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Cultural context index: A geospatial measure of social determinants of health in the United States

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ABSTRACT

Minority populations will continue to grow in the United States. Such pluralism necessitates iterative, geospatial measurements of cultural contexts. Our objective in this study was to create a measure of social determinants of health in geographic areas with varying ethnic, linguistic, and religious diversity in the United States. We extracted geographic information systems data based on community characteristics that have known associations with population health disparities from 2015 to 2019. We used principal component analysis to construct a Cultural Context Index (CCI). We created the CCI for 73,682 census tracts across 50 states and five inhabited territories. We identified hot and cold spots that are the highest and lowest CCI quintile, respectively. Hot spots census tracts were mostly located in metropolitan areas (84.8%), in the Southern census region (41.5%), and also had larger Black and Hispanic populations. The census tracts with the greatest need for culturally competent health care also had the sickest populations. Census tracts with a CCI rank of 5 ('greatest need') had higher prevalences of self-reported poor physical health (17.2%) and poor mental health (17.4%), compared to either the general population (13.9% and 14.5%) or to CCI rank of 1 ('lowest need') (11.9% and 10.8%). The CCI can pinpoint census tracts with a need for culturally competent health care and inform supply-side policy planning as healthcare and social service providers will inevitably come in contact with consumers from different backgrounds.

1. Introduction

Demographic heterogeneity across geographies is expected to increase in the ensuing decades. The year 2030 is a demographic turning point because, starting that year, net international migration will become the primary driver of population growth for the United States (Vespa et al., 2020). This driver will not only change the composition of the American populace, but where cultural contexts are formed within contiguous areas. The *cultural* in cultural contexts encompasses the norms, behaviors, customs and values shared by members of the same racial, ethnic, or other collective identity groups (Minkov & Hofstede, 2012). The complexity of culture has been reductively conceptualized and ineffectively operationalized in health research (Kagawa Singer et al., 2016). By *context*, Michael Marmot considers geography to be a "proxy for the individual", "telling us something about place", and a "locus for action" (Weil, 2020). Context is further complemented by spatial concentration, a distinguishing characteristic of collective identity communities that is driven by high ethnic concentration, characteristic cultural identity, and economic activity (Wilson & Portes, 1980).

Cultural contexts and health disparities are inextricably linked. Health disparities persist in the United States because people of specific demographic groups either delayed or fail to initiate care (Snowden & Yamada, 2005), especially for stigmatized conditions such as mental disorders (Wang et al., 2005). Patients of color have different experiences in navigating the American healthcare and/or social service systems than non-Hispanic white ones, even if their underlying medical

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conditions and insurance coverage are the same (Williams & Rucker, 2000). Their perception of care quality, adherence to treatment, and satisfaction with service providers, who may or may not demonstrate cultural competency, have meaningful consequences in addressing health disparities (Brach & Fraserirector, 2000). Even when individuals and families move outside the bounds of ethnic-concentrated spaces (formerly referred to as “ethnic enclaves”) and into ethno-sparse spaces (formerly “ethnoburbs”), or neighborhoods with lower coethnicity, there are still discernible patterns in their health-seeking behavior and, as a result, their health status (Wang-Schweig et al., 2022). The antecedents and consequences of health-seeking behavior are ecologically influenced. Therefore, inaccurate portrayal of culture in places and spaces inadvertently perpetuates health disparities (Asabor et al., 2022; Williams et al., 2019). The purposes of this paper are to present the Cultural Context Index (CCI), a new geospatial measure of social determinants of health (SDOH) with culture embedded in it and validate the CCI’s association with physical and mental health outcomes. SDOH capture the multitude of factors that influence population health status, with culture as one determinant. Culture is the tangible and intangible aspects of social life shared in common by a group of people. People linked by ethnic, linguistic, and/or religious commonality may be situated in geographical locations. To us, the Social and Community Contexts domain is the center point of the Healthy People 2030 SDOH framework (Healthy People 2030, 2021). The CCI distinguishes itself from previous geospatial indices in that we explicitly operationalized culture as ethnic, linguistic, and religious differences in census tracts in the Social and Community Context domain of the Healthy People 2030 framework. Its necessity lies in addressing fractionalization in America (Alesina et al., 2003). The CCI is also necessary because we use three measures of fractionalization and SDOH to explain heterogeneity in population health outcomes. Integration of cultural contexts with health in research has the potential to show specific vulnerability in collective identity communities. Our spatial analysis with the CCI shows health outcomes differences where cultural contexts are located, informing policymakers and practitioners of the geographic variation in the need for culturally competent healthcare and social services.

2. Methods

2.1. Sample

The area under study is all 50 states in United States and five inhabited territories. We included all 73,682 census tracts nationally in the final sample, in accordance with the 2010 Decennial Census.

2.2. Health outcome measures

We used two Behavioral Risk Factor Surveillance System (BRFSS) 2020 measures as outcomes of interest. In the Healthy Days Core Module, BRFSS survey respondents were asked: “Now thinking about your physical health, which includes physical illness and injury, how many days during the past 30 days was your physical health not good?”. They were also asked: “Now thinking about your mental health, which includes stress, depression, and problems with emotions, how many days during the past 30 days was your mental health not good?”. The CDC categorized adult who reported 14 or more days as being in poor physical health and, separately, used the same cut-off to determine poor mental health. We analyzed the data for these two questions to indicate the United States population’s health. More specifically, we aggregated the percentage of adults with poor physical health and poor mental health to a census tract level.

