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A regional approach to militarized riskscapes: An environmental justice analysis of military proximity and air pollution in United States Environmental Protection Agency's regions

Daniel Shtob^{1,2} [] Camila Alvarez³ | Nicholas Theis⁴

¹Brooklyn College, Sociology and Urban Sustainability, Brooklyn, New York, USA

²Earth and Environmental Sciences, CUNY The Graduate Center, New York, New York, USA

³Sociology, University of California Merced, Merced, California, USA

⁴Sociology, University of Oregon, Eugene, Oregon, USA

Correspondence

Daniel Shtob, Earth and Environmental Sciences, CUNY The Graduate Center, 365 5th Avenue, New York, NY 10016-4309, USA. Email: daniel.shtob@brooklyn.cuny.edu

Abstract

Recent advances in sociological appreciation of risk have culminated in the concept of riskscapes, which describe how the social, political, biophysical, and technological drivers of risk are embedded within different spaces in ways that can reinforce systemic inequities. The U.S. military has long been recognized as an important structural and institutional contributor to environmental problems and therefore potentially riskscapes. However, the regional environmental injustice consequences of military presence have received little attention. To address this need, here we construct a regionalized military riskscapes modeling strategy that focuses on understanding environmental riskscapes across regional contexts. Using multilevel models with random intercepts, our exploratory analysis reveals differences in racial and ethnic environmental health exposure associated with proximity to military facilities across the 10 administrative regions used by the United States Environmental Protection Agency. Furthermore, we find that the relative contributions to local air pollution profiles arising from military and non-military sources likely differ by region, as do consequent environmental justice concerns. For example, in the Midwest, Central Mountain, and West/Southwest regions neighborhoods with more Latinx residents experience intensified air pollution inequalities associated with proximity to military installations. Neighborhoods with more

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Black residents in the Midwest reported greater environmental health risk from air toxics associated with nearby military facilities. These results underscore the usefulness of viewing the environmental consequences of domestic military facilities and their activities as regionally specific and spatially contingent. We further suggest that scholars studying environmental inequalities relating to military and other sources of pollution should consider how regional processes contextualize the existence and persistence of environmental injustice.

KEYWORDS

conflict, environmental sociology, peace, race and ethnicity, sociology of war

1 | INTRODUCTION

Owing in part to popular and scholarly recognition of the environmental consequences of militarism and military action, over the past few decades environmental sociologists and scholars in related disciplines have sought to better understand the relationships between military action, environmental harm, and environmental injustice (e.g., Alvarez et al., 2022; Babcock, 2007; Bonds, 2016; Dillon, 2015; Downey, 2015; Frey, 2013; Hamilton, 2016; Hooks & Smith, 2004, 2005; Jorgenson, Clark, and Kentor, 2010; Smith et al., 2013). These efforts have included case studies and theoretical development of military-environment relationships (Hooks & Smith, 2004, 2005), analysis of the release of hazardous pollutants in the air, on land, and into water sources by military agencies (Bonds, 2016; Downey, 2015; Frey, 2013), and the environmental justice consequences of military action and activities in the United States and abroad (Alvarez et al., 2022; Jorgenson, Clark, and Kentor, 2010).

One recent development is risk-transfer militarism, which observes that as technology advances and certain elements of military action occur remotely, some hazards associated with warfare increasingly manifest away from combatants at the front lines and nearer to civilian and other populations at great distance from battlefields (Alvarez et al., 2021; Smith et al., 2013). A corollary of this development is greater interest in whether and how proximity to military bases in the United States implicates differential exposure to environmental harm—including air pollution—for military personnel and their families who live on or near bases, as well as nearby civilian populations (Alvarez et al., 2021, 2022).

Concurrently, our understanding of environmental risk has been advanced by the development of regional riskscape theory and related frameworks (Müller-Mahn et al., 2018; Davies et al., 2020; see also Morello-Frosch, Pastor, and Sadd, 2001; Morello-Frosch et al., 2002). These posit that environmental and other risks are not regionally homogenous but vary by place because of a complex of spatially contingent socio-environmental factors (Abel & White, 2015; Davies et al., 2020; Liévanos, 2020; Müller-Mahn et al., 2018). Regional riskscapes encourage us to think beyond one-size-fits-all understandings of environmental harm and justice, instead downscaling the ways that we think about global, continental, or national risks (Beck, 1992, 1996) to understand more locally relevant differences. Notwithstanding the rapid development of these literatures, however, to date the application of regional riskscapes to military contexts has been understudied and demands additional review (Davies et al., 2020). In short, accumulating evidence and examples of the spatially contingent nature of environmental experiences suggests the need for a more regionally sensitive approach to the study of structural and institutional producers of environmental harm, including militaries.

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In this exploratory effort, we seek to address this need by merging literature on the environmental justice consequences of military proximity in the United States with regional riskscapes. Our primary aim is to analyze whether regionalized military riskscapes exist across the domestic landscape, with a particular interest in illuminating their patterns and contours. We use multi-level models with random intercepts to explore whether relationships between proximity to military facilities and exposure to carcinogenic air toxins on the census tract level (Alvarez et al., 2022) are homogenous or heterogenous across the United States Environmental Protection Agency's (EPA) 10 administrative regions. In each region, we explore the associations among the proximity of military facilities, the intensity of use of those facilities, and the presence of carcinogenic air toxins (whether they were released by military or non-military sources). In addition to further developing the literature on military presence, proximity, and exposure to air toxics, our goals include supporting fine-grained regional analysis of how miliary-related environmental injustice comes to pass, understanding how these processes and relationships differ across regions, assessing where cases of injustice may result from military or non-military sources, and providing guidance for how to reduce environmental harm and injustice for military personnel, their families, and civilian community members who live, work, or serve on or near military facilities.

While we find additional support for the existence of environmental injustice in exposure to air pollution based on proximity to domestic military facilities, we also find strong regional variation in the existence and magnitude of differential rates of exposure among racial and ethnic groups. Our results also suggest that in discrete regions, observed differences in exposure within these groups may be the product of different pollution profiles from military and non-military emissions sources. These findings illustrate the utility of adapting the emergent study of regional riskscapes to the context of military institutions and militarism, creating militarized regional riskscape models to better understand their patterns, providing caution about generalizing national studies to local contexts or local studies to national contexts, and suggesting some means of studying existing air toxic pollution profiles and disparities in different parts of the country.

2 | LITERATURE REVEW

2.1 | Environmental justice

The environmental justice movement advocates for reducing environmental health and exposure disparities along many lines of social difference, especially racial/ethnic and socioeconomic difference. The academic study of environmental justice started with distributional analyses of unequal exposure to landfills and hazardous waste facilities, with heightened exposure among communities with more Black residents and/or near schools with more Black students (Bullard, 1983; United Church of Christ, 1987). This distributional focus was largely undertaken to establish that these inequalities exist and that they are not only anecdotal but rather form a systemic patterning of how our socio-spatial world is organized. Numerous studies have subsequently analyzed environmentally harmful facilities and environmental exposures employing several quantitative techniques and modes of geographic scaling to develop finely grained and nuanced understandings of how environmental inequality forms across spatial and social contexts (e.g., Ard, 2015; Liévanos, 2015; Mohai & Saha, 2007; Morello-Frosch, Pastor, and Sadd, 2001).

