Johns Hopkins Bloomberg School of Public Health
CCST Center for Climate Smart Transportation
Bloomberg American Health Initiative

WHO SPRAWLS THE MOST?

MAPPING URBAN SPRAWL AND ASSESSING ITS IMPACT ON EVERYDAY LIFE

TECHNICAL REPORT

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ACKNOWLEDGEMENTS

This report was supported by a grant from the Center for Smart Transportation and the Bloomberg American Health Initiative at the Johns Hopkins Bloomberg School of Public Health.

Special thanks to David Berrigan, National Cancer Institute (NCI); Becky Shade and David Park of Center for Smart Transportation; Josh Sharfstein, Michelle Spencer, Caitlin Hoffman, and Su Tellakat of the Bloomberg American Health Initiative.

For details on the methodology and data sources, please see the accompanying technical report.

This report should be cited as:

Hamidi, S., Abdollahpour, S., Azimi, E., & Ewing, R. (2026). Mapping Urban Sprawl and Assessing Its Impact on Everyday Life: Technical Report; Center for Smart Transportation and the Bloomberg American Health Initiative; Johns Hopkins University; Baltimore, MD

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Executive Summary

Urban sprawl has been the topic of a continued heated debate in the U.S. and in recent decades, perhaps one of the all-time major debates among planners who are at the frontlines of planning for more sustainable, healthier, and economically sound land-use policies.

Since 2020, urban sprawl and its impacts have been the center of attention during the COVID-19 pandemic when policymakers blamed compact development for the increased spread and mortality of COVID-19, especially in large cities such as New York City, while several empirical studies found against it.

More recently, urban sprawl has gained momentum since Ezra Klein and Derek Thompson published their bestselling book, *Abundance*, which links housing unaffordability and urban sprawl as key drivers of political outcomes of recent elections. They argue that it is hard to build housing in areas where Democrats govern, which also tend to be large compact and connected cities. This view is echoed by other advocates of sprawl such as the *New York Times* (April 2025).

These ongoing debates underscore a key point: Before we can advocate for or against sprawl, we should first understand its current extent and spatial patterns. Accurate, comprehensive, and updated measurement of urban sprawl is essential for guiding land use, transportation, housing, health, and environmental policy.

In 2014, we conducted one of the most comprehensive efforts to define, measure, and evaluate urban sprawl and its impacts. The 2014 study received extensive media attention and was covered by more than 110 national and local media outlets. The 2014 sprawl indices were also posted on a NIH website and have been widely used by scholars who study the impact of sprawl on a range of social, environmental, transportation, and health outcomes such as transit ridership and car dependency, innovation and economic productivity, disaster management, obesity another chronic diseases, mental health, emergence of food deserts, air quality, housing foreclosure, real estate and housing innovation, economic mobility, traffic crashes and fatalities, and the spread and mortality of the COVID-19 pandemic.

This 2026 report updates and refines the earlier sprawl measures for all metropolitan areas, urban counties, and census tracts in the U.S. using better and more updated data sources. The updated indices offer several improvements compared to the 2010 indices. The 2020 compactness indices are publicly available to researchers, planners, and policymakers and can be used in future studies on the impacts of urban sprawl, especially in the context of recent hot debates. These indices offer local planners and policymakers a data-driven perspective on the degree of sprawl in their jurisdiction and the effectiveness of their land-use policies in the past decade.

Finally, we investigated the impacts of urban sprawl on a series of topical quality-of-life outcomes. The following are some of our highlighted findings:

- People in compact and connected counties spend **higher portions of their income on housing, but less on transportation** than their counterparts in sprawling areas.
- People in compact and connected counties spend a substantially **lower portion of their budget on residential energy costs**. Sprawling counties are home to single-family detached housing and larger houses, which means more exposed surface areas and more space to heat and cool.
- The most notable finding is that compact and connected counties are **more affordable for residents after combining housing, transportation, and energy costs**. In other words, lower transportation and energy costs offset the higher costs of housing in compact and connected counties.
- Compact and connected metropolitan areas provide more **transportation options** such as walking and quality public transit and offer opportunities to own fewer vehicles.
- Compact and connected counties have lower rates of hospitalizations from heat-exacerbated health conditions such as **COPD** and **heart attack** due to improved walkability and greater opportunities for physical activity, better access to healthy food options, and better access to preventive care.
- Sprawling counties experience higher rates of **death from** and **pedestrian fatalities** from car accidents than more compact and connected counties. This is due to the necessity of driving to most destinations and longer automobile trips which are a product of segregated land uses and higher driving speeds.
- Sprawling counties experience higher rates of **disconnected youth** than more compact and connected counties due to highly segregated land uses, poor accessibility, and car dependence, which exacerbate inequalities for low-income groups who face transportation and resource barriers.
- Residents of sprawling counties exhibit lower levels of **social connectivity** and civic engagement (social capital) compared to those in compact, connected counties.
- People in suburban counties are more likely to get infected with **Lyme disease** than their counterparts in more compact counties. Suburban counties have a unique mix of habitat fragmentation with sufficient human-tick interactions which create an ideal environment for the spread of Lyme disease.

We recommend cities and local governments consider planning processes, strategies, and policies that create more connections, facilitate more transportation choices with walkable and livable neighborhoods that offer both local and regional accessibility to residents. Strategies for encouraging compact development follow directly from our operational definition of sprawl. The 2020 compactness indices combine four core dimensions of compact urban form: development density, land-use mix, activity centering, and street connectivity. To achieve a more compact urban form, it is essential to build a coordinated policy framework that improves these dimensions across regional, metropolitan, and local scales. The last chapter offers a set of actionable policies for each of these dimensions.

The 2020 compactness indices and individual dimension scores for metropolitan areas and counties are presented in the appendices and are immediately available to study other costs and benefits of urban sprawl on the Center for Climate Smart Transportation website.

Chapter 1: Introduction

Urban sprawl has been a topic of continued debate in the U.S. (Chettry, 2023; Ewing & Hamidi, 2015a; Glaeser & Kahn, 2004; Su et al., 2010; Wang et al., 2020; Wei & Ewing, 2018; Yasin et al., 2020). A classic example of this debate appeared in the *Journal of the American Planning Association,* where Peter Gordon and Harry Richardson defended urban sprawl as a natural and benign response to consumer preferences in their article *"Are Compact Cities Desirable?"* (Gordon & Richardson, 1997). In contrast, Reid Ewing advocated for compact urban development as an alternative to sprawl in his response titled *"Is Los Angeles-Style Sprawl Desirable?"* (Ewing, 1997).

