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Improvement of Geographic Disparities: Amelioration or Displacement?

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Abstract Progression of geographic disparities in social determinants of health is a global concern. Using an Urban Health Index (UHI) approach, we proposed a framework of examining the change of geographic disparities in social determinants in small areas. Using the City of Atlanta in Georgia (USA) as a case study, we standardized six census-based social determinant indicators in 2000 and in 2010, respectively, and calculated their geometric mean to assign each census tract a UHI value for 2000 and for 2010. We then evaluated the temporal change of the UHIs in relation to the demographic changes using spatial and statistical methods. We found that Atlanta experienced an improvement in social determinant status and a reduction of disparities in the 10 years. The areas that experienced improvement, however, underwent demographic changes as well. This analysis provides support for displacement, rather than improvement, as the underlying factor for apparent change in geographic disparities. Findings suggest the importance of local evaluation for future policies to reduce disparities in cities.

Keywords Disparities · Urban Health Index · Health determinant · GIS · Cities

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Introduction

Importance of Intra-urban Health Disparities

Rapid urbanization leads to growing population in cities, and many new urbanities will likely live in poverty [1–3]. A key question arises as to how a city can evaluate its health disparities and identify pockets of deprivation. Answers to this question may provide evidence and guidance into possible public health intervention to reduce health disparities. Over time, public health workers and policy makers may need to require evaluation of disparity change, for example, after a policy implementation or a major disaster. Where, in a city, is getting better or deteriorating? Who benefits from disparity reduction? To address these questions, we propose to assess intra-urban disparities in social determinants of health and their changes over time.

Social Determinants of Health

Social determinants of health, the conditions where people are born, grow, live, work, and age are mostly responsible for health disparities [4, 5]. Geographic settings provide vital places to support people's physical and social activities [6–8]. Many deprived neighborhoods, often characterized as low educational attainment or low income levels, have experienced increased mortality or morbidity [9–11]. In fact, neighborhood context has uniquely predicted health outcomes, beyond their influence on individual behaviors [12–14]. Thus, examining intra-urban disparities in social determinants of health at small-area levels is not only of value in understanding of such inequality but also may guide resource allocation to disadvantaged communities [15]. Moreover, evaluating the temporal variation of disparities is necessary for cities to understand why they are improved or ameliorated.

Measure Change of Disparities

Many efforts have been devoted to measure the change of disparities at the small-area levels, yet challenges remain. For instance, Messer et al. constructed a neighborhood deprivation index using socioeconomic indicators in multiple domains via principal component analysis [16]. Yet, variable loadings may be inconsistent across different areas or time periods, thus making results difficult to compare. Grineski et al. examined the relationship of extreme heat to the change of heat-related social vulnerability using mean education, percent older adults, and total population density [17]. But, the study did not measure how disparities changed over the years. The Urban Health Index (UHI) approach from the World Health Organization Centre for Health Development (WHO Kobe Centre) provides a flexible method for identifying intra-urban disparities for local evaluation [18, 19]. This approach, however, has not been used for multiyear comparison of disparities. Many studies have evaluated geographic disparities in health outcomes and determinants using geographic information system (GIS) techniques. Measuring the level of intra-urban disparities at the small-area level and their change over time is still needed. Studies [20, 21], for instance, assessed spatial patterns of environmental stressors and explored the associations with socioeconomic variables; however, they did not extend the analysis to a multiyear evaluation. The rapid growth of cities and urban populations poses pressing research questions. How do we examine the progression of disparities? How do we assess the effect of policy implementation or program interventions on disparities? Are disparities deteriorating in a city? An equally, if not more important question is concerning the residents who experience the changes. Dramatic improvements in health, globally and within countries, have occurred in the last 30 years [22]. Although people are optimistic that marked improvements in equity will continue, a hidden question is who will benefit from such improvements and who is suffering. In this regard, it is vital to critically evaluate the demographic changes accompanied with the change in social determinants of health.

Inspired by these questions, we propose to measure the level of disparities and its changes over time using the UHI approach and the social determinants of health. Using Atlanta as a case study, we (1) examine disparity change in social determinants of health measured in two time periods and (2) assess the change in relation to demographic characteristics of neighborhoods. Addressing these questions will be necessary in order to assess disparities and its progression. Besides, they are valuable for local evaluation of how positive changes benefit residents and the underlying contributing factors to the changes.

