Inequalities in Life Expectancy Across North Carolina

A Spatial Analysis of the Social Determinants of Health and the Index of Concentration at Extremes

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Health inequalities are characterized by spatial patterns of social, economic, and political factors. Life expectancy (LE) is a commonly used indicator of overall population health and health inequalities that allows for comparison across different spatial and temporal regions. The objective of this study was to examine geographic inequalities in LE across North Carolina census tracts by comparing the performance of 2 popular geospatial health indices: Social Determinants of Health (SDoH) and the Index of Concentration at Extremes (ICE). A principal components analysis (PCA) was used to address multicollinearity among variables and aggregate data into components to examine SDoH, while the ICE was constructed using the simple subtraction of geospatial variables. Spatial regression models were employed to compare both indices in relation to LE to evaluate their predictability for population health. For individual SDoH and ICE components, poverty and income had the strongest positive correlation with LE. However, the common spatial techniques of adding PCA components together for a final SDoH aggregate measure resulted in a poor relationship with LE. Results indicated that both metrics can be used to determine spatial patterns of inequities in LE and that the ICE metric has similar success to the more computationally complex SDoH metric. Public health practitioners may find the ICE metric's high predictability matched with lower data requirements to be more feasible to implement in population health monitoring.

Key words: Index of Concentration at Extremes, life expectancy, neighborhood metrics, Social Determinants of Health

Life expectancy (LE), a measure of the number of years an average individual can expect to live, is an important indicator of population health.[1] Advancements in public health, medicine, and technology have contributed to longer LE in the United States (US), with LE at birth increasing by nearly 5 years to 78.6 years from 1980 to 2017.[2,3] Although trends in LE data for North Carolina parallel national data, notable disparities have been observed for certain geographic regions and racial and ethnic groups.[4,5] Within the state, affluent communities record the highest LE while poorer counties in the Appalachian region of NC record lower LE.[6] For example, recent NC estimates (2017-2019) reveal notable inequalities in LE for non-Hispanic Black and non-Hispanic American Indian residents compared with non-Hispanic white residents.[7] In general, the LE measure allows for direct comparisons of overall population health across space and provides easy interpretation for policy and public use for understanding health inequalities.

Health disparities encompass a broad spectrum of socioeconomic conditions that contribute to underlying health inequities and varying LE measures.[8,9] While previous studies have explored the spatial trends of LE,[10-13] no research to date has examined how 2 commonly used spatial metrics compare in explaining the geographic variability of LE and how each contributes to health inequalities at a local level. Underlying health inequalities result in higher burdens of illness, injury, disability, and

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mortality and have been shown to contribute to differences in drug overdoses,[10] LE,[11-13] and racial and household income inequities.[14] Spatial indices can assist policy makers to identify geographic regions that require additional allocations or public health interventions, as well as increase the understanding of the geographic drivers of different health outcomes.

To address the multifactorial nature of inequalities among communities, contextual socioeconomic and geospatial indices have been constructed to identify geographic inequities.[15,16] These spatial indices examine contextual environmental parameters and have primarily been applied to the disciplines of hazards, disasters, and resilience to detect communities with lower capacity to prepare for, respond to, and rebound from natural or man-made hazardous events.[17,18] Common indices include the Social Vulnerability Index (SoVI), which predicts socioeconomic and demographic variations in the social burden of disaster impacts,[17] and the Area Deprivation Index, which measures neighborhood disadvantage.[19,20] These vulnerability and deprivation indices share close conceptual ties with the Social Determinants of Health (SDoH),[20-22] and methods from these indices can be readily applied to map the SDoH for public health policy and research needs.

A recently reintroduced health metric, the Index of Concentration at Extremes (ICE), characterizes areas of deprivation and privilege based on area-level concentrations of poverty and racial segregation.[14,23] The ICE has been used to measure social polarization to identify inequalities in income, premature mortality, hypertension, and cancer.[23-26] Unlike other indices, it is a proxy for residential segregation rather than overall deprivation. Segregation and related inequalities have also been shown to negatively impact health and enhance health inequalities and are likely related to changes in LE.[27,28]

Few geography-based studies in the US have examined subcounty trends in LE accounting for the SDoH and measures of polarization such as ICE. Recently, Melix et al[12] performed a statewide analysis and found that specific SDoH factors drive spatial patterns of LE. Yet, they did not account for racial segregation metrics or determine the suitability of place-based metrics for health policy and interventions. The objective of this study was to examine geographic inequalities in LE by comparing the performance of the SDoH and ICE metrics. Results provide insight into the value of each metric for identifying spatial inequality in LE, while also identifying geographic areas that may benefit from targeted interventions.

