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Environmental & Socio-economic Studies

environ ses

DOI:10.2478/environ-2024-0016

Environ. Socio.-econ. Stud., **2024, 12, 3: 11-22**

Original article

Multifaceted contribution of environmental pollution, race and income to health inequities in Texas

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ABSTRACT

Prior studies found links between ethnic background, socioeconomic status, and proximity to toxic environmental contaminants harmful to human health. However, there is no consensus among environmental economists on whether ethnicity or economics are the primary causes of health inequity under the influence of environmental hazard exposure. This paper explores this research question in Texas, the second largest US state, and the most diverse demographically, using a comprehensive framework with twelve main factors as key determinants for environmental-related health outcomes. The matrix of associations among factors of environmental pollution, economic class, race/ethnicity, and state of health is very complicated by multiple inter-correlations among components. To differentiate the relative importance of various factors, twelve statistically large population cohorts were compared, based on four racial/ethnic groups, each with three different levels of poverty. This novel approach allows for more meaningful comparisons, by normalizing groups for ethnicity and prevalence of poverty, two of the most influential socioeconomic factors. Compared to majority-White communities, majority-Hispanic and -Black communities were found to be more disproportionally negatively impacted by environmental pollution and socioeconomic challenges. This resulted in worse health outcomes: higher prevalence of chronic diseases and a shortened life span. The prevalence of poverty appears to play a dominant role in health outcomes across all racial/ethnic groups. Consistent with prior research, the Hispanic community has shown a strong positive correlation with the prevalence of diabetes, while the Black community has a high prevalence of asthma.

KEY WORDS: environmental justice; health disparities, race/ethnicity

ARTICLE HISTORY: received 30 April 2024; received in revised form 5 August 2024; accepted 6 August 2024

1. Introduction

The complicated matrix of associations of environmental pollution, economic class, and race/ethnicity collectively impacts the state of health. This matrix contains multiple inter-correlations among components of those groups, as has been well-known for at least 25 years (Sexton & Adgate, 1999; Hipp & Lakon, 2010; Agyeman et al., 2016; Hsiang et al., 2019). However, the sequential causality of relationships remains debatable, and relationships are not consistent across regions or countries (Bravo et al., 2016; Banzhaf et al., 2019a; Hu et al., 2023). Health outcomes for different socio-economic groups are inherently complicated, resulting from a combination of multiple factors for a person over many years, including parents' genetics (Banzhaf et al., 2019b; Fernandez, 2021). The interpretation is further challenged by the non-linear and time-delayed relationship between an impact and the observed health outcome (NEILL ET AL., 2003; CUSHING ET AL., 2015a, b). The upfront choice of a researcher's framework defines specific factors included as a subject of study and hence influences the results of analysis and conclusions (BOUVIER, 2014; BOYCE ET AL., 2016). In other words, the chosen angle and point of view define the interpretation of the observed inherently very complex picture. Following a thorough review of various factors, we present a comprehensive framework of key determinants for environmental-related health outcomes (Fig. 1).