Data Sources and Methods

The City of Atlanta as a Study Area

The City of Atlanta is an ideal area for this research. Despite racial and demographic transition over the years [23], Atlanta is still segregated in many aspects (Fig. 1). The majority of census tracts in south Atlanta have over 87% of blacks compared with the north where black population is 15% or less. According to US Census Bureau (www.census.gov), Atlanta had 416,474 people in 2000, of whom 138,352 (33.2%) were white and 255,689 (61.4%) were black. Initially stimulated by the centennial Olympics in 1996, Atlanta has had intense revitalization over the last two decades [23]. The city also has experienced a growth of migrants from other areas given its economic development. In 2010, Atlanta increased its population to 420,003 with 161,115 (38.4%) whites and 226,894 (54%) blacks. Blacks became less concentrated around the central business district (CBD), where many corporate or regional headquarters, governments, as well as colleges and tourist attractions are located, whereas the south and the southwest had a substantial increase in their population.

Accompanying such an extremely uneven racial distribution are a variety of social disparities. The annual

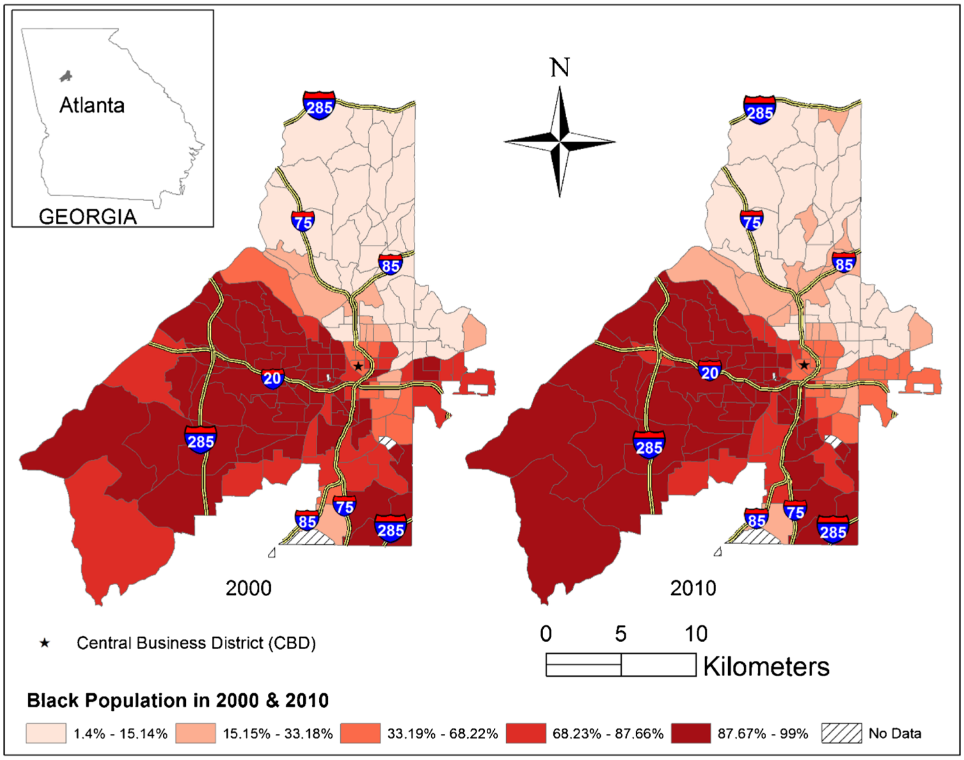

Fig. 1 Study area and distribution of black population at the census tract level, in 2000 and 2010

median income in census tracts with at least 90% black population was \$28,614 compared to \$126,991 in white-majority tracts; similarly, 21.4% of population was unemployed in these black-majority areas compared to 4.4% in white-majority counterparts. More subtle indicators are common as well. Black-majority census tracts have, on average, longer public transit travel time than do white-majority tracts for radiotherapy access [24] or green space access [25]. These stark disparities make Atlanta an appropriate site for this research.

Data Sources

We used six indicators based on the 2000 Decennial Census Summary File 3 (SF3) and the 2008–2012 American Community Survey (ACS). Because the US Census Bureau eliminated the SF3 for the 2010 decennial census, we used the 2008–2012 ACS data to surrogate the 2010 social determinants. These six indicators are proportion employed, proportion of households above poverty line, proportion that are high school graduates, proportion that are college graduates, median income, and mean income. These six indicators were selected because they reflect social stress in community settings and are surrogates for socioeconomic deprivation in the literature [24, 26, 27]. Both high school graduates and college graduates were included to describe two different educational levels. Besides, increasing college attainment is likely to decrease cumulative mortality [27]. Some indicators, such as health insurance coverage, were excluded because they were unavailable in either or both surveys. We observed that there was a significant correlation between median household income, median housing value, gross rent, poverty, and educational attainment ($P < 0.05$) in each year. Therefore, other variables correlated with these indicators may present similar patterns.