2.3. Index measures

We created a census tract area index to motivate the need for culturally-specific contextualization – CCI. We identified candidate measures for inclusion in the CCI based on a priori knowledge of the relationship between neighborhood characteristics that are associated with population health disparities. We grouped measures into the same five SDOH domains of the Health People 2030 framework for our index: Education Access and Quality; Economic Stability; Neighborhood and Built Environment; Social and Community Context; and Health Care Access and Quality.

Within these five Healthy People 2030 SDOH domains, we narrowed the list of measures down to 13 based on conceptualization and correlation. We represented the Education Access and Quality domain using the measure of the percentage of population aged 25 years and older with less than a high school degree. For the Economic Stability domain, we included six measures, specifically, median household income, percentage of civilian labor force population 16 years and older unemployed, percentage of households 100% below the federal poverty level, Gini Index, and percentage of homeowners and renters burdened by the cost of housing (separately). To make these measures directionally uniform, we transformed median household income using a 1/x relationship prior to rasterizing. We represented the Neighborhood and Built Environment domain by two measures of the percentage of households without access to a vehicle and the FEMA National Risk Index. For the Social and Community Context domain, we included three measure of culture: the Theil Index (Iceland, 2004), the percentage of the population age five years and older with English proficiency as “less than very well,” and the rate of adherence to a religious group per 1,000 citizens. Lastly, we represented the Health Care Access and Quality domain by a measure of the percentage of the population which is uninsured.

The data sources for the FEMA National Risk Index, household access to a vehicle, and rate of religious adherence are respectively the Federal Emergency Management Agency, Environmental Protection Agency’s Smart Location Database, and Association of Religion Data Archives. The primary source of data for the other ten measures was the American Community Survey. We obtained five-year 2015–2019 estimates of the American Community Survey from PolicyMap, a mapping and analytics platform (Cromartie, 2022).

In Table 1, we provide details of 13 CCI measures. We cross-walked them, as organized in six domains, against those of six other indices: the Area Deprivation Index (Singh, 2003), Neighborhood Deprivation Index (Andrews et al., 2020), Social Vulnerability Index (Flanagan et al., 2011), Social Deprivation Index (Butler et al., 2013), Social Needs Index (Katz & Nowak, 2018), and the PCCI COVID-19 Vulnerability Index (Parkland Center for Clinical Innovation, 2022) (Appendix A). Compared to the CCI, only one other index, Social Vulnerability Index, included three measures in the Social and Community Context domain, with English proficiency as the sole overlapping measure. The PCCI COVID-19 Vulnerability Index has one measure for the aging population, while the remaining four indices had no measures in this particular domain.

2.4. Index development

We calculated the correlation coefficients of the measures within each domain. We assessed measures with greater than 50% correlation among census tracts, and then we addressed multicollinearity by restricting correlated variables. We used equal weighting in calculations for all measures included in the CCI. We conducted all analyses and generated all maps using ArcGIS Pro 2.7.

We standardized all measures using the z-score method prior to rasterization. We converted all measures from polygon form (e.g., census tract units) to raster units. We utilized raster cell sizes of 0.05 decimal degrees, approximately 10 miles^2, for all measures in all geographies. For the census tracts with missing values, we imputed them using the interpolated values of the six nearest neighbors.

We assigned final index values to census tract units using the sampled value of the final principal component raster at the area

Table 1
Measures included in Cultural Context Index, organized by the Healthy People 2030 social determinants of health domains.

Domain	Measure	Source
Education Access and Quality	1 Population aged ≥25 with <12 years of education (%)	American Community Survey
Economic Stability	2 Median household income ($)	American Community Survey
	3 Gini Index (Income inequality)	American Community Survey
	4 Civilian labor force population aged ≥16 unemployed (%)	American Community Survey
	5 Population less than 100% federal poverty level (%)	American Community Survey
	6 All homeowners who are burdened by housing costs, estimated (%)	American Community Survey
	7 All renters who are cost-burdened, estimated (%)	American Community Survey
Neighborhood and Built Environment	8 FEMA National Risk Index	Federal Emergency Management Agency
	9 Households without access to a vehicle (%)	Environmental Protection Agency's Smart Location Database
Social and Community Context	10 Theil Index (Racial segregation)	American Community Survey
	11 Population age 5 and older speaking English "less than 'very well'", estimated (%)	American Community Survey
	12 Adherents to all denominations and religious groups per 1,000 (rate)	Association of Religion Data Archives
Health Care Access and Quality	13 People without health insurance (%)	American Community Survey

centroids. For area discrepancies based on varying raster overlap with tracts, we used a bilinear interpolation resampling technique to determine the final area value. We display the first principal component, component loadings for 13 measures that are included in the principal component analysis, and the variance explained by each component in Table 2.