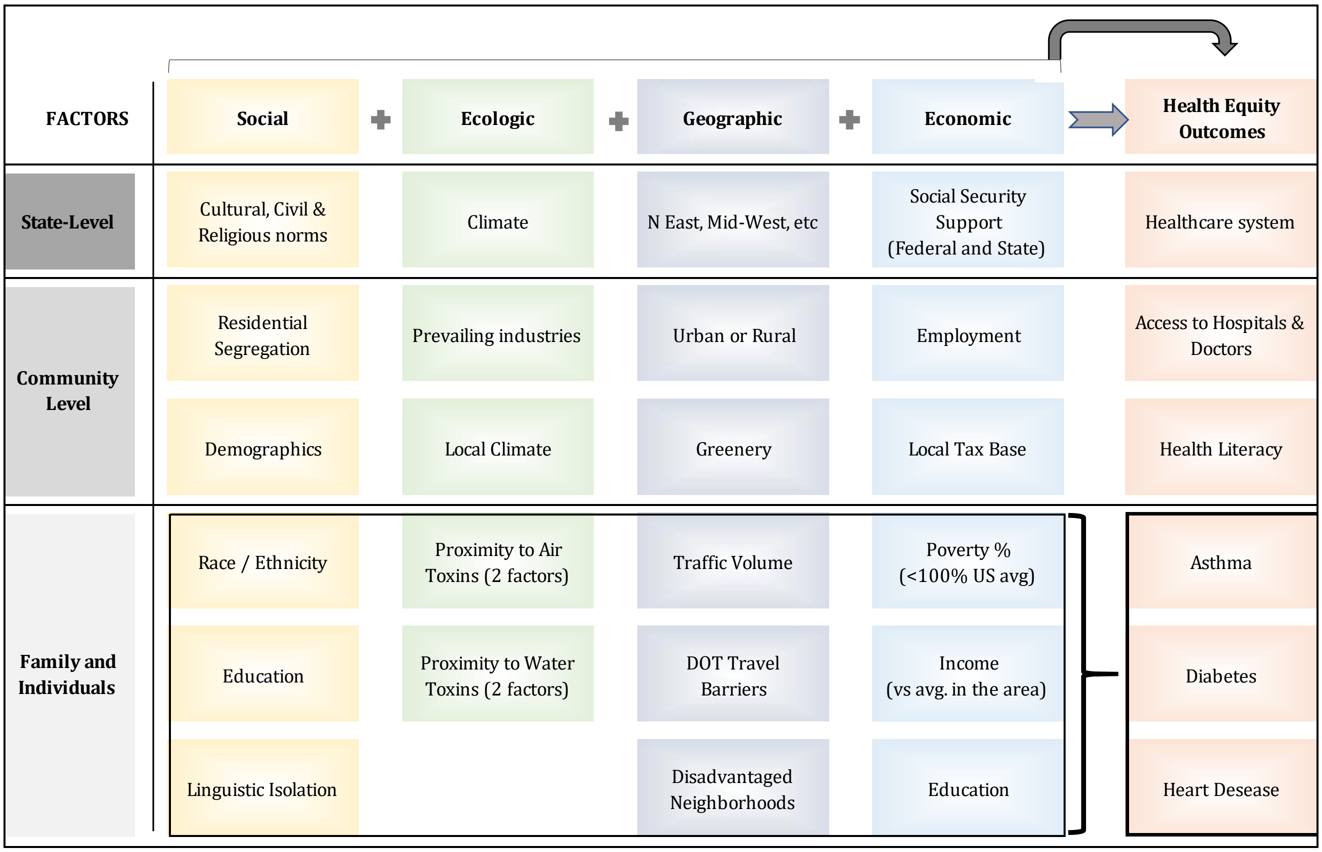


Fig. 1. Framework of key determinants for environmental equity outcomes

Our framework has three levels: a US state (with millions of residents), a large community at the US county level (with ~120,000 residents on average), and an immediate community, US Census tract level (with approximately 4,000 residents on average). In the US Census methodology, a census tract is a small, relatively permanent geographic area within a county that is used to collect census data once in a decade. Tracts have between 2,500 and 8,000 residents in size (about 4,000 residents on average), with boundaries that follow visible features like roads. Therefore, tract is the most granular unit of population suitable for our analysis: small enough and relatively homogenous within.

While numerous factors existat all three levels, the immediate community factors (race, income and proximity to environmental pollutants) are likely to be most influential for health outcomes because residents spend the majority of their time at or nearby their residence. Therefore, we selected twelve individual independent variables at the immediate community (US Census tract) level, and four dependent long-term health equity outcomes, as described in Table 2. This expanded framework enabled a more comprehensive factor pairs analysis and definition of more specific multivariable correlations. In addition, selecting the state of Texas as the large and diverse subject of the study allowed for the identification and analysis of a statistically significant number of areas with a majority ethnic population (White, Hispanic, Black, or Minorities). Despite the overall wealth of the USA, income and poverty distribution among various groups remains very uneven (MIKATI, 2018; SHRIDER & CREAMER, 2023). Poverty is of particular concern, with its disproportionate and usually long-lasting impact on the affected population (Mohai & Saha, 2006; Downey & Hawkins, 2008; Chakraborty et al., 2011; Pais et al., 2014; Isen et al., 2017, Cheeseman et al., 2022).

This study had several aims: 1) introduction of our comprehensive framework of Environmental Justice (EJ); 2) analysis of several of its most impactful components, some as independent (input) variables and others as dependent (outcome) variables and, 3) review results of correlations among variables and advancing hypotheses of causality relationships.

2. Study area

The state of Texas was chosen for analysis for several compelling reasons. It is the second-largest state in the USA (both by area and by population) with a ratio of urban/rural populations close to the US national average value for the ratio. Texas is slightly less skewed in income distribution than the US average, with a lower Gini coefficient. Texas is very close to the US average in terms of house ownership, median cost of rent, computer and internet use, and several other economic indicators. It is exactly at the median percentile of per capita incomeand has slightly lower than the US average cost of living. Overall, Texas is very representative of the current USA average in socio-economic terms. Yet Texas is different in its fast population growth and high ethnical diversity. In 2010–2020 its population grew by 15.9%, more than twice the rate of the overall US, and 95.3% of this growth was attributable to growth in minority population, half of which being Hispanic. As a result, Texas is one of a few so-called "majority-minorities" US states (along with California and Florida), where non-Hispanic whites represent less than half of the total population. Given the current long-term population trends in the United States, Texas represents a future trend in the country's demographic composition.

US Census provided detailed demographic information on Texas' 5,265 census tracts. For analysis of the race impact, the following majority-population areas (US Census tracts) were selected: majority White (>80% of Whites), or "majority Minorities" (>70% of a tract population is represented by either Black or Hispanics, or combination of both Blacks and Hispanics). Texas had no tracts with a majority of Asians or other racial minorities.

Texas has four major metropolitan areas: Houston, Dallas, San Antonio, and Austin, which as shown in darker blue colors in Figure 2 indicate higher population density. With those exceptions, the eastern part of Texas has moderate population density, while the western half is sparsely populated, except for a few southwest counties near the Mexican border. More than half of Texas's population (57.5%) lives in the top ten most densely populated counties, which account for only 3.7% of the total Texas land area. Conversely, the least 100 populated counties (out of 254) account for only 1.9% of the total Texas population despite covering 48% of the area. Given the high percentage of Hispanics in Texas, it is important to understand the specifics of its local prevalence, as it is not equally distributed throughout the state, as illustrated in Figure 3.

