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Posted Date: 24 February 2026

doi: 10.20944/preprints202602.0954.v1

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Spatiotemporal Modeling of Premature Mortality in Mississippi: A County-Level YPLL Analysis, 2015–2025 County Health Ranking Release

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Abstract

Introduction This study examines spatiotemporal trends in premature mortality across Mississippi's 82 counties (2015–2025) using Years of Potential Life Lost (YPLL) before age 75. **Methods** County-level YPLL rates were drawn from County Health Rankings & Roadmaps (2015–2025 releases; underlying deaths ≈2012–2023). Trends were compared with U.S. averages, stratified by education, income, and insurance status, mapped via GIS, analyzed for spatial clustering with LISA, and modeled using spatial lag panel regression with year fixed effects. **Results** Mississippi's YPLL rate rose 35.2% (10,918 to 14,764 per 100,000), far outpacing national trends and widening the state–U.S. gap by ~50%. Contrary to expectation, the largest increases occurred in high-education, high-income, low-uninsured (mostly urban/coastal) counties. High-High clusters intensified in the rural Delta/River counties, while Low-Low clusters vanished from urban and coastal areas. Spatial lag models showed strong spatial dependence ($\varrho \approx 0.32$); injury deaths ($\beta = 58.2$, $p < .001$), percent non-Hispanic Black, and paradoxically higher median income were key drivers. **Conclusion** Mississippi's premature mortality crisis has shifted: rural burdens persist, but rapid deterioration in urban and more affluent counties now drives statewide worsening. Effective policy requires sustained rural investment in chronic disease control alongside urgent urban-focused interventions targeting injury and violence prevention, trauma systems, and mental health/substance-use services.

Keywords: premature mortality; years of potential life lost; Mississippi; spatial analysis; geographic mapping; health status disparities; socioeconomic factors; rural population; urban population

Introduction

Years of Potential Life Lost (YPLL) before age 75 is a public health metric that measures premature mortality by summing years lost when deaths occur before a reference age, assigning greater weight to deaths at younger ages [1]. Unlike crude or age-adjusted mortality rates, YPLL emphasizes preventable causes, chronic diseases, injuries, violence, and substance use, that disproportionately affect working-age populations and impose substantial social and economic costs [2,3]. Its interpretability has made it valuable for prioritizing interventions and quantifying health disparities [4,5].

Mississippi consistently ranks among the worst states for premature mortality, exhibiting a "southern mortality penalty" 20–30% above national averages [6]. As of 2024–2025, the state's YPLL rate exceeds 14,000 per 100,000, far surpassing the U.S. average, driven by cardiovascular disease, cancer, injuries, and widening racial inequities, particularly among non-Hispanic Black residents [7,8]. Despite this persistent burden, no published study has applied spatiotemporal analytic frameworks to examine county-level YPLL trends across Mississippi's 82 counties. National and regional analyses have identified broad patterns [9–11], but they cannot inform state-specific resource allocation or reveal local shifts in clustering and drivers.

The primary objective of this study is to quantify spatiotemporal disparities and trends in YPLL across Mississippi counties from 2015 to 2025 using County Health Rankings & Roadmaps data. Secondary objectives include comparing state and national trajectories, identifying socioeconomic and demographic predictors of elevated YPLL, mapping evolving spatial clusters, and deriving targeted policy recommendations for rural and urban contexts. By filling the gap in state-focused spatiotemporal analysis, this work provides actionable evidence for Mississippi policymakers responsible for health planning, budget allocation, and disparity reduction.

Methods

Data Sources and Measures

This secondary analysis used county-level data from the 2015–2025 releases of County Health Rankings & Roadmaps (CHR&R), a program of the University of Wisconsin Population Health Institute that compiles indicators from multiple national sources, including National Center for Health Statistics mortality files (via CDC WONDER), Behavioral Risk Factor Surveillance System, U.S. Census Bureau American Community Survey, and others [13,14]. Detailed methodology and data sources are available at www.countyhealthrankings.org/health-data/methodology-and-sources. Because the data are publicly available and de-identified, institutional review board approval was not required.

The primary outcome was Years of Potential Life Lost before age 75 (YPLL-75) per 100,000 population, sourced directly from CHR&R. YPLL estimates are calculated from underlying death records as three-year rolling averages, with suppression applied when fewer than 10 deaths occur. Due to processing and reporting lags, the 2015–2025 releases reflect mortality occurring approximately 2012–2023. Mississippi's 82 counties were compared with contemporaneous national YPLL values from the same CHR&R releases.

Covariates included continuous county-level measures of health behaviors (e.g., adult smoking, physical inactivity), clinical care (e.g., uninsured rate, primary care physician ratio), social and economic factors (e.g., median household income, high school graduation rate, children in poverty), and physical environment (e.g., air pollution particulate matter, access to healthy foods). All variables were standardized across releases through harmonization of naming, units, and definitions to enable longitudinal analysis.

