



Original Article

Dynamics of Covid-19 mortality and social determinants of health: a spatiotemporal analysis of exceedance probabilities

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ARTICLE INFO

Article history:

Received 1 September 2020

Revised 13 April 2021

Accepted 17 May 2021

Available online 25 May 2021

Keywords:

Bayesian Analysis

Disparity

Education

Hotspots

Infectious Disease

Residential Segregation

ABSTRACT

Purpose: To determine the association of social factors with Covid-19 mortality and identify high-risk clusters.

Methods: Data on Covid-19 deaths across 3,108 contiguous U.S. counties from the Johns Hopkins University and social determinants of health (SDoH) data from the County Health Ranking and the Bureau of Labor Statistics were fitted to Bayesian semi-parametric spatiotemporal Negative Binomial models, and 95% credible intervals (CrI) of incidence rate ratios (IRR) were used to assess the associations. Exceedance probabilities were used for detecting clusters.

Results: As of October 31, 2020, the median mortality rate was 40.05 per 100,000. The monthly urban mortality rates increased with unemployment ($IRR_{adjusted}: 1.41$, 95% CrI: 1.24, 1.60), percent Black population ($IRR_{adjusted}: 1.05$, 95% CrI: 1.04, 1.07), and residential segregation ($IRR_{adjusted}: 1.03$, 95% CrI: 1.02, 1.04). The rural monthly mortality rates increased with percent female population ($IRR_{adjusted}: 1.17$, 95% CrI: 1.11, 1.24) and percent Black population ($IRR_{adjusted}: 1.07$, 95% CrI: 1.06, 1.08). Higher college education rates were associated with decreased mortality rates in rural and urban counties. The dynamics of exceedance probabilities detected the shifts of high-risk clusters from the Northeast to Southern and Midwestern counties.

Conclusions: Spatiotemporal analyses enabled the inclusion of unobserved latent risk factors and aid in scientifically grounded decision-making at a granular level.

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Introduction

According to the Johns Hopkins University (JHU) data dashboard [1], as of April 13, 2020, more than 31 million people have been infected and almost 562,000 have died from the novel sars-coronavirus-2 (Covid-19) in the U.S. While Covid-19 has been termed a social equalizer [2], it has disproportionately impacted

Blacks and other minorities. About 13% of the U.S. population is Black [3]. However, 52% of the Covid-19 infections and 58% Covid-19 related deaths occurred in the Black population [4]. The Covid-19 positivity rate among the Latino population, the group with historically low insurance and healthcare utilization rates [5], was 40% in Baltimore-DC area [6], and counties with a higher percentage of the Latino population had increased Covid-19 infection rates [7].

World Health Organization (WHO) defines SDoH as the “conditions in which people are born, grow, live, work, and age” [8]. The healthypeople.gov [9] emphasized the five domains of SDoH that impact health: 1. Economic Stability, 2. Education, 3. Social and Community Context, 4. Health and Health Care, and 5. Neighborhood and Built Environment. A large body of evidence [10] has linked social factors such as income level, education, and work conditions to adverse health outcomes. These factors disproportionately affect minorities [11], placing them at high risk of Covid-

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

Conflict of interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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19 infection and mortality [4,7]. Clinically it has been postulated that the stress levels due to low socioeconomic status, social inequalities, and unhealthy behaviors increase cytokine interleukin-6 (IL-6) and immune system dysfunction, which trigger Covid-19 complications [12].

The transmission of most infectious diseases depends on space and time [13]. Spatiotemporal research methods for infectious diseases can be broadly classified into [14]: space-time statistical modeling [15] and spatial transmission dynamic modeling [16]. The first approach addresses the dynamics of disease clusters, while the latter provides a plausible experimental system to understand the mechanisms in which the hosts and their movement patterns in space and time contribute to disease transmission.