Our analysis focused on the census tracts that were wholly or partially within Atlanta's city limit ($n = 143$) after considering the boundary split of census tracts from 2000 to 2010 and missing ACS data in three tracts. An additional consideration is the comparison of 2000 SF3 data and 2008–2012 ACS data. These two datasets were based on different sampling schemes [28]. Nonetheless, the 2010 Census eliminated the SF3 form, so researchers must now rely on the ACS estimates pertaining to socioeconomic characteristics.

Evaluating the change of disparities involves three steps. First, we quantified the disparities in 2000 and 2010, respectively, using the UHI approach. The change of disparities was measured by the UHI difference in the two time periods followed by clustering the trend. We then examined the demographic transformation in the same units associated with the disparity change. These methods are detailed in the following sections.

Evaluating Disparities Using the UHI Approach

The UHI is a flexible approach that measures intra-urban disparities developed by the WHO Kobe Centre (http://www.who.int/kobe_centre). This method is described in Supplement Material 1 and detailed in the literature [18, 19]. We applied the UHI to Atlanta at the census tract level in 2000 and 2010, respectively. All indicators are adjusted to ensure that the higher values denote more favorable social determinants. For instance, the poverty proportion was changed to not-in-poverty proportion to be consistent with the direction of income indicators. To make the two sets of UHI values comparable, we adjusted the 2000 income to 2012 based on the US inflation rate published by the US Department of Labor (www.bls.gov). We scaled each indicator of the two periods using the same upper and lower goalposts so that all UHI values will be in the same range and be comparable.

Clustering of UHI Changes

We calculated the changes by subtracting the 2000 UHI from the 2010 UHI at each census tract. For each census tract undergoing splitting, we assumed its UHI value was uniform before the boundary change. A positive change, representing an increase of its UHI value, suggests the social determinants of health have improved in the underlying census tract, and vice versa.

Using the local Moran's *I* [29], we then assessed the spatial variation in the UHI changes. Local Moran's *I* for a census tract measures the association between its value (UHI change) and the values of its nearby tracts. In this case, a positive *I* means either a high value of UHI change is surrounded by high values (high-high) or a low value is surrounded by low values (low-low). A negative *I* means either a low value (UHI change) is surrounded by high values (low-high) or a high value is surrounded by low values (high-low). Statistical tests for the local Moran's significance levels can be obtained by means of randomization [29].

Demographic Transformation during the Change

We examined the demographic transformation in the 10 years in comparison with the disparity change. For cities undergoing rapid changes, especially being reshaped by gentrification like Atlanta [23], the demographic composition of the neighborhoods has changed. In the areas of UHI improvement or deterioration, therefore, this comparison provides a nuanced approach to the structure of disparity progression in relation to the shift of demographic composition.

In line with the literature [21, 24, 30], we selected eight demographic variables: black population (%), owner-occupied homes (%), professional and managerial jobs (%), households with more than one occupant per room (%), children less than 18 years old (%), seniors older than 64 (%), households paying at least 30% of their income for rent (%), and family size. Family size is the number of people related to (and including) the householder. Each change is defined as the value in 2000 subtracted from the value in 2010. Some other variables were excluded, such as home owners paying more than 30% of their income for mortgage, because of the measurement difference in the survey questionnaire between the ACS and the 2000 statistics.

To investigate the correlation between the UHI change and the demographic transformation, we used the bivariate Moran's *I* implemented in GeoDa 1.6 [31]. Bivariate Moran's *I* evaluates the type of spatial correlation between the value for a variable (i.e., UHI change) at a particular location (i.e., a census tract) and the average value of another variable (i.e., a demographic indicator) at neighboring locations. A positive correlation than that indicated under spatial randomness suggests spatially similar cluster of the two variables. Clusters from the bivariate Moran's *I* can be mapped in four categories: two groups of positive spatial correlation (high-high and low-low) indicating that values are physically surrounded by neighboring census tracts with similar values or spatial cluster, and two groups of negative spatial correlation (high-low and low-high) suggesting values are dissimilar compared to the neighboring tracts. The calculation requires a spatial weights file defined as six nearest census tracts in this research, which is in line with previous studies [30, 32].

We evaluated the correlation between the UHI change and the eight demographic variables while taking into account the effects of all variables using multivariate regressions, i.e., ordinary least squares (OLS) regression and the spatial error model [33]. The OLS model assumes random errors to be independently and identically distributed around a mean of zero. This assumption, however, may be violated if UHI changes are not random. Two commonly used spatial regression models may address this issue: the spatial lag model [33] and the spatial error model [34]. The former includes a weighted average of the dependent variable in neighboring areas as an extra explanatory variable. The latter considers the errors as autoregressive to account for the spatial dependence in the dependent variable. Detailed explanations can be found in the literature [33, 35]. We chose the spatial error model but also tested the spatial lag model for consistency. We report the result using the spatial error model based on the first-order queen contiguity. The second-order queen contiguity and first-order rook continuity weights were alternated to examine the sensitivity of the results.