METHODS

Data

Census tract–level estimates for LE in North Carolina were obtained from the National Center for Health Statistics' US Small Area LE Estimates Project (USALEEP).[3,29] Following Arias et al,[29] the tracts with no population (n = 21) and no LE estimates (n = 201) were excluded from the analysis, resulting in 1970 tracts for analysis. LE was log-transformed and included as the primary outcome for this study.

On the basis of previous studies and the authors' knowledge of factors that contribute to public health, 66 variables were compiled to construct the SDoH index. The author team included academic professionals from geospatial analysis (J.M. and L.A.), epidemiology (J.R.), community planning (E.S.), and medical geography (M.S.). Following Melix et al,[12] Artiga and Hinton,[30] Cutter et al,[17] Cutter,[31] Krieger et al,[14,23] and Tabb et al,[13] tract-level "deprivation" variables regarding race, age, gender, income, poverty, employment, and health were obtained from the 2014-2018 American Community Survey (ACS).[32] While this study deviates from the standard variable set outlined in Cutter et al[17] by including housing, transportation, and employment indicators, it follows recent studies examining geographic inequalities in LE.[11,12,33] Using ArcMap 10.7.1,[34] the North Carolina OneMap (NCOM),[35] Homeland infrastructure foundation-level data (HIFLD),[36] and Health Resources and Services Administration (HRSA)[37] point data were spatially joined to create a sum of points for each tract. The variables included in the SDoH index are provided in Table 1.

SDoH index creation

Following techniques applied to previous geospatial indices,[17,20] the SDoH index combined socioeconomic factors for NC census tracts to measure deprivation (Table 1, part A). In SPSS Statistics version 27.0,[38] variables are normalized using z-score standardization and principal component analysis (PCA) is used to reduce multicollinearity among variables. Data are reversed for directionality when increases in the variable correspond with decreased deprivation (eg, income, employment, services). Table 2 presents a total of 16 components meeting Kaiser's[39] criterion. Cardinality was applied to each component based on an increasing (+) or decreasing (−) influence on health outcomes. Like SoVI, components were assigned unique names based on the top 5 dominant variables without duplicating component names.[40]

TABLE 1. All Data and Data Sources for the SDoH and ICE Metrics

SDoH Index and ICE Metric Variables		
A. SDoH Index		
Variables	**Name**	**Source**
SDoH variables: Tract-level data		
% Total population: Male: <5 y	MPopUnder5	2018 American Community Survey, 5-Year Estimates[32]
% Total population: Male: <18 y (population 5-9, 10-14, 15-17 y)	MPopUnd18	
% Total population: Male: ≥65 y (population 65-74, 75-84, ≥85 y)	MPop65Over	
% Total population: Female: <5 y	FPopUnder5	
% Total population: Female: <18 y (population 5-9, 10-14, 15-17 y)	FPopUnd18	
% Total population: Female: ≥65 y (population 65-74, 75-84, ≥85 y)	FPop65Over	
% Total population: <5 y	TPopUnder5	
% Total population: <18 y (population 5-9, 10-14, 15-17 y)	TPopUnd18	
% Total population: ≥65 y (population 65-74, 75-84, ≥85 y)	TPop65Over	
Median age	MedAge	
% Total population: White alone	PopWhite	
% Total population: Black or African American alone	PopBlack	
% Total population: American Indian and Alaska Native alone	PopAmInd	
% Total population: Asian alone	PopAsian	
% Total population: Native Hawaiian and Other Pacific Islander alone	PopHawaii	
% Total population: Some other race alone	PopOthRace	
% Total population: Two or more races	PopTwoRace	
% Households: Family households: Other family: Female householder, no husband present	FHH_NoHusb	
% Renter-occupied housing units [(Total renter housing/Total housing) × 100]	RentHouse	
% Occupied housing units: With related children of the householder <18 y	OcH_Rchild	
% Renter-occupied housing units: With related children of the householder <18 y	ReH_Rchild	
Average household size	AvgHHSize	
Average household size for renter-occupied housing units	AvgRHHSize	
% Population ≥25 y: Less than high school	Pop_LessHS	
% Population ≥25 y: High school graduate or more (includes equivalency)	Pop_HSGrad	
% Population ≥25 y: Some college or more and bachelor's degree or more	Pop_ColBac	
% Population ≥25 y: Master's degree or more, professional school degree or more, doctorate degree or more	Pop_HighEd	
% Population ≥16 y: in labor force	Pop_LabFor	
% Population ≥16 y: in labor force: in Armed Forces	Pop_ArmFor	
% Population ≥16 y: in labor force: Civilian	Pop_Civil	
% Population ≥16 y: in labor force: Civilian: employed	PopCvEmp	
% Population ≥16 y: in labor force: Civilian: unemployed	PopCvUnem	
% Population ≥16 y: not in labor force	PopNoLabFo	
% Civilian population in labor force ≥16 y: Employed	CvPopEmp	
% Civilian population in labor force ≥16 y: Unemployed	CvPopUnem	
% Housing units: Mobile home	HousMobHom	
% Occupied housing units: Mobile home	OHMobHom	