For subgroup analyses, 11 key socioeconomic indicators were dichotomized annually within each release year separately for Mississippi counties and all non-Mississippi U.S. counties. Cutpoints were set at the median of non-missing values within each stratum, creating comparable "high" and "low" groups that accounted for temporal and distributional differences between Mississippi and the rest of the nation.

GIS Mapping and Spatial Analysis

Geographic Information Systems (GIS) mapping was conducted using Python's geopandas and matplotlib libraries to visualize longitudinal spatial patterns of YPLL across Mississippi's counties. Choropleth maps were generated with Jenks natural breaks classification to highlight geographic disparities [15]. Spatial dependence was assessed using global Moran's I to test for geographical clustering of YPLL rates, implemented via the PySAL library's esda module [12,16]. Local Indicators of Spatial Association (LISA) were calculated to identify high- and low-YPLL clusters, with significance set at $p < .05$. Spatial weights were defined using queen contiguity to account for shared county boundaries, computed with PySAL's libpysal module [17].

Local Spatial Autocorrelation Analysis

Local Indicators of Spatial Association (LISA) were computed annually (2015–2025 releases) using Anselin's Local Moran's I to identify statistically significant clusters of YPLL (12). Year-specific

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analyses were conducted because the underlying three-year rolling mortality averages provided stable estimates for annual inference.

Queen contiguity weights (shared border or vertex) were created and row-standardized with libpysal. Significance was assessed via 999 random permutations ($p < 0.05$). Counties were classified as:

High-High (HH): counties with above-average YPLL surrounded by neighboring counties that also have above-average YPLL (core hotspots)

Low-Low (LL): counties with below-average YPLL surrounded by neighbors with below-average YPLL (low-burden clusters)

High-Low (HL) and Low-High (LH): spatial outliers

Not significant: no significant clustering

Maps for each year were generated in Python using geopandas, matplotlib, and contextily (CartoDB Positron basemap) with 2023 TIGER/Line county boundaries (500 k resolution). A pooled LISA analysis across all 2015–2025 data produced nearly identical clustering patterns, confirming the robustness and temporal stability of the observed spatial disparities. All analyses were performed using pandas, geopandas, libpysal, and esda.

Spatial Lag Regression Model with Temporal Fixed Effects

To assess spatial and temporal clustering in premature mortality (measured as years of potential life lost, YPLL), we estimated a spatial autoregressive lag model (SAR) with year fixed effects [17,18]:

$$y_{it} = \rho \sum_{j} w_{ij} y_{jt} + X_i \beta + \gamma_t + \epsilon_{it}, \epsilon_{it} \sim \mathcal{N}(0, \sigma^2)$$

where:

- y_{it} is the YPLL in county i at time t (2015–2025),
- ρ is the spatial autoregressive coefficient,
- w_{ij} are elements of a row-standardized Queen contiguity weights matrix W (shared boundary or vertex) constructed using libpysal,
- $\sum_j w_{ij} y_{jt}$ is the spatially lagged dependent variable (average YPLL in neighboring counties at time t),
- X_i is a vector of time-invariant, standardized county-level covariates (adult smoking, diabetes prevalence, injury deaths, percent non-Hispanic Black, percent aged 65 and older, uninsured adults, median household income),
- β are regression coefficients,
- γ_t are year-specific dummy variables (fixed effects) to capture temporal trends and shocks, with 2015 as the reference year,
- ϵ_{it} is the idiosyncratic error.

The model was fit using maximum likelihood estimation via the spreg.ML_Lag function in Python's PySpatial package, with robust standard errors. The spatial lag term accounts for endogenous spatial dependence, while year dummies flexibly model non-linear temporal effects, including the abrupt mortality increase observed in 2021–2024. The significance of ρ was tested using a likelihood ratio test against a non-spatial pooled OLS model with year fixed effects. Model performance was evaluated using pseudo-R^2, AIC, and Moran's I on residuals to assess remaining spatial autocorrelation.

Multilevel and Subgroup Analyses

Longitudinal YPLL trends were modeled using mixed-effects linear regression (statsmodels, Python) with county-level random intercepts and fixed effects for year (linear and quadratic terms). Separate models were fitted for Mississippi and non-Mississippi counties to compare trajectories.

Subgroup analyses examined disparities in the most recent period (2023–2025 releases). Using the 22 subgroups defined by the previously described dichotomization procedure, mean YPLL was

 doi:10.20944/preprints202602.0954.v1

calculated for Mississippi and non-Mississippi counties within each subgroup. Absolute differences were tested with two-sample Welch's t-tests (unequal variances), and effect sizes were reported as Cohen's d. All analyses were performed in Python 3.11 using pandas, numpy, and scipy.stats.

