A spatial study of quality of life in the USA

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Abstract

This study's main goal was to develop a comprehensive Quality of Life (QoL) Index based on 31 demographic variables for the 3108 counties in the contiguous USA. Counties were ranked worst in QoL to best, and spatial cluster analysis is used to identify counties with significant low/high QoL clusters. GIS-based mapping was used to create informative heat maps with significant clusters shown. The rate of African Americans, diversity in a race within counties, and upward mobility were studied in a regression analysis in which QoL was predicted from these three covariates. The QoL Index was adjusted for the covariates, and a new spatial heat map with clusters is obtained. It was concluded that as the rate of African Americans increases in a county, the QoL decreases, while the QoL increases when diversity or upward mobility increases.

Keywords Quality of life · Clusters · Spatial · Race · Upward mobility

Introduction

Quality of life (QoL) is a topic that has been widely studied among academics and philosophers for many years. Aristotle regarded the concept of Eudaimonia as the act of “living well,” and being healthy, having wealth (Fowers 2016), and similar resources. These factors promoted the goal of “living well” (Kraut 2018). The

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modern study of QoL has been approached by researchers from a variety of disciplines as it can take many different perspectives of focus, such as social, economic, political, health, environmental, and psychological, among others. This has resulted in various efforts to develop an index or measure for QoL for localized regions, areas, and national scale (Blomquist 2007; Diener 1995; Johnston 1988; Liu 1977).

In our work, we aimed to create a more general QoL Index at the county resolution for the Contiguous USA that considers four sub-indices: the physical and social environment, economics, health, and the natural environment. Using this Index, we will explore the relationship between QoL and the rate of African Americans, diversity, and upward mobility at the county level. Life satisfaction, as reported in the Behavioral Risk Factor Surveillance System between 2005 and 2010, varies spatially (Ahmadiani and Ferreira 2019). Understanding the spatial distribution of our QoL Index and how the three covariates are related improves our understanding of existing disparities in QoL in the USA. In addition to the descriptive information that can be obtained from heat maps, it is of interest to identify any clusters of high and low QoL using the software SaTScan™ (“Software for the spatial, temporal, and space–time scan statistics,” n.d.) Spatial Scan Statistic (Kulldorff and Nagarwalla 1995). It is also important to study the four sub-indices better to understand these metrics’ roles for the QoL Index. The United States is increasingly a multi-lingual, multi-racial, and multi-ethnic country, trending towards an equal rate of minority and non-minority populations in future years (Lee et al. 2012). These results can help local policymakers approach problems of poor QoL by better understanding their communities and the opportunities that they provide to their populations by addressing such problems. Professionals from the fields of social sciences, health, among others, can also benefit from the results, as they can get a better understanding of how race, diversity, and upward mobility are related to QoL and how these are distributed spatially across the contiguous USA.

We aim to answer the following research questions through this work: (1) Are there any geographical areas where the overall Quality of Life Index is significantly higher/lower than the rest of the country? (2) Are there any geographical areas where any sub-indices (Physical and Social Environment; Economics; Health; Natural Environment) are significantly higher/lower than the rest of the country? (3) Are there any significant associations between the overall Quality of Life Index and any of the studied covariates?

Literature

In the literature, there are three main ways to define QoL: using social indicators, using subjective well-being measures, and economic indices (Diener and Suh 1997).

In recent studies, the presence of large, concentrated populations of immigrants has been shown to have adverse effects on QoL in urban areas. Still, large, diverse populations of immigrants dissipate the effects so that racial diversity has a positive effect on economic well-being, social well-being, healthy living, and urban mobility (Wallace et al. 2019). Past studies have shown that African Americans’ subjective well-being in the United States was significantly and consistently lower than that of

whites from 1972 to 1996 (Hughes and Thomas 1998). When addressing the issue of race and QoL, studies have been conducted using a variety of factors or covariates. Some authors have considered life satisfaction, general happiness, marital happiness, mistrust, anomia, and self-rating physical health in studies conducted over surveys (Hughes and Thomas 1998). Survey results have been informative when studying QoL. Still, many argue that the responses to surveys do not adequately reflect how people feel about the quality of their lives, but rather how satisfied they are expected to be based on their life experiences (The Economist Intelligence Unit 2005). Life satisfaction perception can depend on social and culturally specific frames of reference or expectations.