(*continues*)

TABLE 1. All Data and Data Sources for the SDoH and ICE Metrics (*Continued*)

SDoH Index and ICE Metric Variables		
A. SDoH Index		
Variables	**Name**	**Source**
Median gross rent as a percentage of household income in the past 12 mo (dollars)	MGR_HHInc	
% Families: Income below poverty level	FIn_Bpov	
% Workers ≥16 y: Drove alone and carpooled	WrkDA_Cp	
% Workers ≥16 y: Public transportation (includes Taxicab)	WrkPT	
% Workers ≥16 y: Bicycle and walked	WrkB_W	
% Total: No health insurance coverage	NoHlthCov	
% Households with housing costs ≥30% of income	HHcost_30I	
% Own children <18y: Children living with single parents	ChU18LivSP	
Percentage below poverty level—Population for whom poverty status is determined	PerPopBPov	
Percentage of households with no available vehicle	PHH_NoVeh	
Percentage of households with 1 vehicle available	PHH_OneVeh	
SDoH variables: Point-level data, spatially joined, normalized by total population		
Childcare centers per person	Childcare	Homeland Infrastructure Foundation Level Data (HIFLD)[37]
Banks per person	Banks	
Fire stations per person	FireStat	
Mobile homes per person	MobHome	
Public health departments per person	PubHlthDep	
Urgent cares per person	UrgentCare	
Areas of worship per person	Worship	
Colleges/universities per person	College	NC OneMap[35]
Emergency shelters per person	EmergShelt	
Gas stations per person	GasStation	
Hospitals per person	Hospitals	
Nursing home per person	NursHome	
Public libraries per person	Libraries	
Pharmacies per person	Pharmacies	
Private schools per person	PrivSchool	
Public schools per person	PubSchool	
HPSA data—Mental health facilities per census tract	MH_Count	Health Resources and Service Administration (HRSA)[36]
HPSA data—Primary care facilities per census tract	PC_Count	
B. ICE Metric		
Variables	**Name**	**Source**
Total population (B03002) Hispanic or Latino origin by race[c]	TPop_Hisp[c]	2018 American Community Survey, 5-Year Estimates[32]
Not Hispanic or Latino: Black or African American alone[b]	Black_NHsp[b]	
Not Hispanic or Latino: White alone[a]	White_NHsp[a]	
Total population (B19001B) household income in the past 12 mo (in 2018 inflation-adjusted dollars) (Black or African American alone householder)[c]	TP_BHHInc[c] TP_WHHInc[c] BHH_Less25[b] WHH_Grt100[a]	

(*continues*)

TABLE 1. All Data and Data Sources for the SDoH and ICE Metrics (*Continued*)

B. ICE Metric		
Variables	**Name**	**Source**
Total population (B19001H) household income in the past 12 mo (in 2018 inflation-adjusted dollars) (White, not Hispanic or Latino householder)[c]		
Combine income values of <$25 000 for Black or African American householder[b]		
<$10 000 (BHH_L10)		
$10 000-$14 999 (BHH_149)		
$15 000-$19 999 (BHH_199)		
$20 000-$24 999 (BHH_249)		
Combine income values of >$100 000 for White, not Hispanic/Latino householder[a]		
$100 000-$124 999 (WHH_1249)		
$125 000-$149 999 (WHH_1499)		
$150 000-$199 999 (WHH_1999)		
≥$200 000 (WHH_200Up)		
Total population (B19001) household income in the past 12 mo (in 2018 inflation-adjusted dollars)[c]	TPop_HHInc[c]	
Combine income values of <$25 000[b]	HH_Less25[b]	
<$10 000 (HH_L10)	HH_Grt100[a]	
$10 000-$14 999 (HH_149)		
$15 000-$19 999 (HH_199)		
$20 000-$24 999 (HH_249)		
Combine income values of >$100 000[a]		
$100 000-$124 999 (HH_1249)		
$125 000-$149 999 (HH_1499)		
$150 000-$199 999 (HH_1999)		
≥$200 000 (HH_200Up)		

Abbreviations: HPSA, Health Professional Shortage Area; ICE, Index of Concentration at Extremes; SDoH, Social Determinants of Health.
[a]Indicates variables used as A_i in the ICE metric.
[b]Indicates variables used as P_i in the ICE metric.
[c]Indicates variables used as T_i in the ICE metric.