The majority of the quantitative research on SDoH and Covid-19 has focused on racial and ethnic disparities [4,17,18]. While researchers studied the spatial associations of SDoH with Covid-19 mortality [94], there is a lack of understanding about the spatiotemporal dynamics of Covid-19 and how it relates to social factors, which is important for state and county-level resource allocations and safe operations of schools and businesses. There are limited research [19–22] on the spatiotemporal cluster analysis of Covid-19. A recently published study [20] considered Social Vulnerability Indices (SVI) but did not consider differential effects of rurality on SVI. In the U.S., rural/urban residence status creates major healthcare access and health outcomes disparities [23]. The Covid-19 pandemic that started in urban communities has now spread to rural communities [22]. Rural areas lack ventilators and ICU beds [24] and often face challenges with healthcare workforce retention [25]. Rural residents are at greater risk of obesity and chronic diseases due to aging and lack of exercise, nutritional food, education, income [26,27], and preventive care [28]. All of these factors place rural areas at a significant disadvantage for fighting the Covid-19 infection.

The U.S. spends 18% of its GDP on healthcare but among the 11 industrialized countries, it ranks last on healthcare outcomes and equity [29]. Lack of investment in social sectors has contributed to health inequities [30] and structural disparities leading to poor health outcomes, especially among the vulnerable communities.

The objectives of this study were

1) to determine via spatio-temporal analysis, the association of county-level SDoH variables with county-level Covid-19 mortality rates, and 2) to detect the temporal shifts of high-risk mortality clusters in urban and rural counties via estimated county-level standardized mortality ratios (SMR) and exceedance probabilities.

Materials and methods

We used monthly counts (for $T = 7$ months, April through October 2020) of county-level Covid-19 deaths from $N = 3, 108$ counties and county-equivalents across the 48 contiguous U.S. states and District of Columbia obtained from the JHU repository [31] as our outcome measure. The 2019 County-level population estimates from the U.S. Census Bureau [32] were used for calculating SMRs.

We defined SDoH based on its five domains [33]. SDoH variables were obtained from the 2020 estimates of the County Health Rankings and Roadmaps (CHRR) [34,35].

Neighborhood and Built Environment: The *percent population under severe housing cost and residential segregation* were considered. County-level percent of the population under severe housing cost represents the proportion of households that spent at least half of their income on housing between 2014 and 2018. County-level residential segregation, ranging from 0 to 100, with low and high values indicating integration and segregation, respectively, represents the index of dissimilarity between Blacks and Whites.

Economic Stability: The county-level unemployment rates, percent of uninsured individuals, and income inequality ratio, defined as the ratio of average household income at the 80th percentile compared to the 20th percentile, were included.

Education: Most recent county-level estimates of the percent of the population with a college or associate degree were extracted from the Economic Research Services of the U.S. Department of Agriculture (USDA) [36].

Social and Community Context: The county-level data on the percent of individuals aged 65 years and older, the percent of the non-Hispanic Black population, and the percentage of females were extracted from the 2018 U.S. Census Bureau data [34].

Health and Healthcare: Health and healthcare were defined using six county-level measures extracted from the CHRR [37] – percents in frequent physical and mental distress during the past 30 days, diabetes and obesity percentages, and HIV (per million) rates, and percent of adult smokers.

Rural/Urban Designation: Counties were defined as either rural or urban using the Rural-Urban Commuting Area (RUCA) codes [38] based on 2010 Census data. Counties identified as either rural, small-town, or micropolitan low commuting were defined as rural while metropolitan and micropolitan area core and high commuting were defined as urban counties.

Statistical analyses

Crude mortality rates (CMR), SMR, medians, and interquartile ranges for all independent variables by rural or urban designation of the counties were computed. The chance of getting infected increases with population density. Thus, a binary variable indicating rural or urban designation was used as an effect modifier. Time series plots of CMRs and maps of SMRs were used for exploratory examination of the mortality trends. Mann-Whitney U tests [39] were used to assess differences in the independent variables across rural and urban counties.

Due to multicollinearity, we used the variance inflation factor [40], stepwise selection procedure [41], and Watanabe Akaike Information Criteria (WAIC) [43] to decide the independent variables for the final adjusted model. Lower values of WAIC indicate a better fit.