Hispanics tend to be prevalent in the southwest part of Texas, alongside the Mexican border, which is logical given both legal and illegal immigration trends of the past few decades. North and East parts of Texas tend to have a higher proportion of the non-Hispanic White population. The majority of the Black and Asian population lives in the Greater Houston, Dallas, and San Antonio metro areas. Houston area is particularly impacted by both traffic fumes pollution and chemical pollution from the major near-based chemical production areas (Kalnins & Dowell, 2017; Adepoju et al., 2022; Hu et al., 2023).

3. Methods and data sources

3.1. Demographic dataset

Demographic data were obtained from the most recent national US Census (2020), specifically population race/ethnicity, age, education, income, and poverty. The US Census definition of racial groups includes at least five distinct (defined as alone) racial groups: White alone, Black or African American alone, American Indian or Alaska Native alone, Asian alone, Native Hawaiian alone, and two or more races. In addition, there isa census self-reported ethnic group: Hispanic or Latino (of any race). Five major demographic groups were used in this study: White, Black, Hispanic, Asian, and Other. The first four categories account for 97.9% of the US and 99.1% of the Texas population. Texas has a very similar racial profile to the rest of the country, except forhaving twice as many Hispanics and a correspondingly lower percentage of non-Hispanic Whites.

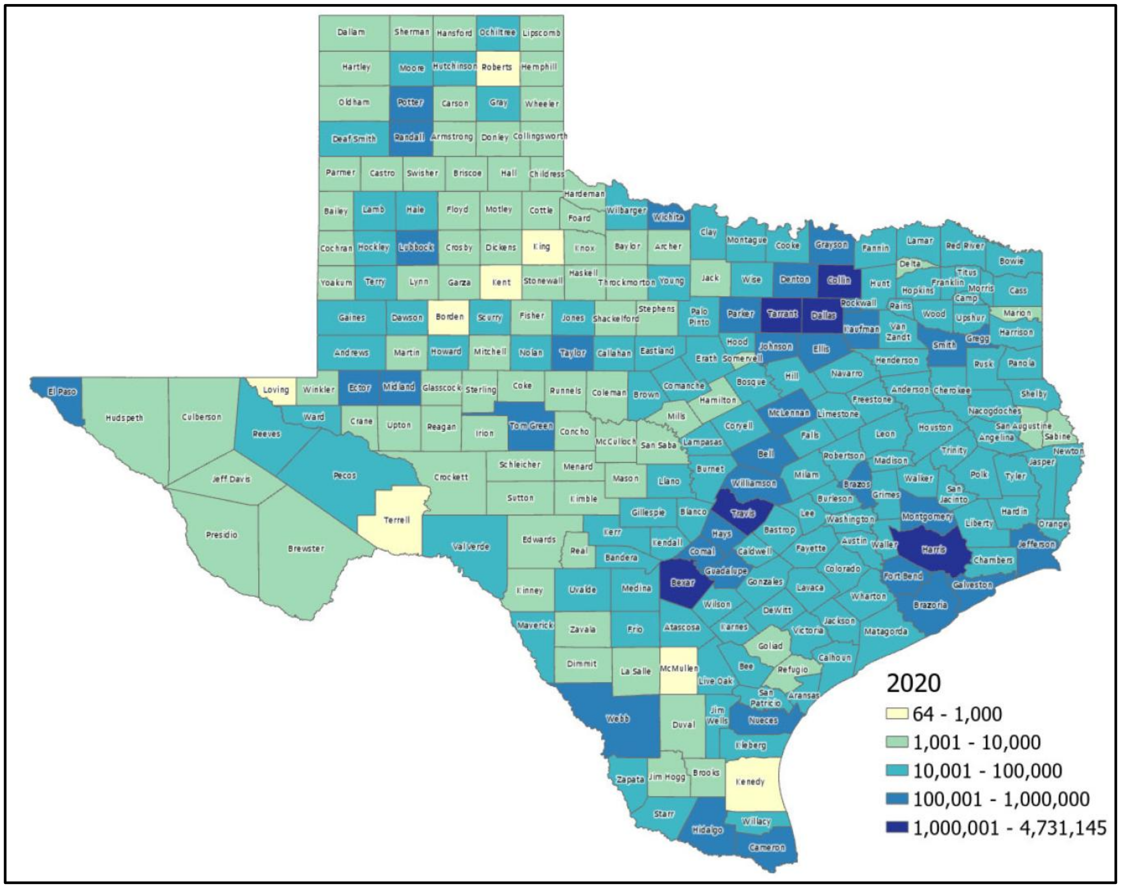


Fig. 2. Density distribution of Texas population (Source: Texas Demographic Center, based on data from US Census 2020)