Final SDoH metrics for analysis included the following: (1) individual SDoH components (Table 1), and (2) the *Total Deprivation* field (Table 2), or the sum of all SDoH components, which allows for a single output of all components for policy and research use. To create the *Total Deprivation* field, the SDoH components were combined in an additive model based on their cardinality using the following equation:

(1) *Total Deprivation* = Poverty + Over 65 Age − Mobile Home Housing − Public (Children) Services − Employment + Over 65 + Population in Armed or Labor Force + Under 5 + Race and Housing − Public Facilities − Higher Education − Public Services + Renter Housing − Public (Station) Facilities + Ethnicities − Health Services and Facilities

This equal weighting technique has been applied in similar indices such as SoVI.[17,41]

ICE index creation

Creating the ICE metric required acquiring variables specified by Krieger et al[14,23] (Table 1). Using ACS data, creating the ICE metric involves the following formula:

$$\text{ICE}(A_i - P_i)/T_i \tag{2}$$

TABLE 2. The PCA Components for the SDoH Metric

Component Number	Cardinality	Component Name	Variance	Top 5 Dominant Variables
1	+	Poverty	16.508	Fln_BPov FHH_NoHusb PerPopBPov PopBlack ChU18LivSP
2	+	Over 65 Age	12.463	PopNoLabFo PopCvEmp TPop65Over FPop65Over MPop65Over
3	–	Mobile Home Housing	10.122	HousMobHom OHMobHome Pop_ColBac Pop_HighEd WrkDA_Cp
4	–	Public (Children) Services	7.586	PubSchool EmergShelt Worship Childcare Banks
5	–	Employment	4.741	Pop_ArmFor WrkB_W PopCvEmp CvPopEmp PHH_OneVeh
6	+	Over 65	3.409	FPop65Over PopNoLabFo TPop65Over OcH_Rchild PopCvEmp
7	+	Population in Armed or Labor Force	3.072	TPopUnder5 Pop_ArmFor MPopUnder5 PopCvUnem CvPopEmp
8	+	Under 5	2.863	TPopUnder5 MPopUnder5 FPopUnder5 MH_Count PC_Count
9	+	Race and Housing	2.423	PopOthRace AvgRHHSize AvgHHSize WrkB_W WrkPT

(continues)

TABLE 2. The PCA Components for the SDoH Metric (*Continued*)

Component Number	Cardinality	Component Name	Variance	Top 5 Dominant Variables
10	–	Public Facilities	2.238	GasStation UrgentCare TPopUnd18 MGR_HHInc FPopUnd18
11	–	Higher Education	1.903	College UrgentCare PopAmInd PrivSchools MobHome
12	–	Public Services	1.763	Libraries Hospitals College PrivSchools PopCvUnem
13	+	Renter Housing	1.708	AvgRHHSize Hospitals UrgentCare AvgHHSize ReH_Rchild
14	–	Public (Station) Facilities	1.677	FireStat Libraries GasStation AvgRHHSize MobHome
15	+	Ethnicities	1.616	PopAsian UrgentCare PopAmInd WrkPT MGR_HHInc
16	–	Health Services and Facilities	1.572	PopWhite MobHome NursHome PubHlthDep CvPopUnem

Abbreviations: PCA, principal components analysis; SDoH, Social Determinants of Health.

where, for the *ICE Income + Race* metric, A_i represents the number of advantaged white persons per tract; P_i represents the number of disadvantaged Black persons per tract, and T_i represents the total population per tract.[14] The method developed by Krieger et al[14,23] identifies areas of extreme racialized and economic segregation. Final ICE metrics included in the analysis were as follows: (1) *ICE Income*, (2) *ICE Race*, and (3) *ICE Income + Race*. ICE measures ranged from −1 (ie, the most deprived populations) to 1 (ie, the most privileged populations).[14] For example, by relying on the *ICE Race* metric, we are comparing LE between majority Black and majority white census tracts. For the *ICE Income* metric, we are comparing low-income versus high-income tracts, and for the

ICE Income + Race low-income, majority Black census tracts are being compared with high-income, majority white tracts.