Denoting by $y(s_i, t)$ the total number of deaths from Covid-19 in the i^{th} county over month t , we assumed a Poisson distribution for $y(s_i, t)$ with mean parameter $\mu(s_i, t)\omega(s_i, t)$. Subsequently, a Gamma distribution with shape and rate parameters τ was assumed for $\omega(s_i, t)$. Integrating out $\omega(s_i, t)$ will result in a Negative Binomial distribution for $y(s_i, t)$ with overdispersion parameter $\mu^2(s_i, t)/\tau$. The mean parameters, $\mu(s_i, t)$, were modeled using a set of county-specific independent variables, X_i , a set of basis functions K_i specified using county centroids (see supplementary document), a set of regression coefficients, β , an autoregressive random walk process of order one, v_t , and spatio-temporal random effects, $\varepsilon(s_i, t)$ as:

$$\log(\mu(s_i, t)) = \log(E(s_i, t)) + \beta X_i + v_t K_i + \varepsilon(s_i, t),$$

$$i = 1, \dots, N; t = 1, \dots, T, \quad (1)$$

where, $E(s_i, t)$, the expected count was used as an offset term and obtained by multiplying the total population of the i^{th} county by the overall mortality rate of t^{th} month for all counties; SMR for the i^{th} county at month t was obtained by $y(s_i, t)/E(s_i, t)$. The spatio-temporal random effects terms, $\{\varepsilon(s_i, t), I = 1, \dots, N, t = 1, \dots, T\}$, were assumed to follow independently and identically distributed zero-mean Gaussian distribution with variance σ^2 . One can interpret this as a nugget variance. Spatial covariances modeled via basis functions provide better flexibility and predictive power compared to traditional spatial conditional autoregressive models for areal data [42].

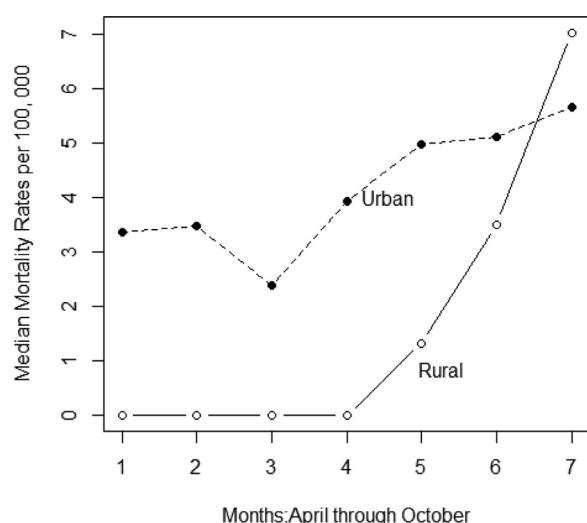


Fig. 1. Monthly median county-level crude mortality rates per 100,000 population.

Our spatiotemporal model described in Eq. (1) decomposes a spatiotemporal process into two parts, a systematic component, which is a function of independent variables that accounts for the large-scale variations, and the random component that takes into account the small-scale variations over space and time. Bayesian analyses require prior distributions on all parameters. We used mostly noninformative priors, such as zero-mean Gaussian priors with variance 10^5 on regression coefficients β . Inverse Gamma priors were used for variance parameters with shape and scale parameters as 0.001 and 0.001, respectively. Bayesian models were fitted using Integrated Laplace Approximation (INLA) [43] in Linux operating systems. We used R/RStudio version 4.0.3 [44], and R-INLA [43] and Semipar [95] packages. An independent variable was considered to be substantially influential if the 95% credible interval (CrI) of the corresponding IRR (exponentiated β) did not include one.

Independent variables that we considered in Eq. (1) are estimates based on census data, they are prone to uncertainties. We conducted sensitivity analyses using Berkson [45] measurement error type models on independent variables that are based on population estimates to assess the bias in incidence risk ratio estimates. The details are provided in the supplementary document.

County-level exceedance probabilities [22] of 50% excess from the expected mortality rates were calculated and used for identifying spatial clusters of high-risk counties and monitoring the dynamic shifts of these clusters over the seven-month study period. SMRs and exceedance probabilities were mapped in ArcGIS Pro-Desktop version 10.8 [46].

Results

Our descriptive analyses started with observing the median CMRs of urban and rural counties from April through October 2020 (Fig. 1). The median CMR for urban counties was 3.36 per 100,000 in April and increased to 5.66 per 100,000 by the end of October 2020. The median CMR for rural counties remained at 0 per 100,000 till July, and then it increased at a steeper rate to 7.02 per 100,000 by the end of October 2020.