Despite decades of debate, there remains limited consensus on how to measure urban sprawl (Banai & DePriest, 2014; Frenkel & Ashkenazi, 2008; Hamidi & Ewing, 2014; Lan et al., 2021; Steurer & Bayr, 2020; Torrens & Alberti, 2000; van Nes, 2021) or how these forms affect key quality-of-life and community outcomes (Enwin & Ikiriko, 2023; Hamidi & Ewing, 2015a; Van Niekerk, 2018) including air quality (Lee, 2019; Stone Jr., 2008), housing affordability (Aurand, 2013; Jiuwen et al., 2024), public health (Garrido-Cumbrera et al., 2018; Genovese et al., 2023), and transportation (Ewing & Hamidi, 2014; Lyu et al., 2025; Yang et al., 2024). A recent example of this debate emerged during the COVID-19 pandemic, as scholars examined the impact of compact development on the spread and mortality rate of the COVID-19 pandemic (Hamidi, Ewing, et al., 2020; Hamidi, Sabouri, et al., 2020; Khavarian-Garmsir et al., 2021).

These ongoing debates underscore a key point: Before we can advocate for or against sprawl or compact development, we should first understand their current extent and spatial patterns. Accurate, comprehensive, and updated measurement of urban sprawl is essential for guiding land use, transportation, housing, and climate policy (Behnisch et al., 2022; Feng & Gauthier, 2021; Zhao, 2010). In an era marked by worsening climate impacts, affordability crises, and uneven urban growth, knowing where and how sprawl is occurring allows planners and policymakers to craft targeted, evidence-based zoning and land-use interventions.

To further improve the measurement of urban sprawl, Ewing et al. (2002) proposed a sprawl index based on four key dimensions: density, diversity, centering, and connectivity. They used principal component analysis (PCA) to develop metrics for each dimension and combined them to compute the overall index. Later, Hamidi and Ewing (2015b) refined this original sprawl index by adding new metrics to each of the four main dimensions, enhancing its accuracy and applicability. Ewing and Hamidi measured sprawl indices for metropolitan areas (Hamidi et al., 2015), counties (Ewing & Hamidi, 2017), urbanized areas (Hamidi & Ewing, 2014), and census tracts in the U.S.

Ewing and Hamidi measured sprawl indices for metropolitan areas (Hamidi et al., 2015), counties (Ewing and Hamidi, 2017), urbanized areas (Hamidi and Ewing, 2014), and census tracts in the U.S. The Ewing and Hamidi's compactness indices are posted on an NIH website[1] and have been widely used by scholars who study the impact of sprawl on a range of social, environmental, transportation, and health outcomes such as transit ridership and car dependency (Ralph et al., 2017; Nelson, 2017, Tian et al., 2018; Ha et al., 2018; Alam et al., 2018; Lee et al., 2022; Singer et al., 2023; Rahman and Antipova, 2024), innovation and economic productivity (Hamidi et al., 2019; Granpayeh et al, 2019), disaster management (Lambert et al., 2015), obesity and other chronic diseases (Ewing et al., 2014; Congdon, 2016, Garfinkel et al., 2017; Nicholson et al., 2017; Hamidi and Ewing, 2020; Bereitschaft 2022; Tian et al., 2023; Cheung et al., 2025), mental health (Cumbrera et al., 2018), emergence of food deserts (Hamidi, 2020), air quality (Lee, 2019a&b) housing and transportation affordability and foreclosure (Hartell, 2018; Hamidi and Ewing, 2015), real estate and housing innovation (Sanderford et al., 2015; McCoy et al., 2015), economic mobility (Xiong et al, 2024; Smith et al., 2021; Carlston and Wei, 2024), traffic crashes and fatalities (Yeo et al., 2015; Ewing and Hamidi, 2015; Ewing et al., 2016), the spread and mortality of the COVID-19 pandemic (Hamidi et al. 2020; Hamidi and Zandiatashbar, 2021) and the overall quality-of-life and life expectancy (Hamidi et al., 2018; Wang, 2022).

Yet the 2010 sprawl indices are outdated and do not provide an accurate and updated picture of the current level of sprawl in the U.S. Since 2010, it is not clear who sprawls the most and who has been more successful in mitigating urban sprawl through land-use interventions. In addition, while the debate over sprawl versus compactness continues, there are emerging social, environmental, and health outcomes such as climate change and extreme weather events and their impacts on health, the significant increase in vector-borne diseases and their link to urban form, and housing supply limitations and affordability which call for an immediate need for more recent measures of urban form.

In the same line, new data sources and updated information (since 2010) provide a great opportunity to refine and improve the original sprawl indices and quantitatively link it to the emerging quality-of-life outcomes. This study aims to refine and update sprawl indices for 2020 with better and more updated data sources for counties, metropolitan areas, and census tracts in the U.S., based on the framework originally developed by Hamidi and Ewing (Hamidi & Ewing, 2016b). We also validated the updated index against transportation outcomes using two analytical approaches: inferential statistics and machine learning. This allows us to assess the relative

[1] https://gis.cancer.gov/tools/urban-sprawl/ accessed April 2026

importance and effective range of each dimension of the index—namely, density, land-use mix, centering, and street connectivity.

Finally, we investigated the impacts of urban sprawl on a series of topical quality-of-life outcomes such as increased temperature and the associated health outcomes including COPD, asthma and heart attack hospitalization, housing, transportation and energy affordability, energy burden, disconnected youth and growth opportunities for children, prevalence of vector-borne disease such as Lyme disease, and traffic crashes and fatalities.

The updated index offers several improvements compared to the 2010 index. First, we employed spatial statistic techniques to identify the location and boundary of urban subcenters (as part of the activity-centering factor) and as a result, we identified 1,247 urban subcenters in 132 metropolitan areas and divisions. This is higher than subcenters in the 2010 study and offers a more comprehensive and updated view of the landscape of polycentricity in the U.S. Second, we used the most recent open-source street data for computing the number and type of intersections (Boeing, 2017) which improved two (out of four) variables contributing to the street connectivity factor. As a result, the percentage of explained variance in the street connectivity factor increased from 50% in the 2010 original study to 61% in this study (see Table 1). Finally, our sample of counties and MSAs has increased from 221 MSAs in 2010 to 233 MSAs in 2020 and from 967 counties in 2010 to 995 counties in 2020.

The 2020 compactness indices should be publicly available to researchers, planners, and policymakers. These indices will facilitate future studies on the impacts of urban sprawl on other quality-of-life outcomes, especially in the context of recent hot debates over the costs and benefits of urban sprawl. These indices also will offer local planners and policymakers a data-driven perspective on the degree of sprawl in their jurisdiction and the effectiveness of their land-use policies in the past decade.

