HAZARD REDUCTION
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ASSOCIATION OF HISTORICAL REDLINING AND SVI(SOCIAL VULNERABILITY INDEX) WITH CANCER-RELATED HOSPITAL UTILIZATION: IN THE CASE OF TEXAS, US

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BACKGROUND AND PURPOSE

Why Studying environmental inequalities and health disparities?

- Environmental inequalities often serve as a catalyst for public health disparities, with the burden felt disproportionately by socially vulnerable populations. Understanding the intricate interplay between environmental factors and social vulnerability in affecting health outcomes can guide the development of informed policy interventions and public health strategies.

In southeast Texas, there are increasing concern over **environmental sustainability and public health**. A growing body of evidence suggests that disparities in environmental conditions can amplify existing health disparities, further burdening those who are already marginalized. Within this context, **gaining a comprehensive understanding of the intricate interplay between environmental factors and social vulnerability** becomes paramount, as it plays a pivotal role in shaping health outcomes within communities. By fostering a deeper understanding of these issues, we aim to **pave the way for more informed and effective policy interventions and public health strategies** that can help mitigate these disparities and promote equitable health for all.

Purpose: Investigating the relationships between social vulnerability indicators, environmental risk factors, and cancer-related hospital utilization, and examining how these factors interact with each other

METHOD

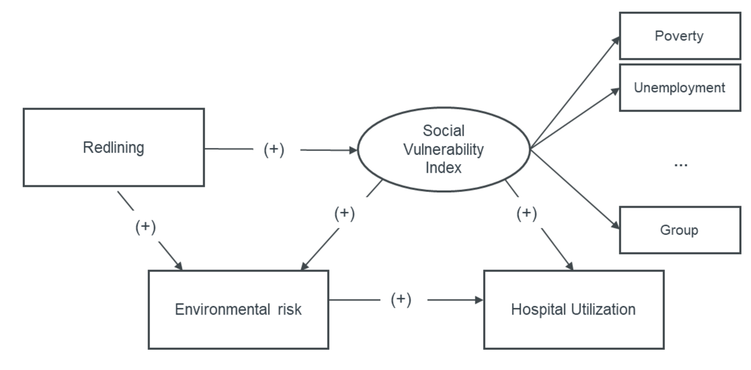
SEM(Structural Equation Model) for Texas state during 2011-2022 as ZCTA Level

- Path analysis: Structural equation modeling (SEM) to analyze the relationships among latent variables—specifically, "Redlining," "SVI," "Environmental Risk," and "Hospital Utilization"—using observable manifest variables.
- Spatial Regression Analysis: To explore the spatial relationships between redlining and other variables, the study employed Ordinary Least Squares (OLS), Spatial Lag Model (SLM), and Spatial Error Model (SEM) to account for spatial autocorrelation in the data.

Variable

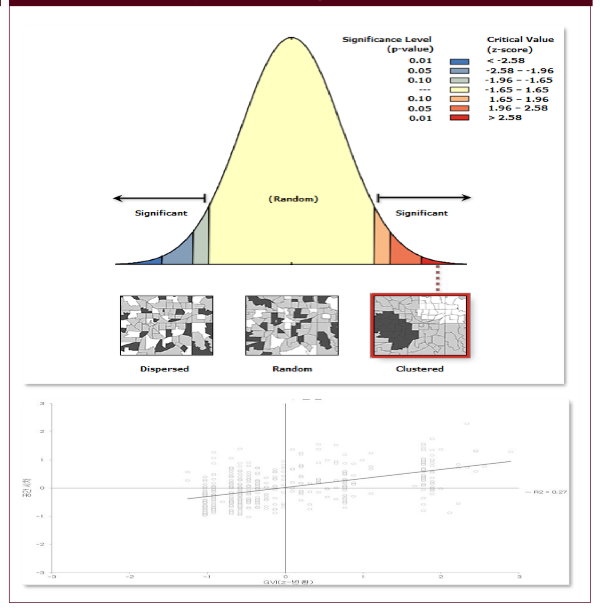
Hospital utilization	Retrieving patient ratio which had Neoplasms as a principle diagnose based on ICD-10-CM (C00-D49) from Texas Health and Human service as Health
SVI	Calculated by ranking each census tract on 16 census variables into four themes from the CDC/ATSDR SVI database.
Environmental Risk	Evaluated using the RSEI model, which calculates risk. Aggregate grid to ZCTA Level
Redlining	Calculated by determining the proportion of land area in a zip code that was designated as hazardous (Type D)