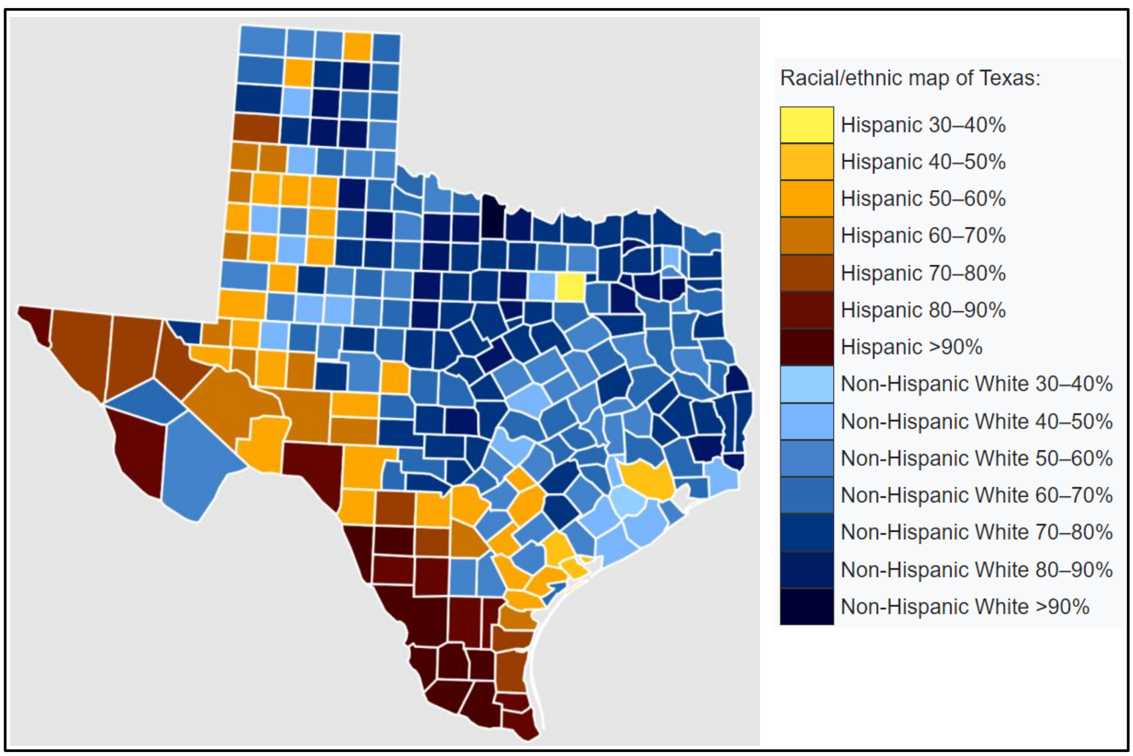


Fig. 3. Regional distribution of Hispanic and White population in Texas (Source: Texas Demographic Center, based on data from US Census 2020)

According to the previously described framework, our research approach requires the use of datasets for community geospatial factors, personal socio-economic status, environmental pollution burden, and health outcomes.The overall research dataset was compiled using specialized datasets from several US government agencies, including the US Census, the US Center for Disease Control, the US Environmental Protection Agency, and the US Department of Transportation. Community geospatial factors included proximity to traffic volume (TRAF), effective local transportation access (TRVL), proximity to disadvantaged neighborhoods (DNBH), and linguistic isolation (LINGO), which is a particularly important factor for Hispanic and Asian communities. The dataset for personal Socio-Economic Status (SES) was obtained from the US Census and included data on median household income (MDHI), unemployment rate (UEMPL), poverty (PVRT, % of tract population below 100% US Federal level), and education (WHSD, % of adults Without a High School Diploma). Environmental pollution data was obtained from the US Environmental Protection Agency (EPA) and included proximity of population areas to Superfund NPL sites (NPL), hazardous waste sites (HAZW), fine dust particle matter (FPM), and diesel particulate matter (DZL). The latest healthcare data on three diseases and life expectancy were obtained from the US Center for Disease Control.

3.2. Selection of independent and dependent variables

The negative impact of environmental pollutants has been extensively studied in the Environmental Justice (EJ) literature (Collins et al., 2016; Paolella et al., 2018; Deryugina et al., 2019; Lefler et al., 2019; Lee, 2021; Hausman & Stolper, 2021; Antonczak, 2023; Casey et al., 2023). Following an extensive literature review, a set of independent variables was selected, primarily based on population proximity to environmental pollution sources, geospatial factors, and socioeconomic exposure to unfavorable living conditions.

All of the variables listed above are expressed in percentiles (compared to the range within the entire US), making it much easier to compare across very different variables. The closer the sources of pollution to a given tract's population or higher the geospatial challenges, the greater the value of the corresponding independent variables. The higher prevalence of major diseases was translated into the higher value of health equity-dependent variables. The dependent variables were defined as Health Equity outcomes, expressed as the frequency of three major chronic diseases: asthma, diagnosed diabetes, coronary heart disease (among adults aged 18 and older), and shorter life expectancy of ethnic and social groups (compared to the US overall national average).