Chapter 2: County Sprawl Index

Urban sprawl is widely characterized by poor accessibility. Sprawl is viewed as any development pattern in which related land uses have poor access to one another, leaving residents with no alternative to long distance trips by automobile. Compact development, the polar opposite, is any development pattern in which related land uses are highly accessible to one another, thus minimizing automobile travel and attendant social, economic, and environmental costs. The following patterns are most often identified in the literature: scattered or leapfrog development, commercial strip development, uniform low-density development, or single-use development (with different land uses segregated from one another, as in bedroom communities). In scattered or leapfrog development, residents and service providers must pass by vacant land on their way from one developed use to another. In classic strip development, the consumer must pass other uses on the way from one store to the next; it is the antithesis of multipurpose travel to an activity center. Of course, in low-density, single-use development, everything is far apart due to large private land holdings and segregation of land uses.

Urban sprawl is a product of land-use patterns (low-development density, single-land use dominated by single-family detached housing and the lack of urban centers), that produce poor local and regional accessibility. Poor accessibility is also a product of fragmented street networks that separate urban activities more than need be. When asked, planners now routinely associate sprawl with sparse street networks as well as dispersed land-use patterns.

Following Ewing and Hamidi (2015), we operationalize county sprawl in four dominations contributing to distinct land-use and street-network characteristics that lead to poor accessibility. The four are development density, land-use mix, population and employment centering, and street connectivity. The dimensions of the new county indices parallel the metropolitan indices, basically representing the relative accessibility provided by the county. The full set of 16 variables is combined to derive a refined set of compactness-sprawl factors via principal component analysis. One principal component represents population density, another land-use mix, a third centering, and a fourth street connectivity. While correlated, as one might expect, the four compactness factors seem to represent distinct constructs based on their bivariate correlations. County principal component values, standardized such that the mean value of each is 100 and the standard deviation is 25, are presented in Appendix B.

Development Density

Low residential density is on everyone's list of sprawl indicators and is operationalized by five distinct but related density variables:

1. Gross population density in persons per square mile (popden)
2. Percentage of the county population living at low suburban densities, specifically, densities between 100 and 1,500 persons per square mile, corresponding to less than one housing unit per acre (lt1500)

3. Percentage of the county population living at medium to high urban densities, specifically, more than 12,500 persons per square mile, corresponding to about eight housing units per acre, the lower limit of density needed to support mass transit (gt12500)
4. Gross employment density of urban and suburban census tracts (empden)
5. Net population density of urban places within the county (urbden)

Our goal is to measure sprawl in developed areas where the vast majority of residents live. Therefore, in deriving population density measures, we excluded census tracts if they had fewer than 100 residents per square mile (corresponding to rural areas, desert tracts, and other undeveloped lands).

For computing the first three variables, we derived data on population and land area from the U.S. Census 2020 from the NHGIS platform.[2] Population and land area data were extracted for all census blocks in all metropolitan counties. About 100 metropolitan counties were lost to the sample because they had no census tracts averaging 100 persons per square mile or more. They were deemed to be rural.

The fourth density variable is analogous to the first, except it is derived with employment data from the 2019 Local Employment Dynamics (LEHD) database rather than population data. The LEHD database provides details about America's jobs, workers, and local economies. We collected the 2019 LEHD data at census block level and aggregated to block groups in order to compute employment-related variables. We opted for the LEHD data for 2019 to avoid the extraordinary impacts of the COVID-19 pandemic on employment dynamics.

The fifth variable, net density of urban areas within the county was computed using the U.S. Geological Survey's National Land Cover Database (NLCD). NLCD serves as the definitive Landsat-based, 30-meter resolution, land cover database for the U.S. It is a raster dataset providing spatial reference for land surface classification (for example, urban, agriculture, forest). It can be geo-processed to any geographic unit. We defined urban land as any cell with the following codes:

21. Developed, Open Space: Areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.

22. Developed, Low Intensity: Areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% of total cover. These areas most commonly include single-family housing units.

[2] https://www.nhgis.org/ accessed August 26, 2025

23. Developed, Medium Intensity: Areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 79% of the total cover. These areas most commonly include single-family housing units.

24. High Intensity: Highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses, and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover.

We aggregated the sum of areas for these cells to obtain the total urban land area for the county.

Principal components were extracted from the five density-related variables, and the principal component that accounted for the greatest variance became the county density factor. Factor loadings (that is, correlations of these variables with the density factor) are shown in Table 2.1. The eigenvalue of the density factor is 3.57, which means that this one factor accounts for more of the variance in the original dataset than three of the component variables combined. In other words, the density factor accounts for more than 71% of the total variance in the data set. As expected, one of the variables loads negatively on the density factor, that being the percentage of population living at less than 1,500 persons per square mile. The rest load positively. Thus, for all component variables, higher densities translate into higher values of the density factor.

Table 2.1. Variable Loadings on the County Density Factor for 2020

Observed variable	Factor loading*
Popden	0.97
lt1500	-0.44
gt12500	0.84
Urbden	0.98
Empden	0.85
Eigenvalue	3.57
Explained variance	71.35%

* Correlation with the density factor

Land-Use Mix

Segregated land uses are also on most lists of sprawl development patterns. Conversely, mixed and integrated land uses sit atop lists of pedestrian-friendly, transit-oriented, and smart growth patterns. Three types of mixed-use measures are found in the land use-travel literature: those representing relative balance between jobs and population within subareas of a region; those representing the diversity of land uses within subareas of a region; and those representing the accessibility of residential uses to nonresidential uses at different locations within a region. In this study, all three types were estimated for counties in our sample and became part of a mix factor.

The first two variables were calculated for each block group using block-level population data from the 2020 Census and block-level employment data from the 2019 LEHD database. For the first variable, each block group centroid was buffered with a one-mile ring, and jobs and population were summed for blocks within the ring. One-mile rings were used to standardize geography for census block groups, which vary widely in size, making balance easier to achieve in the larger block groups. The resulting job and population totals were used to compute a job-population balance measure. The equation used to calculate job-population balance was:

$$\sum_{i=0}^{i=n}(1-(ABS(J_i - JP * P_i))/(J_i + JP * P_i)) * ((BJ_i + BP_i)/(TJ + TP))$$

where:

i = census block group number (excluding those in census tracts with fewer than 100 persons per square mile)
n = number of block groups in the county
J = jobs in 1-mile buffer of the block group population centroid
P = residents in 1-mile buffer of the block group population
centroid JP = jobs per person in the metropolitan area
TJ = total jobs in the county
TP = total residents in the county

This variable equals 1 for block groups with the same ratio of jobs-to-residents within the one-mile ring as the metropolitan area as a whole; 0 for block groups with only jobs or residents within the one-mile ring, not both; and intermediate values for intermediate cases. All values were weighted by the sum of block group jobs and residents as a percentage of the county total to obtain:

1. countywide average job-population balance (jobpop).