Our inferential analyses started with comparing SDoH variables across rural and urban counties using Mann-Whitney U tests (Table 1). We found that percent of the severe housing cost burden, residential segregation, percent of the Black population, and HIV rates per million were significantly higher in urban counties. Rural counties had a significantly higher older population above

65 years of age, obesity rates, percent uninsured, frequent physical and mental distress, diabetes rates, and percent of adult smokers (Table 1).

Under the unadjusted models, all independent variables turned out to be substantially associated with Covid-19 mortality rates. For a 5% increase in the percent under severe housing cost burden, in rural counties, the mortality increased by 13.4% ($IRR_{unadjusted} = 1.13$, 95% CrI = 1.10, 1.17) and in urban counties, the mortality increased by 17.6% ($IRR_{unadjusted} = 1.18$, 95% CrI = 1.14, 1.21). The percent of people in frequent mental and physical distress, obesity rates, and percent of adult smokers were substantially associated with increased mortality rates. However, they were dropped in the adjusted model due to multicollinearity.

In the adjusted analyses, a 5 units increase in the residential segregation index, in urban counties, increased the monthly Covid-19 mortality rate by 3.4% ($IRR_{adjusted} = 1.03$, 95% CrI = 1.02, 1.04), whereas, for a 5% increase in the unemployment rates and percent of uninsured population, the monthly mortality rate increased by 41% ($IRR_{adjusted} = 1.41$, 95% CrI = 1.24, 1.60) and 9% ($IRR_{adjusted} = 1.09$, 95% CrI = 1.04, 1.13). In rural counties, for a 5% increase in uninsured population, the monthly mortality rate increased by 22% ($IRR_{adjusted} = 1.22$, 95% CrI = 1.18, 1.26) and for a 5% increase in older population above 65 years, we noticed mortality rate decreased by 5% ($IRR_{adjusted} = 0.95$, 95% CrI = 0.93, 0.98).

Monthly Covid-19 mortality rates in urban and rural counties substantially decreased (20% in urban and 8% in rural counties) with a 5% increase in the rates of college education and associate degrees, whereas, for a 5% increase in the Black population, both in urban and rural counties, the monthly rates increased by 5% ($IRR_{adjusted} = 1.05$, 95% CrI = 1.04, 1.07) and 7% ($IRR_{adjusted} = 1.07$, 95% CrI = 1.06, 1.08), respectively. Diabetes, percent of the female population, and HIV rates were also associated with elevated Covid-19 mortality rates in both urban and rural counties. Our sensitivity analysis using Berkson error type models indicated that under the assumption of an average 95% margin of error of $\pm 1\%$, there is no substantial impact on the incidence risk ratio estimates (see Table S1 in the supplementary document).

The county-level SMRs and exceedance probabilities of SMR to be greater than 50% helped in identifying clusters of counties with high mortality rates (Figs. 2 and 3). In April, mortality rates were higher in northeastern counties including New York City, southeastern Michigan that includes Detroit, and southern counties of Louisiana. In May and June, mortality rates started increasing in rural and southern counties. From July onwards, while the high-risk clusters in the northeast and New York cleared up, new clusters started appearing in the southern states of Texas, Louisiana, Georgia, and Florida. Finally, in September and October, the high-risk clusters started appearing in Midwest counties of North and South Dakotas (Figs. 2 and 3).

Discussion

The spatio-temporal analyses presented in this article revealed the dynamics of the Covid-19 severity from April through October 2020. In April, New York City became the epicenter of Covid-19 infections and deaths. In a city that is a residence for more than eight million people with diverse racial and ethnic backgrounds, poor, uninsured, and people of color were disproportionately affected, and eastern Brooklyn was in dire need of resources [47].

In May and June, we saw high death rates in Navajo and Apache counties of Arizona. According to the 2010 Census [48], in Apache, 72.9% of the population was Native Americans, and in Navajo, 43.4% of the population was American Indian. The indigenous population was disproportionately affected due to structural inequities in their access to food, safety, and clean water [49].