There is evidence that shows that the association between African American rates and inequality is not the same in all locations across the United States (Curtis and O'Connell 2017). The literature indicates that the contemporary racial disparity is spatially differing and tied to historical racial conditions (Acharya et al. 2016; Billings and Duncan 2000; Levernier and White 1998; O'Connell 2012; Ruef and Fletcher 2003; Snipp 1996). Another related factor to consider is upward income mobility, which is defined as the opportunity of an individual to rise to a higher income position (Chetty et al. 2014). White individuals in areas where the rate of African Americans is higher have lower upward mobility, leading to the belief that racial distribution is essential when studying mobility (Chetty et al. 2014). Factors such as socio-economic status have been associated with health-related QoL (Dwivedi et al. 2019), making upward mobility an interesting covariate to study along with African American rate diversity and how they relate to QoL. However, studies conducted in Switzerland and the United Kingdom on the relationship between upward social mobility and life satisfaction showed no effect and a negative effect, respectively (Hadjar and Samuel 2015). It has yet to be studied in the case of the USA.

Most QoL studies have been conducted based on subjective well-being, where a sample population participated in a survey answering questions related to life satisfaction and/or happiness (Glaeser et al. 2016; Moro et al. 2008; Oswald and Wu 2010). An attempt to bridge the subjective survey-based data to objective measures of quality of life was made in 2005 by The Economist's Intelligence Unit (The Economist Intelligence Unit 2005). In this work, The EIU linked objective data points to subjective measures and using nine variables to develop an objective QoL Index. These measures included the following: 1. GDP per person, 2. life expectancy at birth, 3. political stability and security ratings, 4. divorce rate, 5. church attendance or trade-union membership, 6. latitude, 7. unemployment rate, 8. average indices of political and civil liberties, and 9. ratio of male: female earnings.

Data

Data were obtained on 31 metrics to create a QoL Index for the Contiguous USA based on the latest 5 years of data available at the time of the study. Our goal was to create a QoL Index that is representative of the period 2012–2016. However, some metrics used data from different periods due to availability at the time of the study.

Four sub-indices were defined, as described next, which were then used to create a QoL Index at the county level. The following are the metrics used to develop each sub-index.

Physical and Social Environment Sub-Index

The Economist's Intelligence Unit reports security and community life as two of the main factors when studying QoL (The Economist Intelligence Unit 2005). Some studies have shown a relationship between commuting and subjective well-being in other countries (Zhu et al. 2019). There is also extensive evidence of the effects of crime on QoL in the literature (Chappell et al. 2011; Hale 1988; Reiss 1983).

Considering the literature, we selected the following metrics to create the Physical and Social Environment Sub-Index: (1) murder arrests, (2) robbery arrests, (3) rape arrests, (4) assault arrests, (5) drug-related crime arrests, (6) transport accident rate, and (7) average commuting time to work.

The murder, robbery, rape, assault, and drug-related crime arrests data were collected for the years 2010 to 2014, which at the time of the study was the most recently available data at the county level provided by the crime reports of those years from the Institute for Social Research at the University of Michigan ("Uniform Crime Reporting Program Data Series," n.d.), local law enforcement data ("Florida Department of Law Enforcement—UCR Arrest Data," n.d., "Illinois State Police," n.d.). Because crime incidence data were not available at the county resolution, crime arrest data were used as the metric for crimes present in a county. The transport accident rate data describe the proportion of county inhabitants dying in transportation accidents to counts of population and were collected for the years 2012 to 2016 from the Center of Disease Control and Prevention (CDC) Wonder online database ("CDC Wonder," n.d.). The commuting time to work data represent the average commuting times based on data from the Census Bureau's American Community Survey (ACS) ("Census Data," n.d.). The ACS collects data on the counts of people stating that their travel time to work lies in a specific time interval, ranging from less than 5 min to 90 or more minutes. This product of the counts by the lower bound of each interval was used to generate a new variable for average commuting time to work.