2.5. Statistical analysis

We derived correlations between the CCI and four other indices available at the census tract level nationally (Social Needs Index, Social Deprivation Index, Social Vulnerability Index, Area Deprivation Index) using Spearman correlation coefficients. We ranked the census tracts by quintiles of the CCI's final values. Based on this ranking, a rank of one corresponds to 20% of sampled census tracts with the lowest need for cultural context consideration, whereas a rank of five represents 20% of census tracts with the greatest need for cultural context consideration. We used the Getis-Ord Gi* statistic or G* statistic, a measure of spatial autocorrelation, to identify spatial clustering of high or low values of a specific attribute (e.g., CCI) of each feature (e.g., census tracts) within a geographic area (e.g., United States). The G* statistic produced a z-score for each census tract in the sample. Positive z-scores indicate that the census tracts with high CCI values that are also surrounded by other census tracts with high values ("hotspot"), while negative z-scores indicate that the census tracts with low CCI values that are surrounded by census tracts with low CCI values ("coldspot"). We calculated descriptive statistics (e.g., frequencies, medians, interquartile range [IQR]) for the CCI overall and by each stratified rank. We conducted Pearson's chi square for categorical measures and Kruskal-Wallis non-parametric equality of populations rank tests for continuous measures across CCI quintiles as tests of independence. We conducted analysis categorized by regions and by urbanity. For the former, we adopted the United States Census Bureau's definition of regions (i.e., Northeast, Midwest, South, West). For the latter, we used the rural-urban commuting area (RUCA) codes from the 2010 Decennial Census to classify the tracts as metropolitan (RUCA codes 1–3), micropolitan (4–6), small town (7–9), or rural (10)(Cromartie, 2022). We test the local bivariate linear relationships of the two population health outcome measures with the CCI (i.e., CCI vs. poor mental health [%]; CCI vs. poor physical health [%]) using local entropy with the 30 nearest neighbors and 199 permutations. The census tracts with significant, index pair-wise linear relationships (i.e., negative linear, positive linear) at the α=0.01 threshold. The relationship is visualized by census tracts which have a significant positive linear relationship (i.e., as CCI rank increases self-reported poor health percentage increases). Additionally, those census tracts with positive linear relationships are layered to display areas with convergent CCI and poor overall health.

Table 2
Census tract components, principal component loadings, and variance explained in the Cultural Context Index.

Census Tract Components	Component Loading	Variance Explained
Total Variance Explained		45.8 %
Median household income	+0.05	0.2 %
Poverty	+0.12	1.4 %
Unemployed	+0.34	11.6 %
< High school education	+0.10	0.9 %
Renter burden	−0.06	0.3 %
Homeowner burden	+0.00	0.0 %
No vehicle access	+0.44	18.9 %
FEMA index	+0.12	1.3 %
Rate of religious adherence per 1,000 persons	−0.01	0.0 %
Theil index	−0.03	0.1 %
Non-English speaking	+0.04	0.1 %
Uninsured	+0.24	5.5 %
Gini index	+0.03	0.1 %

3. Results

3.1. Descriptive statistics

CCI values varied geographically across the United States (Fig. 1) and displayed a Moran's I clustering of 0.77 ($p < 0.0001$). Table 3 details the key characteristics of census tracts based on CCI quantile. Census tracts with the greatest need for cultural context consideration, were largely present in the Southern census region of the United States (41.5% of census tracts with a CCI rank of 5; $p < 0.01$; Table 3). The Northeast and the Midwest regions displayed a large proportion of CCI rank 1 representation among census tracts with the lowest need for cultural context consideration (30.1% and 31.1%, respectively; $p < 0.01$).

Census tracts with the greatest need for cultural context consideration had, on average, larger populations per square mile (median = 4,470 census tract residents; IQR = 10,073; $p < 0.01$) than other tracts. Tracts in that quintile had larger sub-populations of Black and Hispanic persons compared to tracts in the other four quintiles (p-value <0.01). White and Asian populations had less representation in tracts of the highest CCI quintile ($p < 0.01$). On average, residents of the quintile with the greatest CCI were younger (median = 33.8 years; IQR = 0.7 years; $p < 0.01$) compared to the rest of the population.

Fig. 2 shows those statistically significant census tracts identified as a hot or cold spot. The same figure also features local snapshots of the four most populous and segregated cities in the United States -Chicago, IL; New York City, NY; Los Angeles, CA; Houston, TX-which we consider as unique cases following the Asabor et al.'s (Asabor et al., 2022) recent finding that their Black and Latinx residents had access to fewer COVID-19 testing sites.

The Social Vulnerability Index and Social Deprivation Index showed positive correlations with coefficients of 0.37 and 0.43, respectively (Table 4; Fig. 3). The Social Needs Index presented an even stronger