Path analysis



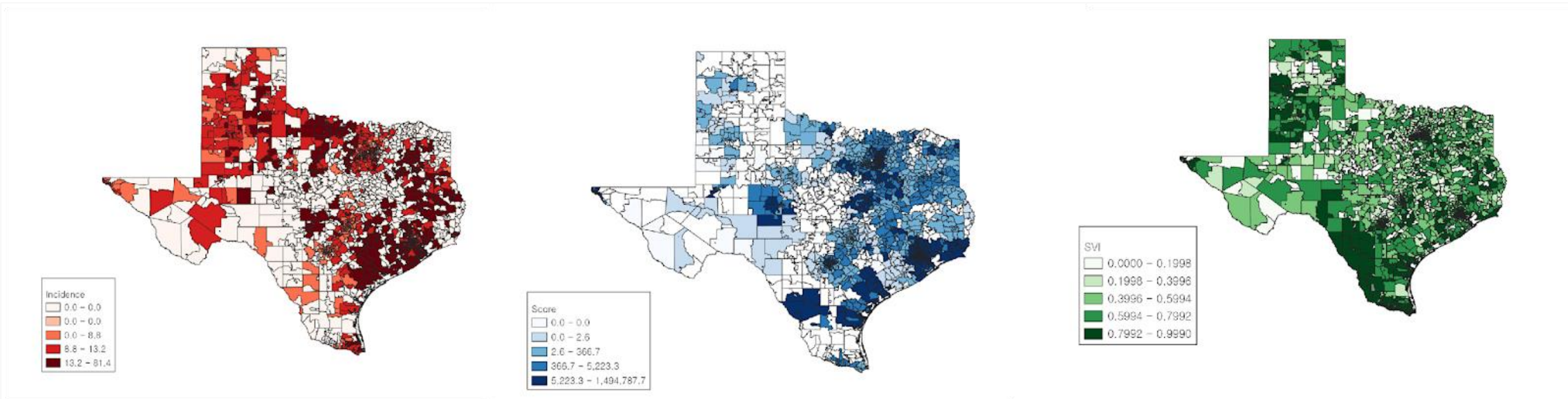
- Path model 1 – Environmental risk, hospital utilization and SVI in TX (n=1,935)
- Path model 2 – Including redlining for Model 2 in TX (n=1,935)
- Path model 3 – Only for 18 counties having a redlining (n=608)

Spatial Regression



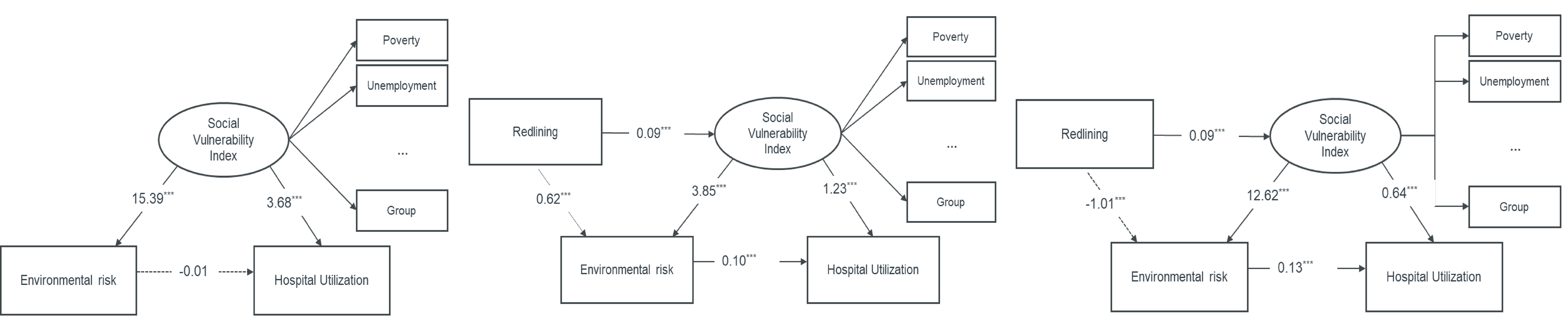
RESULTS

Spatial distribution of hospital utilization(left), Environmental risk(middle) and SVI(right)