Results

Longitudinal Trends in YPLL

County-level Years of Potential Life Lost (YPLL) rates in Mississippi were consistently higher than the national average (Table 1). Mississippi's YPLL rate increased from 10,918.3 per 100,000 in 2015 to 14,763.9 in 2025 (35.2% increase), compared to a national rise from 7,892.0 to 10,275.6 (30.2%). The gap widened from 3,026.3 to 4,488.3 (48.3% increase), with a temporary narrowing in 2019–2020 (2,932.6). Multilevel mixed-effects models confirmed Mississippi's steeper YPLL increase. For Mississippi (901 observations, 82 counties), the quadratic model showed a baseline YPLL of 11,160.9 (SE = 263.1, $p < .001$), with significant upward curvature (year_centered^2: $\beta = 56.0$, 95% CI [47.1, 64.8], $p < .001$), fitting better than the linear model (log-likelihood: -7,799.1 vs. -7,872.1). For non-Mississippi counties (32,980 observations, 3,027 counties), the quadratic model (intercept = 8,018.6, $p < .001$; year_centered^2: $\beta = 28.9$, $p < .001$) also fit better (log-likelihood: -285,100.0 vs. -285,905.7), with a likelihood ratio test statistic of 1,611.4 ($p < .001$). The bigger regression coefficients of Mississippi in Year and Year^2 suggested greater increase during recent years, which may be impacted from factors like COVID-19 or injury death [19].

Subgroup Analyses

Subgroup analysis from the 2023–2025 County Health Rankings releases revealed consistently and significantly higher premature mortality in Mississippi counties compared to non-Mississippi counties across nearly all socioeconomic and demographic subgroups (Table 2). All 22 subgroups with sufficient sample size showed significantly higher YPLL in Mississippi (all $p < .0001$), with Cohen's d ranging from 0.85 to 2.22 (median d = 1.26), indicating large to very large effect sizes. The largest disparities were observed in subgroups that are typically protective in the rest of the U.S.: % children in poverty (low), median household income (high), % some college (high), % Non-Hispanic Black (high), % population ≥65 years (high), and % uninsured children (low).

Choropleth Mapping and Local Indicators of Spatial Association (LISA)

Choropleth maps showed evolving YPLL disparities across Mississippi's 82 counties (Figure 1). In 2015, no counties displayed extreme (red) YPLL rates. By 2018, the Delta region (northwest) and Mississippi River counties (southwest) showed emerging red hues, with other areas trending red. In 2022, the Delta became a "red hot" hotspot (YPLL > 13,000), while by 2025, it turned "dark red" (YPLL ~14,763.9), with the entire state approaching red. Global Moran's I, using the Lagrange Multiplier (LM) lag test statistic via PySAL's esda module, showed significant spatial autocorrelation in 2015–2017 and 2021–2022 ($p < .05$), but weaker/insignificant autocorrelation in 2018–2020, 2023–2025.

Local Indicators of Spatial Association (LISA) analysis identified significant clustering patterns across Mississippi. Figure 2 illustrates the temporal evolution of Local Indicators of Spatial Association (LISA) clustering patterns for YPLL across Mississippi's 82 counties, highlighting marked shifts between the 2015 and 2025 County Health Rankings releases. High-High (HH) clusters increased from 12 counties in 2015 to 21 counties in 2025, with growth concentrated in the Delta and Mississippi River regions. New additions to the HH category include Adams, Claiborne, Leflore, Yazoo, Franklin, Tallahatchie, and Carroll. Meanwhile, Low-Low (LL) clusters declined from 31 counties to just 12, as several central and coastal counties, such as Hinds, Forrest, Monroe, and Chickasaw, transitioned out of LL status. This shift reflects a growing spatial concentration of high values in historically underserved areas, while previously low-performing clusters, particularly in urban and coastal zones, have become more mixed or statistically non-significant.