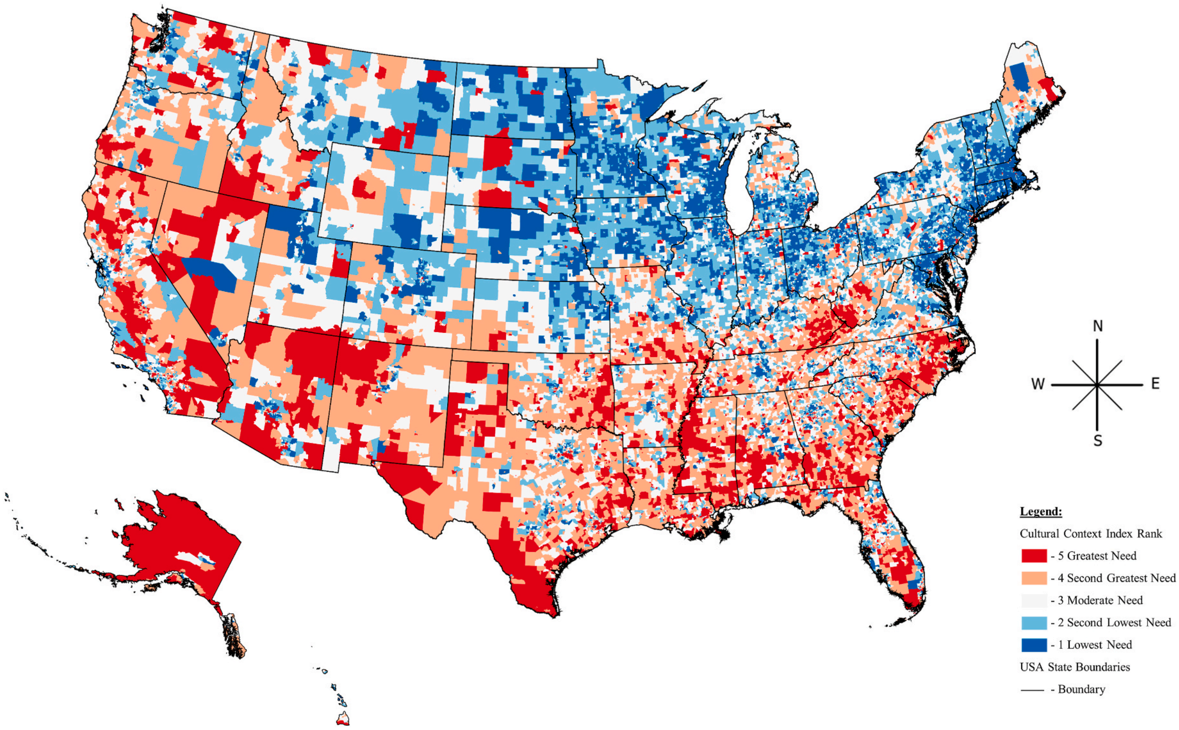

Fig. 1. Map of United States census tracts, by Cultural Context Index quantile.

positive association at 0.45. On the other hand, the Area Deprivation Index indicated only a marginally positive relationship, with a low coefficient of 0.06. Notably, all these relationships were statistically significant with p-values below 0.01.

Hotspots of census tracts with a high CCI quintile measure (i.e., those that warrant cultural consideration) were observed across the Southern United States (Fig. 2). Areas located within the "stroke belt" of the Southern United States, a known geographical region of the United States that has a population with a higher prevalence of many chronic illnesses (Howard, 2021), were identified to a high degree of confidence as hotspots for census tracts with the greatest need for cultural context consideration. Along the Mississippi River within the Southern United States, areas were identified to a high degree of confidence as hotspots for cultural context consideration. A number of significant hotspots were seen in areas outside of the major cities, including: the Navajo Nation Reservation; Choctaw Otsa; Greenville, MS; the intersecting borders of Kentucky, West Virginia, and Virginia; Okeechobee, FL.

Coldspots, on the other hand, are census tracts that do not warrant as much cultural context consideration. Coldspots of CCI were evident across North and Northeastern United States. Clusters of coldspots appeared along the Northeastern coast, covering the major cities of Boston, MA, New York, NY, and Washington D.C. Additionally, major Northern cities such as Minneapolis, MN, Madison, WI, and Milwaukee, WI were coldspots of CCI with a high degree of confidence.

Within major metropolitan areas, there was a pattern of hotspot clusters among the densely urban city center, with coldspot clusters appearing within the metropolitan area, but tangential to the urban centers (Fig. 2). This pattern extends to show the majority of census tracts with the greatest need for cultural context consideration, among those in the highest CCI quintile (84.8%), as well as the lowest need for cultural context consideration, among the lowest CCI quintile (91.8%), were mostly located in metropolitan areas (Table 4). Compared to the overall distribution of urbanization, those tracts with the greatest need comprised less micropolitan (9.01% vs. 6.85%), small town (4.58% vs. 4.07%), and rural areas (4.52% vs. 3.97%), all with p-values less than 0.01.

On average, 13.9% of census tracts reported poor physical health and 14.5% reported poor mental health, as shown in Table 5. Census tracts with the greatest need for cultural competency (i.e., CCI rank=5) displayed 17.2% of the population reported poor physical health and 17.4% reported poor mental health, on average. Whereas areas with the lowest need for cultural competency (i.e., CCI rank=1) displayed 11.9% of the population reported poor physical health and 10.8% reported poor mental health, on average.

There was a positive linear relationship between the CCI and poor physical health (i.e., poor physical health percentage increases as CCI increases) for 26.2% tracts in the United States, as shown in Panel A of Fig. 4. There was also positive linear relationship between the CCI and poor mental health (i.e., poor mental health percentage increases as CCI increases) for 24.76% tracts in the United States (Panel B, Fig. 4). Among those tracts which were identified as having a positive relationship of poor physical health and CCI there was a 50.74% overlap with those tracts which have a positive linear relationship with poor mental health (Panel C, Fig. 4). The convergence of the two population health measures displayed geographic pockets of comorbidity across the United States, including: the Arizona-New Mexico border; Western Maine; Western Alaska; Central South Dakota; Fresno, CA.