Results

The distribution of UHI suggests that Atlanta's disparities were persistent yet slightly improved in the last decade (see indicator summary in Table 1 and UHI summary in Table 2). Disparity ratios (Table 2) suggest that the best-off census tracts were 6.58 times better than the worst-off census tracts in 2000, compared to 4.63 times better in 2010. The improvement is also evidenced by the mean and median UHI values. As greater UHI values indicate better social determinants of health, the increase suggests Atlanta has improved its level of social determinants on average and reduced its disparities.

Graphing the UHI values against their percentiles reveals steep disparities with improvement (Fig. 2). Each of the two graphs shows markedly deviant extremes (below the 10th and above the 90th decile) with considerable variation. The shape of the tail with extremely low UHIs (below the 10th decile) manifests a striking disadvantage of these census tracts compared with the rest of the area. In addition, overlaying the two UHI charts indicates that UHIs in 2010 generally improved compared with UHIs in 2000. The 2010 UHIs have a flatter slope in the middle section (less variation) than the 2000 UHIs. The bulk of improvement was observed in areas with moderate UHI values ranging from 0.4 to 0.7.

Mapping the UHIs (Fig. 3) visualized a swath of low-index census tracts through the midsection in Atlanta. Each map uses its own quantile classification scale in order to locate its deprived pockets (below 10th decile). These areas run roughly along the major interstate highways of I-75/85 and I-20 in both years. The north and south ends, on the other hand, had more favorable social determinants of health or better UHIs. Comparing the two maps reveals that areas in the lowest decile shifted southwestward despite general stagnation along the interstate highways. The average distance between worst-off (or darkest color) census tracts and the CBD increased from 2.85 to 5.43 km. The difference may be interpreted as a net average deprivation relocation of 2.58 km.

Cluster analysis of UHI changes (Fig. 4) shows that both low- and high-index areas in 2000 experienced a significant decrease of UHIs. Compared with the 2000 UHI (Fig. 3a), a majority of negative changes (cross-hatch patterns) occurred in a low-index area (in 2000) in the southwest area; that is, the worst-off areas deteriorated the most. UHIs in this area decreased from 0.36 to 0.29, with all but one below the city average. The other decreased area is located in a high-index area (in 2000) between I-75 and I-85 on the north, where UHIs decreased from 0.69 to 0.54 but still remained above the city averages (0.39 and 0.45 in Table 2). In contrast, the positive changes are present primarily around the CBD, where the UHI changes range from 0.0978 to 0.488 with an average improvement of 0.174. In other words, the low-index areas closer to the city center in 2000 were gentrified. However, these areas further away from the city center, which were already in disadvantaged situation, became even worse.

Figure 5 reveals significant demographic changes within each cluster of UHI changes. The areas within the significant clusters of positive changes experienced decreased proportions of blacks, children, family size, seniors, and households paying at least 30% of their income for rent (Fig. 5a, e–h), whereas home ownership and professional and management jobs increased (Fig. 5b, c). The tracts with deteriorated UHIs on the southwest side, in contrast, had decreased home ownerships (Fig. 5b) and increased proportion of seniors and households paying at least 30% of their income for rent

Table 1 Summary of the six indicators in 2000 and 2010 and their goalposts

	Employment		Not in poverty		High school		Bachelor		Median income		Mean income	
	2000	2010	2000	2010	2000	2010	2000	2010	2000	2010	2000	2010
Mean	0.87	0.86	0.78	0.8	0.74	0.86	0.3	0.43	50,216	51,971	72,583	76,129
Stdev	0.13	0.1	0.17	0.18	0.17	0.11	0.27	0.27	34,982	35,869	49,084	56,365
Min	0.1	0.34	0.27	0.12	0.37	0.57	0	0.02	10,394	5,764	20,582	10,172
10th P.	0.73	0.74	0.58	0.57	0.49	0.72	0.04	0.11	18,990	17,407	35,279	27,308
Median	0.89	0.88	0.81	0.83	0.73	0.87	0.18	0.43	39,999	40,547	54,365	58,805
90th P.	0.98	0.96	0.98	0.99	0.97	0.99	0.73	0.82	91,883	101,632	132,068	146,372
Max	1	1	1	1	1	1	0.84	0.92	217,959	180,714	304,208	290,827
Upper G.	0.101		0.121		0.363		−0.003		5,405.307		9,608.347	
Lower G.	0.998		1		1		0.918		217,959.884		304,208.395	

The first four indicators were measured by proportion. The median income and mean income were measured by dollars

Stdev standard deviation, *P.* percentile, *G.* goalpost

(Fig. 5f, h). The west side of Atlanta had low UHIs in both years with little changes in any indicators. Therefore, the spatial autocorrelation in UHI change was low and presents a weak relationship with these demographic indicators.