doi:10.20944/preprints202602.0954.v1

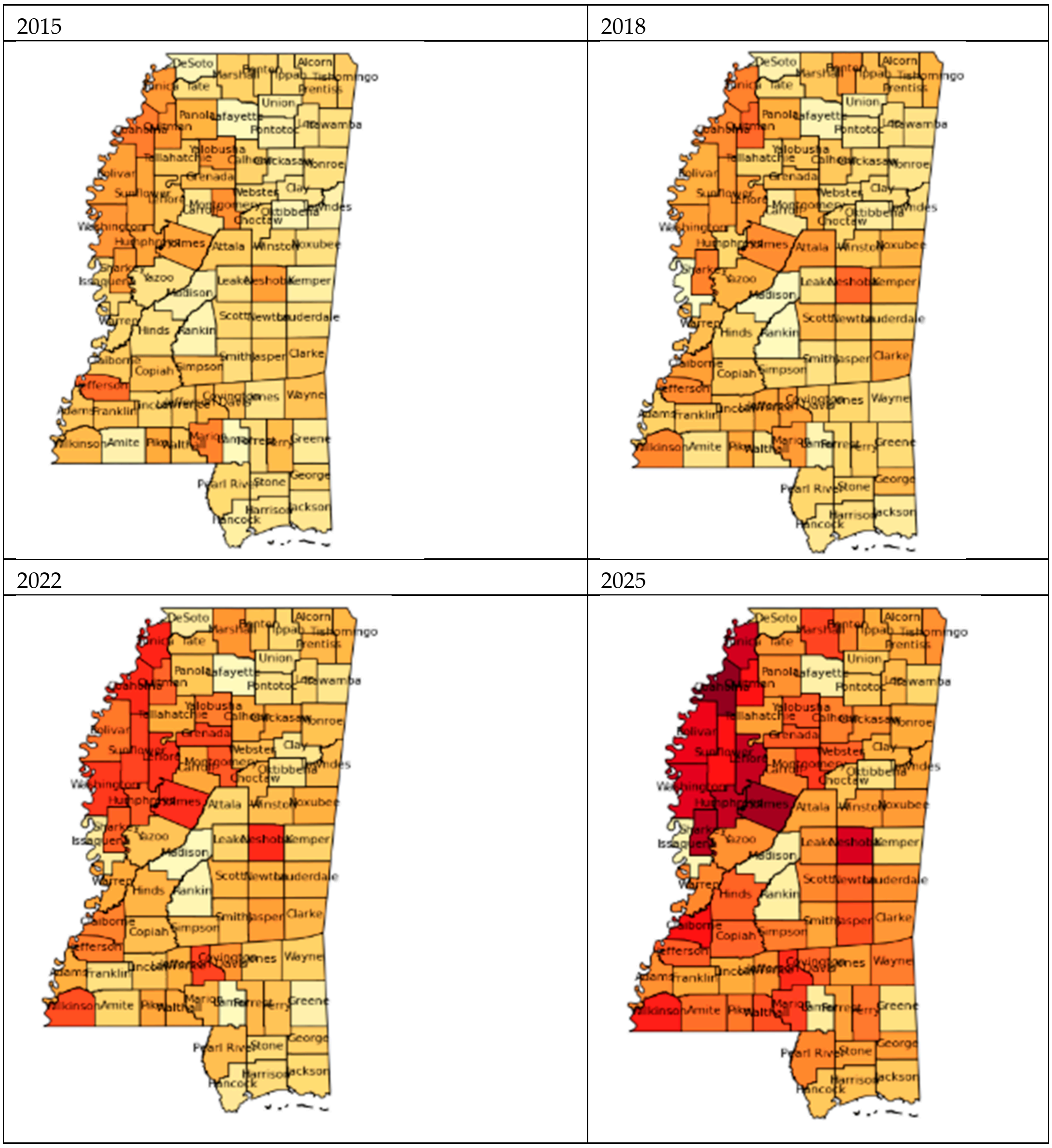

Figure 1. Choropleth map of YPLL rates (2015, 2018, 2022, 2025 release). Note: Colors represent YPLL rates per 100,000 using Jenks natural breaks classification; higher rates in red tones indicate hotspots (e.g., Delta region).

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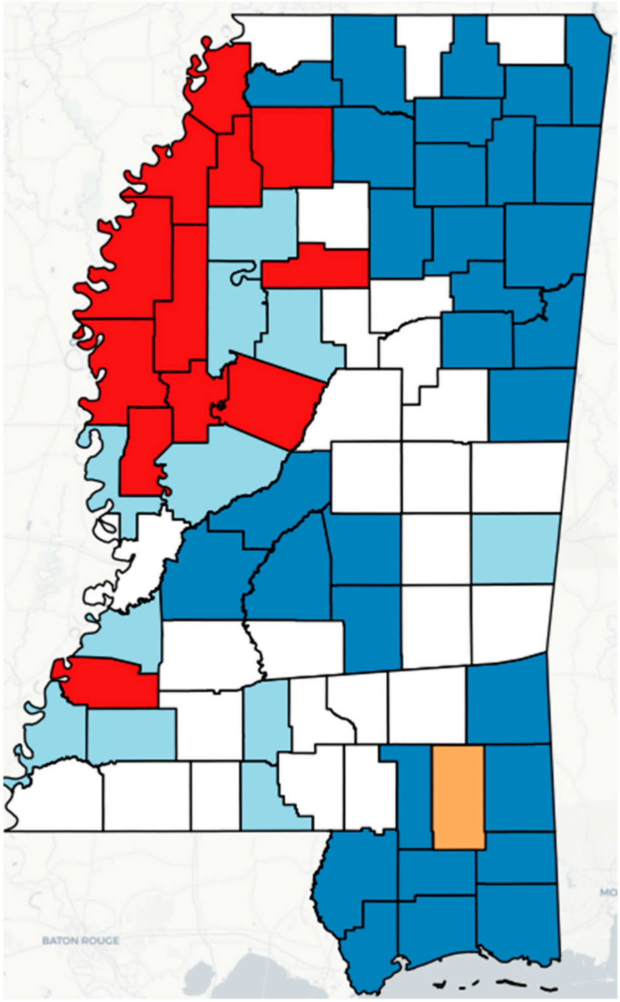