For the second mixed-use variable, each block group centroid was again buffered with a one-mile ring, and jobs by sector were summed for blocks within the ring. An entropy formula was then used to compute a measure of job mix. The equation for this measure is:

$$\sum_{i=1}^{n}\sum_k((P_k * LN(P_k))/LN(k)) * ((BJ_i + BP_i)/(TJ + TP))$$

where:

i = block group number (excluding those in census tracts with fewer than 100 persons per square mile)
n = number of block groups in the county
k = number of sectors
Pk = proportion of jobs in sector k in 1-mile buffer of the block group population
centroid JP = jobs per person in the metropolitan area
BJ = jobs in the block group
BP = residents in the block group
TJ = total jobs in the county
TP = total residents in the county

The variable equals 1 for block groups with equal numbers of jobs in each sector within the ring; 0 for block groups with all jobs in a single sector within the ring; and intermediate values for intermediate cases. The sectors considered in this case were retail, entertainment, health, education, and personal services. Values were weighted by the sum of block group population and employment as a percentage of the county total to obtain:

2. countywide degree of job mixing (jobmix).

A third mixed-use variable uses data from Walk Score, Inc. to measure proximity to amenities, with different amenities weighted differently and amenities discounted as the distance to them increases up to 1.5 miles, where they are assumed to be no longer accessible on foot.[3] Walk Score data for 2025 were acquired for all urban census tracts in the U.S. Values were weighted by the sum of census tracts population and employment as a percentage of the county total to obtain:

3. countywide average Walk Score (walkscore)

Principal components were extracted from the three mix-related variables, and the principal component that accounted for the greatest variance became the mix factor. Loadings of these variables on the mix factor are shown in Table 2.2. The eigenvalue of the mix factor is 2.31, which means that this one factor accounts for more than 77% of the total variance.

Table 2.2. Variable Loadings on the County Mix Factor for 2020

Observed variable	Factor loading*
Jobpop	0.87
Jobmix	0.91
Walkscore	0.85
Eigenvalue	2.31
Explained variance	77.1%

* Correlation with the mix use factor

Population and Employment Centering

Commercial strip development is on most lists of sprawl development patterns. Strips largely guarantee automobile dependence because land uses are spread out over long distances rather than concentrated in walkable centers. Also, the typical pattern of strip development has wide arterials serving auto-oriented land uses set back behind parking lots. The antithesis of strips, urban centers, are concentrations of activity that provide agglomeration economies, support alternative modes and multipurpose trip making, create a sense of place in the urban landscape, and otherwise differentiate compact urban areas from sprawling ones. Centeredness can exist with respect to

[3] A grocery store, for example, gets three times the weight of a book score. The distance decay function starts with a value of 100 and decays to 75% at a half mile, 12.5% at one mile, and zero at 1.5 miles.

population or employment, and with respect to a single dominant center or multiple subcenters. Literature associates compactness with centers of all types, and sprawl with the absence of centers of any type.

Activity centering is the dimension with the most significant improvement compared to Hamidi and Ewing et al.'s 2014 indices, as employment subcenters nationwide for 2019 were identified as a part of this study. Four measures of centering were derived for metropolitan counties. The first centering measure came straight out of the 2020 census:

1. coefficient of variation in census tracts population densities, defined as the standard deviation of census tracts densities divided by the average density of census tracts. The more variation in densities around the mean, the more centering and/or subcentering exists within the county (varpop).

The second centering measure was derived from the LEHD 2019 database and is analogous to the first measure, except for its use of employment density by block group rather than population density to compute:

2. coefficient of variation in census tracts employment densities, defined as the standard deviation of census tracts densities divided by the average density of census tracts. The more variation in densities around the mean, the more centering and/or subcentering exists within the county (varemp).

The last two centering variables measure the proportion of employment and population within CBDs and employment subcenters. We first identified the location of employment subcenters for all metropolitan areas. We assumed no significant change on the location of CBDs in 10 years (since 2010) and therefore used the CBD locations identified in the 2010 study to derive the location of subcenters within metropolitan areas and divisions. Having CBDs for 359 metropolitan areas, we identified urban subcenters as the positive residuals estimated from an exponential employment density using the Geographically Weighted Regression method (GWR) and a multi-criteria filtering process. GWR estimates a smoothed employment density surface using only nearby observations for any data point (block groups), with more weight given to closer observations. The dependent variable of the GWR estimations is the employment density of a block group and the independent variable is the distance of the block group centroid from the CBD. We used the Adaptive kernel type with 30 numbers of neighbors. We incorporated both employment and population thresholds to enhance accuracy. Block groups with high residuals (>1.5) were considered subcenter candidates. We applied additional filters to distinguish between urban subcenters and employment nodes: excluding areas dominated by a single sector, retaining only those with employment-to-population ratios between 2.5 and 15, and keeping block groups with employment densities at least three times the MSA average. A sum of 1,247 urban subcenters within metropolitan areas and divisions were identified in 2020.

Using this procedure, we found 131 metropolitan areas to be monocentric (having only one center) and 228 to be polycentric (having more than one center). This procedure resulted in two new centering variables:

3. percentage of county population in CBD or subcenters (popcen)
4. percentage of county employment in CBD or subcenters (empcen)

Principal components were extracted from the set of centering variables, and the principal component that accounted for the greatest variance became our centering factor. All component variables loaded positively on the centering factor (see Table 2.3). The eigenvalue of the centering factor is 1.99, which means that this one factor accounts for about half of the total variance in the dataset.

Table 2.3. Variable Loadings on the County Centering Factor for 2020

Observed variable	Factor loading*
Varpop	0.26
Varemp	0.72
Popcen	0.78
Empcen	0.88
Eigenvalue	1.9
Explained variance	49.9%

* Correlation with the centering factor

Street Connectivity

Accessibility is a function not only of land-use patterns but of street network design, a fourth dimension of compactness-sprawl. After all, it is the streets that connect the land uses. Street connectivity is related to block size since smaller blocks translate into shorter and more direct routes. A traditional urban neighborhood is composed of intersecting bounding streets that form a grid, with houses built on the four sides of the block, facing these streets. Therefore, the length of each side of that block, and therefore its block size, is relatively small. By contrast, a contemporary suburban neighborhood does not make connections between adjacent cul-de-sacs or loop roads. Instead, local streets only connect with the street at the subdivision entrance, which is on one side of the block boundary. Thus, the length of a side of this block is quite large, and the block itself often encloses multiple subdivisions to form a superblock, a half mile or more on a side. Large block sizes indicate a relative paucity of street connections and alternate routes. So, two street accessibility variables were computed for each urbanized area:

1. average block size excluding rural blocks of more than one square mile (avgblk)
2. percentage of small urban blocks of less than one hundredth of a square mile (smlblk) The

last two street connectivity variables account for the number and type of intersections.