Cumulatively, Health Equity Index (HEI) research hypotheses result in the following equation 1 for a given US Census tract population (i):

$$HEI_i = \beta_0 + \beta_1 * TRAF + \beta_2 * DNBH + \beta_3 * NPL + \beta_4 * HAZW + \beta_5 * FPM + \beta_6 * DZL + \beta_7 * MDHI + \varepsilon_i \quad (1)$$

where HEI Index is the equally weighted average of prevalence for the three major diseases: Asthma, Diabetes, and Heart Disease. All independent variables are described in Table 1.

This paper examined the factors of the proposed research framework by application of traditional methods of econometrics analysis of pair correlation among many variables. Then race/ethnic categories were normalized for the same level of income, and subjected to a more rigorous application of multi-variable linear regression analysis. The goal of this paper was to test independent variables as determinants for health equity outcomes for the Texas population.

4. Results and discussion

While the level of income is a key determinant of many aspects of individuals (home location, living conditions, access to quality food, etc.), the income on the lower end of the distribution curve (close to or at the poverty line) is particularly important. Hence, it is relevant to understand the current distribution of poverty in the Texas population, particularly in areas with an ethnic/racial majority of various ethnic groups. Overall, Texas has an equal proportion of its population (21%) living in US Census tracts with either low or high poverty, as shown in Table 2.

However, the distribution of poverty varies significantly by race: only 2.8% of Whites live in high poverty tracts, compared to 9.7% of Hispanics and 14.6% of mixed Black and Hispanic-majority tracts. This fact confirms that racial/ethnic and socio-economic segregation persists in many parts of Texas, as it has elsewhere in the US (Sheriff & Maguire, 2020; Liu et al., 2021; Shrider & Creamer, 2023). For context, each of the White non-Hispanic and

Hispanic cohorts in Texas account for approximately 40% of the total Texas population. Meanwhile, the combined Black and Hispanic population represents the majority in Texas at 53.6%. After the initial calibration of poverty distribution, we compared the distribution of factors within four Texas ethnic groups: ethnic majority areas of Whites, Hispanics, Blacks, and "Majority Minorities" (including both Blacks + Hispanics), as shown in Table 2. Each ethnic group was divided into three categories: the total group, and sub-groups with either low or high poverty rates. Table 3 shows the resultant twelve categories and their percentile ranking within the US on three groups of variables, as well as a comparison with the Texas average. This granular view provides more detailed insights into the impact of poverty on different racial/ethnic groups, normalizing for income effect, and allowing for meaningful comparisons.

Table 1. Independent and dependent variables

#	Abbrev.	Geospatial challenges	#	Abbrev.	Environmental pollution burden
1	TRAF	Traffic proximity and volume	5	NPL	Proximity to superfund NPL sites
2	TRVL	DOT travel barriers score	6	HAZW	Proximity of hazardous waste sites
3	DNBH	Disadvantaged neighborhoods	7	FPM	Fine particle matter (PM 2.5) in air
4	LINGO	Linguistic isolation	8	DZL	Diesel particles matter in the air

Independent variables (contd.)			Dependent variables		
9	UEMPL	Unemployment rate	1	ASTM	Asthma
10	WHSD	Adults without a high school diploma	2	DBTS	Diabetes
11	PVRT	Poverty (%, income < 100% US level)	3	HART	Heart disease
12	MDHI	Median household income as % of area	4	SHLF	Shorter life expectancy

Table 2. Prevalence of poverty in Texas tracts with prevailing ethnic/racial majoraty (Source: US Census, 2020)

Percent of total TX population	TEXAS			WHITE > 80%			BLK > 70%		HISP > 70%		(BLK + HISP) > 70%		
Poverty %	All	Low	High	All	Low	High	All	High	All	High	All	Low	High
By number of people	100	21	21	7.4	0.1	2.8	0.9	0.5	18	10	31	0.7	15
By number of US Census tracts	100	17	24	8.5	0.2	3.1	1.3	0.8	18	10	32	0.7	17

Poverty is def as % of individuals with income < 100% Fed Poverty Line. Low / High Poverty areas have < 20% / > 80% of population in poverty, respectively. Poverty is defined as the percentage of individuals with income < 100% Federal Poverty Line

The chosen methodology of percentile ranking within the US significantly simplifies the interpretation of results, as lower values for all variables correspond to better outcomes for the population. The only exception was medium household income (MDHI), where higher values represent better outcomes. The two population categories that stand out by having significantly better outcomes are low poverty areas of majority White areas and Texas total areas. The following three categories with better than average health outcomes are 1) majority minorities, 2) majority Hispanic areas with low poverty, and 3) all majority White areas. Texas' overall state values represent a dividing line between the first two relatively advantaged groups and a larger, relatively disadvantaged group. With a few sporadic exceptions, the majority of outcomes are significantly worse than the Texas state average, except for a predominantly white population with high poverty. Hispanics, Blacks, and combined (Hispanic and Black) minority areas with high poverty rates experience the worst outcomes. The findings confirm that Hispanic and Black communities are disproportionately affected by pollution and socioeconomic challenges, resulting in significantly worse health equity outcomes (higher disease prevalence and shorter life span).