 doi:10.20944/preprints202602.0954.v1

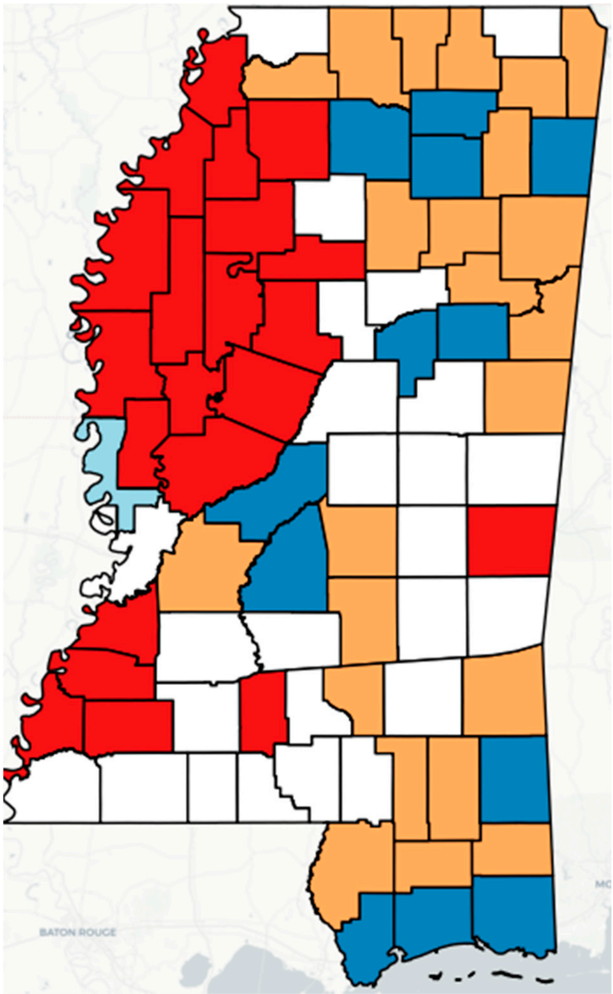

Figure 2. LISA cluster map of YPLL rates (2015 vs. 2025 release). Note: HH (High-High): Counties with high YPLL surrounded by high YPLL counties (hotspots, red); LL (Low-Low): Counties with low YPLL surrounded by low YPLL counties (coldspots, blue); LH (Low-High): Counties with low YPLL surrounded by high YPLL counties (spatial outliers, light blue); HL (High-Low): Counties with high YPLL surrounded by low YPLL counties (spatial outliers, orange); Non-significant: Areas with no significant clustering (gray, $p \geq 0.05$). Significance based on 999 permutations ($p < 0.05$).

Determinants of YPLL from Spatial Lag Modeling

Table 3 reports maximum-likelihood spatial lag (SAR) model estimates of premature mortality (YPLL) for Mississippi counties, 2015–2025 (2015 omitted as reference year). The model shows a sharp, highly significant rise in YPLL starting in 2022 and continuing thereafter (2025: $\beta = 3{,}457.57$, $p < 0.001$; 2024: $\beta = 3{,}017.40$, $p < 0.001$; 2023: $\beta = 1{,}713.12$, $p < 0.001$; 2022: $\beta = 1{,}676.80$, $p < 0.001$), indicating a substantial increase in premature mortality in the pandemic period.

Statistically significant predictors ($p < 0.01$) include injury deaths ($\beta = 58.93$, $p < 0.001$), diabetes prevalence ($\beta = 9{,}124.93$, $p < 0.001$), percentage of Non-Hispanic Black residents ($\beta = 2{,}129.58$, $p < 0.001$), percentage aged 65 and older ($\beta = -10{,}460.82$, $p < 0.001$), and median household income ($\beta = -0.07$, $p < 0.001$). Adult smoking ($\beta = 3{,}500.30$, $p = 0.146$) and uninsured adults ($\beta = -4{,}159.89$, $p = 0.108$) are not statistically significant at conventional levels.

The spatial lag coefficient is positive and highly significant ($\rho = 0.32$, $p < 0.001$), confirming strong spatial dependence: counties with elevated YPLL are clustered together, reinforcing geographic disparities. The model demonstrates strong explanatory power (Pseudo $R^2 = 0.749$; N = 901 county-year observations).

Table 1. YPLL rates for Mississippi and US, with gap (2015–2025 releases).

 doi:10.20944/preprints202602.0954.v1

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
US	7892.0	7928.0	7959.9	8072.0	8404.2	8455.2	8416.9	8814.1	8814.1	9737.0	10275.6
MS	10918.3	11013.0	11063.6	11377.2	11447.7	11387.8	11521.5	12519.7	12519.7	14020.7	14763.9
Gap	3026.3	3085.1	3103.7	3305.1	3043.5	2932.6	3104.5	3705.7	3705.7	4283.7	4488.3

Note: Gap = US YPLL minus Mississippi YPLL.

