134,075	1,294,281	
1000m (<i>Very Near Port</i> population)	4,676,199	2,618,779	
5000m (<i>Near Port</i> population)	31,058,906	16,124,914	

3.2 National Disproportionalities of Near-Port Populations

The full list of results for differences in percentages of sociodemographic groups between the two port geometries and their comparison groups are presented in **Table 4** and **Table 5**.

Category	Demographic Feature	Differences in Percentage of Sociodemographic Groups for Very Near Port Populations (<1000m) vs. Comparison Groups (% pt.)				
		EPA Port Ge	ometry	ACE Port Geometry		
		vs. ICC	vs. CONUS	vs. ICC	vs. CONUS	
	All People of Color	6.4	16.0	10.1	16.	
	Non-Hispanic (NH) White	-6.4	-16.0	-10.1	-16.	
	NH Black	8.5	10.0	3.1	3.	
	Hispanic	-0.5	5.0	6.2	9.	
Race/Ethnicity	NH Asian	-1.8	1.0	0.8	3.	
	NH American Indian/Alaska Native	0.1	0.0	0.0	-0.	
	NH Native Hawaiian/Pacific Islander	0.0	0.0	-0.1	0	
	NH Other Race	0.0	0.0	0.1	0	
	NH Two or More Races	0.0	0.0	-0.1	0	
	Below 0.5x Poverty Threshold	4.6	4.0	4.1	2	
	Below 1x Poverty Threshold	9.3	8.0	8.3	5	
Income	Below 2x Poverty Threshold	13.3	10.0	10.5	5	
	Living in Area of Persistent Poverty	21.0	26.0	11.5	13	
	Less than 5 years old	0.2	0.0	-0.4	-0	
Age	Less than 18 years old	-2.1	-2.0	-5.2	-5	
	Greater than 64 years old	-1.5	-2.0	-1.2	-1	
Language	Households in linguistic isolation	0.2	3.0	5.1	6	
ducational Attainment	Less than HS education	4.9	5.0	4.6	3	
	Occupied Housing Units	-4.4	-3.0	-3.5	-1	
Housing	Renter-Occupied Housing Units	16.9	19.0	31.2	30	

Table 4. Summary of Differences in Percentage of Sociodemographic Groups between Very Near Port Populations and Comparison Groups (within 1000m).

NB: Instances where the very near port population has at least a 1% pt. higher share of population with the listed demographic characteristic than the noted comparison group are shown in bold and outlined. ICC: Intra-county comparison group; CONUS: Conterminous U.S. comparison group

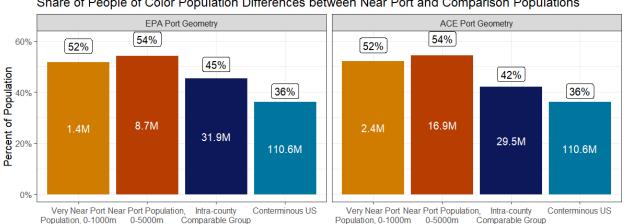
Category	Demographic Feature	Differences in Percentage of Sociodemographic Groups for <i>Near Port</i> Populations (<5000m) vs. Comparison Groups (% pt.)					
Category	Demographic reature	EPA Port	t Geometry	ACE Por	ACE Port Geometry		
		vs. ICC	vs. CONUS	vs. ICC	vs. CONUS		
	All People of Color	8.8	18.0	12.3	18.3		
	Non-Hispanic (NH) White	-8.8	-18.0	-12.3	-18.3		
	NH Black	9.6	12.0	8.9	9.1		
	Hispanic	-1.2	4.0	2.6	6.2		
Race/Ethnicity	NH Asian	0.1	2.0	0.6	3.0		
	NH American Indian/Alaska Native	0.1	0.0	0.0	-0.4		
	NH Native Hawaiian/Pacific Islander	0.0	0.0	0.0	0.0		
	NH Other Race	0.1	0.0	0.1	0.2		
	NH Two or More Races	0.2	0.0	0.0	0.1		
	Below 0.5x Poverty Threshold	3.8	3.0	3.4	2.2		
Incomo	Below 1x Poverty Threshold	7.5	6.0	7.1	4.5		
Income	Below 2x Poverty Threshold	11.0	8.0	10.2	5.5		
	Living in Area of Persistent Poverty	15.4	20.0	10.1	11.9		
	Less than 5 years old	0.3	0.0	0.2	0.0		
Age	Less than 18 years old	-1.7	-2.0	-2.0	-2.0		
	Greater than 64 years old	-1.3	-2.0	-1.0	-1.1		
Language	Households in linguistic isolation	0.8	3.0	3.4	5.1		
Educational Attainment	Less than HS education	3.9	4.0	4.2	3.5		
Housing	Occupied Housing Units	-3.0	-1.0	-2.2	0.0		
Housing	Renter-Occupied Housing Units	17.0	20.0	20.7	19.8		

Table 5. Summary of Differences in Percentage of Sociodemographic Groups between Near Port Populations and Comparison Groups (within 5000m)

NB: Instances where the near port population has at least a 1% pt. higher share of population with the listed demographic characteristic than the noted comparison group are shown in bold and outlined. ICC: Intra-county comparison group; CONUS: Conterminous U.S. comparison group

Overrepresentation of People of Color in Near-Port Populations compared to Comparison Groups

The results of this analysis indicate an overrepresentation of people of color, defined as anyone who does not identify as Non-Hispanic White, living near the 123 major ports in CONUS that were included in this study. This overrepresentation was consistent using either the ACE or the EPA dataset when compared against both the Intra-County Comparison Group and CONUS (Figure 8). Using the ACE port geometries, 52% of the Very Near Port (within 1000m of any port in this study) population and 54% of the *Near Port* (within 5000m of any port in this study) population are people of color. In comparison, only 36% of the population of CONUS are people of color. This overrepresentation of people of color in proximity to a port also holds true in comparison to the Intra-County Comparison Groups (42% for ACE; 45% for EPA).



Share of People of Color Population Differences between Near Port and Comparison Populations

Figure 8. Comparison of the percentage of people of color between near-port populations and comparison groups for 123 ports included in the primary analysis.

For other racial and ethnic data evaluated, both the EPA and ACE near-port buffers contain a higher share of Non-Hispanic Black population and a lower share of Non-Hispanic White population than the CONUS and Intra-County Comparison Groups (Figure 9). The near-port population around ACE port geometries also captures a higher share of Hispanic/Latino population and Non-Hispanic Asian population than the comparison groups. Using the EPA port geometries, however, the difference in percentage of Hispanic populations living near ports versus the Intra-County Comparison Group was not greater than 1% pt., indicating that the share of Hispanic populations near these port geometries is not substantially different from nearby populations, and the disproportionality detected against CONUS may reflect regional differences. For both the EPA and ACE port geometries, there were no difference greater than 1% pt. in the share of Non-Hispanic Other Race, Non-Hispanic Two or More Races, Non-Hispanic Hawaiian and Pacific Islanders, or Non-Hispanic Native Americans between the near-port population and the CONUS or Intra-County Comparison Groups; these racial groups also comprise a smaller portion of the population (0-2% of CONUS).

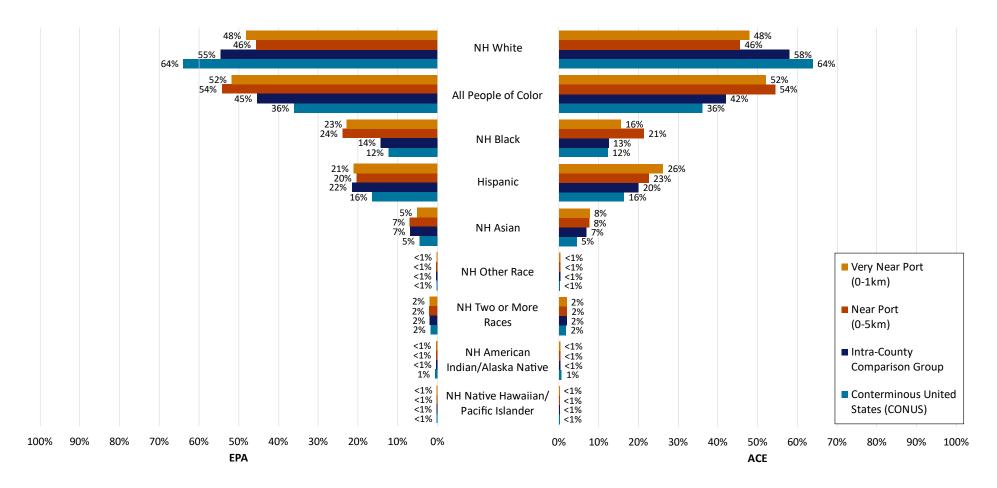
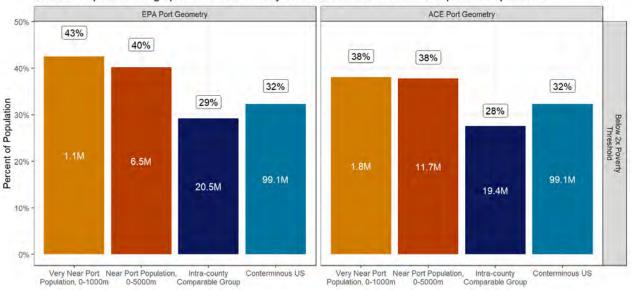


Figure 9. Pyramid plot of the percentage of the population belonging to selected racial and ethnic groups by near-port populations and comparison groups.

Multiple Metrics of Income Point to Economic Disproportionalities between Near-Port Populations & Comparison Groups

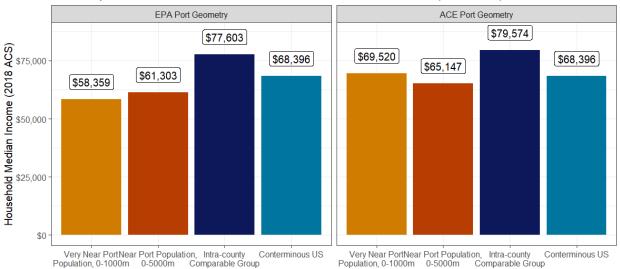
Both analytical tracks revealed the presence of disproportionate socioeconomic conditions between near-port populations and comparison groups. 43% of the *Very Near Port* population around the EPA port geometries, and 38% of the *Very Near Port* population around the ACE port geometries were found to be living below twice the poverty threshold (**Figure 10**). These levels are nearly 10% pt. higher than the share of population in the Intra-County Comparison Group for both port geometries (29% for Intra-County Comparison Group populations around EPA port geometries; 28% for Intra-County Comparison Group populations around ACE port geometries). The percentage of individuals living below twice the poverty threshold was also at least 10% pt. higher among near-port populations than across the Conterminous U.S. (32%).