The observations above mostly agree with results from the non-spatial bivariate analysis (Table 3) and the multivariate regression models (Table 4). The coefficients indicate that tracts with improved UHIs are significantly associated with decreased proportions of black and senior populations, smaller family sizes, and lower proportions of households with more than one occupant per room and renters using 30% of family income for renting. In the areas experiencing improvement or positive changes, demographic composition has shifted greatly. In fact, it might be inferred that disadvantaged groups were displaced.

The regression diagnostics using Moran's I reported a significant spatial autocorrelation for residuals in OLS models ($I = 0.27$; $P = 0.001$) but not in the spatial error models ($I = 0.076$; $P > 0.05$). Even when the other two spatial weights were utilized, Moran's I values were low (−0.0042 and 0.0069) and insignificant. Therefore, the

Table 2 Summary of UHI in 2000 and 2010

Summary statistics of UHI	2000	2010
Mean	0.39	0.45
Standard deviation	0.21	0.2
Min	0.06	0.02
10th percentile	0.17	0.23
Median	0.34	0.42
90th percentile	0.69	0.72
Max	0.97	0.93
UHI disparities and inequalities		
Selected proportion (extreme areas) (%)	20	20
Mean UHI for bottom extreme group[a]	0.12	0.18
Mean UHI for top extreme group[a]	0.8	0.83
UHI disparity ratio	6.58	4.63
UHI disparity difference	0.68	0.65
Slope	0.5	0.53

[a] The extreme groups are the highest and lowest deciles after ranking

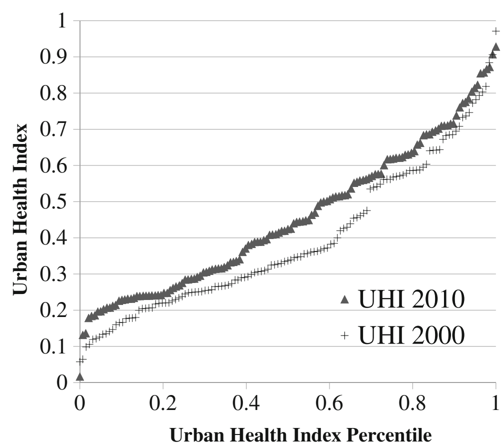

Fig. 2 Urban Health Index (*UHI*) distribution in 2010 and 2000

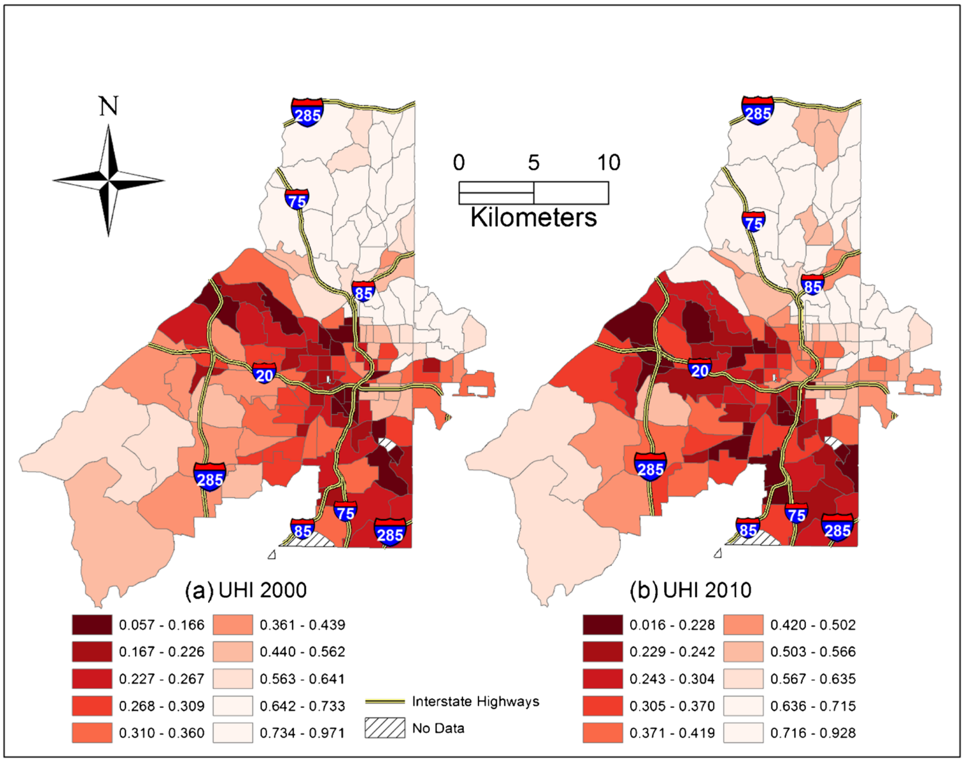

Fig. 3 Urban Health Index (*UHI*) maps in 2000 (**a**) and 2010 (**b**)