Intersections are where street connections are made and cars must stop to allow pedestrians to cross. In his great book *Great Streets*, Allan Jacobs characterizes street networks in terms of intersection density. The higher the intersection density is, the more walkable the city. Intersection density has become the most common metric in studies of built environmental impacts on individual travel behavior (Ewing and Cervero, 2010). Another common metric in such studies is the percentage of 4-or-more-way intersections (Ewing and Cervero, 2010). This metric provides the purest measure of street connectivity, as 4-way intersections provide more routing options than 3-way intersections. A high percentage of 4-way intersections does not guarantee walkability, as streets may connect at 4-way intersections in a super grid of arterials. But it does guarantee routing options. We used the street network dataset provided by Boeing (2017) to calculate intersection density. Boeing (2017) extracted edges and nodes from OpenStreetMap for every street and intersection in the U.S. Edges represent street segments and include attributes such as length and direction, while nodes represent intersections or deadends and store geographic coordinates and connectivity. Using the node and edge datasets, we identified whether each node functions as an intersection and, if so, whether it is a 4-or-more-way intersection.

This procedure resulted in two additional street connectivity variables:

3. intersection density for urban and suburban census tracts within the county, excluding rural tracts with gross densities of less than 100 persons per square mile (intden)
4. percentage of 4-or-more-way intersections, again excluding rural tracts (4-way)

Principal components were extracted from the full set of street-related variables, and the principal component that accounted for the greatest variance became our street connectivity factor. Loadings of these variables on the street factor are shown in Table 2.4. The eigenvalue of the street factor is 2.66, which means that this one factor accounts for about 66 percent of the total variance in the data set. As expected, one of the variables loads negatively on the street accessibility factor, that being the average block size. The rest load positively. Thus, for all component variables, more accessibility translates into higher values of the street factor.

Table 2.4. Variable Loadings on the County Street Factor for 2010

Observed variable	Factor loading*
Avgblk	-0.78
Smlblk	0.94
Intden	0.85
4-way	0.65
Eigenvalue	2.39
Explained variance	66.4%

* Correlation with the street factor

Relationship Among Compactness Factors

It has been said that measures of the built environment are so highly correlated that they should not be represented separately, but instead should be combined into a single index. Thus, for example, overall measures of walkability have been advanced as an alternative to individual measures. This position is not borne out by this study, at least not at the county level. While correlated, as one might expect, the four compactness factors seem to represent distinct constructs. Their simple correlation coefficients are shown in Table 2.5.

Table 2.5. Simple Pearson Correlation between four factors

	density factor	mix factor	centering factor	street factor
density factor	1	0.40	0.51	0.58
mix factor	0.40	1	0.36	0.68
centering factor	0.51	0.36	1	0.47
street factor	0.58	0.68	0.47	1

Overall 2020 County Index

We found no empirical or theoretical justification to assign different weights to the four components for deriving the overall compactness score. All four individual factors contribute to the accessibility or inaccessibility of different development patterns, none presumptively more than the others. Depending on their values, all move a county along the continuum from sprawl to compact development. Thus, they were simply summed, in effect giving each dimension of sprawl equal weight in the overall index.

In order to account for a county's size, we regressed the sum of the sprawl factors on the natural logarithm of the population of the county. The standardized residuals became the overall measure of sprawl. As such, this index is uncorrelated with population. This adjustment for population size does not change the fact that the sprawl index is highly correlated with the sum of the four component factors (r = 0.802). As with the individual sprawl factors, we transformed the overall compactness score into an index with a mean of 100 and a standard deviation of 25. This was done for the sake of consistency and ease of understanding. With this transformation, the more compact counties have index values above 100, while the more sprawling have values below 100.

Appendix B contains compactness factors and refined county sprawl (compactness) indices for 995 county and county equivalents in 2020. The 10 most compact and 10 most sprawling counties are shown in Tables 2.6 and 2.7. The most compact counties are central counties of large, older metropolitan areas. The most sprawling counties are outlying counties of large metropolitan areas or component counties of smaller metropolitan areas. Values range from 460.3 for New York County, as the most compact county, to 55.3 for Harris County in Columbus MSA GA, as the most sprawling county in 2020.

Table 2.6. Top 10 Most Compact Counties in 2020

Rank	County	Metropolitan Area	Index
1	New York County	New York-Jersey City-White Plains, NY-NJ	460.3
2	San Francisco County	San Francisco-San Mateo-Redwood City, CA	252.6
3	Kings County	New York-Jersey City-White Plains, NY-NJ	232.0

4	Bronx County	New York-Jersey City-White Plains, NY-NJ	214.6
5	Suffolk County	Boston, MA	207.2
6	District of Columbia	Washington-Arlington-Alexandria, DC-VA-MD-WV	203.9
7	Philadelphia County	Philadelphia, PA	197.9
8	Charlottesville city	Charlottesville, VA	197.4
9	Alexandria city	Washington-Arlington-Alexandria, DC-VA-MD-WV	193.6
10	Queens County	New York-Jersey City-White Plains, NY-NJ	190.0

Table 2.7. Top 10 Most Sprawling Counties in 2020

Rank	County	Metropolitan Area	Index
986	Paulding County	Atlanta-Sandy Springs-Alpharetta, GA	63.1
987	Fayette County	Memphis, TN-MS-AR	62.6
988	Chambers County	Houston-The Woodlands-Sugar Land, TX	62.1
989	Blount County	Birmingham-Hoover, AL	62.0
990	Currituck County	Virginia Beach-Norfolk-Newport News, VA-NC	61.8
991	Riverside County	Riverside-San Bernardino-Ontario, CA	61.7
992	Powhatan County	Richmond, VA	60.8
993	Grant Parish	Alexandria, LA	60.5
994	Pike County	Atlanta-Sandy Springs-Alpharetta, GA	56.7
995	Harris County	Columbus, GA-AL	55.3

Figures 2.1 and 2.2 present arial imagery for the top four most compact and sprawling counties. We reviewed satellite imagery for the 10 most compact and sprawling counties and confirmed the face validity of the county sprawl measures. The top compact counties are consistent with previous indices and largely expected. The counties rated as most sprawling according to the new four-factor index have census tracts with very low-density residential development. As expected, three out of four most compact counties are located in New York metro division.