4. Discussion

This paper introduces the Cultural Context Index (CCI), a new geospatial index spanning six SDOH domains, and validates its association with physical and mental health outcomes. More specifically, we incorporated measures of ethnic, linguistic, and religious fractionalization into the CCI's Social and Community Context domain. Applying the CCI to 73,682 census tracts of the United States, we found that the census tracts with the highest CCI rank also had the highest prevalences of poor physical health and poor mental health. We also found spatial (i.e., metropolitan areas in the South with large populations) and demographic (i.e., young Black and Hispanic residents) variations among census tracts using the CCI. Our intent behind creating the CCI is to embrace health, diversity, and place with a single index.

Table 3
Key characteristics of census tracts, by Cultural Context Index quantile.

		Cultural Context Index Quintiles					
	Rank	5	4	3	2	1	
Demographics	Overall (N = 73,682)	Greatest Need for Cultural Competency (n = 14,735)	Second Greatest Need (n = 14,735)	Moderate Need (n = 14,736)	Second-Lowest Need (n = 14,739)	Lowest Need for Cultural Competency (n = 14,737)	Chi-Square
	N (%)	*N (%)*	*N (%)*	*N (%)*	*N (%)*	*N (%)*	
Census Region							5845.97**
Northeast	13,494 (18.3)	2,878 (19.5)	1,340 (9.1)	2,087 (14.2)	2,754 (18.7)	4,435 (30.1)	
Midwest	17,018 (23.1)	2,497 (17.0)	2,158 (14.7)	3,217 (21.8)	4,207 (28.5)	4,579 (31.1)	
South	26,199 (35.6)	6,115 (41.5)	7,365 (50.0)	5,588 (37.9)	4,159 (28.2)	3,082 (20.9)	
West	16,061 (21.8)	2,450 (16.6)	3,511 (23.8)	3,842 (26.1)	3,618 (24.6)	2,641 (17.9)	
Urbanization Classification							2016.55**
Metropolitan	60,238 (81.8)	12,497 (84.8)	10,864 (73.7)	11,354 (77.1)	11,991 (81.4)	13,532 (91.8)	
Micropolitan	6,641 (9.0)	1,009 (6.9)	1,945 (13.2)	1,727 (11.7)	1,329 (9.0)	631 (4.3)	
Small Town	3,372 (4.6)	599 (4.1)	1,031 (7.0)	814 (5.5)	633 (4.3)	256 (1.7)	
Rural	3,333 (4.5)	585 (4.0)	880 (6.0)	825 (5.6)	772 (5.2)	310 (2.1)	
	Median N (IQR)	*Median N (IQR)*	*Median N (IQR)*	*Median N (IQR)*	*Median N (IQR)*	*Median N (IQR)*	
Population Size per Mile^2	2,108 (4,889)	4,470 (10,073)	2,007 (4,977)	1,751 (4,569)	1,577 (3,769)	1,694 (3,426)	3602.65**
Sex							
Male	1,961 (1,201)	1,742 (1,226)	1,971 (1,190)	1,983 (1,177)	1,997 (1,195)	2,073 (1,184)	1015.56**
Female	2,039 (1,252)	1,832 (1,254)	2,038 (1,238)	2,064 (1,234)	2,083 (1,261)	2,162 (1,235)	950.60**
Race/Ethnicity							
White	2,905 (2,275)	1,710 (2,172)	2,728 (2,093)	3,090 (2,099)	3,289 (2,139)	3,509 (2,240)	9075.39**
Black	159 (565)	545 (1,483)	241 (772)	144 (459)	98 (299)	86 (222)	6724.92**
Hispanic	241 (661)	413 (1,625)	344 (1,022)	265 (666)	195 (442)	162 (286)	2805.29**
Asian	57 (171)	32 (115)	43 (131)	55 (158)	64 (185)	105 (247)	3143.30**
Median Age	38.3 (9.4)	33.8 (8.6)	37.1 (9.2)	39.0 (8.8)	40.2 (8.4)	40.8 (7.7)	7522.72**
Household Size	2.5 (0.5)	2.6 (0.7)	2.5 (0.5)	2.5 (0.4)	2.5 (0.4)	2.6 (0.5)	1254.29**

