

The impact of smoking prevalence on the spatial relationship between lung cancer screening access and mortality across U.S. counties

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Short Report

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Abstract

Background

Lung cancer is the leading cause of cancer death in the United States, yet uptake of low-dose computed tomography screening remains low. Geographic access to screening facilities is a recognized barrier, but the spatial relationship between screening-center distribution and lung cancer mortality burden has not been formally quantified.

Methods

We conducted a cross-sectional spatial analysis linking 2024 American College of Radiology Designated Lung Cancer Screening Centers with 2018–2022 age-adjusted lung cancer mortality and 2023 CDC PLACES smoking prevalence across 2701 U.S. counties. We used bivariate mapping to identify facility and mortality clusters, and a multivariable Spatial Error Model (SEM) to evaluate the independent association between population-standardized facility density and mortality, adjusting for spatial autocorrelation, smoking prevalence, and rurality.

Results

Bivariate mapping identified Low Facility–High Mortality clusters concentrated in the Southeast and Appalachia. However, spatial regression revealed this ecological pattern was primarily driven by geographic disparities in smoking prevalence (Estimate = 2.04, $p < 0.001$) and rurality. After adjustment, population-standardized screening facility density was not a statistically significant independent predictor of lung cancer mortality (Estimate = 0.28, $p = 0.109$).

Conclusions

The spatial mismatch between screening facilities and lung cancer mortality is heavily confounded by regional smoking prevalence. Needs-based screening expansion must be integrated with comprehensive smoking cessation programs to effectively reduce geographic mortality disparities.

Highlights

- Lung cancer screening access varies geographically across U.S. counties.
- High-mortality counties often had fewer nearby screening centers.
- Screening deserts clustered in the Southeast and Appalachia.
- Spatial mismatch maps may guide screening infrastructure planning.

Introduction

Lung cancer is the leading cause of US cancer death, yet only 4.5% of eligible adults received low-dose computed tomography (LDCT) screening in 2022.^{1–3} Geographic access to screening facilities is a recognized barrier to uptake,^{4,5} but the degree to which facility distribution is geospatially aligned with disease burden has not been formally quantified at the national level. Because such misalignment could limit the public health impact of screening where preventable deaths are highest, we evaluated the spatial alignment between county-level ACR-designated Lung Cancer Screening Centers and county-level lung cancer mortality in the United States.

Materials and Methods

This cross-sectional spatial analysis linked 2 publicly available data sources: the 2024 American College of Radiology (ACR) Designated Lung Cancer Screening Center (LCSC) registry⁶ and age-adjusted lung cancer mortality rates (2018–2022) from CDC WONDER,⁷ aggregated across 2701 U.S. counties. Counties classified as topological islands (lacking contiguous neighbors) were excluded to ensure geospatial continuity.

To properly define screening access and account for population distributions, raw facility counts were converted into a population-standardized facility density metric (facilities per 100,000 residents) using 2023 US Census Bureau county-level population estimates. Furthermore, to address potential unmeasured confounding in the spatial relationship between screening infrastructure and lung cancer mortality, we incorporated county-level age-adjusted current cigarette smoking prevalence from the 2023 CDC PLACES dataset, alongside 2023 Rural-Urban Continuum Codes. Because ecological analyses often suffer from spatially autocorrelated errors, a multivariable Spatial Error Model (SEM) was fitted using the spatialreg package in R. The SEM evaluated whether population-standardized facility density was independently associated with age-adjusted lung cancer mortality, after controlling for spatial dependence, smoking prevalence, and county urbanicity. The primary spatial analytic method was bivariate Moran's I, a geospatial autocorrelation statistic that quantifies the degree to which 2 variables co-vary across geographic space. Global bivariate Moran's I was computed with 999 permutations to generate a pseudo-P value. Local Indicators of Spatial Association (BiLISA) identified county-level clusters classified into 4 types: High Facility–Low Mortality, Low Facility–High Mortality, High–High, and Low–Low. Bivariate choropleth mapping used Fisher-Jenks natural breaks classification. Analyses were performed in R version 4.4.1 (R Foundation) using the spdep and spatialreg packages. This study used only deidentified, publicly available aggregate data and was exempt from institutional review board review. This study followed the STROBE reporting guideline.

Results and Discussion

When standardizing screening access by population, the previously observed raw spatial correlation between facility count and mortality was attenuated ($r = 0.005$, $p = 0.77$) (Figs. 1A and 1B). Bivariate

mapping (Fig. 1C) and BiLISA cluster mapping (Fig. 1D) still identified distinct geographic clusters; however, multivariable spatial regression revealed that these ecological patterns were primarily driven by underlying geographic disparities in risk factors rather than physical access to screening facilities alone. In the Spatial Error Model (SEM), which successfully accounted for significant spatial autocorrelation ($\text{Lambda} = 0.51, p < 0.001$), county-level smoking prevalence was a highly significant, independent predictor of lung cancer mortality (Estimate = 2.04, $p < 0.001$). Urban county status was also significantly associated with mortality (Estimate = 0.99, $p = 0.007$). Crucially, after adjusting for these covariates, population-standardized facility density was no longer a statistically significant predictor of lung cancer mortality (Estimate = 0.28, $p = 0.109$).

In this national geospatial analysis, county-level screening infrastructure was inversely correlated with county-level lung cancer mortality. Many high-mortality counties were located in areas with relatively few ACR-designated screening centers, suggesting that access to screening infrastructure may be more limited in regions where the potential population benefit of screening is greatest. To our knowledge, this study provides the first national bivariate geospatial assessment of this misalignment.