Table 2. Subgroup Analysis of YPLL Differences Between Mississippi and Non-Mississippi Counties, 2023–2025.

	Mississippi			Non-Mississippi				
Subgroup	Mean	SD	n	Mean	SD	n	Diff (MS – non-MS)*	Cohen's d
Children in poverty (low)	12187.0	2346.5	125	7640.4	2037.5	4528	4546.6	2.22
Median household income (high)	12290.0	2503.2	123	7769.8	2171.8	4500	4520.2	2.07
Some college (high)	12932.4	3083.7	123	8011.3	2472.1	4447	4921.1	1.98
% Non-Hispanic Black (high)	15162.5	3340.7	123	10001.1	3051.8	4559	5161.3	1.69
% Population ≥65 years (high)	14194.7	2533.7	123	9641.6	3060.6	4446	4553.0	1.49
Uninsured children (low)	14358.1	3656.5	123	9298.9	3418.5	4562	5059.2	1.48
Uninsured adults (low)	13078.4	3234.9	123	8636.2	3045.0	4515	4442.3	1.46
Unemployment rate (low)	12447.9	2429.0	123	8638.2	2984.3	4459	3809.7	1.28
% Non-Hispanic White (high)	12554.6	2463.4	123	8979.6	2830.9	4477	3575.0	1.27
Unemployment rate (high)	15088.3	3391.4	123	10560.6	3575.9	4553	4527.7	1.27
% Population <18 years (low)	13118.0	2724.8	123	9358.1	2998.7	4498	3759.9	1.26
High school graduation (low)	14324.3	3202.0	134	9733.0	3696.8	5492	4591.2	1.25
High school graduation (high)	13102.7	3143.8	112	9416.5	2967.0	3520	3686.1	1.24
% Non-Hispanic White (low)	14981.6	3446.5	123	10231.2	3839.3	4535	4750.4	1.24
% Population <18 years (high)	14418.1	3555.1	123	9859.8	3801.8	4514	4558.3	1.20
Children in poverty (high)	15401.4	3206.3	121	11597.7	3411.0	4484	3803.7	1.12
Median household income (low)	15246.1	3200.7	123	11444.1	3479.0	4512	3802.1	1.10
Uninsured adults (high)	14457.8	3080.9	123	10586.6	3523.3	4497	3871.2	1.10
% Population ≥65 years (low)	13341.5	3758.8	123	9578.0	3761.5	4566	3763.5	1.00
Some college (low)	14603.8	3162.0	123	11166.2	3522.9	4565	3437.6	0.98
Uninsured children (high)	13178.1	2616.0	123	9927.7	3420.1	4450	3250.4	0.96
% Non-Hispanic Black (low)	12373.7	2415.6	123	9208.4	3742.8	4453	3165.4	0.85

*P-value for all mean differences were <0.0001.

Table 3. Regression Coefficients for Predictors of YPLL in Mississippi Counties, 2015–2025 (Spatial Lag Model with Additional Variables).

Variable	Coefficient	Std. Error	P-value
Constant	3798.27	1333.83	0.004**
Year Effects (2016)	392.33	223.03	0.079
Year Effects (2017)	115.66	229.18	0.614
Year Effects (2018)	295.43	257.76	0.252
Year Effects (2019)	382.16	274.31	0.164
Year Effects (2020)	300.73	272.6	0.27
Year Effects (2021)	363.08	285.98	0.204
Year Effects (2022)	1676.8	271.61	<0.001***
Year Effects (2023)	1713.12	284.68	<0.001***
Year Effects (2024)	3017.4	300.04	<0.001***
Year Effects (2025)	3457.57	325.74	<0.001***
Adult Smoking	3500.3	2408.96	0.146
Diabetes Prevalence	9124.93	2357.81	<0.001***
Injury Deaths	58.93	2.77	<0.001***
% Non-Hispanic Black	2129.58	395.94	<0.001***
% 65 and Older	-10460.82	2189.73	<0.001***
Uninsured Adults	-4159.89	2587.97	0.108
Median Household Income	-0.07	0.01	<0.001***
Spatial Lag (W_YPLL)	0.32	0.05	<0.001***

Notes: *** p<0.01, ** p<0.05, * p<0.10; Dependent variable: Years of Potential Life Lost (YPLL); N = 901 observations (82 Mississippi counties × 11 years, 2015–2025); Reference year: 2015 (omitted); Spatial lag coefficient (ϱ) = 0.32 ($p < 0.001$); Pseudo $R^2 = 0.749$.