Economics Sub-Index

Economic and subjective, and social indices are used to assess the quality of life (Diener and Suh 1997). Socio-economic status has been shown to be influential in QoL measures and subjective well-being (Cassedy et al. 2013; Howell and Howell 2008; Thumboo et al. 2003). GDP is often considered a good indicator of the quality of life. However, studies have shown that in some locations around the world, quality of life is not often predicted by GDP. For example, the United States was ranked 13 in QoL and 2 in GDP per person, as reported by *The Economist* (The Economist Intelligence Unit 2005). This leads us to consider non-monetary measures that can predict the opportunities of being economically successful, such as employment

rate, education, and metrics that are indicators of economic stability. Considering the literature, we selected the following metrics to create the economics sub-index: (1) employment rate, (2) median home value as a percent of income, (3) college graduates, (4) poverty, (5) GINI income inequality, (6) median household income adjusted by RPP, (7) mortgage status ratio, (8) median gross rent as a percent of income, and (9) STEM degrees.

All the data used to create the economics sub-index were obtained from the Census Bureau's ACS ("Census Data," n.d.). The employment rate data represent the percentage of employed individuals aged 16 and older in a county. The median home value as a percent of income variable was computed as the rate of median home value and median household income, allowing us to compare how the average price of a home compares to the average income of the people living in the home. The college graduate's variable represents the percentage of 18 years or more population who have graduated from college; the poverty variable is the percentage of families in a county below the poverty level. The STEM degree variable represents the percentage of the population who have completed a college degree in a STEM (science, technology, engineering, math)-related field. This variable is a proxy for jobs with higher wages and more upward mobility. The GINI income inequality variable is a well-regarded income inequality index that measures the inequality among income distribution values, where lower values represent more equal incomes and higher values represent more disparity between incomes. The median household income adjusted by RPP is defined as the ratio of median household income to regional price parity index, obtained from the Bureau of Economic Analysis ("Regional Price Parities by State and Metro Area," n.d.), allowing for a dollar-for-dollar comparison between counties. The mortgage status ratio variable is the number of homes exceeding the 4.0 ratio of mortgaged home value to household income, as areas with a high concentration of excessively leveraged homes are less desirable because their corresponding housing markets are not stable.

Another variable that represents a ratio is the median gross rent as a percent of income. In this case, we aim to compare how the average rent relates to the median household income in each location. The last variable considered in the Economics Sub-Index was STEM degrees. This variable represents the percentage of the population who have a college degree in a STEM-related field. This characteristic is a proxy for jobs with higher wages and more upward mobility, representing a more desirable place to live concerning employment and wages.

Health Sub-Index

Spatial variations on factors related to poor health have been observed across the contiguous USA, showing that counties located in the southwest have a higher percentage of their population experiencing frequent physical and mental distress (Dwivedi et al. 2019). These factors directly affect the quality of life. Factors such as obesity, cancer, cardiovascular disease, smoking, and access to medical insurance have been shown to have an impact on the quality of life (Chen et al. 2007, 2012; Crothers et al. 2005; Kaplan 1988; Reeve et al. 2009; Taylor et al. 2013).

Considering the literature, we selected the following metrics to create the health sub-index: (1) cancer incidence, (2) cardiovascular disease, (3) opioid deaths, (4) obesity prevalence, (5) smoking, (6) uninsured, and (7) mental health.