Share of Population living up to Twice the Poverty Threshold in Near Port and Comparison Populations

Figure 10. Comparison of percentage of the population living below twice the poverty threshold between near-port populations and comparison groups for 123 ports included in the primary analysis.

We also observed a difference for near-port populations using median household income as an indicator of socioeconomic status (**Figure 11**). The median household income for the *Very Near Port* populations is \$58k around EPA geometries and \$70k around ACE geometries; the median household income for *Near Port* populations is \$61k around EPA geometries and \$65k around ACE geometries. Meanwhile, the ACE Intra-County Comparison Group has a median household income that is nearly 15% higher than it is among the *Very Near Port* populations (\$79.6k vs. \$69.5k). The EPA Intra-County Comparison Group has a median household income that is among the *Very Near Port* population (\$77.6k vs. \$58.4k). This difference is also reflected when compared to the median household income of CONUS, which is 10% higher than the *Near Port* population for ACE port geometries. However, the median household income of the ACE *Very Near Port* population is 2% higher than the median household income for CONUS.



Summary of Household Median Income between Near Port and Comparison Populations



In addition to these income and poverty metrics, we also identified a considerably higher percentage of renters, households with less than a high school education, and households living in linguistic isolation in *Very Near Port* and *Near Port* populations as compared to the Intra-County Comparison Group and CONUS (**Figure 12**). While these characteristics are not necessarily reflective of household wealth or poverty, the differences further underscore sociodemographic differences between populations living near ports and those living father away from ports.

Finally, we examined the index of the threshold income for quality of life, a metric found within EPA's EnviroAtlas that estimates the baseline income for a "positive quality of life and accompanying emotional well-being", with which the basic needs of life are met, including the cost of housing, food, and health care.⁴⁵ The index is based on a national value of \$75k in 2009 dollars (equal to \$110k in 2024 dollars), and further adjusted to reflect county-level cost of living. The higher the index value, the greater share of the population found to be living below the county-level threshold income. As shown in **Figure 13**, the Quality of Life index for all near-port populations explored in this study ranged from 73 to 76, while the comparison groups had values between 61 and 64, further supporting the quantifiable differences between near-port populations and those living farther away discussed above.

⁴⁵ U.S. EPA. (2019) EnviroAtlas Fact Sheet EPA, EnviroAtlas Fact Sheet, 2019, Accessed September 6, 2024

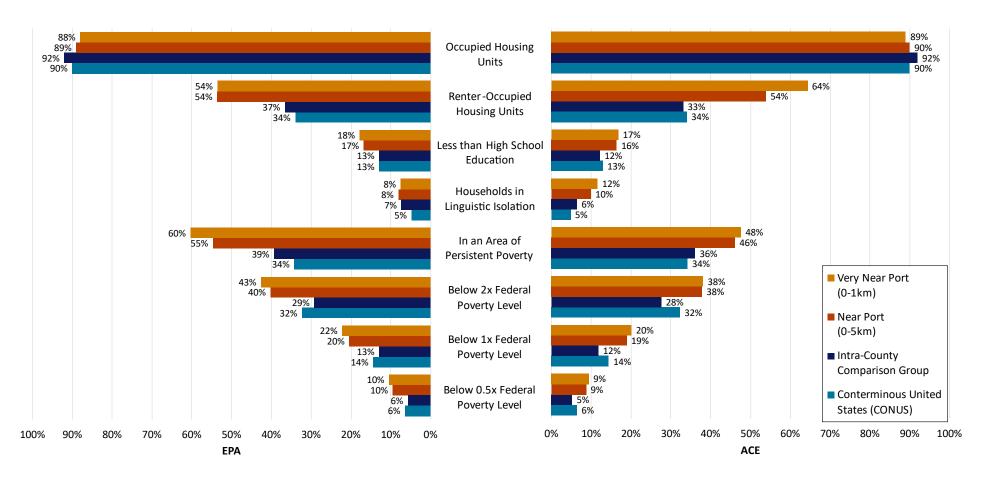
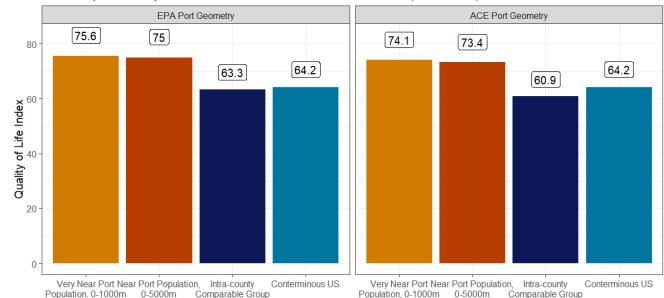


Figure 1212. Pyramid plot of the percentage of the population belonging to selected socioeconomic groups by near-port populations and comparison groups.



Summary of Quality of Life Index between Near Port and Comparison Populations

Figure 13 13. Comparison of Quality of Life index, equal to the percentage of the population living below the Quality of Life income threshold, between near-port populations and comparison groups for 123 ports included in the primary analysis.

No detectable disproportionalities among vulnerable age groups in Near-Port Populations

There were no detectable disproportionalities for vulnerable age groups in the near-port populations compared to the comparison groups. In fact, there were smaller shares of people aged 64 or older in the *Very Near* (11.3% and 11.8% for EPA and ACE, respectively) and *Near Port* populations (11.4% and 12% for EPA and ACE) compared to both the Intra-County Comparison Group (12.8% and 13% for EPA and ACE) and Conterminous U.S. (13%; see *Figure A- 3* in the Appendix F). We observed a similar trend among the two younger populations examined as well. For children less than 5 years old, there was less than 1 percentage point difference between the near-port populations and the comparison groups. Children less than 5 years old made up 6.6% and 5.9% of the *Very Near Port* populations (for EPA and ACE, respectively); they made up 6.4% (EPA) or 6.3% (ACE) of the Intra-County Comparison Group and 6.5% of the CONUS population. Children less than 18 years old made up 21.6% and 18.8% of the *Very Near Port* populations for EPA and ACE geometries, respectively, and they made up 22% of the *Near Port* population using both port geometries. These proportions were lower than both the Intra-County Comparison Groups (23.6% for EPA and 24% for ACE) and the Conterminous U.S. (24%). Taken together, these results indicate that there is not an overrepresentation of vulnerable age groups in near-port communities.

3.3 Top 10 Ports Supplemental Analysis Supports Conclusions of National Analysis

Estimates of Near-Port Populations & Comparison Groups

As discussed earlier, a supplemental analysis of the top 10 ports by tonnage was developed to further evaluate the validity of the national-level results of the primary analysis. The purpose of this

supplemental analysis was to understand whether the sociodemographic patterns observed in the primary analysis were driven solely by the busiest ports by tonnage, which also aligned with major metro areas. Further, we sought to understand if there were meaningfully different disproportionalities or sociodemographic characteristics surrounding the top 10 busiest ports, which may also contribute the most emissions related to port activity.

While the top 10 ports were selected based on tonnage thresholds, the populations surrounding these ports also contain a large subsample of the total population featured in the primary analysis. As shown in **Figure 14**, the *Near Port* population of the top 10 ACE port geometries is 13.1M, which is approximately 42% of the total *Near Port* population in the primary analysis of 123 ports (31.1M); the *Near Port* population of the top 10 EPA port geometries is 5.1M, which is approximately 31% of the total *Near Port* population in the primary analysis of 123 ports (31.1M); the *Near Port* population in the primary analysis of 123 ports (16.1M). Similarly, 55% of the *Very Near Port* population of ACE port geometries are in proximity to one of the top 10 ports (2.6M vs. 4.7M), and 41% of the *Very Near Port* population of EPA port geometries are in proximity to one of the top 10 ports (1.1M vs. 2.6M).

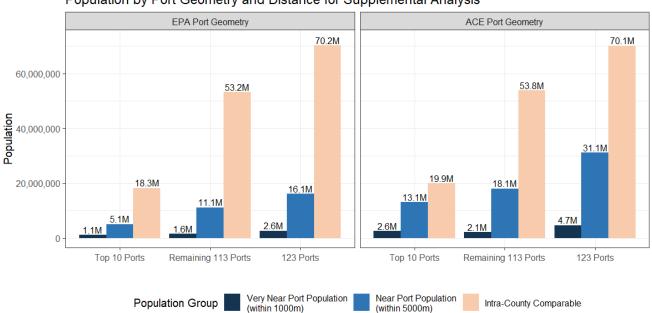




Figure 14. Comparison of Very Near Port, Near Port, and Intra-County Comparison Group populations for the supplemental analysis.

There are important sociodemographic differences between the populations in proximity to the top 10 busiest ports by tonnage and those in proximity to the remaining 113 ports included in this study. Generally, there is a higher proportion of people of color near the top 10 ports than there is near the remaining 113 (**Table 6** and **Table 7**). For both port geometries (EPA and ACE) and buffer sizes (1000m and 5000m), this pattern is largely driven by differences in the percentage of Hispanic and Non-Hispanic Asian populations; among the *Very Near Port* population of the EPA port geometries, there is also a notably higher percentage of Non-Hispanic Black for the top 10 ports as compared to the remaining 113. Near-port populations surrounding the top 10 ports also have a higher proportion of households in linguistic isolation, renter-occupied housing units, and individuals with less than a high school education

than the populations surrounding the remaining 113 ports. Although the top 10 ports are located in areas with higher median household incomes and a lower percentage of the population living in areas of persistent poverty, their surrounding populations also have a greater proportion of households below the Quality of Life income threshold as compared to those of the remaining 113 ports.