Developments in theorizing environmental (in)justice center the importance of state-sanctioned violence in the formation of environmental inequalities (Pellow, 2017; Pulido, 2017). These interventions stem from a history of institutional scholarship questioning the role of the state as arbiters of justice, with explanations ranging from industry capture to organizational inertia (e.g., Faber, 2008; Harrison, 2019; Shilling et al., 2009), and employ theories of how racial formation takes place through state policies and practices (e.g., Goldberg, 2002; Omi & Winant, 1994). Kurtz (2009) illuminates how state institutions and practices shape and are shaped, including how government perpetuates racial differences and differential racial outcomes through the promotion of abstracted homogeneity (see also Goldberg, 2002) in the context of the environment. Environmental justice movements and scholarship

on race and ethnicity not only focus on distributional analyses to show disparities but also highlight the processes, procedures, and policies that inform the sociohistorical formation of racial and ethnic environmental inequalities (Pellow, 2000).

In our case, we investigate how the U.S. military, as a state institution, contributes to environmental inequality. Military presence and related activities were important foci of early environmental justice activism, as articulated by Principle 15 of the First National People of Color Environmental Leadership Summit's Principles of Environmental Justice: "Environmental Justice opposes military occupation, repression and exploitation of lands, peoples and cultures, and other life forms" (Principles of EJ, 1991). Sociological research on environmental inequality focusing on the military has been surprisingly light, with the notable exception of the treadmill of destruction (e.g., Hooks & Smith, 2004, 2005). Nevertheless, recent quantitative efforts emphasize how proximity to domestic military sites differentially impacts racial/ethnic groups in the United States in general (Alvarez et al., 2022) and those areas surrounding Las Vegas in particular (Alvarez, 2021).

2.2 | Military and the environment

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Increasingly, social scientists are paying attention to the extent of the military's impact on the natural world, and the mechanisms that foster it. While several dates for the commencement of the Anthropocene—the period of human-induced climatic and environmental change—have been proposed, one recent and prominent indicator is how nuclear bomb testing during the Cold War influenced the geological record through radioactive debris (Subramanian, 2019; see also Angus, 2017). The association between military activity and climate change does not end with the influence on the geological record, however, as studies have displayed relationships between capital-intensiveness of national military operations and emissions, their ecological footprints, and their energy use (e.g., Clark et al., 2010; Jorgenson, Clark, and Kentor, 2010). Indeed, through its worldwide operations the U.S. military alone emits more carbon dioxide than several industrialized nations (Crawford, 2019). In short, military activity contributes to the Anthropocene in general and climate change in particular, a force that perpetuates and propagates global environmental problems.

Military influences on the environment are not only global but also local, and do not end with these observed greenhouse gas effects. For example, while nuclear bomb testing significantly altered the geological record and brought on a new epoch, these effects are not evenly distributed across space. Specifically, the U.S. military's testing was disproportionately conducted in the American Southwest near domestic Native American reservations and Bikini Atoll in the Marshall Islands with disregard for Native and Bikinian ways of life, livelihood, self-determination, environmental quality, and sense of place in the process (Guyer, 2001; Kuletz, 1998). Moreover, practices such as dumping of chemical weaponry in the Pacific (Mitchell, 2020), the use of Agent Orange in Vietnam, Laos, and Cambodia (Frey, 2013; Mitchell, 2020), and open pit burning of trash in Iraq and Afghanistan (Bonds, 2016) are only a few of the many ways in which the American military has contributed to environmental problems abroad.

While the environmental harms of American military activity may be felt most harshly and abrasively abroad, recent work in other academic domains demonstrates that practices designed to expand the American "sphere of influence" may be coming home (Go, 2020). The dramatic and intensive nature of warfare is commensurate with its impacts to environmental health, and subsequently, human health. However, subtler forms of risk and pollution spatially distant from test sites and battlefields nevertheless are important to understanding the full extent of military pollution (Alvarez et al., 2021, 2022). From increased unexploded ordnances on Native lands (Hooks & Smith, 2004) to increased air toxics exposure for communities with more Latinx and Black residents near domestic military sites (Alvarez et al., 2022) and polluting surface and ground water via firefighting foam (US GAO, 2018), some means in which domestic military activity contributes to the deterioration of environmental health have been documented. The dramatic nature of warfare, therefore, should not occlude analysis of the destructiveness of war preparation (Downey, 2015), which may take place in the everyday practices of domestic military sites with health consequences

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for military personnel, their families, and civilians who live or work on or near these sites. While prior studies consider environmental risk from domestic military facilities on national scale (Alvarez et al., 2022), here we assess regional variations in relationships between proximity to facilities, neighborhood composition, and air toxics cancer risk.

2.3 | Regional riskscapes

Notwithstanding the existence of many case studies and a few national studies assessing environmental harm and injustice associated with nearby military facilities and activities in the United States, the regional patterning of these outcomes has received comparatively little attention. Recently developed insights into regional riskscapes (Davies et al., 2020; Müller-Mahn et al., 2018) provide an opportunity to explore this patterning. The term "riskscape" has long been used in the social sciences to denote heterogenous risk profiles across ecological and social landscapes, including in analyses linking race and other demographic factors to differential exposures to air toxics and subsequent health effects (Morello-Frosch et al., 2002; Morello-Frosch, Pastor, and Sadd, 2001).

These early efforts focused on the socioeconomic and institutional drivers of toxic emissions and associated environmental health inequality in order to move past analysis of individual sites and develop a composite appreciation for the political economy and complexity of differential exposure. Employing advances in spatial and quantitative methodologies, for example, they analyzed both the sources of exposure and how they affected communities in different regions of Southern California based on those areas' racial composition (Morello-Frosch et al., 2002; Morello-Frosch, Pastor, and Sadd, 2001). As useful as these efforts were to synthesize a number of factors that contribute to environmental injustice through differential health risks and outcomes, they typically used the term "riskscape" without developing a meaningful theoretical sense of what riskscapes are, how they form, and what specific factors contribute to their existence.

Recent scholarship has sought to address this need by bringing together environmental justice literature in sociology and related fields such as geography at the intersection of "risk, space, and practice" by "locating perils...within a spatial framework" and "providing orientation in potentially perilous terrain" (Müller-Mahn et al., 2018, pp. 197–198). Produced at the crossroads of "social dynamics and material processes," these accounts emphasize the contributions of governments and other institutions to inequality and environmental vulnerability, as well as an appreciation of landscapes of risk and uncertainty arising from warfare (Davies et al., 2020; Müller-Mahn et al., 2018). They serve to link variations in community practice and subjectivities with materiality, temporality, power relations, and ideology, with the effect of pushing back on the assumption that the globalization of risk (cf. Beck, 1992, 1996) renders its spatial elements irrelevant (Müller-Mahn et al., 2018).

While environmental riskscapes have, for example, been studied in institutional contexts like the catastrophe (re)insurance market (Taylor & Wienkle, 2020), in specific cities (Abel & White, 2015; Liévanos, 2020), and across countries (Müller-Mahn et al., 2018), each approach shares an emphasis on the embedded and interlocking material, ecological, and social elements that drive and mediate the patterning of risk across landscapes. Notwithstanding an expressed need, as Davies et al. (2020) observe, to date environmental riskscapes have been unfortunately understudied in the context of warfare and militarism. Here, we address this need by further developing the early United States regional or subregional riskscape focus (Morello-Frosch et al., 2001), examining the divergent environmental justice implications of domestic military proximity (Alvarez et al., 2022) across the EPA's 10 administrative regions (see Figure 1).

Environmental sociologists and others in related fields have engaged in this type of regional comparative analysis using the EPA's demarcations (Ard, 2015; Liévanos, 2019; Zwickl et al., 2014). These regions differentiate the agency's geographically heterogenous bureaucratic offices that depend on sometimes variant interpretations of law in different regional federal appellate courts (to which they have been traditionally tied), as well as different cultures and philosophies related to enforcement, coordination, and delegated policy-making power. This is based in part on their territorially-bound regional purview, which requires greater interaction with different sets of state and local officials, as well as absorption of local socio-ecological conditions and public desires.