spatial error model shows a better fit than the OLS model. The explanatory variables presented weak multicollinearity because the multicollinearity condition number (4.66) is less than the suggested threshold of 30 [31]. The normality of the explanatory variables (demographic changes) and the dependent variable (change in UHI) may be a concern for the regression models. We made natural logarithm transformation after each value added by 2 (to avoid zero). The normality was slightly improved. The skewness of the UHI changes, for instance, changed from 0.883 to 0.629. The pattern of significance of the coefficients in the spatial error model after transformation, however, remained consistent despite minor shift. The Breusch-Pagan test for heteroskedasticity was significant regardless of variable transformations (71.8 and 21.87; $P < 0.05$), suggesting some relationships are non-stationary. Geographically weighted regression (GWR) [36] accounts for spatially varying relationships, yet it has an issue of multiple dependent hypothesis tests [37–39] and "should be applied to datasets with several hundred features for best results" [40]. The small dataset ($n = 143$) in this case study, therefore, is less ideal for the GRW approach. When the other two spatial weights were used, all relationships remained consistent except that changes of senior population and family size became insignificantly related to the UHI change. Results from the spatial lag model agreed with findings based on the spatial error model above, which is in line with the literature reporting the consistency between the two in general [35, 41].

Discussion

Understanding the social determinants provides proactive measures to address urban disparities [26]. Using Atlanta as an example, this study provides an evaluation framework by focusing on the assessment of disparities in social determinants in conjunction with demographic shifts. The approach may be used directly by local governments and public health workers to examine the intra-urban disparities and investigate the changes at the small-area levels.

Using a standard approach to demonstrate temporal change at small areas, this research revealed that Atlanta