	Port subset					
-	То	tal 123		Тор 10	Ren	naining 113
ACE	Port G	eometries				
Race/Ethnicity (% of population)						
NH White		47.9		39.8		57.7
People of Color		52.1		60.2		42.3
NH Black		15.6		15.9		15.2
Hispanic		26.2		33.0		17.9
NH Asian		7.7		9.1		6.1
NH Other Race		0.4		0.4		0.3
NH Two or More Races		1.9		1.6		2.2
NH American Indian/Alaska Native		0.3		0.2		0.5
NH Native Hawaiian/Pacific Islander		0.1		0.0		0.1
Socioeconomic status (% of population)						
Occupied Housing Units		89.1		91.0		86.7
Renter-Occupied Housing Units		53.9		70.8		56.4
Less than High School Education		16.8		18.5		14.7
Households in Linguistic Isolation		11.6		14.5		8.0
In an Area of Persistent Poverty		47.6		47.1		48.2
Below 2x the Poverty Threshold		38.1		36.8		39.6
Below 1x the Poverty Threshold		20.1		19.2		21.3
Below 0.5x the Poverty Threshold		9.4		8.7		10.2
Median Household Income	\$	69,519.87	\$	74,448.98	\$	62,934.26
Quality of Life Index		74.1		75.3		72.1
EPA	Port G	eometries				
Race/Ethnicity (% of population)						
NH White		48.2		36.6		56.1
People of Color		51.8		63.4		43.9
NH Black		22.8		30.9		17.2
Hispanic		21.1		25.7		17.9
NH Asian		5.2		4.8		5.4
NH Other Race		0.2		0.2		0.3
NH Two or More Races		2.0		1.4		2.4
NH American Indian/Alaska Native		0.4		0.3		0.5
NH Native Hawaiian/Pacific Islander		0.1		0.1		0.2
Socioeconomic status (% of population)						
Occupied Housing Units		87.8		88.7		87.1
Renter-Occupied Housing Units		53.5		52.7		54.2
Less than High School Education		17.8		20.5		15.9
Households in Linguistic Isolation		7.5		9.2		6.3
In an Area of Persistent Poverty		60.3		59.4		61.1
Below 2x the Poverty Threshold		42.6		43.1		42.2
Below 1x the Poverty Threshold		22.2		22.2		22.3
Below 0.5x the Poverty Threshold		10.4		10.4		10.4
Median Household Income	\$	58,358.87	\$	58,098.73	\$	58,485.34
Quality of Life Index	7	75.6	Ŧ	75.5	Ŧ	75.6

 Table 6. Sociodemographic Characteristics of Very Near Port Populations (within 1000m)

	Port subset					
	Т	otal 123		Тор 10	Ren	naining 113
ACE	E Port (Geometries				
Race/Ethnicity (% of population)						
NH White		45.6		36.3		52.5
People of Color		54.4		63.7		47.5
NH Black		21.4		21.5		21.3
Hispanic		22.6		29.7		17.5
NH Asian		7.6		10.1		5.7
NH Other Race		0.4		0.5		0.3
NH Two or More Races		2.0		1.6		2.2
NH American Indian/Alaska Native		0.2		0.2		0.4
NH Native Hawaiian/Pacific Islander		0.1		0.1		0.1
Socioeconomic status (% of population)						
Occupied Housing Units		90.3		91.7		89.4
Renter-Occupied Housing Units		53.9		61.7		48.0
Less than High School Education		16.4		18.9		14.6
Households in Linguistic Isolation		9.9		13.9		7.0
In an Area of Persistent Poverty		46.1		43.8		47.7
Below 2x the Poverty Threshold		37.8		37.1		38.2
Below 1x the Poverty Threshold		18.9		18.4		19.2
Below 0.5x the Poverty Threshold		8.7		8.1		9.0
Median Household Income	\$	65,147.06	\$	68,567.21	\$	63,572.33
Quality of Life Index		73.4		75.0		72.6
EPA	Port (Geometries				
Race/Ethnicity (% of population)						
NH White		45.7		36.9		49.8
People of Color		54.3		63.1		50.2
NH Black		23.9		25.0		23.4
Hispanic		20.4		27.0		17.4
NH Asian		7.0		8.8		6.1
NH Other Race		0.3		0.2		0.3
NH Two or More Races		2.1		1.6		2.4
NH American Indian/Alaska Native		0.4		0.2		0.4
NH Native Hawaiian/Pacific Islander		0.1		0.1		0.2
Socioeconomic status (% of population)						
Occupied Housing Units		89.2		89.8		88.9
Renter-Occupied Housing Units		53.6		58.3		51.4
Less than High School Education		16.8		20.3		15.2
Households in Linguistic Isolation		8.1		11.5		6.6
In an Area of Persistent Poverty		54.7		52.4		55.7
Below 2x the Poverty Threshold		40.2		40.7		40.0
Below 1x the Poverty Threshold		20.4		20.3		20.5
Below 0.5x the Poverty Threshold		9.5		9.0		9.8
Median Household Income	\$	61,302.89	\$	63,215.48	\$	60,406.98
Quality of Life Index	Ŷ	75.0	Ŷ	75.9	Ŷ	74.6

 Table 7. Sociodemographic Characteristics of Near Port Populations (within 5000m)

Disproportionalities of Near-Port Populations

Race and Ethnicity Demographic Features

In the primary analysis of this study, we detected higher percentages of people of color and Non-Hispanic Black populations living within 5000m of a port (using either EPA or ACE geometries) compared to the Intra-County Comparison Group and CONUS. When subset to understand the demographic differences around the top 10 ports and the remaining 113 ports, there is still a higher percentage of Non-Hispanic Black population living in near-port populations compared to the CONUS and Intra-County Comparison Groups for both port geometries studied (**Figure 15**).

Related to people of color, the supplemental analysis generally supported the findings of the primary analysis; however, it did reveal some surprising nuances. Among populations near the top 10 ports (using either EPA or ACE geometries), there is still a disproportionately higher share of people of color as compared to CONUS. However, the difference in percentage of people of color between near-port populations and their Intra-County Comparison Group is much smaller for the top 10 ports as compared to the primary analysis of 123 ports. In fact, the relationship reverses around EPA port geometries, with the percentage of people of color within the *Near Port* population being 2 points lower than it is in the Intra-County Comparison Group. These findings indicate that the overrepresentation of people of color in the *Near Port* population versus the Intra-County Comparison Group is not being driven by the population around the top 10 ports, but rather by the 113 remaining ports.

We also observe that the attenuated overrepresentation of people of color near the top 10 ports versus the Intra-County Comparison Group is partially driven by Hispanic and Non-Hispanic Asian, among whom there is an even more pronounced reversal of population dynamics. For example, the Hispanic population comprises 27% of the *Near Port* population around the top 10 EPA port geometries, which is 11 percentage points higher than CONUS (16%), but 11 percentage points lower than the Intra-County Comparison Group (38%). This finding suggests that the near-port population around the top 10 most active ports is comprised of relatively fewer people who are Hispanic or Non-Hispanic Asian than the neighboring populations. As a result, we do not observe an overrepresentation of total people of color around the top 10 ports as compared to the Intra-County Comparison Group, even though this overrepresentation for Non-Hispanic Black populations is similar or greater than it is in the primary analysis of 123 major U.S. ports.

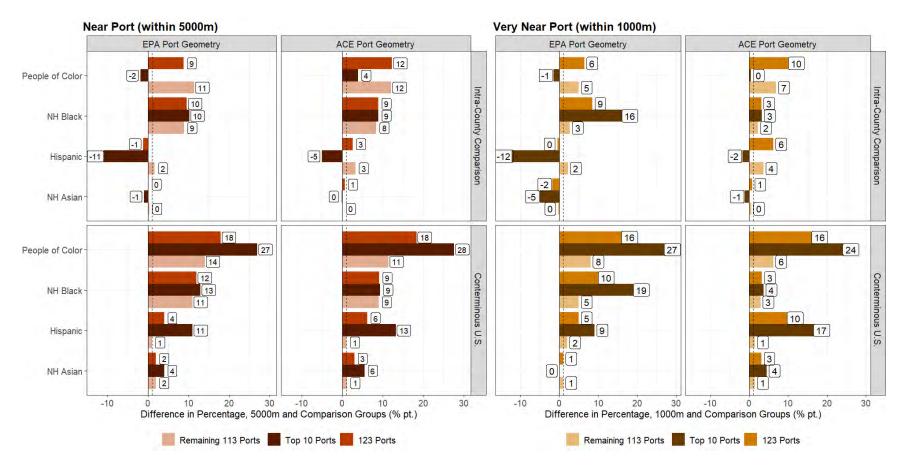


Figure 15. Comparisons by race/ethnicity between near-port populations and comparison groups for the 123, top 10, and remaining 113 ports. The difference in percentage by race/ethnicity between the near-port populations and comparison group is printed next to each bar; bars with positive values indicate a higher percentage of that demographic group in the near-port populations than the comparison group, while negative values indicate a higher percentage in the comparison group. Only demographic characteristics with differences in percentage greater than 1% pt. in the primary analysis are shown.

Socioeconomic Features

For almost all socioeconomic variables, the results of the supplemental analysis for the top 10 and remaining 113 ports support the national findings of the primary analysis. Mainly, there was consistent overrepresentation in the near-port populations of individuals living below twice, once, and half the poverty threshold as compared to CONUS and the Intra-County Comparison Groups. Using the ACE port geometries, we also observed patterns that were generally consistent in the supplemental analysis and in the primary analysis for other socioeconomic variables, like the percentages of occupied housing units, renter-occupied housing units, adults with less than a high school education, and households in linguistic isolation. Using the EPA port geometries, evidence of disproportionalities in proximity to the top 10 ports based on renter occupancy, educational attainment, and linguistic isolation tended to be stronger in comparison to CONUS than the Intra-County Comparison Group. For example, the percentage of adults with less than a high school education living within 5000m of one of the top 10 ports was 7 points higher than in CONUS (20% vs. 13%); it was only 1 percentage point higher than the Intra-County Comparison Group (20% vs. 19%).

Based on the comparison group that was used, some contrasting results did emerge from the supplemental analysis for measures of income and poverty. For example, the proportion of the population living in areas of persistent poverty was higher in the top 10 near-port populations than it was in CONUS (by 18 percentage points using EPA port geometries) but lower than it was in the Intra-County Comparison Groups (by 13 percentage points using EPA port geometries). Interestingly, the percentage of households living below the Quality of Life income threshold in the top 10 near-port populations was still higher than it was in the Intra-County Comparison Groups. We hypothesize that the largest ports are important contributors to economic activity in their metropolitan areas or regions, but that disproportionalities in who is most likely to live near these ports still remain. This hypothesis can also help explain why median household income and the percentage of households living below the Quality of Life threshold are both higher in the top 10 supplemental analysis that they are in the primary analysis (**Table 6** and **Table 7**). Although there may be wealthier regions that surround the top 10 ports, we still identified consistent socioeconomic disproportionalities in their near-port populations as compared to CONUS and the Intra-County Comparison Groups. The supplemental analysis illustrates the importance of using comparison groups in the same parts of the country as the near-source groups.