Table 1Summary statistics of the independent variables across rural ($n = 2, 107$) and urban counties ($n = 997$)

Variables	Rural	Urban	p-value
<i>Neighborhood and Built Environment</i>			
Percent Severe Housing Cost Burden	10.23 (3.91)	12.25(4.57)	< 0.0001
Residential Segregation Index	33.54 (46.63)	45.27 (22.24)	< 0.0001
<i>Economic Stability</i>			
Percent Unemployed	3.80 (1.70)	3.50 (1.20)	< 0.0001
Percent Uninsured	11 (7)	10 (6)	<0.0001
Income Inequality Ratio	4.39 (0.87)	4.42 (0.84)	0.02882
<i>Education</i>			
Percent Some College or Associate Degree	30.75 (7.30)	30.10 (6.05)	< 0.0001
<i>Social and Community Context</i>			
Percent Black population	1.28 (5.06)	7.02 (15.07)	< 0.0001
Percent Above 65 years	19.87 (4.96)	16.58 (4.79)	< 0.0001
Percent Female population	50.11 (1.66)	50.74 (1.23)	< 0.0001
<i>Health and Health Care</i>			
Percent Frequent Physical Distress	12.14 (3.53)	11.70 (2.75)	< 0.0001
Percent Frequent Mental Distress	13.16 (2.96)	12.70 (2.35)	< 0.0001
Percent Diabetes	12.10 (5.60)	11.10 (4.50)	< 0.0001
HIV Rate Per Million	610 (1280)	1500 (1730)	<0.0001
Percent of Adult Smokers	17.26 (4.98)	16.715 (4.49)	< 0.0001
Percent Obesity	34 (7)	32 (8)	<0.0001

Medians and interquartile ranges, IQR, were used as summary statistics and rural-urban differences were compared using Mann-Whitney two-sample tests.

Table 2

Unadjusted and adjusted incidence rate ratios for mortality rates using spatio-temporal negative binomial regressions

Variables	Unadjusted		Adjusted	
	Rural	Urban	Rural	Urban
<i>Neighborhood and Built Environment</i>				
Percent Severe Housing Cost Burden	1.13 (1.10, 1.17)	1.18 (1.14, 1.21)	—	—
Residential Segregation Index	1.01 (1.01, 1.02)	1.03 (1.02, 1.04)	1.01 (1.00, 1.01)	1.03 (1.02, 1.04)
<i>Economic Stability</i>				
Percent Unemployed	1.41 (1.30, 1.53)	1.69 (1.54, 1.86)	1.08 (0.97, 1.20)	1.41 (1.24, 1.60)
Percent Uninsured	1.32 (1.30, 1.35)	1.34 (1.30, 1.37)	1.22 (1.18, 1.26)	1.09 (1.04, 1.13)
Income Inequality Ratio	1.01 (1.01, 1.01)	1.01 (1.01, 1.01)	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)
<i>Education</i>				
Percent Some College or Associate Degree	0.79 (0.78, 0.81)	0.78 (0.76, 0.80)	0.92 (0.90, 0.95)	0.80 (0.77, 0.83)
<i>Social and Community Context</i>				
Percent Black Population	1.11 (1.10, 1.12)	1.10 (1.08, 1.11)	1.07 (1.06, 1.08)	1.05 (1.04, 1.07)
Percent 65 Years and Above	0.91 (0.89, 0.93)	0.92 (0.90, 0.95)	0.95 (0.92, 0.98)	1.03 (0.98, 1.07)
Percent Female Population	1.19 (1.14, 1.26)	1.20 (1.14, 1.26)	1.17 (1.11, 1.24)	1.3 (1.22, 1.38)
<i>Health and Health Care</i>				
Percent Frequent Mental Distress	1.26 (1.17, 1.34)	1.32 (1.22, 1.42)	—	—
Percent Frequent Physical Distress	1.21 (1.17, 1.34)	1.31 (1.22, 1.40)	—	—
Percent Diabetes	1.09 (1.06, 1.12)	1.13 (1.09, 1.17)	1.09 (1.06, 1.13)	1.06 (1.01, 1.11)
HIV Rate per Million	1.12 (1.11, 1.13)	1.05 (1.04, 1.06)	1.02 (1.01, 1.03)	1.01 (1.00, 1.02)
Percent Adult Smoker	1.10 (1.06, 1.14)	1.14 (1.09, 1.18)	—	—
Percent Obesity	1.17 (1.15, 1.20)	1.18 (1.15, 1.20)	—	—