Most of the cancer incidence data were obtained from the CDC's National Cancer Institute ("National Cancer Institute," n.d.) for the years 2008 to 2012. However, for states such as Kansas, Minnesota, and Nevada, the data were obtained directly from their local state cancer registries. This variable, which represents the total cancer incidence rate, had missing data for six counties in Texas, for which we used the state average instead. The cardiovascular disease variable is obtained as mortality rates per 100,000 from the Global Health Data Exchange ("IHME," n.d.) for 2010–2014. The opioids death variable consists of data of counts of six opioid specific causes of death, which include opium, heroin, other opioids, methadone, other synthetic narcotics, and other and unspecified narcotics, obtained from the CDC Wonder online database ("CDC Wonder," n.d.). The obesity prevalence data were obtained from the CDC indicators database ("CDC Indicators Data," n.d.) for the most recent time interval available (2009–2013) at the moment the study was being conducted, which defines the variable as the percentage of adults in each county who have a body mass index of 30 or higher. Smoking data consisting of the percentage of adults who are current smokers were also used as part of the Health Sub-Index. Lack of access to affordable health care is another factor that needs to be considered when studying a Health Sub-Index for a county. For this, we considered the rate of the population under age 65 without insurance. The mental health variable is a metric for the average age-adjusted number of mentally unhealthy days reported during the year in monthly intervals. The smoking, no insurance, and mental health data were obtained from County Health Rankings ("County Health Rankings," n.d.).

Natural Environment Sub-Index

Amenities like climate, geography, environmental-related externalities, and other local public goods explain part of the variety in life satisfaction reported across the United States counties (Ahmadiani and Ferreira 2019). Local amenities such as climate, geographic characteristics, air pollution, and other related urbanization explain a fraction of the variation in subjective quality of life, providing a major point of consideration in environmental management and regulation. Considering the literature, we selected the following metrics to create the Natural Environment Sub-Index: (1) air toxicity, (2) water toxicity, (3) land toxicity, (4) extreme heat, (5) extreme precipitation, (6) weeks of drought, (7) ozone levels, and (8) PM 2.5.

The air, water, and land toxicity were retrieved from the US Environmental Protection Agency's Toxic Release Inventory (TRI) for 2012 to 2016. TRI data measure over 650 ("Toxics Release Inventory Program," n.d.) toxic materials released into the air, water, and land by industrial sources in pounds. All extreme weather variables data were obtained from the CDC's National Environmental Health Tracking Network (EPH) ("National Environmental Public Health Tracking Network," n.d.), as well as the ozone levels and particulate matter 2.5 (PM 2.5) variables. The extreme precipitation events are usually associated with damaging effects of wind,

torrential rain, hail, and flooding, which can impact QoL negatively. Specifically, the extreme precipitation variable represents the annual number of high precipitation days as established with a 95th percentile relative threshold. The weeks of drought variable is the annual number of weeks of drought. The extreme heat is the annual number of extreme heat days using daily maximum temperature as a metric and a 95th percentile relative threshold. The ozone-level variable represents the annual average ground-level ozone levels, like the PM 2.5 variable, which measures the in-air concentration of particulate matter smaller than 2.5 μm . High ozone levels can cause breathing and pulmonary problems, as well as exacerbate existing lung conditions. Particulate matter smaller than 2.5 μm are often associated with cardiac and pulmonary health risks while also being damaging to the environment. Data for these last two variables were obtained from 2012 to 2014 from the CDC's EPH ("National Environmental Public Health Tracking Network," n.d.).

Race, upward mobility, and diversity

Immigration issues have been the cause of debate in the United States in recent decades, including the effects of immigrant population growth and dispersion on quality of life (Wallace et al. 2019). In other studies, it has been observed that the coexistence of racial inequality and its experiences produces racial differences in quality of life. Understanding how the distribution of black-white inequality is related to QoL is an important topic to study. It gives us a picture of how historical racial contexts shape the United States of today. For this reason, we selected the following covariates to test their relationship with our QoL Index: (1) diversity, (2) rate of African Americans, and (3) upward mobility.