Previous studies have documented differences in screening uptake by race, socioeconomic position and access to care^{1,9} as well as individual-level barriers including insurance status, provider recommendation, and health literacy.¹⁰ Our findings add a structural dimension to this evidence by suggesting that the geographic distribution of screening infrastructure may itself be misaligned with areas of higher mortality burden. This misalignment may contribute to transportation burden, fragmented referral pathways, and lower access to screening in rural and underserved communities.^{4,5}

The attenuation of the spatial association between screening facility density and mortality after adjusting for smoking prevalence highlights a critical nuance in cancer control planning. Our findings suggest that simply building new screening centers may not be sufficient to close geographic mortality gaps if deployed in isolation. While physical access is necessary, the lack of an independent statistical association in the multivariable model underscores that structural disparities in mortality are heavily influenced by a combination of high regional smoking prevalence and complex downstream factors. These include variations in the clinical stage at diagnosis, financial toxicity, and patient adherence to follow-up survivorship care.

This study is subject to several limitations. First, as a cross-sectional ecological analysis, the observed county-level associations cannot be directly translated to individual-level screening access or behaviors (the ecological fallacy). Second, we utilized lung cancer mortality data from 2018–2022 alongside screening facility data from 2024. This temporal misalignment may underestimate the current alignment of screening infrastructure, as new facilities may have recently opened in historically underserved areas. Finally, our access metric relies on county-level facility density rather than precise spatial accessibility measures, such as travel time or floating catchment areas, which may obscure highly localized disparities in access.

Consequently, screening initiatives must be deeply integrated with comprehensive smoking cessation programs. As smoking remains the most powerful driver of lung cancer mortality, concurrent investments in both prevention and early detection are essential to achieve equitable, population-level reductions in lung cancer burden.

Declarations

Author Contributions: Concept and design: Zhang, Hochhegger. Acquisition, analysis, or interpretation of data: Zhang, Capellan, Menezes, Ohannesian, Braithwaite. Drafting of the manuscript: Zhang. Critical review of the manuscript for important intellectual content: Capellan, Menezes, Ohannesian, Braithwaite, Hochhegger. Statistical analysis: Zhang, Capellan. Supervision: Hochhegger.

Conflict of Interest Disclosures: Not applicable.

Ethics approval: Not applicable.

Consent to participate: Not applicable

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Written Consent for publication

Data Access, Responsibility, and Analysis: I had full access to all the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. Dr Zhang conducted and is responsible for the data analysis. All data was retrieved by public available datasets.

Code availability: No applicable.

Authors' contributions: J.M.F.Z. and B.H. conceptualized the study. J.M.F.Z., J.C., I.R.M., V.A.O., and D.B. conducted the methodology, formal analysis, and investigation. J.M.F.Z. wrote the main manuscript text. J.C., I.R.M., V.A.O., D.B., and B.H. reviewed and edited the manuscript. B.H. supervised the study. All authors reviewed the manuscript.

Written Consent for publication: Not applicable.

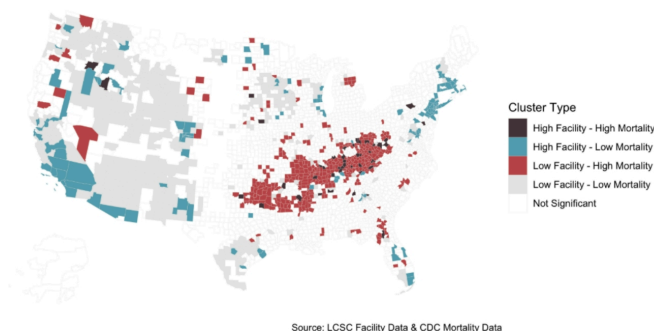
Additional Contributions: We thank the American College of Radiology (ACR) for maintaining the public Lung Cancer Screening Center registry used in this analysis. No compensation was received for these contributions.

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Figures

Spatial Inequity in Lung Cancer Screening Access
Significant Bivariate Clusters ($p < 0.05$)



LCSC Facilities and Lung Cancer Mortality by County

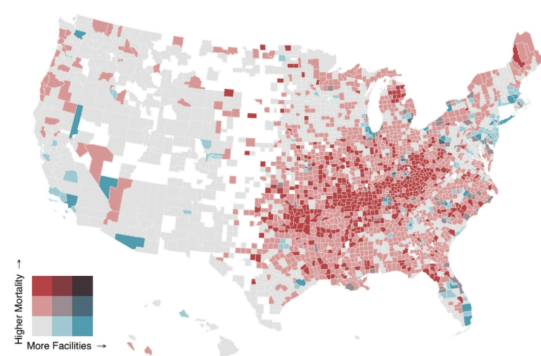


Figure 1

Geospatial Distribution of Screening Access and Lung Cancer Outcomes. Figure 1A shows population-standardized American College of Radiology (ACR)-designated Lung Cancer Screening Center density (facilities per 100,000 residents) across U.S. counties. Figure 1B shows county-level age-adjusted lung cancer mortality rates per 100,000 (2018–2022). Figure 1C is a bivariate choropleth map showing the joint spatial distribution of screening center density and lung cancer mortality using Fisher-Jenks natural breaks. Figure 1D is a Local Indicators of Spatial Association (BiLISA) cluster map identifying statistically significant bivariate clusters, where red indicates Low Facility–High Mortality areas and blue indicates High Facility–Low Mortality areas.