FIGURE 1 EPA regions. The Environmental Protection Agency's (EPA) has 10 regional offices that reflect geographical boundaries. EPA regions do not subdivide states: each region aggregates multiple states and (in some cases) territories.

In short, different regional offices feature distinctive capacities and foci. They therefore provide a useful tether for development of regional riskscapes because they operate within slightly variant legal regimes but also reflect the differences among the states and localities they serve in culture, politics, environmental views, and views about the appropriate role and limits of government (Hunter & Waterman, 1992; Liévanos, 2019). For example, in addition to hosting regionally specific program offices like those operating near and specific to the Great Lakes or Chesapeake Bay, as of 2018 only two had a land division and only four an office of environmental justice or similar offices (Blank & Rosen-Zvi, 2018). While they operate under the same authorizing statutes as the agency generally and are subject to many of the same laws and requirements, these EPA offices and their projects are therefore best understood as regionally administratively and culturally differentiable and contingent.

Additionally, these regions reflect commonly recognized socio-environmental portions of the country (Zwickl et al., 2014). For example, ecologically, culturally, and in terms of political economy distinctions are easily drawn between the southwest and northeast portions of the United States, and each is distinctive from the southeast and Rocky Mountain states. Much in the same way that differences in landscape and demographics between neighborhoods in a city, or parallel differences among countries that share a continent have allowed researchers to develop differential environmental riskscapes in those contexts (Liévanos, 2020; Müller-Mahn et al., 2018), the EPA's regions provide an opportunity to develop riskscapes domestically across the breadth of the United States. In fact, employing pollution exposure microdata in U.S. cities, Zwickl et al. (2014) found variation in exposure by income when comparing racial and ethnic groups across regions.

West/Southwest 80 Northeast Southeast South Central Pacific Northwest Mid-Atlantic Cancer Risk from Air Toxics Central Central Plains Mountains Midwest New 40 England 20 Est. 0 7 1 2 3 4 5 6 8 9 10 excludes outside values



For these reasons, while we certainly accept that there are other justifiable ways to regionally subdivide the United States for the purpose of environmental justice analysis, we view the EPA's 10 regions (which are coterminous with state boundaries and therefore census tracts) as useful and salient means of determining regionality. To these ends, Figure 2 shows the overall variation in average carcinogenic air toxic exposure for each of the 10 regions, with each box showing the middle 50th percentile of exposure results surrounding the mean and the whiskers extending up and down the upper and lower 25th percentile ranges, respectively. This suggests that these concerns may not be homogenous across these regions. Based on these factors—in combination with regional riskscapes—we suspect that environmental (in)justice concerns associated with the military proximity will be regionally heterogenous. Accordingly, we have developed the following two hypotheses.

3 | HYPOTHESES

3.1 | Null hypothesis

H0. There will be no regional variation in environmental inequalities from military installations.

3.2 | The regional militarized riskscapes hypothesis

H1. There will be significant regional variation in racial and ethnic environmental inequality based on the relative proximity between census tracts and the nearest military installations.

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4 | METHODS AND RESULTS

4.1 | Dependent variable: Estimated cancer risk from air toxics

The outcome of interest is the estimated cancer risk from air toxics per million persons, which is derived from the Environmental Protection Agency (EPA) National Air Toxics Assessments (NATA) (Office of Air Quality Planning and Standards, 2018). We use the latest version of NATA, which was based on 2014 data and published in 2018. The EPA estimates human health risk from air pollution by compiling data on hazardous facilities, meteorological and atmospheric modeling, travel diaries, and population estimates. NATA is preferable to measures of raw toxicity for the purpose of assessing threats to human health because it derives from "a rigorous multi-stage process beginning with (the EPA) compiling the National Emissions Inventory, which is then used to estimate ambient concentrations of air toxics through computer modeling of meteorological and photochemical processes. Environmental health risk is estimated by combining air toxics emissions concentrations with models of daily human outdoor activity" (Alvarez et al., 2022, p. 7). Moreover, the estimated cancer risk variable is a standardized measure (i.e. "per million persons") of human health risk as compared to toxicity concentrations and has been used in previous environmental justice research (Liévanos, 2015). An additional benefit of using a standardized measure as compared to raw toxicity is the ability to compare across different geographic areas or population sizes.

4.2 | Independent variables: Military installation proximity and military intensity

We developed our primary independent variable of interest—the proximity of each census tract to the nearest military installation—from The Defense Installations Spatial Data Infrastructure Program, which publishes a GIS shapefile of most military installations (some are excluded for national security reasons) (Department of Defense, 2019). We transposed the military installation and census tract shapefiles, and then created centroids for each census tract. Using ArcGIS, we calculated the proximity of the nearest military installation border to each census tract centroid. The military installation proximity variable measures distance from the nearest military facility in kilometers.

Recognizing that military facilities may differ in their intensity of use, we then constructed a measure to account and control for these differences. We did this by merging the previously described spatial dataset with The Base Structure Report published by the Department of Defense (DoD), which reports the plant replacement value (PRV) for each military facility (Department of Defense, 2015). The PRV is the replacement cost of the facilities and supporting infrastructure. To capture the financial intensity of each military installation, we calculate the "military intensity" by dividing the PRV by the area of the installation. The military intensity variable shows lower values for military sites with lower financial value per acre and higher values for military sites with greater financial value per acre. In effect, this allows for the development of a measure that reflects the fact that not all military facilities are of the same type, the same use, or the same intensity of use.¹ We constructed these measures instead of other methods of meaningfully capturing the spatial extent of military facilities (e.g., areal percentage of tracts occupied by military bases; military facility kernel density) to (1) avoid a significant number of zero values and (2) maintain an easily-intelligible variable while effectively gauging proximity to nearby military sites and the relative intensity of those sites.

4.3 | Independent variables: Tract-level demographics and county-level indicators

To assess regional environmental inequality, we evaluate several independent variables at the tract and county level. First, we use demographic data from the American Community Survey (ACS), specifically the five-wave 2010–2014 dataset. This dataset came from the National Historical Geographical Information System (Manson et al., 2018) and includes data about race/ethnicity composition. From this, we use percent Black residents, percent Latinx residents,

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percent Native residents, and percent Asian-Pacific Islander (API) residents. Additionally, we use a pair of ACS socio-economic indicators: median household income and the Gini income inequality index. Second, we include data on the urbanicity of census tracts from U.S. Economic Research Services Rural-Urban Continuum Codes (RUCC). Specifically, we recode the RUCC 1–3 as "metro" and 4–7 as "non-metro." Third, county-level gross domestic product per capita (GDP) data comes from the Bureau of Economic Analysis (2018).