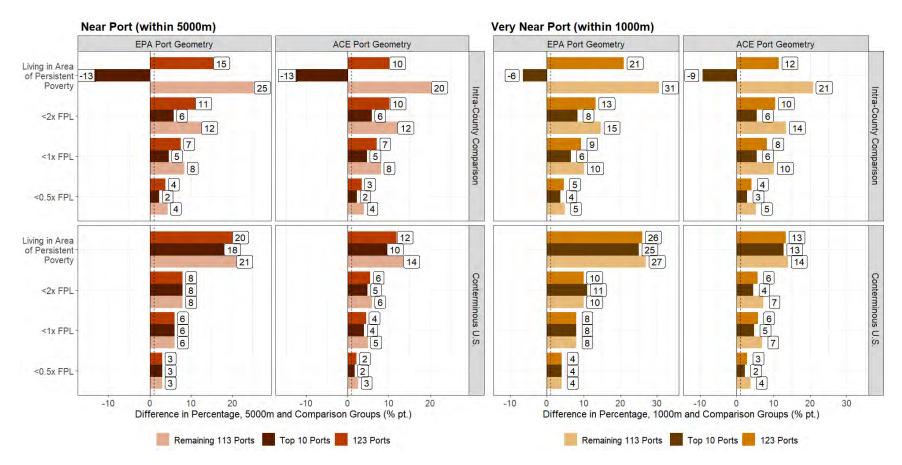


Figure 16. Comparisons by poverty-related factors between near-port populations and comparison groups for the 123, top 10, and remaining 113 Ports. The difference in percentage between the near-port population and comparison group is printed next to each bar; bars with positive values indicate a higher percentage of that group in the near-port population than the comparison group, while negative values indicate a higher percentage in the comparison group. Only socioeconomic characteristics with differences in percentage greater than 1% pt. in the primary analysis are shown.

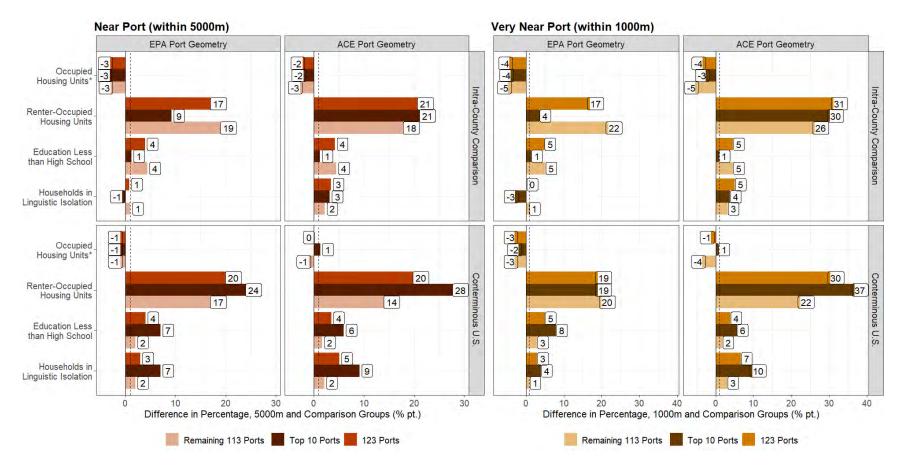


Figure 17. Comparisons by other socioeconomic between near-port populations and comparison groups for the 123, top 10, and remaining 113 Ports. The difference in percentage between the near-port population and comparison group is printed next to each bar; bars with positive values indicate a higher percentage of that group in the near-port population than the comparison group, while negative values indicate a higher percentage in the comparison group. Only demographic characteristics with differences in percentage greater than 1% pt. in the primary analysis are shown.



Figure 18. Comparison of median household income between near port populations and comparison groups for the top 10 ports.

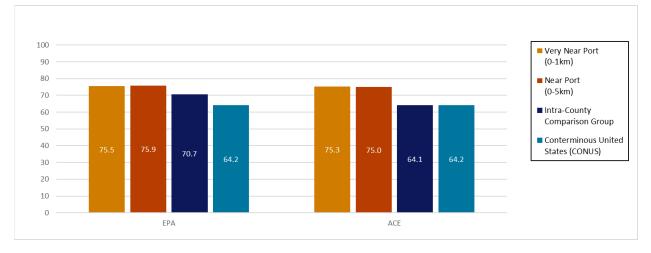


Figure 19. Comparison of Quality of Life index, equal to the percentage of the population living below the Quality of Life income threshold, between near port populations and comparison groups for the top 10 ports.

4. Discussion

4.1 Summary of Results

There is not a single authoritative source for the geospatial extent of U.S. ports; therefore, we estimated the total population living in proximity to a subset of major U.S. ports (n=123) using data from two different federal agencies: U.S. EPA (EPA) and U.S. Army Corps of Engineers (ACE). Using the EPA geometries, we estimate that 16.1M people live within 5000m of a major U.S. port, equal to ~5% of the total population of CONUS (2010). Using the ACE geometries, we estimate that 31.1M people, or ~10% of the total population of CONUS (2010), live within 5000m of a major U.S. port.

Furthermore, we have identified sociodemographic patterns across the 123 ports included in this study that show consistent disproportionalities, which may suggest potential disparities that exist among near-port populations at a national scale. Specifically, we have found that there is a disproportionate overrepresentation of people of color, non-Hispanic Black, and Hispanic populations living within 1000m and 5000m of U.S. ports when compared to neighboring populations (i.e., Intra-County Comparison Group) and to the rest of the conterminous United States. The results of a supplemental analysis further supported these national-level findings, with clear evidence that these trends are not solely attributable to the demographic characteristics of populations in proximity to the largest ports in the U.S. The results of this study also reveal important socioeconomic disproportionalities among near-port populations as represented by factors associated with income, poverty, and housing. Specifically, we observed overrepresentation among near-port populations as compared to their neighboring communities and CONUS of individuals living below twice the poverty threshold, renters, individuals living in areas of persistent poverty, adults with less than a high school education, households in linguistic isolation, and households living below the Quality of Life income threshold.

While we did not estimate air quality or exposure in this study, our results do characterize the populations that live in close proximity to ports and are most likely to be exposed to harmful air emissions from port activities, which are also the populations that are most likely to benefit from efforts to lower port-related mobile source emissions. These communities are overrepresented by people of color, non-Hispanic Black, Hispanic, and low-income populations. Additionally, actions taken to make the top 10 ports with the largest tonnage throughput cleaner may have an outsized impact on the national near-port population, as their near-port populations account for approximately 30-40% of the total population living in proximity to a major port in CONUS.

4.2 Differences between the EPA and ACE Shapefiles and Impact on Population Totals

We identified significant qualitative differences between the two geometries at the individual port-level, such as the differences shown in **Figure 2**. There are only 4 ports (out of the 123 studied) for which all the points corresponding to active docks from the ACE dataset are wholly contained within the EPA polygons.⁴⁶ Furthermore, the majority of ACE active dock points fall outside of the corresponding EPA polygon at almost 75% of the ports (92 out of 123). While we used these datasets to approximate where both waterside and landside mobile source activity may occur, all of the ACE points and 40 of the EPA polygons do not geospatially cover potential landside operations, and as a result may underestimate the spatial extent of where port activity is.

To further illustrate the distinct geometries between the two port geometry datasets and the resulting impact on population found withing the geodesic buffer, consider the way that each dataset describes the port of Chicago in **Figure 20**, and the resulting impact on the defined near port population for each analytical track. Nationally, the total area enclosed by the 5000m buffer around ACE port

⁴⁶ The ports with active docks from ACE that are wholly contained within the EPA shapefiles are: Port Dolomite MI; Marcus Hook PA; Silver Bay, MN; and Two Harbors MN.

geometries was over 10,000 square miles, which is 54% larger than the area enclosed by the 5000m buffer around EPA port geometries.

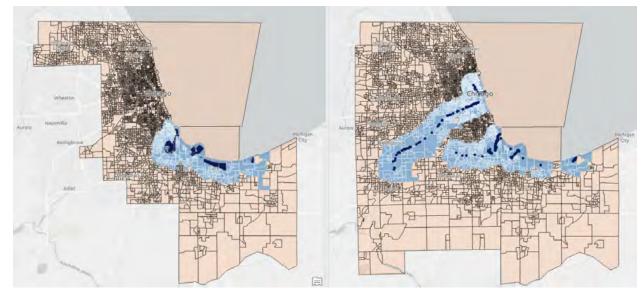
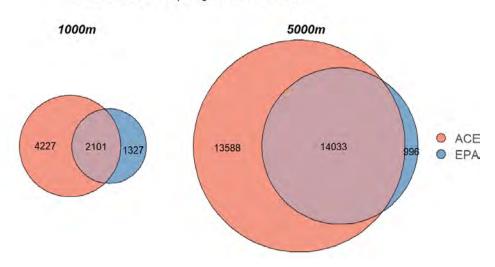


Figure 20. Map comparing the differences between the EPA (left) and ACE (right) port geometries and the resulting impact on differences in the extent of block groups in Near Port populations (shown in light blue) and the extent of the Intra-County Comparison Groups (shown in peach) using Chicago as an example. Note block groups with zero population are included in the figure above.



Number of near-port block groups captured by one or both of the port geometries studied

Figure 21. Visualization of the number of near-port block groups captured by the ACE port geometries, the EPA port geometries, or both.

To depict the overlap of Census data that were allocated to the EPA and ACE near-port populations, we have visualized the number of *Very Near Port* (within 1000m) and *Near Port* (within 5000m) block groups that were similar or different between the two (**Figure 21**). We see that the majority of EPA near-port block groups (61% for *Very Near Port* and 93% for *Near Port*) were also ACE near-port block groups. Yet, each port geometry retained distinct populations not found in the vicinity of the other. Because the ACE port geometries captured more near-port block groups in total, a lower percentage were also shared by the EPA near-port populations (33% for *Very Near Port* and 51% for *Near Port*).

Given these differences in overall area and the distinct populations captured as 'near-port' between the two geometries, we chose to analyze and report the results of the two port geometry datasets separately, rather than as ranges or averages. As **Figure 21** shows, there is a large degree of overlap in near-port block groups of the EPA and ACE port geometries, but we observe that the two near-port populations are distinct.