Diversity was measured using the Entropy Index, which represents how uniformly members of a population are spread in an area, where lower values represent homogeneity, and higher values heterogeneity (equal representation of populations). This covariate does not consider the communities' racial-ethnic structure or which are the specific groups present in each location (Lee et al. 2012). In other words, this Index measures the *magnitude of diversity* and not structure. The diversity data were retrieved from the American Communities Project of Brown University ("American Communities Project," n.d.). To address the structural aspect of diversity, the rate of African Americans was used as a second covariate. These data were obtained from the CDC's EPH demographics dataset ("National Environmental Public Health Tracking Network," n.d.). The upward mobility data were obtained from the Opportunity Insights dataset, specifically the "Geography of Mobility: County Intergenerational Mobility Statistics and Selected Covariates" dataset ("Opportunity Insights," n.d.). This dataset contains many variables, but our interests were in using their "Absolute Upward Mobility" metric, which is a statistic developed by Dr. Raj Chetty et al., which characterizes intergenerational mobility using income records of more than 40 million children and their parents between 1996 to 2012, giving us a clear picture of mobility at the county level. In essence, this variable measures how a child's social and economic opportunities are dependent on the parent's own social and economic situation (Chetty et al.

2014). Absolute upward mobility possesses geographical variations, which makes the study of it as a covariate interesting.

Methods

Using the 31 metrics, four sub-indexes (Physical and Social Environment, Economics, Health, and Natural Environment) were created and used to create a more general QoL Index. Each of the metrics within a sub-index was given identical weight. Let $SI(i)$ denote sub-index with $i = (1, 2, 3, 4)$, and let $M(j, i)$ denote metric j in sub-index i , with total metrics k for each $SI(i)$. The QoL Index also assigns equal weights to each of the four sub-indices, such that $SI(i) = -\sum_{j=1}^k \frac{M_{ji}}{k}$ and $QoL = \sum_{i=1}^4 \frac{SI(i)}{4}$. All metrics were ranked and normalized with the proc rank procedure using the SAS[®] statistics and analytics software so that it is more meaningful to average the metrics for each sub-index. The QoL Index, the average of the four sub-indices, is approximately normally distributed since all metrics were normalized from the start. Since most metrics impact the quality of life negatively as their value rises, all metrics impacting the quality of life positively were multiplied by -1 . This ensured that the interpretation was consistent among all metrics. In this sense, when looking at the sub-indices, it was easier to interpret using the opposite sign, such that a low score represented a poor sub-index. Therefore, our QoL Index is interpreted in the same way; high scores represent a better quality of life based on the studied metrics.

To identify geographical variations in the counties' quality of life in the contiguous United States of America, the software SaTScan[™] was used to detect significant clusters. Since the QoL Index is continuous, we used the Normal Model in SaTScan[™] (Kulldorff et al. 2009) to perform a purely spatial analysis of each sub-index and the QoL Index, identifying clusters of high and low observations. The purely spatial scan statistic identifies significant clusters by imposing a window over the map, including different neighbor counties using their centroid (longitude and latitude), and continuously testing the null hypothesis that the studied metric is equal over all 3,108 counties in the contiguous USA against the alternate hypothesis that it is not equal (Kulldorff 1997).

To study the association between the QoL Index and rates of African Americans, diversity, and upward mobility in a county, a multiple regression model using the SAS[®] statistics and analytics software and the proc reg procedure was conducted to estimate the effect of each covariate. The effects were estimated, and as a next step, a cluster analysis was repeated for the QoL Index after adjusting for the three covariates. A purely spatial analysis was done using the residuals from the regression analysis, with the purpose of identifying locations in which the high or low QoL index is can be predicted by the covariates, locations that can't be predicted, and others that were not previously identified.

Results

In this study, a high QoL Index value is shown as green-colored counties, while a low QoL Index value is shown as red counties. Figure 1 shows significant spatial clusters of QoL, where clusters (1,3,5) are identifying high QoL counties while clusters (2,4,6) reveal low QoL. Table 1 shows that in Cluster 1, the mean QoL Index value is 0.39 standard deviations better than in the rest of the USA, while in Cluster 2, the mean QoL value is 0.31 standard deviations worse than in the rest of the country.