**p < 0.01.

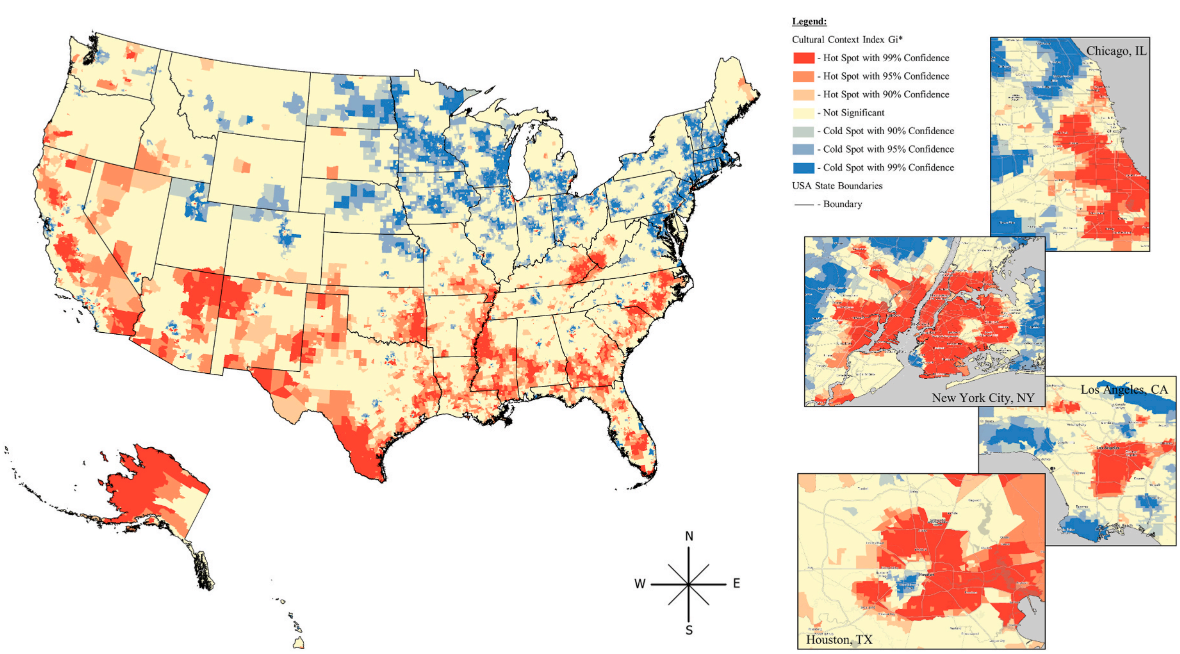

Fig. 2. Map of United States hot and cold spots of Cultural Context Index quantiles.

Table 4
Relationship between Cultural Context Index and other indices.

Index of Comparison	Spearman Correlation Coefficient	Positive Linear N (%)	Negative Linear N (%)	Median p-value
Social Vulnerability Index	0.37**	18,013 (24.8)	832 (1.1)	0.14
Social Deprivation Index	0.43**	30,087 (41.6)	315 (0.4)	0.11
Social Needs Index	0.45**	5,577 (18.1)	166 (0.5)	0.29
Area Deprivation Index	0.06**	3,065 (4.2)	3,881 (5.3)	0.34

** p-value <0.01.
Linear tests were conducted using tests of local entropy; p-value represents the median of all census tracts across the United States included in the test of local entropy.

People –immigrants, in particular-have shaped and reshaped the American landscape through the reproduction of their cultures in or ex situ. This landscape is far from static, so too should be geographic research. We developed the CCI to locate micro-cultures. We offer it as an alternative geospatial index for measuring the variegated cultural mosaic. We are raising attention to hotspots flagged by the CCI, namely the census tracts with high cross-index convergence, in spite of differences in design between the CCI and other indices. These differences encompass the domains of SDOH, indicators selected as domain elements, and the geographic unit of analysis (Kaalund et al., 2022; Trinidad et al., 2022). Our findings suggest that culturally competent interventions would greatly enhance the quality of life in selected neighborhoods.

Previous literature has already brought to the foreground the significance of culture in public health praxis. The philosophy of culturally competent care is to account for sets of beliefs and values in service provision (Brach & Fraserirector, 2000; Campinha-Bacote, 2002). With increasing emigration and international migration driving population growth, health care and social service providers will inevitably come in contact with more and more consumers who come from backgrounds different than themselves. The moral imperative, adding to what Don Berwick (2020) had said, is to meet consumer needs where they reside within the jurisdictional borders of the United States. Carrying this sentiment forward, the transformation of health care and social services so that they become culturally *customized* requires that providers take into account ethnic, linguistic, and religious differences in their consumer base. With CCI, we reinforce the need for culturally customized care in key geographic areas. The CCI's utility is in highlighting areas where healthcare stakeholders (e.g., policymakers, providers, etc.) and community advocates need build strategic partnerships in order to provide culturally customized care for diverse populations.

Cultural embeddedness is spatially- and temporally specific. The growth and uneven settlement of collective identity groups across the United States has public health implications. Non-White populations will continue to grow. The United States Census Bureau projected the immigrant population nationwide to be 69 million by 2060, exceeding the historic high of foreign-born people living in the country in 1890 (Vespa et al., 2020). Secondary to the continuation of historic trends is whether Hispanics and Asians would remain spatially concentrated (Martin et al., 2017). Over time, what is considered as the core and the periphery of areal units, metropolitan areas in particular, will change.

Table 5
Population health status compared with the Cultural Context Index.