This distinction is most clearly manifested in the stark differences in the population totals (**Table 3**) and further underscores the pivotal role that underlying source geometries play in developing proximity analyses. Neither ACE nor EPA port geometries represent official port boundaries, and port-related operations can occur outside these estimated limits. Questions remain about the NEI polygons that comprise the EPA dataset in this analysis, including how the specific set of ports were determined given that ACE's Master Docks Plus included many more ports. Due to uncertainties involved in defining areas of port activity and port boundaries as well as recent port reorganizations, we cannot accurately report port-level results that represent current conditions on the ground using either the EPA or the ACE dataset. Improvements in the geospatial depiction of port operations, including geometries that are corroborated with on-the-ground experience, would greatly enhance future quantifications of near-port populations.

4.3 Other Study Limitations

While this study improves upon past work and is reflective of the most recent agency guidance, it does have limitations. One limitation of this analysis stems from aggregating results to the national level. The 123 ports included in this study are diverse, representing a variety of geographic regions, urban/rural classifications, and port activities. We reasonably assume that their near-port populations are also sociodemographically unique, as some areas of the country have greater shares of certain racial, ethnic, and socioeconomic groups than others. Aggregating all these near-port areas in a national-level analysis may mask demographic patterns and disproportionalities that exist on a port-by-port or regional basis.

Another limitation of this analysis stems from the differing resolutions of the Census data and the dasymetric population model. To allocate Census sociodemographic characteristics to the more highly resolved dasymetric population counts, we assumed that sociodemographic characteristics are distributed evenly throughout a block group. Because equally high-resolution Census data are not available, we cannot perfectly characterize the differences between the populations on opposite sides of the near-port buffer boundary when census block groups are bisected by the buffer.

We were unable to include Alaska, Hawaii, Puerto Rico, the U.S. Virgin Islands, and other territories and insular areas outside of CONUS because of the coverage of the dasymetric population model used in this study. Ports in these areas serve as vital economic links to the rest of the country. By excluding these areas, we underestimate the total number of people living near ports and may have especially missed certain demographic groups in near-port populations (e.g., Native Hawaiian and Other Pacific Islander or American Indian and Alaska Native). The 2020 dasymetric population model has been released since the bulk of this study was completed, and in addition to updated data to reflect 2020 populations, this dataset includes Alaska, Hawaii, Puerto Rico, and the U.S. Virgin Islands. As a result, future work for this effort may apply these methods to the updated population dataset to encompass key ports beyond CONUS.

Finally, the total populations presented here are likely to be underestimations of the total population impacted by port activity. The population data used reflects those residing near ports and does not capture the share of people working at or around ports who may be occupationally exposed to emissions from ports. Additionally, this study did not include every port across the country, as it was limited to ports represented by both port geometries, the geographic extent of the dasymetric data, and the ACE Principal Ports list. As a result of these inclusion criteria, the populations presented here exclude those living in proximity to ports outside of the conterminous U.S., ports that primarily serve cruise passengers or offer ferry services, and ports used by Tribes for non-commercial activities. Additionally, because complementary shapefiles were not available in both datasets, two major U.S. ports were excluded: the Port of Virginia and the Port of Detroit. Finally, the choice of buffer distances used in the study (1000m and 5000m) cover a proximity that may exclude areas that are impacted by port operations and air quality pollutants, such as particulate matter, which can be transported over much larger distances than 5000m.

5. Conclusion

We have conducted a national analysis of 123 major ports in CONUS to understand the sociodemographic characteristics of the 2010 near-port population in the U.S. We leveraged two different federal datasets to represent unique definitions of ports and port-related activity. Further characterizing the sociodemographic breakdown of two comparison groups also allowed us to identify disproportionalities that may be indicative of disparities between near-port populations and neighboring communities or CONUS. Ultimately, we observe that the near-port population is overrepresented by non-Hispanic Black, Non-Hispanic Asian, and Hispanic, people of color, and individuals belonging to socioeconomically vulnerable groups as compared to neighboring populations and the general population of CONUS. Efforts to reduce port-related emissions could benefit as many as 16-31 million people living near major CONUS ports and address environmental injustices for vulnerable groups who are overrepresented in proximity to port operations.

Works Cited

- Adar, S., Adamkiewicz, G., Gold, D., Schwartz, J., Coull, B., & Suh, H. (2007). Ambient and microenvironmental particles and exhaled nitric oxide before and after a group bus trip. *Environmental Health Perspectives*, *115*(4), 507-512. doi:10.1289/ehp.9386
- Agrawal, H., Eden, R., Zhang, X., Fine, P. M., Katzenstein, A., Miller, J. W., . . . Cocker, D. R. (2009).
 Primary Particulate Matter from Ocean-Going Engines in the Southern California Air Basin.
 Environmental Science & Technology, 43(14), 5398–5402. doi:10.1021/es8035016
- Baynes, J., Neale, A., & Hultgren, T. (2022). Improving intelligent dasymetric mapping population density estimates at 30 m resolution for the conterminous United States by excluding uninhabited areas. *Earth Syst Sci Data*, 14(6), 2833–2849. doi:10.5194/essd-14-2833-2022
- Boogaard, H., Patton, A., Atkinson, R., Brook, J., Chang, H., Crouse, D., . . . Van Vliet, E. (2022). Long-term exposure to traffic-related air pollution and selected health outcomes: A systematic review and meta-analysis. *Environment International, 164*, 107262. doi:10.1016/j.envint.2022.107262
- Boothe, V. L., Boehmer, T. K., Wendel, A. M., & Yip, F. Y. (2014, April). Residential traffic exposure and childhood leukemia: a systematic review and meta-analysis. *American Journal of Preventative Medicine*, *46*(4), 413-22. doi:10.1016/j.amepre.2013.11.004
- Collins, T. W., & Grineski, S. (2022). Racial/Ethnic Disparities in Short-Term PM2.5 Air Pollution Exposures in the United States. *Environmental Health Perspectives*, *130*(8). doi:10.1289/EHP11479
- Eastern Research Group. (2010). Documentation for the Commercial Marine Vessel Component of the National Emissions Inventory Methodology. Filed as 'cmv_report4.pdf' within the 2008 NEI Reference List Download. Retrieved from https://www.epa.gov/air-emissions-inventories/2008national-emissions-inventory-nei-data
- Flater, D., & ESRI Geoprocessing Development Team. (2011). *Understanding Geodesic Buffering*. Retrieved from ArcUser Online: https://www.esri.com/news/arcuser/0111/geodesic.html
- Gillingham, K., & Huang, P. (2021). Racial Disparities in the Health Effects from Air Pollution: Evidence from Ports. *National Bureau of Economic Research*. doi:10.3386/w29108
- Greenburg, M. R. (2021). Ports and Environmental Justice in the United States: An Exploratory Statistical Analysis. *Risk Analysis*, *41*(11). doi:10.1111/risa.13697
- Jbaily, A., Zhou, X., Liu, J., Lee, T.-H., Kamareddine, L., Verguet, S., & Dominici, F. (2022). Air pollution exposure disparities across US population and income groups. *Nature, 601*(7892), 228-233. doi:10.1038/s41586-021-04190-y.
- Karner, A., Eisinger, D., & Niemeier, D. (2010). Near-roadway air quality: synthesizing the findings from real-world data. *Environmental Science & Technology*, 44(14), 5334–5344. doi:10.1021/es100008x

- Laden, F., Hart, J., Smith, T., Davis, M., & Garshick, E. (2007). Cause-specific mortality in the unionized U.S. trucking industry. *Environmental Health Perspectives*, 115(8), 1192-1196. doi:10.1289/ehp.10027
- Marshall, J. D. (2008). Environmental inequality: Air Pollution exposures in California's South Coast Air Basin. *Atmospheric Environment, 42*(21), 5499-5503. doi:10.1016/j.atmosenv.2008.02.005
- Mohai, P., Pellow, D., & Roberts, J. T. (2009). Environmental Justice. *Annual Review of Environment and Resources*, *34*, 405-430. doi:10.1146/annurev-environ-082508-094348
- Peters, A., von Klot, S., Heier, M., Trentinaglia, I., Hormann, A., Wichmann, H., & Lowel, H. (2004). Exposure to traffic and the onset of myocardial infarction. *New England Journal of Medicine*, *351*(17), 1721-1730. doi:10.1056/NEJMoa040203
- Pickard, B. R., Daniel, J., Mehaffey, M., Jackson, L. E., & Neale, A. (2015). EnviroAtlas: A new geospatial tool to foster ecosystem services science and resource management. *Ecosystem Services*, 14, 45-55. doi:10.1016/j.ecoser.2015.04.005
- Rosenbaum, A., Hartley, S., & Holder, C. (2011). Analysis of Diesel Particulate Matter Health Risk Disparities in Selected US Harbor Areas. *American Journal of Public Health*, *101*(S1), S217-S223. doi:10.2105/AJPH.2011.300190
- Rowangould, G. M. (2013). A census of the near-roadway population: public health and environmental justice considerations. *Transportation Research Part D: Transport and Environment, 25*, 59-67. doi:10.1016/j.trd.2013.08.003.
- Svendsen, E. R., Reynolds, S., Ogunsakin, O. A., Williams, E. M., Fraser-Rahim, H., Zhang, H., & Wilson, S.
 M. (2014). Assessment of Particulate Matter Levels in Vulnerable Communities in North Charleston, South Carolina prior to Port Expansion. *Environmental Health Insights, 8*, 5-14. doi:10.4137/EHI.S12814
- Tessum, C. W., Paolella, D. A., Chambliss, S. E., Apte, J. S., Hill, J. D., & Marshall, J. D. (2021). PM2.5 polluters disproportionately and systemically affect people of color in the United States. *Science Advances*, 7(18). doi:10.1126/sciadv.abf4491
- U.S. Army Corps of Engineers Institute of Water Resources. (2018). *Principal ports of the United States,* 2017. Retrieved from USACE Digital Library: https://usace.contentdm.oclc.org/digital/collection/p16021coll2/id/3114/rec/5
- U.S. Army Corps of Engineers Navigation and Civil Works Decision Support Center, Waterborne Commerce Statistics Center. (2019). Master Docks Plus Public Extract. Retrieved May 2019, from https://ndclibrary.sec.usace.army.mil/resource/ed0949e6-19a1-4767-9fbd-17d0de5f727e
- U.S. Census Bureau. (n.d.). Understanding Geographic Identifiers (GEOIDs). Retrieved from Guidance for Geography Users: https://www.census.gov/programs-surveys/geography/guidance/geo-identifiers.html
- U.S. Department of Transportation. (2021). Areas of Persistent Poverty & Historically Disadvantaged Communities. Retrieved from RAISE: https://www.transportation.gov/RAISEgrants/raise-apphdc