Figure 1 shows a heat map with clusters of the QoL, where green-colored counties are counties with high QoL values, and red-colored counties reflect a low QoL, where the red rings reflect the three significant spatial clusters of low QoL, while the blue rings reflect the significant spatial clusters of high QoL in the contiguous USA.

Figure 2 identifies significant QoL clusters for the Physical and Social Environment Sub-Index. Clusters 1 and 4 are counties with high values for this sub-index, while Clusters 2, 3, and 5 have a low Physical and Social Environment Sub-Index. Table 1 shows the mean levels inside each cluster and outside the cluster in the USA, expressed in standard deviations away from the US mean.

Figure 2 shows a heat map with clusters of the Physical and Social Environment Sub-Index, where green-colored counties are counties with high Physical and Social

Fig. 1 Spatial clusters map of Quality of Life Index from 2012 to 2016

Table 1 Purely spatial clusters details

Cluster	Mean inside	Mean outside	Type	<i>p</i> value
Quality of Life Index				
1	0.39	− 0.12	High	0.001
2	− 0.31	0.10	Low	0.001
3	0.25	− 0.0074	High	0.001
4	− 0.26	0.0056	Low	0.001
5	0.15	− 0.0092	High	0.001
6	− 0.23	0.0040	Low	0.033
Physical and Social Environment Sub-Index				
1	0.48	− 0.15	High	0.001
2	− 0.31	0.10	Low	0.001
3	− 0.70	0.021	Low	0.001
4	0.39	0.56	High	0.001
5	− 0.41	0.0087	Low	0.003
Economics Sub-Index Cluster				
1	0.41	− 0.082	Low	0.001
2	− 0.39	0.083	High	0.001
3	− 0.17	0.041	High	0.001
Health Sub-Index Cluster				
1	0.56	− 0.19	High	0.001
2	− 0.54	0.18	Low	0.001
3	− 0.64	0.014	Low	0.001
4	0.32	− 0.019	High	0.001
5	0.39	− 0.013	High	0.001
Natural Environment Sub-Index				
1	0.41	− 0.082	High	0.001
2	− 0.39	0.083	Low	0.001
3	− 0.17	0.041	Low	0.001
4	0.39	− 0.019	High	0.001
5	0.28	− 0.012	High	0.001
6	0.42	− 0.0062	High	0.001
7	− 0.67	0.0037	Low	0.001

Environment Sub-Index values, and red-colored counties reflect a low Physical and Social Environment Sub-Index.

There are only three significant clusters for the Economics Sub-Index, as shown in Fig. 3. Cluster 1 (red ring) shows counties with a significantly lower Economics mean level than the rest of the USA. In contrast, the other two significant clusters (as blue rings) include counties with high Economics Sub-Index.

Figure 3 shows a heat map with clusters of the Economics Sub-Index, where green-colored counties are counties with high Economics values, and red-colored counties reflect a low Economics Sub-Index.

Fig. 2 Spatial clusters map of Physical and Social Environment Sub-Index from 2012 to 2016

Figure 4 identifies significant clusters of high Health Sub-Index (blue rings) and low Health Sub-Index clusters (red rings). The high clusters are (1, 4, 5) with mean values ranging between 0.39 and 0.64 standard deviations above the US mean, while the low clusters have mean values ranging from -0.64 to -0.54 . The Southeast of the country shows low Health Sub-Index values.

Figure 4 shows a heat map with clusters of the Health Sub-Index, where green-colored counties are counties with high Health values, and red-colored counties reflect a low Health Sub-Index.

Figure 5 identifies significant clusters of the Natural Environment Sub-Index. There are 4 clusters (1,4,5,6) of high Natural Environment Sub-Index values (shown as blue rings), and there are three clusters (2,3,7) of low Natural Environment values (shown as red rings).