4.4 | Methods

Multilevel models are a sophisticated and rigorous statistical approach that accounts for group-clustering of multiple observations (Alvarez et al., 2022; Evans et al., 2018). We use multilevel modeling to account for administrative homogeneity, meaning that census tracts in the same county are more likely to be similar than those in a different local administrative system and/or at greater distance. We conducted a multi-level model analysis for each EPA region. Our multi-level structure is a two-level model with census tracts (level 1) nested within counties (level 2):

$$egin{aligned} & \mathbf{y}_{ij} = eta \delta + \mu_{0j} + e_{0ij} \ & \mu_{0j} \sim N\left(0, \sigma_{\mu}^2
ight) \ & e_{0ij} \sim N\left(0, \sigma_{e}^2
ight) \end{aligned}$$

Here, y_{ij} is estimated cancer risk for tract *i* within county *j*. The vector of coefficients including the intercept and fixed effects is δ and the row vector of corresponding variable values is β . The random effect for the county level is μ_{0j} and is assumed to be normally distributed with a variance of σ_{μ}^2 . The random effect for the tract-level is e_{0ij} for the tract-level with a normal distribution with a variance of σ_e^2 . We estimated two series of models: (1) models without interactions; and (2) models with interactions. Within each series 11 models are estimated, with one national model and one for each of the 10 EPA regions. Note that the national model includes a three level nesting structure (tracts in counties in states) while the regional models include a two level nesting structure (tracts in counties) because of the small number of states in each EPA region.

5 | RESULTS

As indicated in Table 1, the national average of estimated cancer risk from air toxics is about 32 additional cases of cancer as a consequence of air toxics per million persons with a wide range of variation among tracts (ranging from 6 to 1505 additional cases of cancer per million persons). Figure 2 shows this regional variation, with the highest regional average of estimated cancer risk from air toxics in the South Central, Southeast, and West/Southwest regions. On the other hand, the Central Mountains, New England, and Midwest have the lowest estimated cancer risk from air toxics, showing regional variation in environmental health risk. The nationwide average for the nearest military installation to each census tract was 41 km with the closest at 0 km to farthest at 1337 km. The regions with the lowest average distance to the nearest military installation are the Mid-Atlantic, the West/Southwest, and New England. Regions with the highest average distance are the Central Mountains, South Central, and the Central Plains. To statistically assess regional differences, we conducted a series of multilevel models predicting air toxics cancer risk by racial/ethnic neighborhood composition, proximity to closest military installation, and other community demographic information.

To start at a baseline, we will first review the series of models without interactions shown in Table 2 and Figure 3. This revealed a nationwide patterning of significantly unequal estimated cancer risk from air toxics for census

	Mean	SD	Min	Median	Max
Est. cancer risk from air toxics per million persons	31.65	12.92	6.17	31.00	1505.12
Black (%)	13.71	22.09	0.00	4.04	100.00
Latinx (%)	16.22	22.38	0.00	6.53	100.00
Native (%)	1.18	4.72	0.00	0.25	100.00
Asian/Pacific Islander (%)	4.70	8.97	0.00	1.44	92.07
Median household income (in \$10,000)	5.73	2.85	0.25	5.10	25.00
Metro (binary)	0.83	0.37	0.00	1.00	1.00
GDP per capita (in \$1000)	54.94	34.61	4.90	49.38	715.81
Gini index	0.46	0.04	0.33	0.46	0.65
Closest military installation (km)	41.02	43.75	0.00	27.55	1337.41
PRV density (In)	4.78	1.98	-4.61	4.98	11.06

TABLE 1 Descriptive statistics of dependent and independent variables.

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tracts with greater percentages of Black and Latinx residents, supporting the results of earlier nationwide analyses of air toxics and environmental inequality (e.g., Downey, 1998; Ard, 2015; Liévanos, 2015, 2019; see also Alvarez et al., 2022). Similarly reflective of existing research (e.g., Grineski et al., 2017, 2019; Liévanos, 2015, 2019), we also found significantly greater estimated cancer risk from air toxics for tracts with greater percentages of Asian and Pacific Islander residents. The variance partition coefficient (VPC) reports the amount of variation explained by the higher levels (such as state and county levels). The VPC for all regions is 66.45% (i.e., the amount of variation that is explained by the state and county levels). The EPA regions' VPC ranges from 7.42% to 77.20%, in each this is the percentage of variation explained by the county level in each region. The range in VPC demonstrates that county-level variation is stronger in certain EPA regions like Northeast, Southeast, and Pacific Northwest, as compared to regions Mid-Altantic and Central Plains.

Now, we will explain the series of models with interactions, shown in Table 3. Each interaction coefficient represents how the effect of racial/ethnic neighborhood composition on air toxics cancer risk is moderated by military facility proximity, and vice versa. A negative and significant coefficient indicates that, as military facility proximity increases (a tract is further away from the nearest military site), the magnitude of the effect of racial/ethnic neighborhood composition decreases. And, vice versa, that as racial/ethnic neighborhood composition increases, the effect of greater distance from the nearest military site decreases. In plain language, a negative and significant coefficient indicates that tracts closer to military facilities experience greater air toxics cancer risk when racial/ethnic composition increases relative to tracts further from military facilities. And, that tracts with more residents of the specified racial/ethnic groups experience more air toxics cancer risk when distance from the nearest site decreases relative to tracts with fewer residents of the specified racial/ethnic group.

The nationwide model found estimated cancer risk from air toxics worsens as the percentage of Latinx residents increases *and* with closer military installations. We find similar results for percentage of Black residents. On the other hand, we find estimated cancer risk from air toxics worsens for neighborhoods with greater Native populations and further distance from the nearest military installation. We find similar results for tracts with a higher percentage of API residents. The findings for the interaction between percent Black and Latinx residents and military facility proximity support prior work (Alvarez et al., 2022) while results for percent Native and API residents augment our understanding of relationships of racial/ethnic neighborhood composition, military proximity, and air toxics cancer risk. The VPC for the interaction models are similar to the non-interaction models.

To evaluate H0 and H1, we compare the coefficient values of the interaction terms in Table 3 (see also Figure 4). For Latinx neighborhoods, we find significant regional differences across the models. We find that Latinx environmental inequality *associated with military installations* is significantly worse in the Midwest, Central Mountains, and West/Southwest regions. Results show greater *overall* environmental health risk as percent of Latinx residents

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		SE	0.003	0.004	0.023	0.010	0.026	0.335	0.011	4 3.215E-(6.357	0.003	0.051	2.645									(Cor
EPA 5	Midwest	Est.	0.010	0.043	-0.025	0.037	-0.234	1.787	0.044	7.527E-0	26.393	-0.049	0.019	12.407	13,005	524			24.967	9.534		27.63%	
		d	* *	* * *		* *	* * *	* *		4	* *	* *		* *									
	st	SE	0.002	0.003	0.015	0.010	0.018	0.444	0.013	4 2.725E-	6.575	0.003	0.025	3.066									
EPA 4	Southeas	Est.	0.032	0.048	0.018	0.097	-0.060	1.536	0.008	7.108E-0	25.869	-0.044	0.010	23.092	13,760	736			28.212	10.788		27.66%	
		d		* * *			*	* *	* *	4				*									
	tic	SE	0.009	0.019	0.146	0.035	0.072	1.064	0.025	14 2.802E-0	15.592	0.014	0.154	6.639									
EPA 3	Mid-Altan	Est.	0.017	0.089	0.218	0.025	-0.247	4.454	0.087	-2.811E-0	16.102	-0.005	-0.082	15.637	6564	232			134.442	33.079		19.75%	
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	t	SE	0.002	0.003	0.011	0.004	0.015	1.096	0.017	5 3.090E-0	14.392	0.002	0.046	5.961									
EPA 2	Northeas	Est.	0.002	0.039	-0.031	0.037	-0.069	7.094	-0.003	1.490E-0	94.476	-0.007	0.917	-27.661	6953	111			8.080	21.506		72.69%	
		d	* *	* * *		* *		* *		8		* *		*									
	gland	SE	0.004	0.003	0.019	0.007	0.015	0.562	0.017	и 2.089Е-(13.118	0.003	0.027	5.411									
EPA 1	New Eng	Est.	0.035	0:030	-0.017	0.116	- 0.002	. 3.178	0.024	2.840E-C	5.171	-0.016	-0.044	16.226	3346	68			3.594	3.974		52.51%	
		d	* *	* *		* *	* *	* *	* *	05 *		* *	*	*									
	de	SE	0.002	0.003	0.009	0.005	0.016	0.402	0.009	05 2.530E-	6.031	0.002	0.031	2.846									
	Nationwid	Est.	0.010	0.044	-0.004	0.037	-0.162	2.291	0.043	-5.840E-(1.533	-0.041	0.248	24.286	71,317	3087	51		65.680	84.680	51.67754	67.49%	
			Black (%)	Latinx, not black (%)	Native (%)	API (%)	Med. household inc	Metro	GDP per capita	(GDP per capita)-squ	Gini index	Milit prox (km)	PRV density (In)	Constant	# Of tracts	# Of counties	# Of states	Random effects	Tract-level	County-level	State-level	VPC	

TABLE 2 Random-intercept multilevel model without interactions.