However, the prevalence of poverty appears to play a more significant role in health outcomes across all racial/ethnic groups, as shown in Table 4. In areas of low poverty prevalence (<20% of people in a tract), the prevalence of diseases was significantly below the US average (left column in Table 4). For four ethnic groups (except for the Black-majority), the average values increased significantly compared to the low cases and became comparable amongst each other for high poverty cases. Black-majority areas were severely disadvantaged in health aspects, as even the average index of diseases for the Black-majority group was already in the 95th percentile of the US population.

The link between socio-economic status (SES) and chronic illnesses (which lead to premature death) has been known for many decades, first expressed as the "Preston curve" and later developed by others (Van Wyk & Bradshaw, 2017). It is well established that the curve (projecting health as a function of income) is steepest at very low-income levels (within a given country) and then flattens out as income per capita rises. Intuitively, this makes sense, as the lowest income groups make the most costly and consequential trade-offs between health care and other pressing family needs (food, safety, shelter). As a result, rather than looking at the total median income in a given area (Antonczak, 2023), it would be more informative to focus on poverty and near-poverty prevalence (the lower left side of the income distribution curve within a community). It is especially important for chronic poverty (Sapkota et al., 2021) and for more vulnerable age groups, such as children (Lee, 2021) and the elderly, whose immune systems are most sensitive to environmental stresses (Perez et al., 2023).

The values of the SES group correlate with health outcomes with an R2 of 0.796, whereas the Environmental Pollution group has a very poor correlation with health outcomes (R2 = 0.129). Such a large difference in the relative correlations of SES and Environmental Pollution is both novel contribution and fundamental to the field of EJ research (Fig. 4).

Table 3. Median values of variables for different sub-groups of Texas population

		Population %			Pollution factors				Socio-economic status (SES)					Health inequity			
Ethnic group description	@ Poverty level	BLK	HISP	(B + H)	DZL	TRAF	FPM	NPL	HAZW	UEMPL	WHSD	PVRT	DNBH	ASTM	DBTS	HART	SHLF
Whites > 80%	a) Low	1	7	9	40	37	76	33	27	26	7	7	0	6	30	33	25
TX Total	Low	4	15	22	46	45	77	39	34	29	17	9	0	6	24	14	29
b) Tot Minorities >70%	Low	21	55	81	39	46	78	54	42	35	63	12	33	18	57	14	60
Whites > 80%	All	1	8	10	16	20	67	20	12	36	47	40	28	24	63	67	51
Hispanics >70%	Low	0	88	90	37	52	78	13	34	27	77	12	39	1	64	14	53
TX Total	All	6	31	47	42	50	75	37	36	48	66	56	40	24	67	47	56
Whites > 80%	c) High	4	4	12	11	17	73	22	7	85	68	84	59	57	88	92	80
Tot Minorities >70%	All	6	75	88	48	59	77	56	44	65	93	81	83	35	89	57	67
Hispanics >70%	All	1	88	91	38	59	78	44	39	64	96	83	88	24	91	60	62
TX Total	High	8	64	86	46	60	76	42	43	68	93	89	83	46	91	71	73
BLACK > 70%	All	78	13	94	62	53	83	75	52	86	79	88	85	89	98	85	94
Tot Minorities >70%	High	5	81	92	48	61	79	53	44	69	96	90	100	43	94	72	70
HISP >70%	High	0	91	94	36	60	80	39	39	67	97	90	100	32	94	71	62
BLACK > 70%	High	79	13	95	60	52	80	72	52	90	86	92	89	92	99	92	96

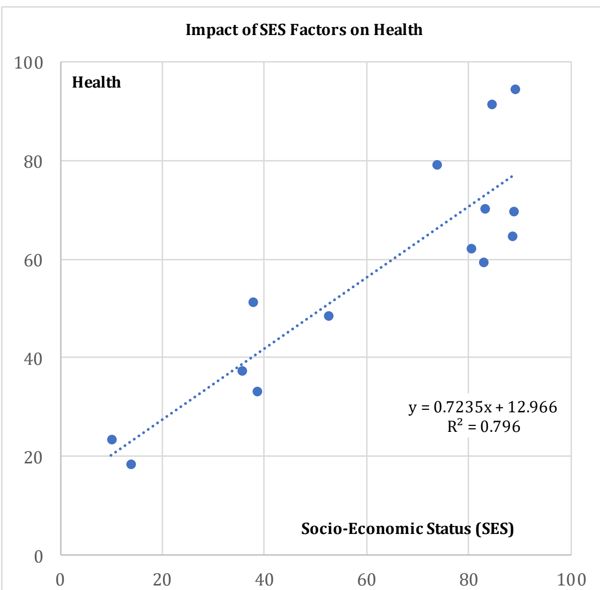
a) Low Poverty areas with < 20% population in a tract in in poverty; b) Total Minorities = All population excl. WHITE Non-Hispanics; c) High Poverty > 80% population has < 100% of Federal Poverty Income. All values are in % within USA set of values (scale 1-100)