Figure 5 shows a heat map with clusters of the Natural Environment Sub-Index, where green-colored counties are counties with high Natural Environment values, and red-colored counties reflect a low Natural Environment Sub-Index.

A multiple regression model is used to predict the QoL Index from three covariates (rate African Americans, diversity, and upward mobility). Our goal is to identify the role of each covariate in explaining the variation in QoL. The model produced a correlation coefficient of $r^2 = 49\%$. Therefore, about half of the QoL index's total variability is accounted for by the regression model. All the predictors were shown to be statistically significant for the QoL index. Table 2

Fig. 3 Spatial clusters map of Economics Sub-Index from 2012 to 2016

lists the effects, t test values, and corresponding p values. Each covariate is significant (very small p values), with the sign of each t test revealing the role of each covariate or predictor variable. The t tests are partial tests that test the significance of each of the three predictor variables when they are added last to the regression model, with the intercept and the other two predictor variables already in the model.

Regarding the rate of African Americans in each county ($t = -12.98$), the regression coefficient is -0.09465 . As the rate of African Americans increases by one unit, the corresponding QoL decreases by 0.09465 units (when holding the other two covariates constant). If the rate increases by around ten units, we expect the QoL Index to decrease by around one standard deviation since the QoL is based on normal scores. This is a considerable decrease in QoL while holding diversity and upward mobility constant.

Diversity and upward mobility each has a positive t test, indicating that when a county has an increase in diversity or upward mobility value, the corresponding QoL is higher. The largest t value ($t = 33.5$) is for upward mobility, with an effect of 0.1948. This is the most significant covariate here. County populations with high Upward Mobility also have a high QoL. As the upward mobility in a county increases by one unit, we expect the QoL for this county to increase by around 0.2 standard deviations. Diversity inside counties is the least significant for predicting the QoL with an effect of 0.04 and a t test of 7.08, even though it is significant.

Fig. 4 Spatial Clusters Map of Health Sub-Index from 2012 to 2016

The above information is beneficial to have. We will adjust our initial spatial map for QoL (Fig. 1) by the three covariates to obtain a unique map of QoL after adjusting for the rates of African Americans, diversity, and upward mobility. It is best to compare Fig. 6 with Fig. 1 to quickly identify the changes in the three covariates.

Figure 6 shows how the rate of African Americans, diversity, and upward mobility is associated with significant clusters in Fig. 1.

Orange identifies counties in which the low QoL score was unaffected by the covariates. We used six colors to identify covariate effects for low scans and high scans. There are counties seen in Fig. 1 as falling into low or high clusters and that is shown not to be associated with the three covariates. Such counties are shown in Fig. 6 as dark blue (persisted-high) and as orange (persisted-low). The second group of cluster counties in Fig. 6 are counties that “vanished” after using the three covariates (rate of African Americans, diversity, upward mobility). In such counties, the covariates “explain” the high or low QoL. For high QoL, such counties are shown in green, and for low QoL, such counties are shown in red. A third group of cluster counties in Fig. 6 are the counties that without the covariate adjusting were not inside any cluster in Fig. 1. These are counties in “new clusters” when taking into account the rate of African Americans, diversity, and upward mobility. There are several locations on the map in Fig. 6 where light blue-colored counties are shown, indicating significant high QoL counties. In contrast, the yellow counties are counties with low QoL only after we adjusted for the covariates.

Fig. 5 Spatial clusters map of Natural Environment Sub-Index from 2012 to 2016

Table 2 Regression analysis results predicting QoL from rate African Americans, diversity, and upward mobility

Covariate	Estimate	SD	<i>t</i> value	<i>p</i> value
Rate of African Americans	− 0.09465	0.00738	− 12.98	< 0.0001
Diversity	0.04394	0.00620	7.08	< 0.0001
Upward mobility	0.19480	0.00581	33.50	< 0.0001

Table 1 lists all significant spatial clusters for the overall QoL index and each of the five sub-indices used. The mean quality score inside and outside each cluster is given, in addition to the type of cluster and its *p* value.