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South central south centralCentral painsCentral pains		EPA 6			EPA 7			EPA 8			EPA 9			EPA 10			-W
Et         E         F         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E         E		South central			Central plai	ns		Central moun	tains		West/South	ıwest		Pacific North	west		IL/
def(s)         0015         014         0007         0005         014         0005         014         0005         014         0015         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014         014 </th <th></th> <th>Est.</th> <th>SE</th> <th>d</th> <th>Est.</th> <th>SE</th> <th>a</th> <th>Est.</th> <th>SE</th> <th>d</th> <th>Est.</th> <th>SE</th> <th>a</th> <th>Est.</th> <th>SE</th> <th>d</th> <th>LE</th>		Est.	SE	d	Est.	SE	a	Est.	SE	d	Est.	SE	a	Est.	SE	d	LE
invariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariateinvariate	ack (%)	-0.015	0.014		0.007	0.005		-0.061	0.059		0.023	0.005	* *	0.042	0.018	*	Y-
tive (%)         -0053         0046         -0043         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046         0046     <	cinx, not black (%)	0.001	0.015		0.017	0.008	*	0.101	0.020	* *	0.046	0.002	* *	0.023	0.008	*	
(%)         -0055         0042         0047         0027         0         0077         0087         0087         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0         0 <td>tive (%)</td> <td>-0.053</td> <td>0.046</td> <td></td> <td>-0.043</td> <td>0.046</td> <td></td> <td>0.010</td> <td>0.026</td> <td></td> <td>0.002</td> <td>0.008</td> <td></td> <td>-0.020</td> <td>0.014</td> <td></td> <td></td>	tive (%)	-0.053	0.046		-0.043	0.046		0.010	0.026		0.002	0.008		-0.020	0.014		
click         0.036         0.108         0.031         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037         0.037 <th< td=""><td>1 (%)</td><td>-0.055</td><td>0.042</td><td></td><td>0.047</td><td>0.022</td><td>*</td><td>0.077</td><td>0.087</td><td></td><td>0.028</td><td>0.004</td><td>* *</td><td>0.106</td><td>0.012</td><td>* *</td><td></td></th<>	1 (%)	-0.055	0.042		0.047	0.022	*	0.077	0.087		0.028	0.004	* *	0.106	0.012	* *	
tro5.3702.322t2.9096.51u6.8820.984u4.6771.752u3.2500.934uP per capita)0.1270.045v-0.0750.012v0.0530.013v0.027v0.0270.027P per capita)-squ5.901E-043.215E-043.205E-058.505E-058.505E-051.571E-045.0370.0271.411E-04P per capita)-squ5.901E-043.25282.83347.504v9.727E-045.956E-051.411E-041.111E-04P per capita)-squ0.014vv0.0230.024vv9.205E-051.92700.2271.411E-04P per capita)-squ0.0140.014vv0.0230.024vv0.0250.0240.0240.024V density(n)0.0160.2790.014v0.0250.0341.92000.0340.0250.0340.035V density(n)0.0160.2790.013v0.025v0.0250.025v0.0250.0340.025V density(n)0.0160.2790.0230.0230.023v0.025v0.025v0.025v0.025V density(n)0.0160.229v1.82000.025v1.9200v0.025v0.025vvvV density(n)0.016v1.02010.025v1.0202v1.0420 <t< td=""><td>ed. household inc</td><td>-0.036</td><td>0.108</td><td></td><td>-0.310</td><td>0.037</td><td>* *</td><td>-0.567</td><td>0.120</td><td>* * *</td><td>-0.201</td><td>0.018</td><td>* *</td><td>-0.233</td><td>0.037</td><td>* * *</td><td></td></t<>	ed. household inc	-0.036	0.108		-0.310	0.037	* *	-0.567	0.120	* * *	-0.201	0.018	* *	-0.233	0.037	* * *	
Ppercapita         0.127         0.046         "         -0075         0.013         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         "         0.027         0.027         "         1.026         0.027         "         1.026         0.027         1.026         1.026         0.027         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026         1.026 <th1.02< th="">         1.026         1.026<!--</td--><td>etro</td><td>5.370</td><td>2.322</td><td>*</td><td>2.909</td><td>0.551</td><td>* *</td><td>6.882</td><td>0.988</td><td>* * *</td><td>4.677</td><td>1.752</td><td>*</td><td>3.250</td><td>0.934</td><td>* *</td><td></td></th1.02<>	etro	5.370	2.322	*	2.909	0.551	* *	6.882	0.988	* * *	4.677	1.752	*	3.250	0.934	* *	
DP per capita)-que         -5901E-04         3.19E-04         4.164E-04         9.730E-05         **         -9.740E-05         1.571E-04         5.550E-05         **         -1.509E-04         1.31E-04           vintek         -11.124         3.2328         26.334         7.504         **         2938         1.920         28.702         28.709         1.31E-04         1.31E-04           If prox(km)         -0.091         0.014         **         -0.032         0.004         **         -0.005         0.002         1.4170         1.4170         1.4170           V density(n)         -0.016         0.279         0.013         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014         0.014	<b>JP</b> per capita	0.127	0.046	* *	-0.075	0.012	* *	0.053	0.018	* *	-0.099	0.032	*	0.039	0.027		
index $-11.124$ $3.258$ $2.6334$ $7.504$ $\pi$ $2.958$ $11.920$ $32.792$ $28.709$ $-13.720$ $14810$ It prox(m) $0.014$ $0.14$ $-0.033$ $0.004$ $1.920$ $0.05$ $0.03$ $1.920$ $10.97$ $0.079$ $0.074$ $1.610$ V density(n) $0.016$ $0.279$ $0.014$ $1.020$ $0.02$ $0.03$ $1.920$ $0.02$ $1.810$ V density(n) $0.016$ $0.279$ $0.012$ $0.012$ $0.026$ $0.032$ $0.03$ $0.024$ $0.024$ V density(n) $0.016$ $0.279$ $1.8042$ $3.266$ $1.9267$ $3.268$ $1.9268$ $1.9268$ V tracts $8554$ $412$ $2642$ $2.902$ $1.2687$ $1.926$ $0.032$ $0.035$ $0.035$ V tracts $503$ $1.126$ $3.266$ $1.2687$ $0.1267$ $2.526$ $1.9266$ V tracts $503$ $1.126$ $1.769$ $1.769$ $1.169$ $1.166$ V tracts $503$ $1.126$ $1.126$ $1.0369$ $1.2687$ $0.032$ $0.035$ V tracts $503$ $1.126$ $1.126$ $1.126$ $1.126$ $1.126$ $1.126$ V tracts $1.126$ $1.126$ $1.126$ $1.126$ $1.126$ $1.126$ V tracts $1.126$ $1.126$ $1.126$ $1.126$ $1.126$ V tracts $1.126$ $1.126$ $1.126$ $1.126$ $1.126$ V tracts $1.126$ $1.126$ $1.126$ $1.$	DP per capita)-squ	-5.901E-04	3.219E-04		4.164E-04	9.730E-05	* *	-9.740E-05	9.850E-05		1.571E-04	5.950E-05	*	-1.509E-04	1.311E-04		
It prox (w1)-0.0910.014···-0.0330.004······-0.0750.003···-0.0790.004······V density (ln)-0.0160.2790.0190.0190.0190.0160.0250.032···0.0350.035···N density (ln)-0.0160.2790.7190.0780.7530.1940.5550.032···0.5520.035···N tracts85540.3161.3265···1.30875.355··10,43012.6870.502···N tracts85540.312.4222.642··10,43012.6870.5120.502···N counties503.·4122.6422.9010,4302.5661.992.566···N counties503.·10,4309.310,4302.5661.991.956···N counties503.·10,4309.310,4302.566···1.956···N counties503.·10,4309.310,4302.566···1.956···N counties11.522.·11.52211.5221.53431.03695.7062.086···N countiese11.53431.03691.03695.7062.0862.0862.0862.0861.009N countiese1.15221.03691.03691.03691.03691.03691.03691.03691.0369N counties	ni index	-11.124	32.528		26.334	7.504	* *	2.958	11.920		32.792	28.709		-13.720	14.810		
V density (ii)         -0.016         0.279         -0.191         0.078         *         0.336         0.194         0.555         0.032         **         0.524         0.085         **           nstant         39.701         15.038         *         18.424         3.266         **         13.087         5.355         *         17.099         12.687         0.085         **         **         0.524         0.085         **           It tracts         8554         15.038         *         18.424         5.355         *         10,430         12.687         1*         1*           It tracts         8554         12         2         2         2         10,430         10.430         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*         1*	lit prox (km)	-0.091	0.014	* *	-0.033	0.004	* *	-0.009	0.006		-0.055	0.003	* *	-0.079	0.004	* *	
nstant         39.701         15.038         **         18.424         3.266         **         1.009         12.687         3.2128         6.502         ***           Of tracts         8554         3497         3497         242         10,430         12.687         32.128         6.502         ***           Of tracts         8554         3497         242         242         10,430         2566         **         **           Of counties         503         412         290         290         93         119         *         *         **         *         *         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **         **	V density (In)	-0.016	0.279		-0.191	0.078	*	0.336	0.194		0.555	0.032	* *	0.524	0.085	* * *	
It tracts         8554         3497         2642         10,430         2566           It conties         503         412         290         93         119           It factes         1         290         93         119           It states         1         1         1         1           It states         1         1         1         1         1           It states         1         1         1         1         1         1           It states         1         1         1         1         1         1         1           It states         1         1         1         1         1         1         1         1         1         1         1         1         1         1         1         1         1         1         1         1         1         1         1         1         1	nstant	39.701	15.038	*	18.424	3.266	* *	13.087	5.355	*	17.099	12.687		32.128	6.502	* * *	
If counties         503         412         290         93         119           If states         If states         If states         If states         If states         If states           Indom effects         If states         If states         If states         If states         If states           Indom effects         If states         If states         If states         If states         If states           Introle         855.222         If states         If states         If states         If states           It stelevel         If states         If states         If states         If states         If states           PC         60.91%         57.11%         If states         If states         If states	Of tracts	8554			3497			2642			10,430			2566			
of states       If states         ndom effects       11.522         ract-level       311.385       11.522         county-level       485.222       15.343       10.848         county-level       485.222       15.343       10.848         tate-level       57.005       20.886         tate-level       57.11%       7.70%       76.85%	Of counties	503			412			290			93			119			
ndom effects         11.522         130.069         17.167         10.097           ract-level         311.385         11.522         130.069         17.167         10.097           county-level         485.222         15.343         10.848         57.005         20.886           county-level         485.222         15.343         10.848         57.005         20.886           state-level           7.006         7.005         20.886	Of states																
fract-level311.38511.522130.06917.16710.097County-level485.22215.34310.84857.00520.886State-level </td <td>ndom effects</td> <td></td>	ndom effects																
County-level         485.222         15.343         10.848         57.005         20.886           itate-level                                                                                                              <	ract-level	311.385			11.522			130.069			17.167			10.097			
state-level bate-level 7.70% 76.85% 67.41% 7.00% 76.85% 57.11% 7.00% 7.6.85% 57.41%	County-level	485.222			15.343			10.848			57.005			20.886			
/PC 60.91% 57.11% 7.70% 76.85% 67.41%	itate-level																
	/PC	60.91%			57.11%			7.70%			76.85%			67.41%			