Posterior medians of the incidence risk ratios and within parentheses its 95% Credible Intervals are exhibited under 5 units change in the independent variable. The independent variables in the final adjusted model were included based on multicollinearity analyses, variable selection procedures, and Watanabe Akaike Information Criterion (WAIC). The adjusted model with all the variables had WAIC = 73,258.29 and the adjusted model without Percent Severe Housing Cost Burden, Percent Frequent Mental Distress, and Smokers Rate had WAIC = 73,384.38. There is no substantial change in WAIC values between the two models.

After the 4th of July weekend, Covid-19 infections and deaths became widespread in the southern U.S, including Florida, where the percent of the population above 65 years is about 21% [50]. In September and October, the severity of the disease became widespread in Midwestern states, to name North and South Dakota. These states are predominantly rural and lack healthcare infrastructure [51].

Our findings suggest that in urban counties, increased mortality rates were associated with residential segregation and unemployment rates. While urban residents have access to rich infrastructure in healthcare and education, several barriers exist, and people of higher socioeconomic status [52] disproportionately benefit from such infrastructure [53]. Urban inequities stem from variations in individual residence status, such as slum areas, inner cities, middle-income communities, and higher-income neighbor-

hoods [54]. Residential segregation is detrimental to keeping good health and contributes to structural racism and creates socioeconomic immobility [55] and geographic disparities in health [56,57].

One's adaptation of a healthy lifestyle and well-being throughout life heavily depend on educational level [58]. Higher education, employment status, and good health are interlinked [59,60]. Lack of education and unemployment elevate the risk of poor health, social isolation, and chronic diseases [61–63], including the comorbid conditions for Covid-19 such as heart disease [64], lung disease [65], and diabetes [66]. Adults with lower education often work in jobs that do not provide them the opportunity to maintain public health safety guidelines and disproportionately expose them to the risk of Covid-19 infection [67,68]. In our study, the unemployment rate was positively associated with county-level monthly mortality in urban counties, whereas higher education was negatively asso-

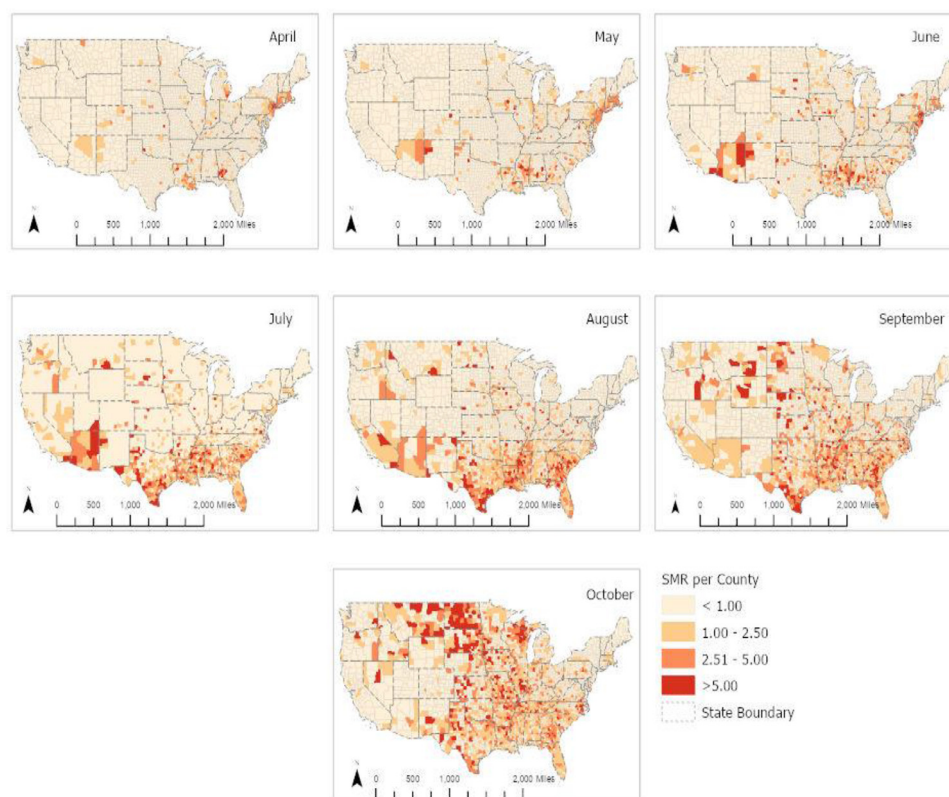


Fig. 2. County-level crude standardized mortality ratios (SMR) over 7 months from April through October 2020.