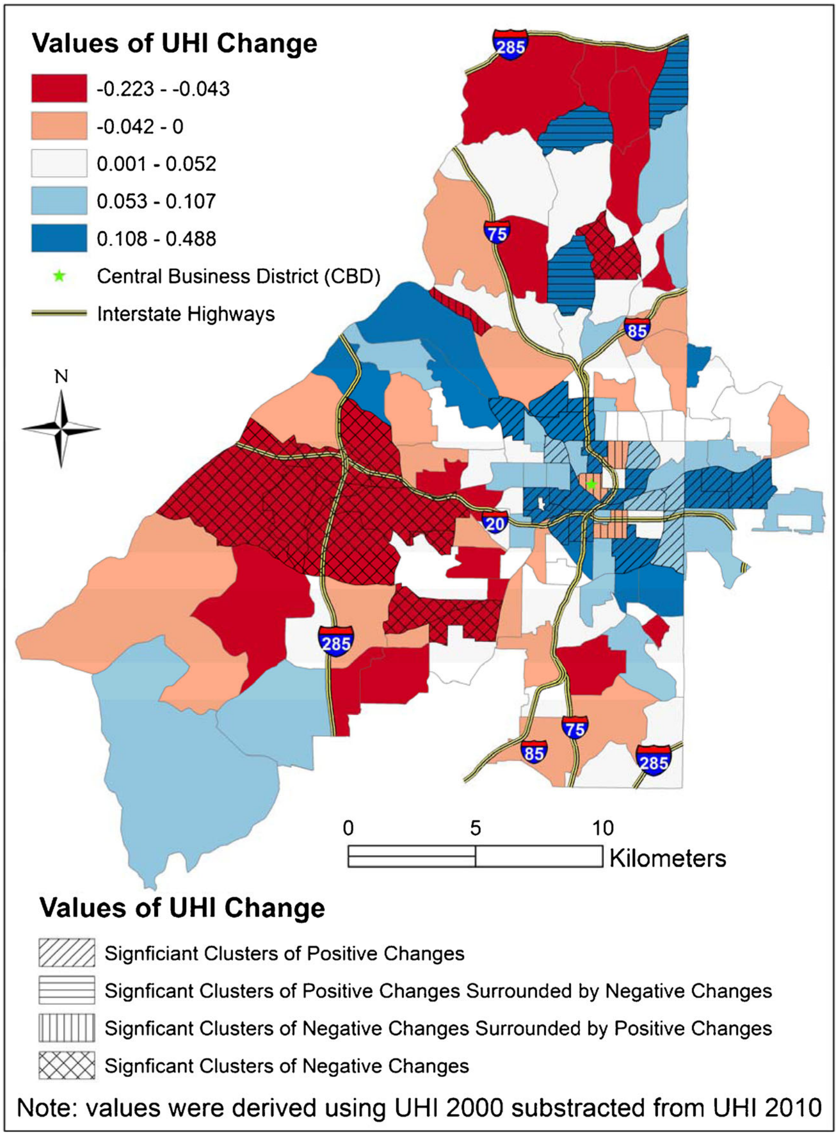

Fig. 4 Clustering of Urban Health Index (*UHI*) changes

has experienced a gradual improvement in the overall social determinants evidenced by a narrowing disparity ratio and an increase in the average UHI. Such improvement, however, may not benefit all racial and socioeconomic groups equally. In fact, this analysis suggests that the improvement may be less the result of amelioration of disparities and more related to displacement of disadvantaged groups. Like many fast-growing US cities, Atlanta experienced downtown revitalization—the result of a complex interplay of various factors. Economic growth and job creation, particularly in historically under-utilized or underdeveloped areas such as former industrial sites or warehouse spaces, have made substantial gains in the last decade. For example, Atlantic Station, a former brownfield site of the Atlantic Steel mill, was transformed in mid-2000 into a vibrant neighborhood full of retails, office spaces, restaurants, and residential lofts. The overall economic prosperity in the city, however, has not benefited all residents. In fact, growing concerns arise regarding gentrification, decreased living affordability, and displacement of existing residents [23]. Observed single-family property values have increased to 102.1% from 2000 to 2006 in Atlanta, thus reducing the living affordability for the

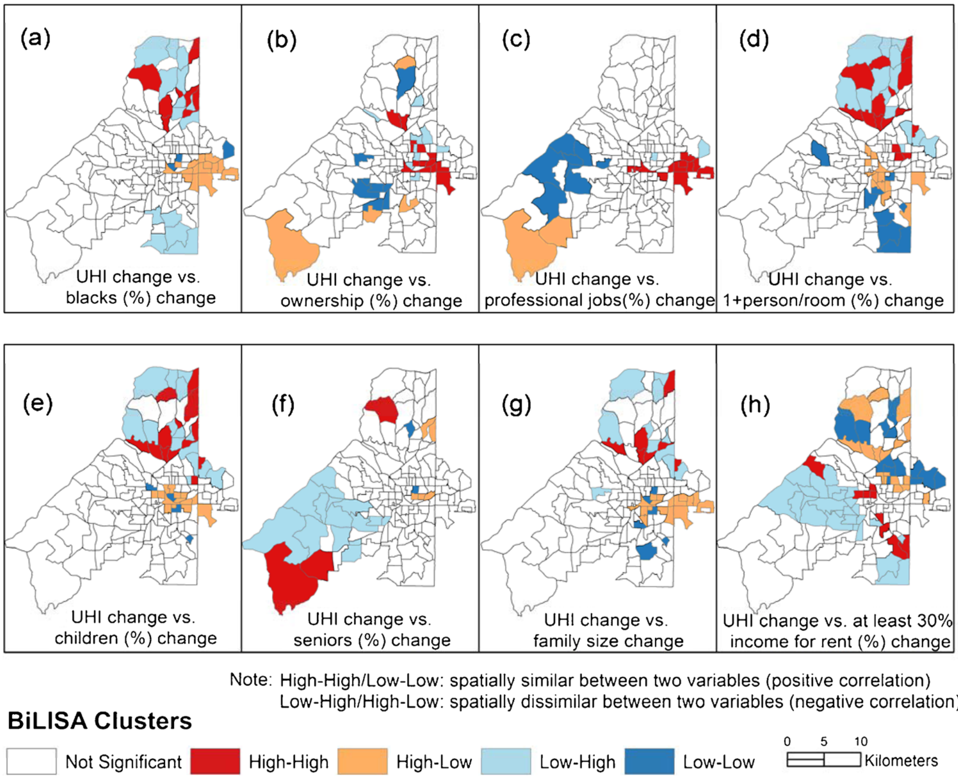

Fig. 5 BiLISA cluster maps: relationship between the Urban Health Index (*UHI*) change and demographic change

urban poor and involuntarily relocating its residents [23]. Urban revitalization from gentrification is virtually synonymous with the displacement of urban poor and minority groups by higher-income households [42, 43]. This urban renewal of low-income neighborhoods forced the poor residents into more deprived conditions elsewhere and "was particularly hard on minority populations clustered in downtown slums" [44]. The decline of minority, elderly, and economically challenged residents in the *improved* neighborhoods near downtown Atlanta, which this research revealed, echoes such concern. Addressing negative effects on the urban poor in prospering areas is critical for true amelioration of disparities.