Population Health	All N (*Mean % [SD]*)	Greatest Need for Cultural Competency (CCI rank=5) *N (Mean % [SD])*	Lowest Need for Cultural Competency (CCI rank=1) *N (Mean % [SD])*
Poor Physical Health	18,946 (13.9 [3.7])	3,491 (17.2 [4.2])	3,052 (11.9 [2.1])
Poor Mental Health	17,904 (14.5 [3.3])	3,345 (17.4 [3.4])	3,138 (10.8 [2.2])
Convergent Poor Health	9,613	1,928	1,504
Physical Health	(14.1 [3.7])	(17.4 [4.1])	(10.8 [2.0])
Mental Health	(14.7 [3.2])	(17.6 [3.3])	(12.0 [2.0])

SD=standard deviation.

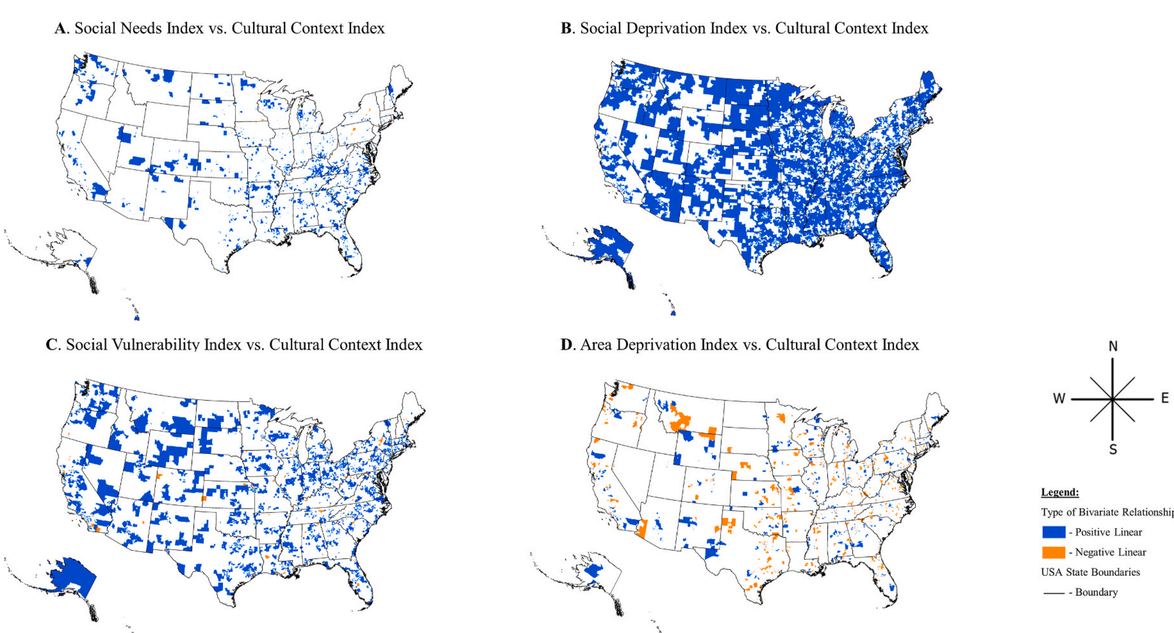

Fig. 3. Pairwise comparison of Cultural Context Index with alternative indices.