Statistical analysis

To identify how well the ICE and SDoH variables explained geographic variation in LE, regression and simple correlation analysis were conducted for each index with LE as a dependent variable. Originally, an ordinary least squares (OLS) regression was conducted; however, spatial autocorrelation measured using Moran's *I* statistic was detected in the regression residuals, indicating the need for spatial regression methods.[42,43] Lagrange multiplier tests indicated that a spatial error regression model was the best fit over a spatial regression lag model due to smaller *P* values. For spatial error models and regression analysis, GeoDa version 1.14[44] was used to create a queen's contiguity weight matrix, which considers all directly adjacent census tracts as neighborhoods in the spatial model.[45] Spatial error regressions were constructed for (1) the individual SDoH components, (2) *Total Deprivation* (ie, the sum of the SDoH components), (3) *ICE Income*, (4) *ICE Race*, and (5) *ICE Income + Race*. All regressions were bivariate with the exception of the individual SDoH components, which included all 16 components. A Moran's *I* test was performed to check for the presence of spatial autocorrelation in the spatial error regression residuals and was found to be insignificant across all spatial regression models. Confounders and covariates were not included, as the purpose of this study was to evaluate the predictability of common health indices (eg, ICE, SDoH) for population health indicators (eg, LE). These health indices are often considered independently when evaluating inequalities across health outcomes.[14,23,41]

RESULTS

The average LE across all NC tracts was 77.4 (SD = 3.51) years. Of the SDoH components, *Poverty* had the strongest positive correlation with LE ($r = 0.58$, $P < .05$) while *Over 65 Age* had the strongest negative correlation ($r = -0.83$, $P < .05$).

SDoH *Total Deprivation* scores were mapped on the basis of standard deviations from the mean into 7 classes ranging from less than −2.5 to more than 2.5 (Figure 1). Of the 2171 tracts, less than 1% were classified as most deprived, 4% as highly deprived, 22.4% as moderately deprived, 47.4% as the mean, 20.6% as moderately privileged, 3.5% as highly privileged, and 1.3% as most privileged.

In contrast, the ICE metric(s) represented polarization with values ranging from 1 to −1 (Figure 1). The ICE metric values were mapped using the geometric interval classification method, a method designed for classifying continuous data by determining break values based on class intervals having a geometric series.[46] For *ICE Race*, results indicated 17.1% of tracts were more privileged and 8.6% were more disadvantaged. For *ICE Income*, 65.2% of tracts were most deprived compared with the 10.3% most privileged. The combined *ICE Income + Race* showed that 45.2% of tracts were most deprived, while 16% were most privileged.

Ordinary least squares results

The OLS results indicated that the SDoH components best predicted LE ($R^2 = 52.37\%$), followed by *ICE Income* ($R^2 = 48.19\%$). *Total Deprivation* (the sum of all SDoH components) predicted less than 1% ($R^2 = 0.68\%$) compared with the individual SDoH components ($R^2 = 52.37\%$). While results showed that individual SDoH components explained more variability in LE than the sum of all SDoH components (*Total Deprivation*), the *ICE Income* metric performed equally as well as individual SDoH components. In addition, the *ICE Income + Race* ($R^2 = 45.07\%$) outperformed the sum of all SDoH components ($R^2 = 0.68\%$) (Table 3).

Spatial error model results

Like the OLS results, the spatial error model results indicated that the individual SDoH components predicted the most variability in LE ($R^2 = 56.9\%$), followed by the *ICE Income* metric ($R^2 = 53.4\%$). *Total Deprivation* predicted the least variability ($R^2 = 35.8\%$) and underperformed in regard to the composite *ICE Income + Race* ($R^2 = 52.41\%$) (Table 3).

All predictors of the dependent variable, LE, were significant at the 95% confidence level. The ICE metrics (eg, *Race*, *Income*, *Income + Race*) predicted the greatest variability in the LE measure, with *Income + Race* (0.13) and *Income* (0.12) being the highest. The SDoH coefficients predominately predicted decreases in LE. Exceptions include the *Public Services* component (component 12), representing a lack of access to educational and health services, as well as unemployment, decreased LE. The SDoH *Under 5* component (component 8), representing age under 5 years and the presence of mental health/primary care facilities, predicted the greatest positive increases in LE (0.0016), whereas *Poverty* (component 1) was the greatest predictor of LE decreases (−0.025), followed by *Employment* (component 5) (−0.013).

Bivariate mapping was used to reveal where the 2 metrics intersect and diverge (Figure 2). The highest concentration of spatial deprivation and segregation occurred in the middle and eastern portions of