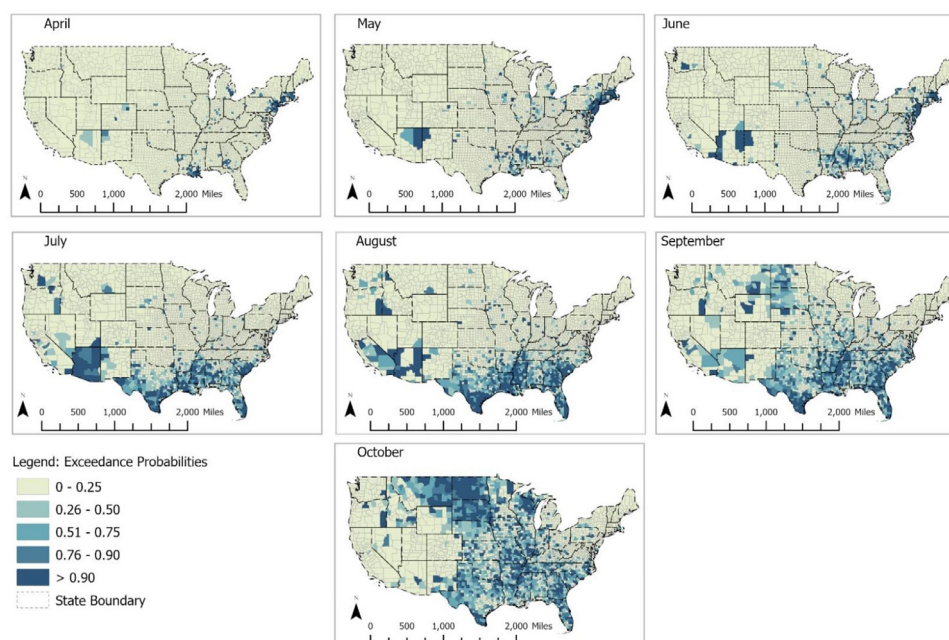


Fig. 3. County-level exceedance probabilities of SMR to be greater than 50% over 7 months from April through October 2020. The exceedance probabilities were estimated from the final adjusted model via spatiotemporal Negative Binomial regression.

ciated with Covid-19 mortality in rural and urban counties. Also, in rural counties, we found that the income inequality ratio was positively associated with increased Covid-19 mortality. In this study, counties with a higher percentage of the uninsured population were associated with increased mortality from Covid-19 in both rural and urban regions. Similar associations were also observed by Fielding-Miller et al. [69] when they conducted county-level anal-

yses across U.S. Lack of insurance coverage is higher among the communities of color and as a result, they delay or unable to cover their treatment for chronic conditions and comorbidities, placing them at increased risks of Covid-19 infections and mortality [70].

We found a significant association of HIV rates with Covid-19 mortality. Data on HIV infections as a comorbid condition for Covid-19 are limited. However, a recent study [71] found that

Covid-19 complications may increase in patients with HIV who are already immunocompromised and the presence of other underlying comorbid conditions in conjunction with HIV elevates the risk of Covid-19 mortality [72]. Further research is needed for a better understanding of the risk factors that place HIV patients at increased risk of Covid-19 mortality.