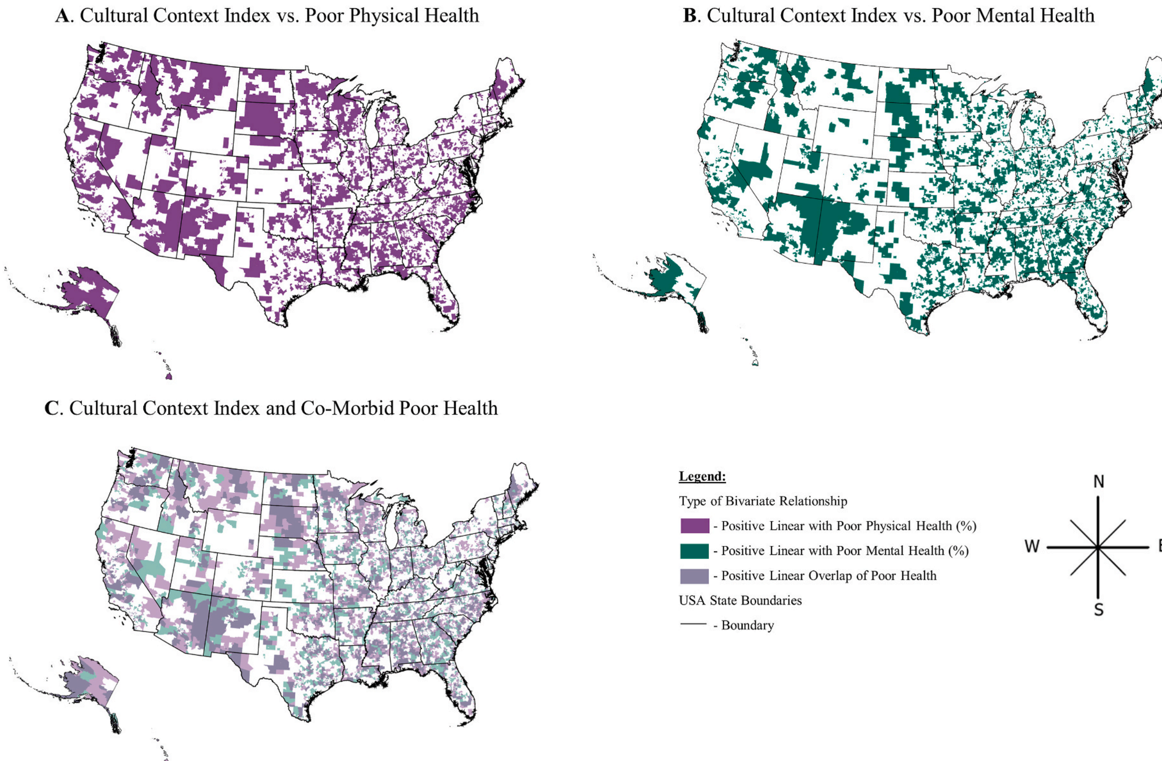

Fig. 4. Pairwise comparison of Cultural Context Index and health status indicators.

Such pluralism necessitates iterative, geospatial measurements of cultural contexts. The CCI embodies our joint efforts in measuring the diversity within locales.

4.1. Limitations and future research directions

Our study has three main limitations. First, our study is cross-sectional. Culture is not an immutable object, but a "constantly, multi-dimensional, multi-level process that encompasses all aspects of the human condition" (Kagawa Singer et al., 2016, p. 242). Over time, the CCI will need to be updated with indicator- and domain-specific data to account for the evolving cultural characteristics of neighborhoods. Second, we situated the CCI at the census tract level. Cultural groups may not reside within the same bounds as a census tract, the size of which ranges between 1,200 and 8,000 people. This phenomenon may be better illustrated with available secondary data at other analytic levels. Nonetheless, the CCI is a unique marker that draws attention to SDOH and health disparities within cultural contexts.

Lastly, we chose three measures of culture. Their indicators, all in the Social and Community Context domain, collectively explain 0.2% of the total variance of the principal component analysis. Undoubtedly, the CCI stands to be more sophisticated, though we should point out that researchers have traditionally developed indices using differing combinations of factors aimed at explaining their own particular facets of the SDOH. Culture is not merely symbolic. Alongside the movement of diversity, equity, and inclusion in domestic public health is a critique of post-colonialism in global public health, both of which prompted us to ask whether conventional ways of mapping are suitable for pluralistic contexts. We are not agnostic to the contestation in mapping inhabited spaces in geography (Williams et al., 2019), let alone struggles over interpreting cultures in anthropology (Crang, 2013). Culture has been conceptualized as a toolkit (Swidler, 1986) and as an asset map (Martin et al., 2017), both metaphors of place-based inventories that can be utilized to address health disparities. This inquiry is interdisciplinary in nature.

The study is a precursor of future research about geodemand and geosupply. The premise that merits further investigation is whether the location of consumers ('geodemand') and providers ('geosupply') of healthcare and social services are at an equilibrium. Hospitals, for instance, are like supermarkets in that both types of organizations are not at equilibrium because their performance depends on competition as well as location (Horwitz, 2005; Roig-Tierno et al., 2013). Providers' optimum location has downstream consequences for population health. Optimum location can be an explanation for delay and failure in seeking products and services (Guagliardo, 2004). Second, spatial accessibility falls short of explaining care quality, which is subject to market segmentation (Henriksen et al., 2012), cultural attenuation (Beach et al., 2006), and cultural diversity of health care teams (Schmidt et al., 2023). The need for cultural competency among providers and systems to equitably provide quality health care has been garnering attention since the National Culturally and Linguistically Appropriate Services (CLAS) Standards were published in 2000. CLAS Standards are intended to improve organizational capacity to address health disparities. However, future research about cultural measures of quality is needed to address systematic shortfalls so that iterative changes made would ultimately be focused the on diversity of consumer values and perspectives and account for the multifaceted nature of cultural differences (Beach et al., 2006; Lin et al., 2022).

5. Conclusion

Culture is a social determinant of health, yet it has not been effectively operationalized in geospatial analyses. The Cultural Context Index is a new composite measure that takes into account ethnic, linguistic, and religious fractionalization. Applying it to the United States, we also found spatial and demographic variations among census tracts. These census tracts have the greatest need for culturally customized health care. The United States will be even more diverse with a projected demographic transition between 2030 and 2060, necessitating research and practice considerations that stress cultural plurality and contextual multiplicity.

Conflict of interest declaration

The authors declare that they have no conflicts of interest with regard to the research, authorship, and publication of this manuscript.

Ethical statement

The authors declare that they have no conflicts of interest, financial or otherwise, related to this research. No external funding was received to conduct this study. All listed authors have made significant contributions to the conceptualization, design, execution, and/or interpretation of the results. All authors have participated in drafting, revising, and approving the final manuscript and accept responsibility for its content.

CRediT authorship contribution statement

Alaina M. Beauchamp: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Gordon C. Shen:** Conceptualization, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Syed H. Hussain:** Conceptualization, Data curation, Formal analysis, Investigation, Writing – original draft. **Atif Adam:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Writing – review & editing. **Linda Highfield:** Supervision, Validation, Writing – review & editing. **Kai Zhang:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation.

Data availability

Data is available at an online repository: https://data.mendeley.com/datasets/mgxdkznby7/1.

Appendix A. Supplementary files

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2023.101591.

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