Discussion

This study documents a profound and accelerating divergence in premature mortality between Mississippi and the rest of the United States. Over the 2015–2025 County Health Rankings releases, Mississippi's age-standardized YPLL rate increased 35.2%, from approximately 10,918 to 14,764 per 100,000, substantially outpacing the national rise of 30.2% and widening the state–U.S. gap by nearly 50%. Multilevel mixed-effects models confirmed not only a steeper linear trend but also a pronounced quadratic acceleration in Mississippi, consistent with the disruptive impact of the COVID-19 pandemic and a simultaneous surge in injury-related deaths [20,21].

Subgroup analyses for the most recent period (2023–2025 releases) revealed that Mississippi counties exhibited significantly higher YPLL across all 22 socioeconomic and demographic strata, with effect sizes ranging from large to very large (Cohen's d > 0.8–1.5 in most cases). Strikingly, the largest absolute and relative excesses occurred in subgroups traditionally considered protective: low child poverty, high median household income, high postsecondary education, and low uninsured rates. These findings demonstrate a near-complete flattening of the social gradient in health within Mississippi—socioeconomic advantage confers dramatically less mortality protection than in the rest of the nation [22,23]. At the same time, historically marginalized subgroups—particularly those with high proportions of non-Hispanic Black residents and older adults—continued to bear extreme burdens, reflecting the enduring consequences of structural racism, residential segregation, and chronic disinvestment in the Mississippi Delta [24–26].

Local Indicators of Spatial Association (LISA) revealed two concurrent and geographically contrasting phenomena. First, High-High (HH) clusters, counties with elevated YPLL surrounded by similarly high-burden neighbors, nearly doubled from 12 to 21, consolidating along the rural Mississippi Delta and River counties. These areas, among the poorest and most racially segregated in the United States, have long suffered from limited healthcare infrastructure, high comorbidity burdens (diabetes, hypertension, obesity), and, during 2020–2022, some of the nation's highest COVID-19 case-fatality rates [26,27]. Second, Low-Low (LL) clusters collapsed from 31 to 12 counties, as previously low-mortality urban and coastal areas, most notably Hinds (Jackson), Harrison (Gulfport-Biloxi), Rankin, and Forrest counties, experienced rapid deterioration. This erosion of former "bright spots" signals an emerging urban mortality penalty driven predominantly by firearm-related homicide and suicide (disproportionately affecting young Black men), motor-vehicle fatalities, opioid and polysubstance overdoses, and lingering excess COVID-19 mortality among working-age adults.

The spatial lag panel model confirms strong geographic dependence ($\varrho = 0.32$, $p < 0.001$; Pseudo $R^2 = 0.749$). Injury deaths are by far the strongest predictor ($\beta = 58.93$, $p < 0.001$), followed by diabetes prevalence ($\beta = 9{,}124.93$, $p < 0.001$) and percentage of Non-Hispanic Black residents ($\beta = 2{,}129.58$, $p < 0.001$). Higher median household income ($\beta = -0.07$, $p < 0.001$) and a larger share of residents aged 65 and older ($\beta = -10{,}460.82$, $p < 0.001$) are associated with lower YPLL. Adult smoking and uninsured rates were not significant in this specification. Year fixed effects for 2022–2025 show a large pandemic increase in premature mortality, while the significant spatial lag term underscores spillover effects that amplify disparities across neighboring counties.

In summary, Mississippi's worsening premature mortality reflects a lethal and self-reinforcing combination of several interlocking forces: a dramatic surge in injury-related deaths (especially firearm homicide, suicide, motor-vehicle crashes, and drug overdoses) that emerged as the single most powerful predictor in the spatial lag model; a deeply entrenched diabetes burden that continues to exact an enormous toll, particularly in the Delta; persistent racial inequities that place counties with higher proportions of Non-Hispanic Black residents at significantly greater risk even after extensive controls; and strong spatial contagion ($\varrho = 0.32$, $p < 0.001$) that causes high-mortality

 doi:10.20944/preprints202602.0954.v1

counties to pull their neighbors upward through spillover effects. These drivers have collectively overwhelmed the protective effects traditionally conferred by higher income, education, and insurance coverage, effects that remain robust elsewhere in the United States but have been almost completely neutralized within Mississippi. As a result, previously low-mortality urban and suburban counties have rapidly deteriorated, erasing former “bright spots” and transforming them into new hotspots of preventable early death, while long-standing High-High clusters in the rural Delta have further intensified. The convergence of these structural, behavioral, and geographic forces has produced a statewide mortality crisis that is both broader and more geographically pervasive than at any point in the past decade.

Strengths and Limitations

Key strengths of this study include the integration of complementary longitudinal, spatial, and stratified analytic approaches within a single, fully reproducible open-source Python/Geopandas/PySAL workflow that can be readily updated with each annual County Health Rankings & Roadmaps (CHR&R) release. The use of 11 consecutive years of consistently defined, policy-relevant county-level indicators permitted robust detection of both gradual trends and abrupt pandemic shifts. The combination of multilevel trend models, detailed subgroup stratification across 22 socioeconomic and demographic domains, Local Indicators of Spatial Association (LISA) for cluster evolution, and a formal spatial lag panel regression provided convergent evidence from multiple methodological perspectives. Finally, the county-level resolution and explicit mapping of changing hot- and cold-spots offer actionable geographic targeting for Mississippi-specific interventions.