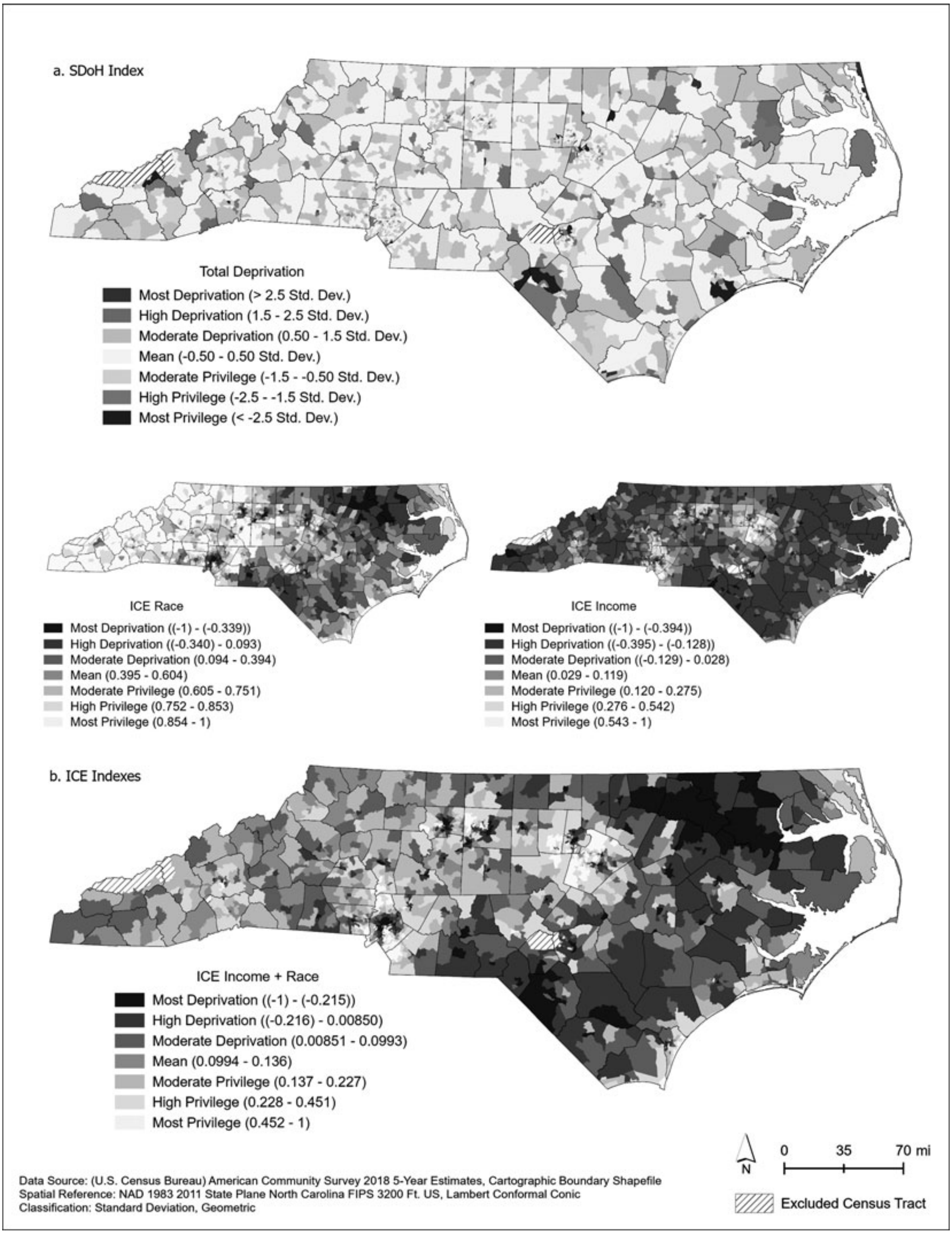

Figure 1. Maps of the (A) SDoH and (B) ICE metrics. The 21 tracts with no population, including those in the Great Smoky Mountains National Park, were excluded from the analysis, resulting in a total of 2171 tracts. ICE indicates Index of Concentration at Extremes; SDoH, Social Determinants of Health.

TABLE 3. Results of the OLS Regression (ArcGIS Pro) and Spatial Error Model (GeoDa) Regressions Comparing LE With the SDoH and ICE Metrics