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FIGURE 3 Beta coefficient for percentage of race and ethnicity of residents. This reports coefficients from the models without interactions. Star indicates at least p < 0.05.

increases in the Northeast, Mid-Atlantic, Southeast, and Pacific Northwest regions. This suggests that in these regions, environmental inequality from air pollution in Latinx communities may be more strongly associated with emissions from non-military facilities.

The models reveal significant regional variation based on the percentage of Black residents. Black environmental inequality associated with military installations is significantly worse in the Midwest. We find significant Black environmental inequality in the Northeast, Mid-Atlantic, and Pacific Northwest regions that suggests non-military contributors: as distance increases from military sites tracts with more Black residents experience greater air toxics cancer risk in these regions. There was no significant regional variation of military-associated environmental inequality for percent of Native and API residents.

Table 3 demonstrates significant general API environmental inequality from air pollution for New England and Midwest that appears to be not connected to military facility proximity: in these regions, as the distance from the nearest military facility increases, the effect of more API residents in the tract is an increase in air toxics cancer risk. Taken in total our results support H1, in that we find significant regional variation in human health risks from air pollution associated from military installations for census tracts with higher percentages of Latinx and Black residents. Moreover, there appears to be a slight regional variation in environmental inequality associated with military installations for census tracts of Native populations. The region with the highest Latinx environmental inequality from military sites was region 8: the Central Mountains. Interestingly, this region reports the greatest average distance from the nearest military facility. We found Black environmental inequality from military installations only in Midwest (region 5). We did not find support for Native or API environmental inequality derived from military sites, based on the demarcations of EPA regions.