Figure 2.1. The four most compact counties in 2020 (New York, NY; San Francisco, CA; Kings, NY; and Bronx, NY)

Figure 2.2. The four most sprawling counties in 2020 (Powhatan VA; Grant Parish, LA; Pike, GA; and Harris, GA)

The comparison of county-level development patterns between 2010 and 2020 reveals that in 2020, the most compact counties are located in large metropolitan areas with higher densities and mixed land uses. Counties such as New York County (NY), San Francisco County (CA), Hudson County (NJ), Suffolk County (MA), and Philadelphia County (PA) continue to rank among the most compact, reflecting their dense urban cores and transit-oriented development. In 2010, these same counties already occupied the top ranks, although their relative positions shifted slightly. Overall, compactness has remained concentrated in established urban areas, with only minor changes in rank between 2010 and 2020.

On the opposite end, sprawling counties in 2020 are largely suburban areas in the South and West, such as Riverside County (CA), Gwinnett County (GA), Maricopa County (AZ), and Collin County (TX). These areas are characterized by rapid population growth, auto-dependent development, and dispersed land-use patterns. In 2010, many of these same counties were already near the bottom of the compactness rankings, and they have largely retained their sprawling character over time. The persistence of these patterns indicates that sprawl remains closely linked to ongoing growth pressures and prevailing suburban development models in fast-growing regions, showing little evidence of substantial change in growth management practices within these areas.

Chapter 3: Metropolitan Sprawl Index

Urban sprawl is defined as scattered and unplanned land expansion (Barman et al., 2024), low-density development (Surya et al., 2021), and a lack of mixed land uses (D'Agata et al., 2023). Other key features often cited are automobile dependency due to poor street connectivity, segregation of residential, commercial, and industrial areas, extensive presence of single-family detached housing, and a general absence of centralized urban cores or focal points (Anthony, 2004; Pendall & Carruthers, 2003; Robinson et al., 2005). Together, these characteristics may contribute to inefficient land use, increased infrastructure costs, environmental degradation, and social isolation (Brueckner & Largey, 2008; Trubka et al., 2010).

Since the early 2000s, scholars began efforts to measure and operationalize metropolitan sprawl and compact development (Fulton et al., 2001; S. Malpezzi & W.-K. Guo, 2001). Starting in the 2000s, many studies focused primarily on one dimension of sprawl, such as population or employment density (Lopez & Hynes, 2003; Pendall & Carruthers, 2003). While these single-factor measures made comparisons easier and provided useful insights, they often failed to capture the full complexity of the urban sprawl concept (Zhu et al., 2024). Recognizing the shortcomings of earlier measures (S. Malpezzi & W. Guo, 2001; Torrens, 2008), researchers moved toward creating a more comprehensive, multidimensional sprawl measure (Zhang et al., 2023). One of the earliest attempts was by Galster et al. (2001) who developed an index based on eight dimensions—"density, clustering, heterogeneity, proximity, continuity, centrality, unclarity, and concentration"—and applied it to 13 urbanized areas in the U.S. Building on this, Cutsinger et al. (2005) updated Galster's index for 50 U.S. metropolitan areas.

In 2014, Ewing and Hamidi developed compactness indices for metropolitan areas that account for 21 built environmental variables representing four distinct dimensions of urban form (development density, land-use mix, activity centering, and street connectivity). Compactness indices were published in an NIH website and have been employed extensively to measure quality-of-life outcomes of urban sprawl (Ewing et al., 2016; Hamidi et al., 2018). Using these indices, the impacts of sprawl on various quality-of-life outcomes from housing affordability to upward mobility, traffic safety, emergence of food deserts, innovation and economic productivity, commuting patterns, public transit and congestion, pandemic and other physical and mental health outcomes, air quality, and the overall life expectancy have been quantified (Ewing et al., 2014; Ewing et al., 2016; Hamidi, 2020; Hamidi et al., 2018; Hamidi & Hamidi, 2021; Hamidi et al., 2019).

Nevertheless, and despite their popularity, the Ewing and Hamidi 2010 compactness indices are outdated and offer little information on who sprawls the most and who has been more successful in mitigating urban sprawl since 2010. In addition, there have been several emerging social, environmental, health and climate change quality-of-life outcomes since 2010 that could greatly inform the debate over sprawl versus compactness but have not been studied due to the lack of updated sprawl measures. Finally, updated sprawl measures are needed to help local planners and policymakers evaluate their smart growth efforts over the past decade and develop more informed land-use interventions for future developments. Continuous refinement and updating of multidimensional indices are essential to capture the dynamic nature of sprawl and its diverse impacts on social, environmental, and economic outcomes. Updating and validating these indices with recent data and incorporating new analytical methods can provide more robust tools for policymakers and planners to address contemporary urban challenges.

This study aims to refine and update sprawl indices for 2020 with better and more updated data sources for 233 large and medium-sized metropolitan areas and divisions in the U.S., based on the framework originally developed by Ewing et al. (2003) and later refined by Hamidi and Ewing (2015b). The 2020 metropolitan compactness index is a continuous measure of the degree of sprawl in 233 metropolitan areas and divisions ranging from 54.32 for the most sprawling MSA (Riverside, CA) to 242.91 for the most compact MSA (San Francisco, CA) in the U.S. New York, NY, metro division and Philadelphia, PA, metro division are other top compact areas while Atlanta, GA, and Nashville, TN, rank among the most sprawling. MSA rankings are generally consistent with the 2010 index, with a few exceptions which are explained in the results and discussion section.

Methods

Study Areas and Unit of Analysis

This study measures urban sprawl for 233 metropolitan areas and divisions in the U.S. with a population of at least 200,000. This is based on the rationale that the concept of urban sprawl has limited relevance in small MSAs—such as Iowa City—where low population levels and development intensity do not align with the theoretical and empirical dimensions of sprawl. This refined selection ensures that our analysis is both methodologically robust and contextually appropriate, targeting urban regions where sprawl dynamics are most likely to be significant and policy relevant.

Metropolitan areas in the U.S. are delineated by the Office of Management and Budget. A metropolitan statistical area (MSA) is a region centered around an urban core that meets a minimum population threshold and exhibits high levels of social, economic, and transportation integration. It is important to note that metro divisions are considered in certain cases. A metro division is a subdivision of a metropolitan statistical area (MSA) with a population of 2.5 million or more, used to further delineate large MSAs into distinct, meaningful subregions. For this study, we use metropolitan divisions in place in the 11 largest MSAs to capture the greater spatial complexity and heterogeneity of these large urban regions (MSAs with divisions: Boston–Cambridge–Newton, MA–NH; Dallas–Fort Worth–Arlington, TX; Detroit–Warren–Dearborn, MI; Chicago–Naperville–Elgin, IL–IN–WI; Los Angeles–Long Beach–Anaheim, CA; Miami–Fort Lauderdale–Pompano Beach, FL; New York–Newark–Jersey City, NY–NJ–PA; Philadelphia–Camden–Wilmington, PA–NJ–DE–MD; San Francisco–Oakland–Berkeley, CA; Seattle–Tacoma–Bellevue, WA; and Washington–Arlington–Alexandria, DC–VA–MD–WV).