	Spatial Regression Results: OLS Regression and Spatial Error Models			
	OLS Regression			
	Estimate	Adjusted R^2	AIC	P
ICE (Race)	0.045	19.60%	−6990.78	<.001*
ICE (Income)	0.13	48.19%	−7856.75	<.001*
ICE (Income + Race)	0.13	45.07%	−7741.68	<.001*
SDoH (individual components)	. . .	52.37%	−8007.73	. . .
Component 1	−0.025	. . .	. . .	<.001*
Component 2	−0.0031	. . .	. . .	<.001*
Component 3	−0.0076	. . .	. . .	.022**
Component 4	−0.0032	. . .	. . .	<.001*
Component 5	−0.013	. . .	. . .	<.001*
Component 6	−0.0037	. . .	. . .	<.001*
Component 7	−0.0039	. . .	. . .	.00100***
Component 8	0.00091	. . .	. . .	.31
Component 9	−0.0087	. . .	. . .	<.001*
Component 10	−0.0073	. . .	. . .	<.001*
Component 11	−0.0019	. . .	. . .	.00633***
Component 12	−0.0083	. . .	. . .	<.001*
Component 13	−0.0057	. . .	. . .	<.001*
Component 14	−0.0018	. . .	. . .	.037**
Component 15	−0.0034	. . .	. . .	<.001*
Component 16	0.000067	. . .	. . .	.93
Total Deprivation	−0.0011	0.68%	−6574.25	<.001*
	Spatial Error Model Regression, Robust Lagrange Multiplier Test			
	Estimate	Pseudo R^2	AIC	P
ICE (Race)	0.054	45.64%	−7589.94	<.001*
ICE (Income)	0.12	53.40%	−8008.75	<.001*
ICE (Income + Race)	0.13	52.41%	−7950.34	<.001*
SDoH (individual components)	. . .	56.93%	−8316.79	. . .
Component 1	−0.025	. . .	. . .	<.001*
Component 2	−0.0017	. . .	. . .	.045**
Component 3	−0.006	. . .	. . .	.053
Component 4	−0.0027	. . .	. . .	.00333***
Component 5	−0.012	. . .	. . .	<.001*
Component 6	−0.0037	. . .	. . .	<.001*
Component 7	−0.0039	. . .	. . .	.00191***
Component 8	0.0016	. . .	. . .	.08
Component 9	−0.0074	. . .	. . .	<.001*
Component 10	−0.0068	. . .	. . .	<.001*
Component 11	−0.0021	. . .	. . .	.00130***
Component 12	−0.0087	. . .	. . .	<.001*
Component 13	−0.005	. . .	. . .	<.001*
Component 14	−0.0019	. . .	. . .	.019**
Component 15	−0.0026	. . .	. . .	<.001*
Component 16	−0.0013	. . .	. . .	.12
Total Deprivation	0.0005	35.83%	−7234.07	.042**

Abbreviations: ICE, Index of Concentration at Extremes; LE, life expectancy; OLS, ordinary least squares; SDoH, Social Determinants of Health.
*$P < .001$.
**$P < .05$.
***$P < .01$.

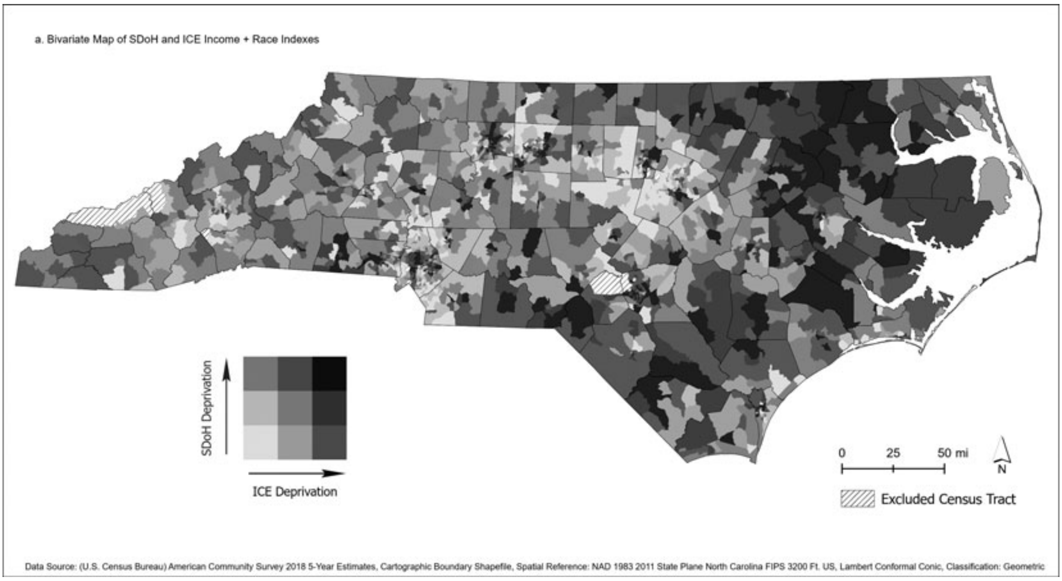

Figure 2. A bivariate map showing the *ICE Income + Race* metric and the *Total Deprivation* field of the SDoH metric. By combining the 2 fields, the tracts with the most privilege and the most deprivation are highlighted. ICE indicates Index of Concentration at Extremes; SDoH, Social Determinants of Health.

North Carolina. Western North Carolina showed more deprivation with the SDoH metric and more privilege (higher income and fewer minorities) with the ICE metric.

DISCUSSION

Our study evaluated the performance of 2 health indices, SDoH and ICE, and how well each explained geographic variability in LE. Using a widely cited method,[17,20] we developed an SDoH index to identify the spatial patterns of deprivation across North Carolina. To complement the SDoH metric, we calculated extremes of racialized and economic segregation using Krieger's ICE metric.[14,23] Results from this study indicated that the computationally less-intensive ICE metric (*ICE Race + Income*) ($R^2 = 53\%$) performed comparably with the individual components of the SDoH metric ($R^2 = 57\%$).