- U.S. Environmental Protection Agency. (2014). 2011 Port Shape Files. Retrieved from 2011 National Emissions Inventory (NEI) Data: https://www.epa.gov/air-emissions-inventories/2011-national-emissions-inventory-nei-data
- U.S. Environmental Protection Agency. (2015). Dasymetric Allocation of Population, Conterminous U.S., 2010 v.3, Raster. Retrieved May 2021, from https://www.epa.gov/enviroatlas/data-download
- U.S. Environmental Protection Agency. (2016). *Technical Guidance for Assessing Environmental Justice in Regulatory Analysis*. Retrieved July 2024, from https://www.epa.gov/sites/default/files/2016-06/documents/ejtg_5_6_16_v5.1.pdf
- U.S. Environmental Protection Agency. (2017). 2014 Port Shape Files. Retrieved from 2014 National Emissions Inventory (NEI) Data: https://www.epa.gov/air-emissions-inventories/2014-national-emissions-inventory-nei-data
- U.S. Environmental Protection Agency. (2018). *EnviroAtlas Data Fact Sheet: Threshold Income for Quality* of Life. Retrieved September 2024, from EnviroAtlas Fact Sheets: https://enviroatlas.epa.gov/enviroatlas/DataFactSheets/pdf/Supplemental/Thresholdincomefor qualityoflife.pdf
- U.S. Environmental Protection Agency. (2020). Retrieved from 2017 National Emissions Inventory (NEI) Data: https://www.epa.gov/air-emissions-inventories/2017-national-emissions-inventory-neidata
- U.S. Environmental Protection Agency. (2020). *Ports Primer for Communities Glossary: "Port"*. Retrieved February 2023, from Ports Initiative: https://sor.epa.gov/sor_internet/registry/termreg/searchandretrieve/glossariesandkeywordlists /search.do?details=&vocabName=Ports%20Primer%20Glossary
- U.S. Environmental Protection Agency. (2021). Request for Applications for 2021 Diesel Emissions Reduction Act (DERA) National Grants. Section I.B.7.b.2; page 19. Retrieved from https://www.epa.gov/sites/default/files/2021-03/documents/2021-3-2-dera-rfa-final.pdf
- U.S. Environmental Protection Agency. (2022). *Port and Goods Movement Emission Inventories*. Retrieved 2024, from U.S. EPA Ports Initiative: https://www.epa.gov/ports-initiative/port-and-goods-movement-emission-inventories
- U.S. Environmental Protection Agency. (2023). Analytical Tools Interface for Landscape Assessments (ATtILA) Toolbox. Retrieved July 2024, from https://www.epa.gov/enviroatlas/attila-toolbox
- U.S. Environmental Protection Agency. (2023). DRAFT 2023 Technical Guidance for Assessing Environmental Justice in Regulatory Analysis. Retrieved from https://www.epa.gov/system/files/documents/2023-11/ejtg_revision_110823_508compliant_0.pdf
- U.S. Environmental Protection Agency. (2024). *Clean Ports Program*. Retrieved September 2024, from U.S. EPA Ports Initiative: https://www.epa.gov/ports-initiative/cleanports
- U.S. Environmental Protection Agency. (2024). *EPA Collaboration on International Air Pollution* Standards for Ships. Retrieved September 2024, from Regulations for Emissions from Vehicles

and Engines: https://www.epa.gov/regulations-emissions-vehicles-and-engines/epa-collaboration-international-air-pollution-0

- U.S. Environmental Protection Agency. (n.d.). *Diesel Emissions Reduction Act (DERA) Funding*. Retrieved September 2024, from https://www.epa.gov/dera
- U.S. Environmental Protection Agency. (n.d.). *Learn About How Mobile Source Pollution Affects Your Health*. Retrieved 2024, from https://www.epa.gov/mobile-source-pollution/learn-about-howmobile-source-pollution-affects-your-health
- U.S. Environmental Protection Agency. (n.d.). *Ports Initiative*. Retrieved September 2024, from https://www.epa.gov/ports-initiative
- Valencia, A., Serre, M., & Arunachalam, S. (2023). A hyperlocal hybrid data fusion near-road PM2.5 and NO2 annual risk and environmental justice assessment across the United States. *PLOS ONE*. doi:10.1371/journal.pone.0286406
- Weaver, G. M., & Gauderman, W. J. (2018). Traffic-Related Pollutants: Exposure and Health Effects Among Hispanic Children. *American Journal of Epidemiology*, 187(1), 45-52. doi:10.1093/aje/kwx223
- Zanobetti, A., Stone, P., Spelzer, F., Schwartz, J., Coull, B., Suh, H., . . . gold, D. (2009). T-wave alternans, air pollution and traffic in high-risk subjects. *American Journal of Cardiology*, *104*(5), 665-670. doi:10.1016/j.amjcard.2009.04.046

Appendices

A. List of Ports Included in Study

 Table A-1. List of ports included in study (n=123).

Port Name	Port ID	Port Name	Port ID
Albany, NY	C0505	Morehead City, NC	C0764
Alpena, MI	L3617	Mount Vernon, IN	12332
Anacortes, WA	C4730	Nashville, TN	12370
Ashtabula, OH	L3219	New Castle, DE	C0299
Baltimore, MD	C0700	New Haven, CT	C1507
Baton Rouge, LA	C2252	New Orleans, LA	C2251
Beaumont, TX	C2395	New York, NY and NJ	C0398
Boston, MA	C0149	Oakland, CA	C4345
Bridgeport, CT	C0311	Olympia, WA	C4718
Brownsville, TX	C2420	Palm Beach, FL	C2162
Brunswick, GA	C0780	Panama City, FL	C2016
Buffington, IN	L3737	Pascagoula, MS	C2004
Burns Waterway Harbor, IN	L3739	Paulsboro, NJ	C5252
Calcite, MI	L3620	Penn Manor, PA	C0298
Camden-Gloucester, NJ	C0551	Pensacola, FL	C2007
Charleston, SC	C0773	Philadelphia, PA	C0552
Chattanooga, TN	12372	Pittsburgh, PA	12358
Chester, PA	C0297	Plaquemines, LA, Port of	C2255
Chicago, IL	L3749	Port Angeles, WA	C4708
Cincinnati-Northern KY, Ports of	12338	Port Arthur, TX	C2416
Cleveland, OH	L3217	Port Canaveral, FL	C2160
Conneaut, OH	L3220	Port Dolomite, MI	L3627
Coos Bay, OR	C4660	Port Everglades, FL	C2163
Corpus Christi, TX	C2423	Port Fourchon, LA	C1910
Drummond Island, MI	L3813	Port Hueneme, CA	C4150
Duluth-Superior, MN and WI	L3924	Port Inland, MI	L3803
Escanaba, MI	L3795	Port Jefferson, NY	C0522
Everett, WA	C4725	Port Manatee, FL	C2023
Fairport Harbor, OH	L3218	Portland, ME	C0128
Freeport, TX	C2408	Portland, OR	C4644
Galveston, TX	C2417	Portsmouth, NH	C0135
Gary, IN	L3736	Presque Isle, MI	L3845
Grays Harbor, WA	C4702	Providence, RI	C0191
Greenville, MS	12271	Redwood City, CA	C4340
Gulfport, MS	C2083	Richmond, CA	C4350
Guntersville, AL	12371	San Diego, CA	C4100
Helena, AR	12293	San Francisco, CA	C4335
Hempstead, NY	10514	Sandusky, OH	L3213

Hopewell, VA	C0738	Savannah, GA	C0776
Houston, TX	C2012	Searsport, ME	C0112
Huntington - Tristate	12348	Seattle, WA	C4722
Iberia, LA	C2030	Silver Bay, MN	L3928
Indiana Harbor, IN	L3738	South Louisiana, LA, Port of	C2253
Jacksonville, FL	C2017	Southeast Missouri Port, MO	12301
Kalama, WA	C4626	St. Clair, MI	L3509
Kansas City, MO	12385	St. Louis, MO and IL	12310
Lake Charles, LA	C2254	St. Paul, MN	12320
Lake Providence, LA	12269	Stockton, CA	C4270
Long Beach, CA	C4110	Stoneport, MI	L3619
Longview, WA	C4622	Tacoma, WA	C4720
Lorain, OH	L3216	Tampa, FL	C2021
Los Angeles, CA	C4120	Terrebonne, LA, Port of	C2224
Louisville, KY	12333	Texas City, TX	C2404
Marblehead, OH	L3212	Toledo, OH	L3204
Marcus Hook, PA	C5251	Tulsa, Port of Catoosa, OK	16109
Marquette, MI	L3844	Two Harbors, MN	L3926
Matagorda Port Lv Pt Com, TX	C2410	Vancouver, WA	C4636
Memphis, TN	12294	Vicksburg, MS	12276
Miami, FL	C2164	Victoria, TX	C2411
Milwaukee, WI	L3756	Wilmington, DE	C0554
Mobile, AL	C2005	Wilmington, NC	C0766
Monroe, MI	L3202		

B. Summary of Geospatial Port Data Sources

 Table A-2. Summary of geospatial port data sources used in this study.

	Geospatial Representation featured in this study	Data Source(s)
EPA Port Polygons (EPA)	Polygons: 135 polygons representing 100 ports from the 2011 NEI; and 40 polygons representing 23 ports from the 2014 NEI	2011 and 2014 National Emissions Inventory. Accessed May 2019 from: <u>https://www.epa.gov/air-emissions-</u> <u>inventories/2011-national-emissions-</u> <u>inventory-nei-data</u> and <u>https://www.epa.gov/air-emissions-</u> <u>inventories/2014-national-emissions-</u> <u>inventory-nei-data</u>
U.S. Army Corps of Engineers Active Docks (ACE)	Points: 6,728 points representing 123 ports in the Conterminous U.S.	Master Docks Plus Public Extract. Accessed May 2019 from: https://ndclibrary.sec.usace.army.mil/resource/ ed0949e6-19a1-4767-9fbd-17d0de5f727e)

C. Summary of Port Definitions from Various Federal Agencies and Programs

There is no single definition of a "port" and below is an illustrative list of port definitions from various Federal agencies and programs. This list is meant to illustrate the variety of definitions in use and does not necessarily reflect all definitions currently in use.