- Hospital utilization demonstrated a relatively even distribution with notable concentrations in the central, southeast, and northwest regions.
- Environmental risks were predominantly elevated in major urban areas located in the southeastern part of the state.
- The spatial representation of the SVI indicated variability across different areas, with some regions showing higher vulnerability than others.

Conceptual framework for Path model 1, 2, and 3



- **Path Model 1** demonstrated a positive association between SVI and environmental risk [β (SE): 15.39 (0.95)], and between SVI and hospital utilization [0.27 (0.30)], with no significant direct link between environmental risk and hospital utilization [−0.01 (0.01)], suggesting SVI mediates this relationship.
- **Path Model 2** extended this by including redlining, revealing positive associations between redlining and environmental risk [β (SE): 0.62 (0.15)] and SVI [0.09 (0.01)], and direct links from both environmental risk [0.10 (0.01)] and SVI [1.23 (0.29)] to hospital utilization. This model highlighted how historical redlining exacerbates both environmental risks and social vulnerabilities, thereby increasing healthcare demands.
- **Path Model 3** focused on historically redlined regions, finding an inverse association between redlining and environmental risk [β (SE): −1.01 (0.36)], and strong positive associations between SVI and environmental risk [12.62 (2.79)], and between both environmental risk [0.09 (0.01)] and SVI [0.64 (0.13)] with hospital utilization. This suggests that in redlined areas, SVI significantly impacts environmental risks and hospital utilization, despite a localized reduction in environmental risk due to redlining.

Spatial Regression (N = 1,915)

		Environmental risk		Hospital Utilization		SVI
		SVI	Redlining	Environmental risk	SVI	Redlining
OLS	Coef	6.56***	0.09***	0.20***	0.08***	0.10***
	R2	0.46		0.56		0.37
	Log likelihood	-3756.09		-1207.42		94.5
SLM	Coef	6.20***	0.15***	0.19***	0.08	0.08***
	R2	0.51		0.61		0.4
	Log likelihood	-3687.01		-1126.17		141.63
	Likelihood ratio	138.14		577.81		94.27
SEM	Coef	6.48***	0.16***	0.22***	0.18***	0.08***
	R2	0.53		0.69		0.4
	Log likelihood	-3672.38		-918.51		-131.48
	Likelihood ratio	167.40***		535.39		73.95

DISCUSSIONS

This study investigated the direct and indirect relationships between environmental risk, cancer-related hospital utilization, SVI, and historical redlining in Texas for the year 2020. Using ZCTA as the unit of analysis, the research explored interactions among these factors. The findings revealed that historical redlining significantly influences both hospital utilization and environmental risk. Path analysis models showed that SVI is a crucial factor, strongly associated with environmental risk and hospital utilization. In areas with a history of redlining, SVI positively correlated with environmental risk and hospital utilization, highlighting the long-lasting impact of discriminatory policies. While SVI directly affected hospital utilization, the direct effect of environmental risk on hospital visits was less pronounced and likely mediated by SVI. Spatial regression analysis confirmed these relationships, underscoring the importance of spatial dependencies.

NEXT STEPS

The findings from this study underscore the need for addressing social vulnerabilities and the enduring impacts of historical redlining to mitigate environmental risks and improve health outcomes. Future research will focus on exploring the temporal dynamics of these relationships by conducting longitudinal studies. This approach will provide a deeper understanding of how environmental risks, social vulnerabilities, and hospital utilization evolve over time. To further investigate health disparities, we will employ spatial regression and Bayesian models, specifically examining different types of cancer. These advanced modeling techniques will help identify the explanatory power of environmental and social factors in influencing health outcomes.

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