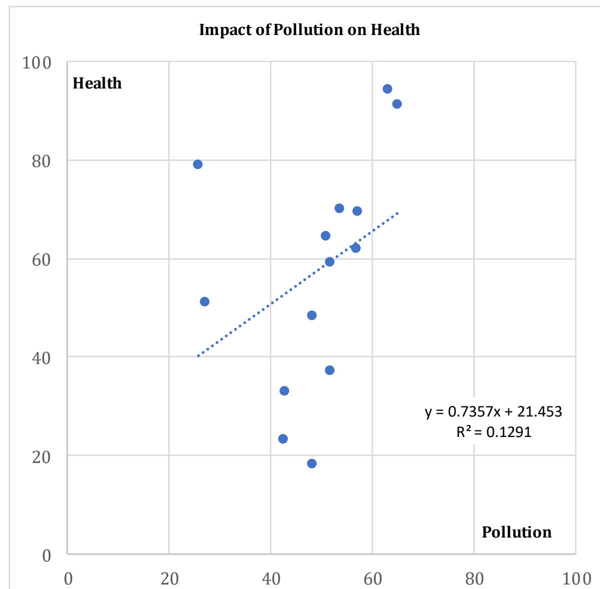
Table 4. Summary impact of poverty on prevalence of chronic diseases (equally weighted index)

Poverty prevalence	Low	Total Avg	High	Difference: Avg - Low	Difference: High - Avg
Whites > 80%	24	37	79	13	42
Total Texas	18	49	70	31	21
HISP >70%	33	59	65	26	6
Total Minorities >70%	37	62	70	25	8
BLACK > 70%	n.m.	92	95	n.m.	3

a)Low Poverty with < 20% population in poverty; b) High Poverty with > 80% population in poverty; c) Total Minorities include both Black and Hispanics in any ratio; d) There were not enough Majority Black areas with low poverty for analysis, hence n.m.

Fig. 4. Impact of SES factors and environmental pollution on population health





The majority of studies linked both air pollution and socioeconomic status to health problems, particularly among racial and ethnic minorities (Chakraborty et al., 2011; Bravo et al., 2016; Banzhaf et al., 2019a, b; Cheeseman et al., 2022; Hu et al., 2023). Our findings support this general observation; indeed, both play a role. However, researchers did not define relative priorities for those relationships to health problems, as evidenced by our findings, which show that poverty plays the most significant role in disease prevalence across all ethnic groups. Rural areas face an additional logistical disadvantage because there are 71 rural counties without a hospital, forcing local residents to travel longer distances to receive adequate regular medical care and posing a significant challenge for emergency care.

The correlation between SES and Environmental Pollution groups was also low (R2 = 0.215), which could be explained by the fact that the majority of the relatively wealthier Texas population lives in urban and suburban areas with high traffic density and thus fuel combustion emissions. Wealthy ranchers comprise only a small minority of the Texas population, with less than 200,000 people compared to the seven million urban residents of Houston and Dallas.

A pair correlation test is useful for uncovering degrees of association among various variables, as shown in Table 5. The highest correlation coefficients were found among variables within a functional group, notably among the Socioeconomic and Health Equity groups. The Hispanic community has shown a strong positive correlation with diabetes, consistent with previous findings (Rodriguez et al., 2012; Schneiderman, 2014; Shaw et al., 2018, TESSUM ET AL., 2019). Meanwhile, the Black community showed a high prevalence of asthma, consistent with prior observations (PRATT ET AL., 2015; CHAKRABORTY ET AL., 2017; DAYA & BARNES, 2019; TESSUM ET AL., 2021).

In addition, we conducted a linear multi-variable regression analysis of all four environmental pollution factors and two prominent socioeconomic factors: median household income and proximity to disadvantaged neighborhoods, as shown in Table 6. Except for the correlation between hazardous waste proximity correlation with asthma, all variables had avery high level of statistical significance at >95% confidence level. Given the very large data sample (5,224 tracts in Texas) and well-established diversity within a large state of Texas, R2 coefficients were relatively high, averaging 59% (although with a some what lower value for asthma).

Table 5. Summary of factors' pair correlations

	Ethnicity/Race		Geospatial Challenges				Environmental Pollution				Socioeconomic Challenges				Health Equity (Diseases)			
FACTORS	BLACK	HISP	TRAF	TRVL	DNBH	LINGO	NPL	HAZW	FPM	DZL	UEMPL	WHSD	PVRT	MDHI	ASTM	DBTS	HART	SHLF
(B + H)	5%	93%	37%	24%	62%	67%	33%	35%	27%	10%	34%	67%	59%	-48%	18%	55%	24%	33%
BLACK	*	-31%	8%	13%	-8%	-14%	4%	13%	5%	21%	14%	-7%	6%	-15%	50%	-13%	-16%	25%
HISP		*	33%	18%	62%	69%	30%	28%	24%	2%	27%	66%	54%	-40%	-1%	57%	28%	23%
TRAF			*	-38%	17%	37%	33%	50%	28%	63%	3%	11%	28%	-25%	3%	6%	-2%	13%
TRVL				*	32%	11%	-9%	-26%	1%	-32%	26%	48%	33%	36%	41%	45%	36%	28%
DNBH					*	45%	0%	6%	10%	-9%	30%	69%	64%	-55%	33%	68%	59%	39%
LINGO						*	9%	27%	24%	16%	21%	57%	51%	-44%	12%	43%	23%	21%
NPL							*	52%	11%	50%	10%	-5%	1%	-5%	-15%	6%	-11%	10%
HAZW								*	28%	64%	12%	4%	15%	-13%	5%	1%	-12%	11%
FPM									*	30%	3%	2%	10%	7%	-7%	-4%	-15%	-7%
DZL										*	-6%	-17%	0%	-7%	-3%	-22%	-27%	5%
UEMPL											*	33%	36%	-34%	37%	29%	21%	29%
WHSD												*	72%	-67%	46%	79%	63%	53%
PVRT													*	-76%	62%	63%	55%	49%
MDHI														*	-61%	-57%	-52%	-56%
ASTM															*	36%	42%	57%
DBTS																*	88%	47%
HART																	*	40%
SHLF																		*