Counties with a higher percentage of the Black population faced higher Covid-19 mortality rates [4,17,73,74,94]. In this study, the association of the percent of the Black population with elevated Covid-19 mortality was similar in both urban and rural counties. Nationally, 25% of the essential workforce is Black [75], but the Black population has experienced disproportionately higher mortality rates from Covid-19 infection [76]. Higher risks of chronic diseases, such as diabetes [77], chronic obstructive pulmonary diseases (COPD) [78], and severe heart conditions [79], among Black adults, increase their risk of Covid-19 mortality [80]. Our county-level analyses also found positive associations between diabetes rates and Covid-19 mortality in urban and rural counties, consistent with findings from other researchers [81,82,83]. We observed that an increase in the county-level proportion of the older population (65 years and above) was associated with lower death rates. This county-level pattern of mortality among the older population should not be misconstrued for the individual-level risk associated with increasing age [84,85]. Increasing age is a risk factor for Covid-19 mortality [84,85], although a recent study found that age, in the absence of existing co-morbid conditions, was not a predictor of Covid-19-related mortality [86]. Our analysis is ecological, we looked at the associations at the county level rather than at the individual level. We cannot make any causal statements from this analysis but only comment on associations. One possible explanation could be that older people have less mobility and thus they had less exposure. While the areas with a higher percentage of the younger population had a lot more exposure and older people living in areas with a high younger population are at higher risk of exposure and death.

The field of infectious disease epidemiology on respiratory diseases, vector-borne illnesses, and sexually transmitted diseases benefitted from the spatio-temporal analysis by monitoring how time spent at a particular location contributes to disease emergence and virus circulation [14]. Space-time disease surveillance helps with the early detection of pandemics for timely implementation of public health mitigation efforts [87].

Jia et al. [88] used spatio-temporal analyses to study the growth patterns of Covid-19 infections based on population outflow from Wuhan, China. A spatio-temporal Tobit-type model on prevalence rates helped Paul et al., [22] to assess how Covid-19 progressed from urban counties to rural areas in the U.S. Based on space-time data from Spanish provinces, Briz-Redón et al. [89] found no evidence that Covid-19 infection rates decreased with an increase in daily temperature. The importance of the spatio-temporal approach in mitigating Covid-19 spread and deaths is further underscored by the National Science Foundations' Spatiotemporal Innovation Center [90], which created a task force that facilitates data science-based approaches to aid in policy decisions, environmental factors detection, disease spread monitoring, and sentiment analyses [91].

The innovation in our approach is the inclusion of spatiotemporal latent factors, $\nu_t K_t$, in Eq. (1). While one of our study aims was investigating associations of SDoH with monthly Covid-19 county-level mortality rates, it is imperative to understand that other unknown latent factors impact the disease mortality. By enabling the inclusion of latent risk factors, spatio-temporal factor analyses improved the predictive power of the model's fit. Though our model considered a time-invariant systematic component, a function of covariates that do not change with time, it assumed that the relationship between the death rates and SDoH variables remain constant over time. However, according to our model, the fluctuations

in death rates that we have seen over seven months are accounted for by the small-scale variations, that are due to short-term local events, such as, enacting and uplifting of state/county restrictions, holiday events, beach season, summer travel, etc. The time-invariant assumption of the effect of SDoH is not unrealistic, as over these seven months there was no major policy change occurred that was specifically tied to SDoH variables considered in the analysis (other than the CARES [92] act).

Our study has certain limitations. Our analysis was based on aggregated county-level data, that are prone to ecological fallacy. Thus our aggregate level analyses should not be used to address individual-level risk factors to draw causal inferences. While researchers [4,22,93] considered the JHU data repository to be the most comprehensive and reliable, certain errors, such as underreporting are unavoidable. Despite these limitations, spatio-temporal analyses could be a useful tool for detecting high-risk clusters and prioritizing resources.

Conclusions

The use of spatio-temporal analyses helped identify social factors that predisposed high-risk and vulnerable communities to Covid-19 mortality. Counties with a higher percent of Black, residential segregation, unemployment, uninsured, and comorbidities, such as diabetes and HIV had substantially high SMR and exceedance probabilities.

Spatiotemporal analysis also helped detect the dynamics of high-risk clusters and identify the population residing in those clusters so that effective mitigation efforts including the supply of test kits, personal protective equipment, ventilators, financial needs for businesses and schools, and prioritization of vaccine distributions, can be effectively designed. Decisions on the supply of resources, lockdowns, and phased reopenings are often made at a granular level, and space-time analyses aid in data-driven, evidence-based, and scientifically grounded decision process.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.annepidem.2021.05.006.

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