The final sample reflects a wide range of urbanization patterns, socio-economic characteristics, and spatial development trends across the country.

Data Sources

We used two main data sources to compute urban compactness indices. Specifically, we utilized the Longitudinal Employer-Household Dynamics (LEHD) data for employment at the block level for 2019. Additionally, we used decennial census data at the block level for population figures in 2020. These datasets were aggregated to the block group level using census block group boundary geometry data from the Topologically Integrated Geographic Encoding and Referencing (TIGER) system, separately for 2010 and 2020. Other data sources employed to measure metropolitan sprawl include census tract level Walk Score data from Walkscore Inc. and total urban area of the MSA derived from the National Land Cover Database (2020). We included four land cover classes (developed open space, developed low intensity, developed medium intensity, and developed high intensity) in our calculation of urban lands in the MSA. Finally, we obtained data on the number, type, and location of intersections from Boeing (2017).

Of 21 variables contributing to our compactness index, six variables are associated with the location and boundary of urban centers (both Central Business Districts and urban subcenters) within the metropolitan area. Urban centers are critical components of the degree of centrality (versus dispersed structure) of the MSA. To compute these variables, we first determined the location of CBDs using Local Moran's I and identified the location and boundary of urban subcenters through Geographically Weighted Regression (GWR). In sum, we identified a total of 359 CBDs and 1,247 urban subcenters in 2020 (manuscript in review).

Measuring Metropolitan Compactness

Following Hamidi and Ewing (2015), we applied principal component analysis (PCA) to extract four key dimensions of sprawl: development density, mixed-use, degree of activity centering, and street connectivity. Each dimension consists of a set of correlated but distinct variables that account for various aspects of the dimension. In sum, we measured 21 built environmental variables for all 233 metropolitan areas and divisions in the U.S. and combined them into the four dimensions using Principal Component Analysis (PCA). Table 1 provides a full list of all variables along with their definitions for each sprawl dimension. For more details on each metric, including definitions and computation methods, please refer to Hamidi et al. (2015).

The first sprawl dimension, development density, consists of eight variables: 1) gross population density of urban tracts (with population density of at least 100 persons per square mile) in the MSA; 2) gross employment density of urban census tracts (with population density of at least 100 persons per square mile) in the MSA; 3) the percentage of population living in census tracts with a population density of 1,500 people per square mile or less to capture the proportion of low-density areas in a given MSA; 4) the percentage of population living in census tracts with a density of 12,500 people per square mile or more to capture the proportion of very high-density areas in a given MSA; 5) urban population density based on the proportion of urban land area (according to National Land Cover Database 2020); 6) estimated central density of metropolitan areas derived from a negative exponential population density function; 7) weighted average population density of urban centers; and 8) weighted average employment density of urban centers. The last two variables were weighted based on the sum of employment and population in urban centers relative to the MSA's sum of population and employment.

The second sprawl dimension, mixed-use, consists of three variables. The first is the weighted job-population balance, calculated using a one-mile buffer around the centroid of each block group within metropolitan areas. This measure equals 1 when there is a perfect balance (relative to the ratio of jobs to population in the MSA) and 0 when the block group buffer contains only jobs or only residents (perfect imbalance). The second indicator is weighted average land-use entropy, which, like the job-population balance, is derived using a one-mile buffer. This entropy score reflects the diversity of employment in service sectors within the area: a value of 1 indicates an equal distribution of jobs across all service sectors, while a score of 0 represents complete dominance by a single sector. The service sectors are sectors that residents would visit on a regular basis and consist of retail, entertainment, healthcare, education, and personal services. Both variables are measured for block groups within MSAs and weighted based on the sum of employment and population in block groups relative to the MSA's sum of population and employment to obtain the weighted average values for the MSA. The third metric is the weighted average Walk Score, obtained from Walk Score, Inc. This score ranges from 0 to 100 and assesses accessibility to various amenities, assigning higher weights to certain amenities and reducing their influence as the walking distance increases by foot.

The third sprawl dimension, degree of activity centering, consists of five variables. The first is the coefficient of variation in population density at the census block group level, calculated as the standard deviation of block group population densities divided by their mean. The second is a similar measure but based on employment density instead of population. More variation in population and employment density (higher values of these two variables) are indicators of more centering/subcentering within the MSA. The third variable captures the density gradient from the central business district (CBD), estimated using a negative exponential function. A steeper decline in density with increasing distance from the CBD suggests a more monocentric (and centralized) urban structure. The fourth and fifth indicators assess the concentration of population and employment within identified CBDs and subcenters (see more details under the Data Sources section). Again, higher values of these variables represent more centering/subcentering within the MSA.

Likewise, street connectivity, as the fourth dimension of our compactness-sprawl index consists of five variables. The first three variables are the average block length; average block size; and the percentage of blocks smaller than 1/100 square mile. Extensive literature links smaller blocks to better street connectivity and more walkability (Sevtsuk, 2016 #114). The last two variables, intersection density and the percentage of 4-or-more way intersections, represent higher levels of street connectivity (Choi & Ewing, 2021). Intersection density is calculated by dividing the total number of intersections by the land area and the percentage of 4-or-more-way intersections is determined by dividing the number of such intersections by the total number of intersections within each MSA.

For each compactness-sprawl dimension, we measured the associated variables as explained earlier for all metropolitan areas and divisions in our sample. Next, we applied Principal Component Analysis (PCA) to extract one factor for each dimension that represents the common variance among its corresponding variables. Each dimension factor is a weighted combination of its individual variables, and higher factor loadings for each individual variable is an indicator of more weight for that variable in the overall PCA factor. Table 1 provides the factor loadings (indicating the strength of correlation between each variable and the component), eigenvalues (reflecting the component's explanatory power), and the proportion of total variance explained.

We normalized each PCA factor to obtain four dimension-scores (development density, mixed-use, degree of activity centering, and street connectivity) which have a mean of 100 and standard deviation of 25. The normalization process makes the interpretation and case comparison of scores more intuitive. In the next step, following Ewing and Hamidi's (2017) methodology, we added four dimension-scores to derive the overall index. We simply found no justification to give more weight to one dimension over others. Finally, we sought to create a compactness index that is independent of the MSA size (larger MSAs appear more compact due to their size), so we regressed the final score (sum of four dimensions) against the MSA population and obtained the standardized residuals. We normalized them on a scale with a mean of 100 and standard deviation of 25 to derive the final compactness indices. This method aligns with Ewing et al. (2002) and Hamidi and Ewing (2015b) approaches. Findings and MSA score comparisons are presented in the Results section.