Despite these strengths, study included some limitations primarily inherent to the CHR&R data ecosystem. First, YPLL and most covariates reflect deaths and conditions that occurred 2–4 years before the release year (e.g., 2025 estimates primarily capture 2021–2023 mortality), introducing a systematic lag that may underestimate the most recent injury-death surges or delay detection of potential reversals. Second, several behavioral and socioeconomic covariates (e.g., adult smoking, uninsured rate) are model-based small-area estimates or periodic survey measures with varying reference periods and precision, potentially attenuating associations during periods of rapid change. Third, county-level aggregation obscures substantial within-county heterogeneity, especially in larger urban counties such as Hinds and Harrison. Fourth, the global spatial autoregressive (SAR) specification assumes a single, homogeneous spatial dependence parameter (ϱ) across the state, does not allow coefficients to vary spatially, and cannot simultaneously incorporate multilevel random effects for counties and years. Ongoing work is directly addressing this constraint by comparing the current SAR results with Bayesian hierarchical spatiotemporal models (e.g., BYM2 and space–time separable specifications implemented in INLA and PyMC) that permit spatially varying coefficients, explicit county- and year-level random effects, and fuller propagation of uncertainty: approaches expected to refine geographic targeting and uncertainty quantification in future iterations of this surveillance system. Finally, as with any ecological analysis, individual-level causal inference is not possible.

Policy Implications

Mississippi can no longer rely on a monolithic rural-focused strategy. The Delta and River counties continue to require long-term investment in primary care expansion (especially FQHCs), chronic disease management, broadband-enabled telehealth, and social determinants (housing, nutrition, education). Simultaneously, urban and coastal counties demand immediate, evidence-based interventions targeting the preventable drivers now dominating their YPLL increases: hospital- and community-based violence interruption programs, focused deterrence, enhanced trauma systems, expansion of crisis response and mental health services, and comprehensive traffic safety measures. The fact that even Mississippi’s most educated, insured, and affluent counties dramatically exceed national YPLL benchmarks underscores systemic failures, underfunded emergency and behavioral-health infrastructure, racial inequities in service access, and insufficient political prioritization, that blunt the protective effects seen elsewhere. Targeted, data-driven resource allocation guided by these spatial and subgroup findings is essential to reverse the state's worsening trajectory.

Conclusion

Between 2015 and 2025 release, Mississippi transformed from a state with longstanding rural premature-mortality hotspots to one where preventable early death has diffused across virtually all socioeconomic strata and geographic settings. The persistence and intensification of Delta High-High clusters alongside the abrupt disappearance of urban/coastal Low-Low clusters illustrate how structural inequities and new preventable-death drivers, injury, violence, and behavioral-health crises, interact with place. Reversing this crisis will require bold, equity-centered, and geographically nuanced policies that confront both historic disinvestment in rural Black communities and the emerging urban penalty now claiming thousands of additional potential years of life annually.

Summary Box

What is already known on this topic? Mississippi has long exhibited a "southern mortality penalty," with premature mortality (YPLL) rates 20–30% above national averages, driven primarily by chronic disease and socioeconomic disadvantage concentrated in rural Delta counties.

What is added by this report? This is the first spatiotemporal county-level analysis (2015–2025) showing that Mississippi's YPLL crisis has dramatically worsened and shifted: rural High-High clusters have intensified while former urban/coastal Low-Low clusters have collapsed, producing the largest disparities in socioeconomically advantaged counties and strong spatial dependence dominated by injury deaths.

What are the implications for public health practice? Mississippi requires a dual-track strategy: continued rural investment in chronic disease control alongside urgent urban/coastal interventions targeting violence prevention, trauma systems, and behavioral-health services, with data-driven geographic targeting to reverse the state's accelerating premature mortality burden.

Author Contributions: Dr. Jae Eun Lee conceived and designed the study, performed all spatial analyses (including GIS mapping, LISA clustering, choropleth mapping, and spatial lag panel regression), conducted the primary modeling, created all figures and tables, and drafted the manuscript. Dr. Junghye Sung acquired and harmonized the data, performed the statistical analyses, interpreted the results, and drafted and critically revised the manuscript for important intellectual content. Dr. Ji-Young Lee interpreted the results, helped draft the manuscript and critically revised it for important intellectual content. Drs. Barner, Offiah, and Hays helped draft the manuscript and critically revised it for important intellectual content. All authors reviewed and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

Acknowledgments: The authors declare no potential conflicts of interest with respect to the research, authorship, or publication of this article. The authors received no external financial support for the research, authorship, or publication of this article. No copyrighted material, surveys, instruments, or tools were used in the research described in this article.

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