Environmental Protection Agency

From EPA Clean Ports Program (source: <u>Clean Ports Program: Zero Emission Technology Deployment</u> <u>Competition Notice of Funding Opportunity</u>)

• Water port: Places on land alongside navigable water (e.g., oceans, rivers, or lakes) with one or more facilities in close proximity for the loading and unloading of passengers or cargo from ships, ferries, and other commercial vessels. This includes facilities that support non-commercial Tribal fishing operations.

From EPA Diesel Emission Reduction Act (source: <u>Diesel Emissions Reduction Act Request for</u> Applications, FY2021)

• **Ports:** Places alongside navigable water with facilities for the loading and unloading of passengers and/or cargo from ships, ferries, and other vessels.

U.S. Department of Transportation

U.S. Maritime Administration

From MARAD Port Infrastructure Development Program (source: <u>Port Infrastructure Development</u> <u>Program under the Infrastructure Investment and Jobs Act and Consolidated Appropriations Act, 2024</u> <u>Notice of Funding Opportunity</u> (A.3. Definitions)

- **Coastal seaport**: A port on navigable waters of the United States or territories that is subject to the U.S. Army Corps of Engineers regulatory jurisdiction for oceanic and coastal waters under 33 C.F.R. 329.12 or that is otherwise capable of receiving oceangoing vessels with a draft of at least 20 feet (other than a Great Lakes port).
- **Great Lakes port**: A port on the Great Lakes and their connecting and tributary waters as defined under 33 C.F.R. 83.03(o).
- **Inland river port**: A harbor, marine terminal, or other shore side facility used principally for the movement of goods that is not at a coastal seaport or Great Lakes port.
- Small Port: A coastal seaport, Great Lakes, or inland river port to and from which the average annual tonnage of cargo for the immediately preceding three calendar years from the time an application is submitted is less than 8,000,000 short tons, as determined by using U.S. Army Corps of Engineers data or data by an independent audit if the Secretary determines that it is acceptable to use such data instead of using U.S. Army Corps of Engineers data.

From MARAD Glossary of Shipping Terms (2008):

• **Port**: Harbor with piers or docks.

Bureau of Transportation Statistics

From <u>BTS Port Performance Freight Statistics Program Glossary</u>:

• Port:

(1) The land, facilities, and adjacent body of water located on a coast, river, or Great Lake where cargo is transferred between ships and other ships, trucks, trains, pipelines, or storage facilities. A port is typically located within a harbor;

(2) A place in which vessels load and discharge cargoes and passengers. Facilities normally include berths, cargo handling equipment and personnel, cargo storage facilities, and land transportation connections. Often with a city, town, or industrial complex.

Excerpt from BTS 2016 Port Performance and Freight Statistics Annual Report:

Section 2.1: Definition of Ports

Ports are commonly recognized as places where cargo is transferred between ships and trucks, trains, pipelines, storage facilities, or refineries. Ports are more difficult to define for statistical purposes when such places are close to one another or when activity related to a port blends in with surrounding neighborhoods. Many ports are located adjacent to closely related land uses (e.g., railyards and truck depots) or to other ports. Continuous waterfront may be divided into separate ports by administrative boundaries, such as the Ports of Los Angeles and Long Beach, or the series of Mississippi River terminals in Louisiana divided between the Ports of New Orleans and Baton Rouge. In contrast, the Port of New York and New Jersey and the Ports of Cincinnati and Northern Kentucky are treated as single entities, even though the former has a river and a state line dividing its facilities and the latter has terminals that stretch along 226 miles of two rivers through two states. Further, for more detailed performance assessments, the appropriate entity may be an individual terminal, not a port comprised of multiple terminals with diverse ownership, cargo, and operating methods.

The Federal government defines ports in many different ways. For example, U.S. Customs and Border Protection (CBP) defines some "ports" as a single port and others as units comprising multiple ports. The U.S. Census Bureau relies on the CBP definitions for reporting on trade. The USDOT Maritime Administration (MARAD) defines a port as "a harbor with piers or docks" in its Glossary of Shipping Terms.

The U.S. Army Corps of Engineers (USACE) identifies ports in different ways for planning and managing port and waterway improvement projects and for the collection and tabulation of waterborne commerce statistics. The USACE Waterborne Commerce Statistics Center (WCSC) aligns ports with their enacting legislation. In contrast, a USACE project area may encompass multiple ports along a shared stretch of water (like the Ports of Los Angeles and Long Beach which are both assigned to the same harbor), or multiple projects might be encompassed by a single port (as is the case with the Port of New York and New Jersey).

Ports are organized and governed in a variety of ways, with implications for port definition and data availability. Most ports are governed by port authorities or harbor districts, usually part of local government. Some governing bodies are state entities (e.g., the Maryland or Georgia Port Authorities) or interstate authorities (e.g., The Port Authority of New York and New Jersey). A port's jurisdiction typically extends over land, where it may include concession and construction approval and policy decision-making authorization, and over water, where it is primarily focused on navigation.

A port authority is a government entity that either owns or administers the land, facilities, and adjacent water body where cargo is transferred between modes. A port authority promotes overall port operating efficiency and development, maintains port facilities, and interacts with other government bodies. Additional activities include business development and infrastructure finance. While the structure, powers, and role of port authorities vary, the American Association of Port Authorities (AAPA) states that they "share the common purpose of serving the public interest of a state, region or locality." Port authorities may act as:

- Landlords, building and maintaining terminal infrastructure and providing major capital equipment, but are not engaged in operations. The Ports of Los Angeles, New York and New Jersey, and Oakland are examples of landlord ports. Ports may also offer concessions to tenants that make infrastructure improvements. For example, the Maryland Port Administration granted a 50-year concession for the Baltimore Seagirt Marine Terminal that included a commitment by the concessionaire to deepen the channel.
- <u>Operating ports</u>, directly operating some or all of the terminals in the jurisdiction. For example, the Port of Houston Authority is an operating port.
- Jurisdictional bodies, under which private terminals are responsible for providing and operating their infrastructure. For example, the Ports of Cincinnati and Northern Kentucky is a jurisdictional body.

A port may own and operate an extensive range of facilities over a large area, many of which may not be water related. Several port authorities (e.g., Port of Oakland, Massachusetts Port Authority) also operate airports. The Port Authority of New York and New Jersey operates airports, tunnels, bridges, and transit systems as well as the seaport.

Some states, such as South Carolina and Georgia, have statewide port authorities to administer some or all of the ports within their jurisdiction. These entities are typically led by boards of appointed members. They may also directly operate port facilities within the state. A state port authority may be a separate state department, or be located within that state's DOT.

Some port authority jurisdictions cross state boundaries. The Port Authority of New York and New Jersey and the Ports of Cincinnati and Northern Kentucky are examples.

Port authorities typically have jurisdiction over public terminals. Private (usually bulk) terminals are normally outside the public port authorities' jurisdiction although they are still subject to U.S. Coast Guard and Federal regulation.

U.S. Army Corps of Engineers From <u>USACE Engineering Pamphlet 1130-2-520</u>:

• Port Area:

(1) Port limits defined by legislative enactments of state, county, or city governments.
(2) The corporate limits of a municipality.

Geospatial data of defined port areas represented as polygons is available from <u>USACE</u> <u>Geospatial Platform</u>.

From USACE Master Docks:

Geospatial data for docks designated by port ID are represented as points and are available from USACE Waterborne Commerce Statistics Center Master Docks Plus.

D. Additional Notes about the Dasymetric Model

This study used a highly resolved population distribution model to quantify the population living near ports (see 2.2 Higher Resolution Population Estimates for more) to align with a larger cross-EPA effort to quantify populations living near transportation infrastructure. **Table A-3** shows the comparison of between how the near port populations by port geometry and buffer distances differed between these two population models. Note, the population totals for the EPA Port Geometries listed below differ from the totals included and discussed in the body of this report due to using a pre-processed raw data file to accurately compare equal area and dasymetric estimates.

Table A-3. Comparison of Equal Area and Dasymetric Population Distribution Totals

Near-port population estimates using equal area approach versus dasymetric model approach

	Buffer size					
	0-100m	0-200m	0-500m	0-1000m	0-5000m	
ACE (n=123)						
Dasymetric model estimate	24,473	123,354	1,134,075	4,676,199	31,058,906	
Equal area estimate	84,631	279,276	1,407,661	4,840,956	30,988,627	
Difference ^a	60,158	155,922	273,586	164,757	-70,279	
% difference	245.8%	126.4%	24.1%	3.5%	-0.2%	
NEI (n=404) ^b						
Dasymetric model estimate	481,571	697,418	1,531,146	3,299,055	22,748,983	
Equal area estimate	601,780	818,132	1,590,573	3,268,649	22,600,496	
Difference ^a	120,209	120,714	59,427	-30,406	-148,487	
% difference	25.0%	17.3%	3.9%	-0.9%	-0.7%	

^a Negative difference and percent difference values indicate that the population estimates were lower using the equal area method than they were using the dasymetric method.

^b The near-port population estimates using NEI port geometries included in this table do not align with the near-port population estimates from the primary analysis (see Table 3). This inconsistency is because equal area estimates were only available for an earlier version of NEI port geometries that represented more than the 123 major CONUS ports that were included in this study. The comparison of these equal area and dasymetric population model approach estimates still illustrate the potential differences in results that could be expected between the two proximity analysis methodologies.

We found that near-port population estimates derived using an equal area approach tended to overestimate the population living in very close proximity (0-100m, 0-200m, and 0-500m) as compared to the dasymetric population model approach. This finding implies that there are uninhabitable areas in very close proximity to ports that are captured by the high-resolution dasymetric population model. The dasymetric near-port populations living in proximity to the ACE port geometries were more disparate from the equal area approach estimates than those in proximity to the NEI port geometries. This finding may be illustrative of the differences in the two port geometries' land versus waterfront coverage. The overestimation using the equal area approach as compared to the dasymetric population model approach attenuated with larger buffer sizes.