### 5.1 | Sensitivity analysis

Recognizing that tract-level ACS-derived variables can sometimes inhere high degrees of uncertainty across and within regions, to test the robustness of the findings we ran a sensitivity analysis by modifying the data to specific

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		SE	0.004	0.007	0.057	0.014	0.026	0.336	0.011	3.211E-0	6.348	0.003	0.051		7.740E-C	1.688E-C	4.241E-0	3.355E-C	2.643		
۸5	łwest		23	53	076	<u>)</u> 5	237	27	4	64E-04	001	045	80		122E-04	323E-04	78E-04	31E-03	108	005	
EP/	, Μi	p Est.	*** 0.02	*** 0.06	-0.0	*** 0.00	***	*** 1.90	0.0	** 7.40	*** 26.0	*** -0.0	0.0		-4.1	*	4.07	1.03	*** 12.4	13,0	524
		ш	.002	.005	.034	.014	.018	444	.013	.724E-04	.579	.003	.025		.870E-05	.170E-05	696E-04	.450E-04	.069		
	east	S	Ő	Ő	Ó	Ö	Ö	Ö	Ó	-04 2	<b>v</b>	Ö	Ő		-05 4	-04 9.	E-04 6	94	с,	_	
EPA 4	Southe	Est.	0.030	0.041	0.051	0.091	-0.062	1.522	0.008	7.141E	25.853	-0.045	0.006		2.580E	1.925E	-7.474	2.110E	23.211	13,760	736
		d			*		* *	* *	* *	-04	~	*			* 40	*** 	-03	-03	*		
	ic	SE	0.012	0.027	0.208	0.053	0.072	1.055	0.025	1 2.765E	15.38	0.015	0.155		5.857E	1.085E	8.696E	3 2.698E	6.553		
A 3	d-Altan		012	042	08	40	286	25	93	865E-0∠	035	033	37		89E-03	24E-03	566E-02	779E-03	704	54	2
ED	Ξ   Ξ	p Est	.0 - ***	0 - ***	* 0.4	0.0 ***	0- ***	*** 4.0	0.0	-2.	*** 15.	·O- ***	*** 0.0		*** 1.4	* 6.6	-1.	-1.	*** 16.	65	23:
			003	004	013	004	015	117	018	170E-05	.703	202	<b>346</b>		530E-05	124E-04	530E-05	010E-05	<b>3</b> 84		
	ieast	SI	9 0.0	0.0	7 0.0	0.0	8 0.0	1	6 0.0	E-05 3.3	3 1/	2 0.0	0.0		E-04 8.	E-04 1.4	E-05 4.	E-04 9.0	48 6.(		
EPA 2	North	Est.	* -0.00	* 0.029	-0.02	* 0.032	-0.06	* 6.890	-0.00	1.910	97.30	* -0.01	0.878		4.729	3.600	1.990	1.159	-28.2	6953	111
		d	**	*		*	10	*		E-04	8	*			E-04	E-04	E-03	E-04 *	*		
	and	SE	0.007	0.006	0.042	0.014	0.015	0.561	0.017	2.087	13.09	0.004	0.027		4 2.171	4 2.054	1.013	5.170	5.403		
PA 1	ew Engl	ŗ.	042	038	0.053	086	0.002	172	024	832E-04	866	0.017	0.035		l.979E-0	2.920E-0	467E-04	220E-03	6.339	346	~
Ξ	z	Ъ	.0 ***	*** 0	)- * *	*** 0.	)- ***	*** *	.0 ***	5 ** 2.	4	)- ***	)- ***		`i' *	***	**	+ +	*** 10	Ř	<u>'</u> 9
		щ	.003	.003	.013	900;	.016	.401	600	560E-05	.015	.003	.031		.350E-05	.390E-05	.980E-05	.679E-02	.846		
	nwide	S	0	0	0	0	0	0	0	DE-05 2	9	0	0		DE-04 6	4E-04 6	5-04 7	E-04 1	3	~	
	Natio	Est.	0.016	0.058	-0.03!	0.032	-0.15	2.293	0.046	-7.61(	1.301	-0.03	0.234		-1.64(	-4.67	2.114	. 3.4201	24.02;	71,317	3087
			()	not black	(%		ousehold		r capita	er ta)-squ	ex	ox. (km)	nsity (In)	ions	(%) X : prox.	(%) X	e (%) X prox.	6) X milit. 6.	ant	racts	ounties
			Black (%	Latinx, r (%)	Native (	API (%)	Med. hc inc	Metro	GDP pe	(GDP pé capi	Gini ind	Milit. Pr	PRV der	Interact	Black milit	Latinx milit	Native milit	API (% prox	Const	# Of ti	# Of c

TABLE 3 Random-intercept multilevel models with interactions.

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			A 1		EPA 2			EPA 3		EPA 4	_		EPA 5		
Ζ	<b>Jationwide</b>	ž	ew Engle	nd	Northe	ast	-	<b>Mid-Altantic</b>		South	least		Midwest		
	ist. SE	ه   ۲	Ļ	SE	o Est.	SE	a	Est. S	ш	p Est.	SE		9 Est.	SE	d
# Of states 5	11														
Random effects															
Tract-level	5.628	ຕໍ	581		8.011			133.590		10.78	ŝ		24.861		
County-level 8	33.954	с. С	961		22.391		.,	31.870		28.20	Q		9.500		
State-level	33.1947														
VPC	;7.64%	52	2.52%		73.65%			19.26%		72.34	%		27.65%		
	EPA 6			EPA 7			EPA 8			EPA 9			EPA 10		
	South centra	F		Central plain	S		Central mo	untains		West/South	west		Pacific North	nwest	
	Est.	SE	٩	Est.	SE	d	Est.	SE	d	Est.	SE	d	Est.	SE	d
Black (%)	-0.002	0.019		0.001	0.006		-0.124	0.069	<	0.025	0.008	* *	-0.010	0.028	
Latinx, not black (	%) 0.022	0.019		0.007	0.010		0.141	0.026	* * *	0.063	0.003	* * *	0.006	0.011	
Native (%)	-0.078	0.074		-0.073	0.069		-0.031	0.058		-0.021	0.016		-0.014	0.028	
API (%)	-0.025	0.073		0.076	0.029	*	0.044	0.110		0.023	0.006	* * *	0.125	0.021	* *
Med. household ii	0.016 -0.016	0.109		-0.315	0.038	* * *	-0.529	0.121	* * *	-0.196	0.018	* * *	-0.231	0.038	* *
Metro	5.485	2.324	*	2.890	0.549	* * *	6.644	0.990	* * *	5.267	1.745	* *	3.131	0.949	* *
GDP per capita	0.127	0.046	*	-0.076	0.012	* * *	0.050	0.018	* *	-0.092	0.031	*	0.035	0.028	
(GDP per capita)-s	iqu -5.893E-04	3.217E-C	4	4.188E-04	9.690E-05	* * *	-9.100E-05	9.810E-05		1.398E-04	5.910E-05	*	-1.343E-04	1.333E-04	
Gini index	-9.665	32.556		26.881	7.481	* * *	4.539	11.894		26.299	28.542		-11.426	15.152	
Milit. prox. (km)	-0.074	0.017	* *	-0.035	0.004	* * *	-0.007	0.007		-0.034	0.005	* * *	-0.084	0.005	* *
PRV density (In)	-0.031	0.279		-0.181	0.078	*	0.330	0.194		0.527	0.033	* * *	0.552	0.086	* *
Interactions															
Black (%) X milit prox.	-2.548E-04	3.046E-C	4	2.106E-04	1.862E-04		3.589E-03	2.290E-03		-7.270E-05	3.432E-04		2.886E-03	1.172E-03	*
														(Conti	nues)

(Continued)

TABLE 3

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	EPA 8 EPA 9 EPA 10	Central mountains West/Southwest Pacific Northwest	p Est. SE p Est. SE p Est. SE p	4 -7.599E-04 3.253E-04 ** -6.885E-04 8.330E-05 *** 3.826E-04 1.837E-04 *	3 2.122E-04 2.959E-04 8.210E-05 1.178E-04 -3.530E-05 2.448E-04	4 1.109E-03 2.354E-03 3.925E-04 2.571E-04 -8.902E-04 7.409E-04	*** 12.386 5.334 * 18.648 12.612 31.522 6.649 ***	2642 10,430 2566	290 93 119			129.765 17.037 10.032	10.563 56.268 21.644		7.53% 7.676% 68.33%
	EPA 9	West/So	p Est.	** -6.885E-	8.210E-C	3.925E-C	* 18.648	10,430	93			17.037	56.268		76.76%
		ntains	SE	3.253E-04	2.959E-04	2.354E-03	5.334								
	EPA 8	Central mou	Est.	-7.599E-04	2.122E-04	1.109E-03	12.386	2642	290			129.765	10.563		7.53%
			d				* * *								
		IS	SE	1.137E-04	1.106E-03	5.812E-04	3.254								
	EPA 7	Central plair	Est.	1.937E-04	5.241E-04	-9.046E-04	18.333	3497	412			11.511	15.183		56.88%
			d				*								
		_	SE	2.484E-04	5.262E-04	1.345E-03	15.089								
10	EPA 6	South centra	Est.	-4.168E-04	1.527E-04	-5.449E-04	37.986	8554	503			311.274	484.322		60.88%
				Latinx (%) X milit. prox.	Native (%) X milit. prox.	API (%) X milit. prox.	Constant	# Of tracts	# Of counties	# Of states	Random effects	Tract-level	County-level	State-level	VPC