Table 2 gives summary statistics for the regression analysis for predicting the QoL score from the rate of African Americans, diversity, and upward mobility.

Fig. 6 Spatial clusters map of Quality of Life Index adjusted by all covariates from 2012 to 2016

Discussion

Improving QoL in the United States is an effort of many individuals and organizations. Examples include individual attempts to leave a legacy of health and wealth to their children and government actions attempting to improve opportunities for personal growth and economic advancement. As an integral part of the American culture and part of the attraction to this culture by immigrants worldwide, there is a continuous intellectual search for QoL indicators. Through such improved measures that can be tested and improved individuals and other decision makers can focus resources on the most salient factors to improve population QoL. In the present study, to utilize the power of SatScan, a QoL index was derived using 31 indicators selected based on both prior research of QoL instruments and the availability of county-level data. Such an analysis provides researchers an encompassing unique, detailed, high-resolution spatial perspective on QoL across the contiguous United States.

In this study, this powerful technique provided a snapshot in time of the variance of QoL at the county level, identifying low and high QoL areas compared to the mean of the entire United States. Such a tool can be re-examined at the frequency with which county data are updated. Initially, this experimental model tested the hypothesis that QoL is equally distributed across the country. It was

observed that the distribution of QoL is not uniform and similar to others' findings, QoL is highest in the Western US and lowest in the Southern region.

A distinguishing feature of the present spatial analysis is the resolution at the county level combined with regression analysis. Among the variables related to QoL, upward mobility was a significant and large contribution. Similar to prior work, while causality cannot be addressed here, an examination of the relationships between upward mobility, race, or diversity showed that when holding upward mobility and race constant, areas with high diversity had a significant positive effect on QoL. Simultaneously, QoL tended to decrease based on racial composition when holding upward mobility and diversity constant.

The present findings show that QoL varies at the resolution of the county level. Extrapolation of these results, based on the finding that percentages of African Americans and diversity play a role and that the variation of upward mobility likely varies on more localized opportunities for economic advancement, could potentially vary at a higher resolution within a given county. With these observations, it appears evident that diversity and racial composition, while impactful, are secondary to economic opportunity as assessed through upward mobility. Therefore, the present findings suggest that measures taken by local, state, and federal officials, whose objective is to improve QoL, could focus efforts in counties found statistically to be outliers in the present study. Focusing on specific counties in contrast to larger, state-wide, or national plans would likely result in a higher cost–benefit. Additionally, these data suggest that such governmental, and non-governmental groups could narrow these efforts further on issues that drive upward mobility to garner the largest return. Given that there is a strong correlation between perceived QoL and more objective measures, such attempts would not only improve QoL but also the community morale that could indirectly foster further societal gains beyond the limits of QoL quantitative gains.

Conclusion

A comprehensive Quality of Life Index for all counties in the Contiguous US was developed based on 31 demographic variables. This index is then analyzed spatially via heat maps and a purely spatial cluster analysis with the disease surveillance software SaTScan. This is the only cluster analysis-based spatial study of a QoL Index for the USA in the literature. Clusters of counties with unusually low (or high) QoL are identified and tested for significance based on a scan statistic in SaTScan. The US map shows disparities of low QoL levels in the Southeast and the eastern half of the US. The QoL Index is associated with race, diversity, and upward mobility, as is shown in this study. It was shown that as the rate of African Americans increases in a county, the QoL is low. As diversity inside counties and/or upward mobility increases, the corresponding QoL increases.

Author contributions RWA involved in conceptualization, methodology, supervision, writing-original draft, and review/editing. BRM participated in conceptualization, methodology, software, writing-original

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Data availability All data used are public that can be downloaded from the referenced data sources.

Code availability We used freely available software packages, such as SAS, SaTScan, and ArcMap. No special programming was done.

Declarations

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

Informed consent All co-authors gave us their consent, and no humans were involved in any parts of this project.

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