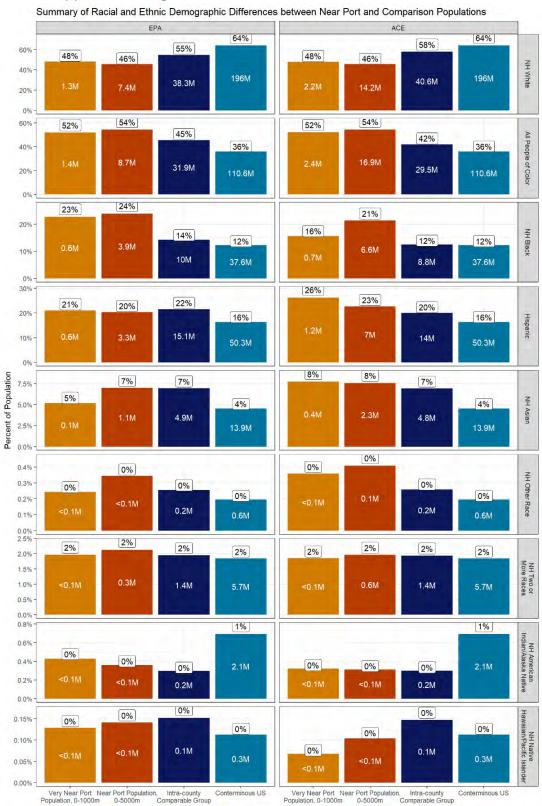
Additionally, for some Census block groups (n=46), there is a small discrepancy between the Census total population and the dasymetric modeled population (difference of less than 1). This discrepancy occurs when a pixel of the dasymetric grid excludes the population of a very small block group (e.g., a block group that is 10 meters wide). In these cases, a portion of the population of the geographically small block group is reallocated to a neighboring block group. This reapportionment accounts for the reallocation of approximately 1,000 people in the entire Conterminous United States. (<0.001% of the population modeled).

E. Data Processing

EPA's Office of Transportation and Air Quality (OTAQ) reviewed published NEI Shapefiles and Master Docks Plus coordinates, selected a subset of ports, and provided port shapefiles to ORD. ORD used ArcGIS Pro to create geodesic buffers at 100m, 200m, 500m, 1000m, and 5000m around each port geometry. The Analytical Tools Interface for Landscape Assessments (ATtILA) ESRI ArcGIS toolbox⁴⁷ was used to extract the dasymetric raster population from these buffers and assign them to the relevant overlapping Census block group. ATtILA was run a total of four times: for both the EPA and ACE port geometries, once with all ports together as a single, multi-polygon object, and once with all ports separately, categorized by their assigned name. ORD then provided the within-buffer dasymetric population estimates by block group in tabular form to OTAQ.

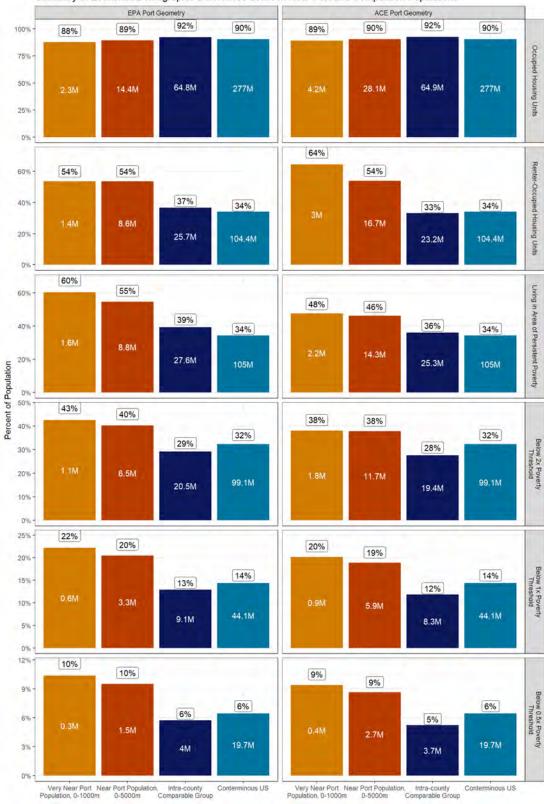
OTAQ merged the tabularized output from ORD with block group-level demographic data obtained from the U.S. Census (2010 Decennial Census and 2014-2018 American Community Survey), EnviroAtlas (2017), and tract-level data for the U.S. DOT RAISE Areas of Persistent Poverty (FY2021). Data was processed using R version 4.4.1.

⁴⁷ U.S. EPA. ATtILA Toolbox: Analytical Tools Interface for Landscape Assessments (ATtILA). Accessed July 2024: <u>ATtILA Toolbox | US EPA</u>



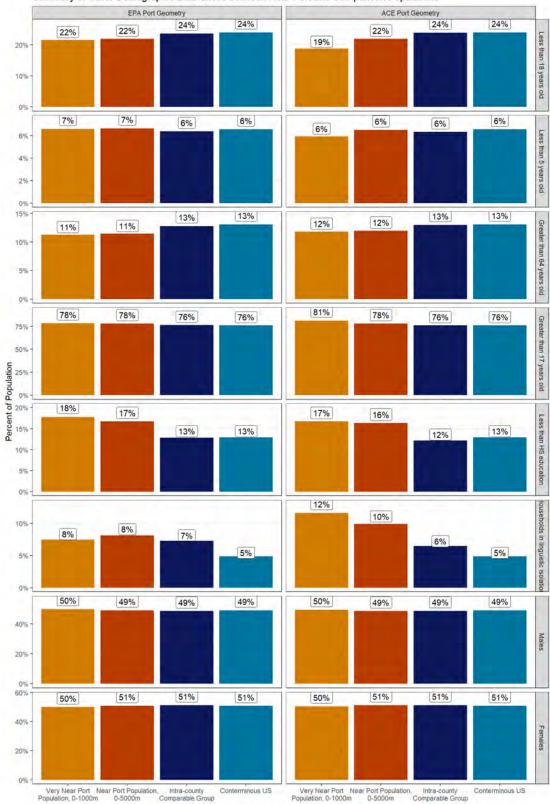
F. Supplemental Figures

Figure A-1. Summary of Racial and Ethnic Demographic Differences between Near-Port and Comparison Populations



Summary of Economic Demographic Differences between Near Port and Comparison Populations

Figure A- 2. Summary of Economic Demographic Differences between Near-Port and Comparison Populations



Summary of Other Demographic Differences between Near Port and Comparison Populations

Figure A- 3. Summary of Other Demographic Differences between Near-Port and Comparison Populations

G. Alternative Comparison Groups Considered

Neighboring Block Groups

The 'Neighboring Block Groups' border near-port block groups (i.e., those that intersect the 0-5000m buffer (Figure A-1). This comparison group was created by EPA ORD at OTAQ's request as a first attempt to create a smaller and more regionally representative comparison group than the entire Conterminous United States. This population is assumed to not be adversely affected by port operations' mobile source emissions.

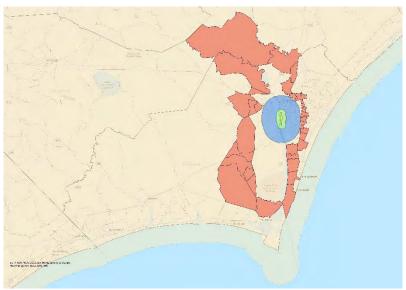


Figure A- 4. Rendering of Neighboring Block Groups, shown in red, around the Port of Wilmington, NC (using the EPA port polygon).

The benefits of the Neighboring Block Groups comparison group are that it is hyper-localized and may offer more insight into regional demographic dynamics than a nationwide comparison. Additionally, this method utilizes entire block group populations as it is a 'contiguity-based neighbor' classification. By doing so, it avoids further sub-setting block group populations and applying any assumption about population demographic distributions within these neighboring block groups. Furthermore, we can easily compare the demographics between the near-port and comparison groups, because the Neighboring Block Groups do not have any overlap with the near-port populations.

Upon generating these comparison groups, it became clear that there were significant challenges associated with them. First, the method used to create the Neighboring Block Groups is complex and computationally intensive.⁴⁸ Additionally, block groups are not uniformly sized or shaped, and the decision to rely on a contiguity-based neighbor classification may have made it seem like there was an epidemiologic-based rationale for such a close neighbor, while the exact distance from a port at which a population is no longer burdened is still under consideration. Because of these complexities, the

⁴⁸ Finding the shared boundary of polygons can be addressed using the <u>Polygon Neighbors analysis tools</u> in ArcGIS Pro; other methods are available through other geospatial analytical tools, such as R's <u>spdep</u> package.

Neighboring Block Groups were only created for the EPA port polygon dataset, after which it was determined that the Intra-County Comparison Group would be faster and simpler to create, while offering similar benefits as the Neighboring Block Groups.

Rural-Urban Continuum Codes

We considered using the U.S. Department of Agriculture's Economic Research Service countybinning Rural-Urban Continuum Codes⁴⁹ (RUCC) to compare populations around ports with populations in different landscapes. However, port buffers often span multiple RUCC codes; additionally, there were insufficient populations near rural ports in comparison to urban and small city near-port areas. Because the RUCC divisions did not produce robust sub-national groupings, we decided to not use them in this analysis.

Balance of State Population

The balance of a state's near-port population was also deemed to be an unsuitable comparison group because port districts often cross state lines. Regional categorization of ports by East Coast, West Coast, Gulf Coast, Inland, and Great Lakes was also considered, but we determined this option to be inappropriate because of how ports can fall into more than one category (e.g., Florida ports, river ports branching to/from Great Lakes).

H. Authors and Acknowledgements

This report is the result of a cross agency team including: Chad Bailey, Deirdre Clarke, Sarah Froman, Sarah Harrison, Marion Hoyer, Ali Kamal, and Grace Kuiper from EPA's Office of Transportation and Air Quality; Jeremy Baynes, Annie Neale, and Jeremy Schroeder from EPA's Office of Research and Development; and Laurina Bird, Stepp Mayes, and Asa Watten from the Oak Ridge Institute for Science and Education (ORISE) Research Participation Program hosted by U.S. EPA.

The authors thank Margaret Zawacki for her review of an early draft of this document, and peer reviewers Michael Aldridge, Elizabeth Chan, and Harold Rickenbacker. The authors also want to thank Eloise Anagnost of OTAQ for her assistance in optimizing the layout and formatting of the report.

⁴⁹ United States Department of Agriculture. Rural-Urban Continuum Codes. Accessed July 2024 <u>Rural-Urban</u> <u>Continuum Codes</u>