Table 3 Summary and correlation between UHI changes and demographic changes

Change of demographic indicators	Mean	Standard deviation	Min	Median	Max	Pearson correlation
UHI change (2010–2000)	0.04	0.1	−0.22	0.04	0.49	1
Housing ownership	0.02	0.1	−0.2	0.02	0.32	0.54[a]
Professional and management jobs	0.07	0.11	−0.19	0.07	0.44	0.56[a]
Black population	−0.03	0.11	−0.39	−0.01	0.29	−0.48[a]
Children (0–17)	0.02	0.07	−0.25	−0.01	0.10	−0.23[a]
Senior population (65 and over)	0.00085	0.04	−0.14	−0.001	0.12	−0.24[a]
Room with more than 1 occupant	−0.05	0.06	−0.23	−0.04	0.03	−0.33[a]
Family size	−0.06	0.27	−0.91	−0.02	0.66	−0.39[a]
Renters with 30% of family income for renting	0.15	0.16	−0.23	0.13	0.56	−0.23[a]

[a] Correlation is significant at the 0.01 level. All are measured by difference in proportion except family size

Table 4 OLS model and spatial error model of UHI changes and the demographic changes

Change of demographic indicators	OLS model		Spatial error model	
	Coefficients	*t* values	Coefficients	*t* values
Housing ownership	0.26[a]	4.31	0.25[a]	4.68
Professional and management jobs	0.14[b]	2.33	0.15[b]	2.68
Children (0–17)	0.26[b]	1.81	0.3[b]	2.38
Black population	−0.22[a]	−3.37	−0.27[a]	−4.01
Senior population (65 and over)	−0.29[b]	−2.12	−0.19	−1.52
Room with more than 1 occupant	−0.55[a]	−4.47	−0.47[a]	−4.31
Family size	−0.07[b]	−2.18	−0.05	−1.81
Renters with 30% of family income for renting	−0.13[a]	−3.17	−0.12[a]	−3.04
Spatial error (λ)			0.51[a]	5.3
R^2	0.58		0.65	

[a] Correlation is significant at the 0.01 level

[b] Correlation is significant at the 0.05 level. All are measured by proportion except family size

Further evidence of the unequal distribution of health determinants is the low UHIs in the swath of census tracts through the midsection of the city. This observation is in line with previous studies reporting similar deprivation [19, 24, 45]. Despite many revitalization efforts, disparities are persistent in the city. Compared with the northern counterparts, the southwest neighborhoods not only remained disadvantaged regarding social determinants of health but also deteriorated in a massive area. Our study observed that the worst-off areas experienced the most deterioration. It would be worthwhile to extend examination of changes in these neighborhoods by 2020 in order to identify persistent and new challenges in reducing health disparities. Decision makers may need to address the distinction between amelioration and displacement as they consider policies and interventions to reduce health disparities.

Our research is subject to uncertainties and limitations. The primary challenge in temporal comparison is survey availability and their difference. The remarkable difference of the two periods shown might not reflect the real change of the population. In 2010, the ACS replaced the long form of the US decennial census and became the major resource to study small-area socioeconomics and demographics, as opposed to using decennial census that may become quickly outdated in rapidly changing areas. Yet, the reliability of small-area ACS estimates is questioned [46, 47]. Our error variance analysis in this research (Supplement Material 2) revealed that large margins of error around the rank of 60th may skew the reliability of some UHIs. Comparing the UHI change thus requires further validation using different indicators. The challenge, of course, is the availability of reliable data for other indicators at small-area levels. In addition, the relationships between the UHI changes and the changes of demographics may be non-linear, and the rates of the UHI changes may be different with respect to values of the demographic changes. The GWR model is capable of analyzing spatially varying relationships. Future research may utilize this model for a detailed local variation of the relationships should a large dataset is involved. Finally, migration in the 10-year period may change the underlying population. The improvement of UHI in a community may not be translated to residing individuals because the human context of these small areas possibly changed. As we had speculated, the improvement in downtown Atlanta, for instance, may result from a change in demographics, rather than an improvement in the social determinants. Despite the increase of black concentration in some communities, further studies are necessary to examine where the former residents move to once being pushed out of the city center, as well as relevant policy and planning that could mitigate the impact.

In summary, this research introduced a framework to evaluate the disparities in social determinants of health over time using the UHI approach. The findings provide city planners with a picture of the progress made in reducing disparities. This study demonstrated the value of the UHI approach in identifying disparities and health needs through local evaluation using data from disparate domains. The stagnant hot spots, that is, the worst-off local areas in the decade, provide targets for improvement in social policies and economic arrangements. The temporal comparison of UHI values, along with its comparison with changes of demographics, permits a dissection of the driving forces in neighborhood change. When multiyear measures of health determinants and outcomes are available, this line of research will be valuable to document disparities in responding to the need for "a global evidence base for understanding the social determinants of health and establishing effective action to promote health equity" [22].

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