FACTORS	BLACK	HISP	TRAF	TRVL	DNBH	LINGO	NPL	HAZW	FPM	DZL	UEMPL	WHSD	PVRT	MDHI	ASTM	DBTS	HART	SHLF
MAX	66%	100%	99	99	100	99	98	91	92	97	98	99	99	356	95	99	99	99
MIN	0%	0%	0	0	0	12	1	0	3	0	0	0	0	17	0	0	0	0
MEAN	8%	45%	48	53	43	65	45	34	73	34	49	58	55	102	26	63	48	53
MEDIAN	5%	40%	47	55	36	70	40	34	75	35	48	63	58	92	22	71	51	56
St. Dev	11%	29%	25	29	37	24	29	19	14	20	27	31	28	44	20	30	30	25
Stdev/Mean	1.26	0.64	0.53	0.55	0.87	0.37	0.65	0.57	0.19	0.58	0.56	0.52	0.52	0.43	0.78	0.47	0.63	0.48

Table 6. Linear multi-variable regression analysis (Source: Authors' own research work)

	Average of 3 diseases		Asthma		Diabetes		Heart	
	Coefficients	P-Signif.	Coefficients	P-Signif.	Coefficients	P-Signif.	Coefficients	P-Signif.
DZL	-0.058	***	0.127	***	-0.238	***	-0.155	***
HAZW	-0.125	***	-0.035	**	-0.107	***	-0.232	***
NPL	0.071	***	-0.029	***	0.157	***	0.059	***
FPM	-0.065	***	0.033	***	-0.077	***	-0.144	***
TRAF	-0.149	***	-0.121	***	-0.060	***	-0.115	***
MDHI	-0.099	***	-0.265	***	-0.184	***	-0.163	***
DNBH	0.183	***	0.097	***	0.435	***	0.310	***
R^2	58%		41%		59%		59%	

Proximity to disadvantaged neighborhoods was found to have the strongest association with a higher prevalence of all diseases. Proximity to the US EPA-designated toxic superfund sites (NPL) was also associated with higher levels of disease. The proximity to smaller hazardous waste sites (HAZW), as well as the amount of diesel particles in the air (DZL), were not among the contributors.

A natural limitation of our study and most other "point of time" studies is the unknown length of residence of the impacted population in a given polluted area. Such data is not captured by the US Census surveys, which are conducted once every 10 years on the overall national scale. This unknown factor is very important, as environmental pollution has clearly a cumulative (albeit non-linear) impact with a length of exposure to toxic substances (Josey et al., 2023, Errisuriz et al., 2024).

5. Conclusions

The study screened demographic profiles using US Census data to identify the distribution of majority ethnic population tracts across Texas, taking into account regional differences in population density and ethnic composition. The ethnic diversity within the state is extremely important for demographic analysis, with Texas Hispanic communities concentrated along the southwest border and significant populations of Blacks and Asians concentrated in the far east part of Texas, closer to the Louisiana border.

The study used datasets on community geospatial factors, personal socioeconomic status (SES), environmental burden, and health outcomes. The proposed research framework focused on the relationship between three groups of independent variables: the prevalence of minority populations, their SES, proximity to pollution sources, and prevalence of chronic diseases. The results showed that Hispanic-majority and particularly Black-majority communities had disproportionately negative health impacts compared to other racial/ethnic groups as a result of environmental pollution and socioeconomic challenges. In addition, poverty prevalence was shown to play a significant role in defining health disparities across all racial/ethnic groups.

Our analysis confirmed thata higher ethnic/racial minority percentage (Hispanic and/or Black population) in a Census tract is positively associated with closer proximity to environmental pollution sources, with statistical confidence above 95%. Closer proximity to environmental pollution sourcesis positively associated with a higher prevalence of diseases among community members. This correlation was valid for three out of four environmental factors, except for the traffic volume factor, which showed a weaker correlation. Closer proximity of environmentally disadvantaged neighborhoods is positively associated with a higher prevalence of diseases among the population in a tract, with statistical confidence above 95%. This association was particularly high for diabetes and heart diseases.

Pair correlation tests revealed significant relationships between multiple factors, particularly within socioeconomic and health equity groups of variables. Multivariable regression analysis uncovered substantial associations between environmental pollutants, socioeconomic characteristics, and health outcomes, emphasizing the interdependence of factors influencing health equality in Texas.

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