Surprisingly, adding SDoH components to create a *Total Deprivation* field, similar to the SoVI,[17] resulted in a lower-performing spatially explicit health metric ($R^2 = 35.8\%$). Our findings suggest SDoH components should not be added to create a single index, although policy- and decision-makers prefer composite indices. This finding also highlights the need for validation and sensitivity analysis of indices across scales (eg, census tract, county, region) to ensure their accuracy and precision in predicting population health.[47] Not many methods are available for validating deprivation indices, which, in part, explains why so few geospatial indices explicitly discuss and perform validation.[47,48] New research suggests that testing deprivation indices with health outcomes such as LE might be one of the best approaches for validation,[47] and our results highlight the potential for validation of deprivation indices at the census tract using health outcomes as a validation exercise.

This study demonstrated that ICE metrics performed nearly as well or better than more statistically complicated deprivation measures. This result is meaningful as the ICE is computationally simplistic compared with deprivation indices such as our SDoH, which often utilize factor analysis.[47] The ICE metric was introduced into the social science literature in 2001[49] and only recently has been applied to public health studies. To date, the ICE has been used to examine a variety of health outcomes, including body mass index,[50] reading level of children,[51] HIV infection,[52] adverse childhood experiences,[53] and anxiety,[54] but has yet to be applied explicitly to assess small-area inequalities in LE. We recommend its use in future health studies, as a feasible approach for mapping neighborhood-level inequalities in both income and race.

In regard to LE, results from the ICE metric indicated that income segregation over racial segregation was the most important driver contributing to spatial inequalities in LE. The role of poverty in LE was also confirmed with the SDoH metric, which also reported a strong association with poverty and LE. Previous research has shown a strong relationship with LE, increasing continuously across the US with income,[55] and also ties to income inequality and LE.[56] Despite the differences in poverty and income segregation, research has indicated correlations between poverty and food insecurity,[57] disease,[58] access to resources,[31] and a low LE at birth in southern US census tracts with a higher proportion of non-Hispanic Black residents.[29] Further analysis is needed to disentangle the relationship between poverty itself and income inequality, as some studies have suggested that correlations among income inequality are largely driven by areas with more inequality having a higher proportion of individuals living in poverty.[55,59,60] Prior research has also shown that instead of relying on the previous literature, researchers should assess distinct characteristics of socioeconomic disadvantage in their unique study regions to better select the most appropriate measures or indices that reflect neighborhood disadvantage.[61] Our research, along with other studies, points to the need for continued health research in understanding the roots of inequities in LE,[23,33] as well as the need for similar studies across other indicators of population health (eg, infant mortality).

Strength and limitations

The strength of our study lies in the inclusion of 2 indices that measured population health inequalities in LE at the census tract. The ICE metric emphasizes the contribution of 2 known determinants of health—segregation of income and race—in areas characterized by extreme deprivation and low LE. The SDoH metric is composed of multiple dimensions of health, including economic, employment, transportation, and housing. The SDoH metric performed well when evaluated as separate components. Yet, existing literature often combines PCA factors such as the *Total Deprivation* field in our SDoH index, which in this study has a low predictability and highlights a limitation of existing literature that requires further research. The strength of the ICE results is the simplified approach and that residential segregation serves as a proxy for structural racism, allowing a closer examination of the root causes of small-area inequalities in LE.

Our study is subject to a few limitations. There are several interacting factors and potential confounders associated with spatial variations in LE that were not captured in our analysis. We used aggregate-level approximations of SDoH factors that were not collected on individuals, and results may be subject to ecological fallacy. LE was also calculated using the USALEEP, which is based on 2010-2015 LE, whereas our indices were calculated using 2014-2018 estimates from the ACS. The temporal mismatch is common in public health studies,[62] and areas of economic deprivation and segregation are likely historical locations with long-standing trends of distress. Finally, our analysis was conducted at a subcounty scale, or the census tract, a preferable spatial unit for health studies,[63] but results were subject to the modifiable areal unit problem.[64]

CONCLUSION

Our findings revealed spatially explicit inequalities in LE using both indices, whereby income was driving much of the geographic variability. The computationally simplified ICE metric effectively captured spatial patterns in health inequalities similar to the 16-component SDoH index. One advantage of the ICE metric is the relatively small number of variables used in the calculation and the narrowed scope on structural factors relating to racial discrimination and poverty. Future studies should compare the performance of these 2 indices in the context of other health indicators, including infant mortality, crime, and opioid use.

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