TABLE 3 (Continued)

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FIGURE 4 Interaction coefficients for % of race and ethnicity of residents. Star indicates at least p < 0.05.

criteria set forth by Folch et al. (2016). The robustness check specifically uses 2010 U.S. Census data for race and ethnicity. Additionally for the median household income variable, tracts with a coefficient of variation—the estimate divided by the margin of error—greater than 0.4 were omitted. With these two conditions in place, the sample size was reduced to 69,498 tracts. The robustness results are reported in Supplemental Table S1. Comparing the results across all models there were some changes in statistical significance to variables that are not central to our analysis. However, the results of military-associated environmental inequality for racial/ethnic communities reported in the results section above remain consistent. Thus, our main findings are robust to ACS data quality concerns.

### 6 | DISCUSSION

Multi-level models represent sophisticated means of disentangling and comparing the various associations and effects that contribute to the risk of environmental inequality. On our most basic analytical level, we find that the relative contributions to local air pollution profiles arising from military and non-military sources likely differ by region, as do consequent environmental justice concerns. For example, in the Midwest, Central Mountains, and West/Southwest regions Latinx neighborhoods experience intensified air pollution inequalities associated with proximity to military installations. The connections made between air force bases in the Southwest and this type of air pollution exposure (Alvarez, 2021) suggests one possible explanation for the risk patterns observed in this region as well as the need for deeper subregional or interregional analysis to understand similarities and differences in the factors driving results across these regions. Neighborhoods with more Black residents reported greater environmental health risk from air toxics associated with nearby military facilities in the Midwest, yet environmental inequality found in the Northeast, Mid-Atlantic, and Pacific Northwest regions may be more associated with non-military factors. This hints that in these cases this form of inequality is driven by factors outside of the military; for example, possibly industrial factors or those related to population or automobile density.

To distinguish these results from nationwide results focusing on similar questions, however, it is important to emphasize what is not found as well as what is. Here, we find that the previously described nationwide patterns

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of environmental injustice that were developed on a nationwide scale (Alvarez et al., 2022) are not regionally homogenous and may not be the result of the same factors—military or non-military—in different parts of the country. By rejecting H0, our results support the findings of Alvarez et al. (2022), which hypothesized and demonstrated associations between military proximity, some differences in racial and ethnic composition of census tracts, and air toxics exposure across the country. This adds further support to a research tradition (e.g., Bonds, 2016) describing different types of military-related environmental degradation and the relationships among environmental justice indicators, exposure to air toxics, and proximity to miliary facilities. The finding of regional heterogeneity in support of H1 likewise provides foundational support for the utility of approaching riskscapes and riskscape theory in the context of regions to understand spatially contingent environmental injustice (and instances of justice) in the United States. In short, for those interested in the environmental and environmental justice consequences of the military and militarism, our exploratory modeling strategy to examine the intersection of environmental risk, health, and justice, the study of the military, and regional riskscapes provides a promising analytical approach.

Using this lens to focus on regional variation itself, across different racial and ethnic populations there was regional variation in census tract air toxics exposure as a function of proximity to military bases not only between the groups, but also within each group. For example, there are regional differences among Latinx populations that may not be reflected in nationwide analyses that aggregate regions (or vice versa), providing caution about the ecological and atomistic fallacies. This suggests the need for additional qualitative and case study analysis within regions to further develop these ideas locally and to expand our view of how and where environmental justice issues may arise. Using regionalized military riskscapes in cases like these might therefore provide guidance for those seeking to better locate regional or subregional research, prevent unsupported inferential leaps across scale, help to regionalize results, guard against ecological fallacy, and prevent the universalizing of particular cases in particular regions, instead using them as comparative tools useful for additional analysis of similarity and difference.

### 7 | CONCLUSION

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Analyses and results like these emphasize the need for regional or subregional downscaling of inquiries and results. Moreover, they draw attention to the need for additional efforts to determine whether discrete instances of environmental injustice are the result of a particular institution like the military or specific processes like the operation of facility, whether such associations are the result of the facility being located in a particular place or near a particular population, whether outside factors are at play, and how efforts to improve and ameliorate instances of environmental injustice should be tailored to particular regional, subregional, or community needs.

In this spirit, continued conceptual and empirical expansion of spatially contingent and regionalized understandings of environmental inequality should continue to embrace military presence and action, while also remaining wary of over-generalizing national results to regional contexts, regional results to subregional or national contexts, and so on. Nor should assumptions carry over regarding cause, as our findings show that likely contributors toward environmental inequality differ not only across regions but also by the racial and ethnic composition of communities. We should be clear, however, that because the NATA dataset does not distinguish between military and non-military sources of pollution our results simply demonstrate and regionalize associations between military facility proximity and intensity, on the one hand, and exposure to carcinogenic air toxics, on the other. They do not support a causal claim that the military is the source of this pollution as opposed to it being the result of intentionally co-located private military support activities or other emissions sources that are coincidentally nearby.

For this reason, the model developed here provides opportunities for additional research into how several causal chains and factors may contribute to instances of environmental inequality, including by using other datasets in local context that provide greater granularity about the sources of emissions. Furthermore, future research could benefit from a more detailed—and possibly qualitative or mixed methodological—lens that focuses on why these variations in riskscapes exist across EPA regions or the broader societal regions upon which they are overlaid: whether these result from reasons of demographics, organizational structure, administrative or political preference, environmental

culture, or other explanations. This is not to say that broad analyses are ineffective or unimportant: clearly given the contributions of studies that identify cases or sources of inequality this is not the case. However, it emphasizes the practical need for environmental inequality research that examines similar issues and communities simultaneously across different spatial scales and contexts.

#### CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

#### ORCID

Daniel Shtob 🕩 https://orcid.org/0000-0002-1695-1762

#### ENDNOTE

¹ For more details into the construction, use, and limitations of these measures see Alvarez et al. (2022).

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### AUTHOR BIOGRAPHIES

**Daniel Shtob** is an assistant professor of Sociology and Urban Sustainability at Brooklyn College, City University of New York (CUNY). He is also a member of the doctoral faculty in Earth and Environmental Sciences at the CUNY Graduate Center. His current research interests include environmental sociology, climate change, natural disaster, environmental justice, law and finance, and urban socio-spatial policies.

**Camila Alvarez** is an assistant professor of sociology at the University of California, Merced. Her areas of expertise are environmental sociology, environmental justice, and critical quantitative methodology. Her research addresses the question: How are social inequalities reinforced through environmental problems?

**Nicholas Theis** is a PhD candidate in the Department of Sociology at the University of Oregon. His research interests include environmental sociology, political economy, environmental justice, social network analysis, and quantitative methods.

#### SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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