Results

Compactness-Sprawl Factors (Dimensions)

The results of PCA analysis for each compactness-sprawl dimension are presented in Table 3.1 including the factor loadings (indicating the strength of correlation between each variable and the component), eigenvalues (reflecting the component's explanatory power), and the proportion of total variance explained. Overall, all factor loadings have the expected signs and are very much aligned with the 2015 Hamidi et al. study.

Table 3.1. Variable loadings of compactness-sprawl factors for 2020

Factors	Explanation	Data Source	Loading
Density			
Population density	Population in urban census tracts divided by land area (square mile)	Census 2020	0.92
Employment density	Employment in urban census tracts divided by land area (square mile)	LEHD 2019	0.93
Suburban population	Percentage of population living in census tracts with density of less than 1500	Census 2020	-0.63
High and medium urban density population	Percentage of population living in census tracts with density more than 12500	Census 2020	0.92
Urban area population density	Total population divided by urban land area (in square miles)	Census 2020, NLCD, 2020	0.94
Estimated central density	Estimated central density (negative exponential function)	Census 2020, TIGER 2020	0.92
Center population density	Weighted average population density of all block groups in centers	Census 2020	0.85
Center employment density	Weighted average employment density of all block groups in centers	LEHD 2019	0.81
Eigenvalue			6.11
Explained variance			76.48%
Mixed-use			
Job-population balance	Job–population balance for block groups	LEHD 2019	0.79
Land-used mixed	Land-use entropy for block groups	LEHD 2019	0.90
Walk score	Weighted average Walk Score of urban census tracts	Walk Score Inc.	0.91
Eigenvalue			2.27
Explained variance			75.70%
Centering			
Variation of population	Coefficient of variation of urban census tracts population densities	Census 2020	0.32
Variation of employment	Coefficient of variation of urban census tracts employment densities	LEHD 2019	0.61
Density gradient	Density gradient moving outward from the CBD (calculated for urban census tracts)	Census 2020, TIGER 2020	-0.10
Population of centers	Percentage of population living in centers relative to MSA's total	Census 2020	0.78
Employment of centers	Percentage of employment located in centers relative to MSA's total	LEHD 2019	0.78
Eigenvalue			1.71
Explained variance			34.35%
Street Factor			
Small blocks	Percentage of block groups with area of less than 0.01 square mile	Census 2020	0.93
Block size	Average block size (in square miles)	Census 2020	-0.84
Block length	Average block length (in miles)	Census 2020	-0.94
Intersection	Number of intersections divided by land area	(Boeing, 2017)	0.82
4-or-more way intersection	Percentage of 4-or-more-way intersections divided by total intersections	(Boeing, 2017)	0.48
Eigenvalue			3.35
Explained variance			67%

Note: Urban census tracts are defined as those with a population density of at least 100 persons per square mile; Centers refer to both central business districts (CBDs) and subcenters.

The results show that the density dimension has a high eigenvalue of 6.11, explaining 76.48% of the variance among the related variables, indicating that it captures a strong association across the variables. Most of the loadings are strongly positive and above 0.85, including population density (0.92), employment density (0.93), urban area population density (0.94), and estimated central density (0.92). These high positive loadings suggest that areas with more concentrated populations and employment tend to define this factor. The negative loading for suburban population (-0.63) aligns conceptually, as higher suburban population indicates less compactness.

The mixed-use dimension has an eigenvalue of 2.27, explaining 75.70% of the variance among its components. This factor reflects the degree to which urban areas integrate residential and employment land uses. All three variables—job-population balance (0.79), land-use entropy (0.90), and walk score (0.91)—have strong positive loadings, suggesting that higher values of this factor are associated with better integration of land uses and pedestrian-friendly environments.

The centering factor has a lower eigenvalue of 1.71, explaining 34.35% of the variance. While the explained variance is modest compared to the previous factors, this dimension captures the degree of centralization of the urban form. The strongest positive loadings come from population of centers (0.78) and employment of centers (0.78), indicating that more centralized populations and job concentrations are key contributors to this factor. Other variables, such as variation of employment (0.61), also contribute moderately. The density gradient has a small negative loading (-0.10). In essence, this dimension indicates how monocentric the metropolitan area is.

The Street Connectivity Factor has an eigenvalue of 3.35, explaining 67% of the total variance. It reflects the connectivity and granularity of the street network. Variables with strong loadings include small blocks (0.93), block size (-0.84), and block length (-0.94), which are logically inverse measures—smaller blocks and shorter block lengths generally indicate higher street connectivity. Intersection density (0.82) also contributes significantly. The loading for 4-or-more-way intersections is weaker (0.48) but still positive. Overall, this factor captures the degree of connectivity of the street network, with higher scores reflecting finer grid-like and more connected street networks typically associated with walkable urban environments.

Overall Compactness-Sprawl Scores for U.S. Metropolitan Areas

The overall compactness-sprawl index was computed by summing four individual component scores. To account for the size of each metropolitan area, we regressed the total score on the natural logarithm of the metro area population. The standardized residuals from this regression were normalized to have a mean of 100 and standard deviation of 25. The index is a continuous variable (score) ranging from the most sprawling (Riverside, CA, with the score of 54.3) to the most compact (San Francisco metro division with the score of 242.9). Interestingly, both most compact and most sprawling MSAs in the U.S. reside in California.

Figure 3.1 provides the spatial distribution of compactness-sprawl scores of 233 metro areas across the U.S. in 2020. The results show that the most compact metro areas—led by San Francisco-

San Mateo-Redwood City, CA, New York-Jersey City-White Plains, NY-NJ, and Philadelphia metro division—exhibit significantly higher overall compactness scores than any undifferentiated metro area in our sample (see Figure 3.2). These compact metro divisions consistently score high across all four dimensions: density, mixed-use, degree of centering, and street connectivity, reflecting highly accessible and connected urban form.

On the other hand, the two most sprawling metro areas are Atlanta-Sandy Springs-Alpharetta, GA, and Riverside-San Bernardino-Ontario, CA, which exhibit the lowest overall compactness-sprawl scores. These metro areas show relatively low density and centering values, indicating more dispersed and less centralized development patterns (See Figure 3.3). While Riverside, CA, shows a moderate mixed-use score, both metro areas demonstrate weaker street connectivity and centering compared to other MSAs in our sample.

Additionally, the spatial distribution (Figure 3.1) highlights regional variations in compactness and sprawl. For instance, coastal metropolitan areas—particularly in California and the Northeast—tend to have higher compactness scores, while many areas in the Midwest and South exhibit lower compactness and more sprawling development patterns.

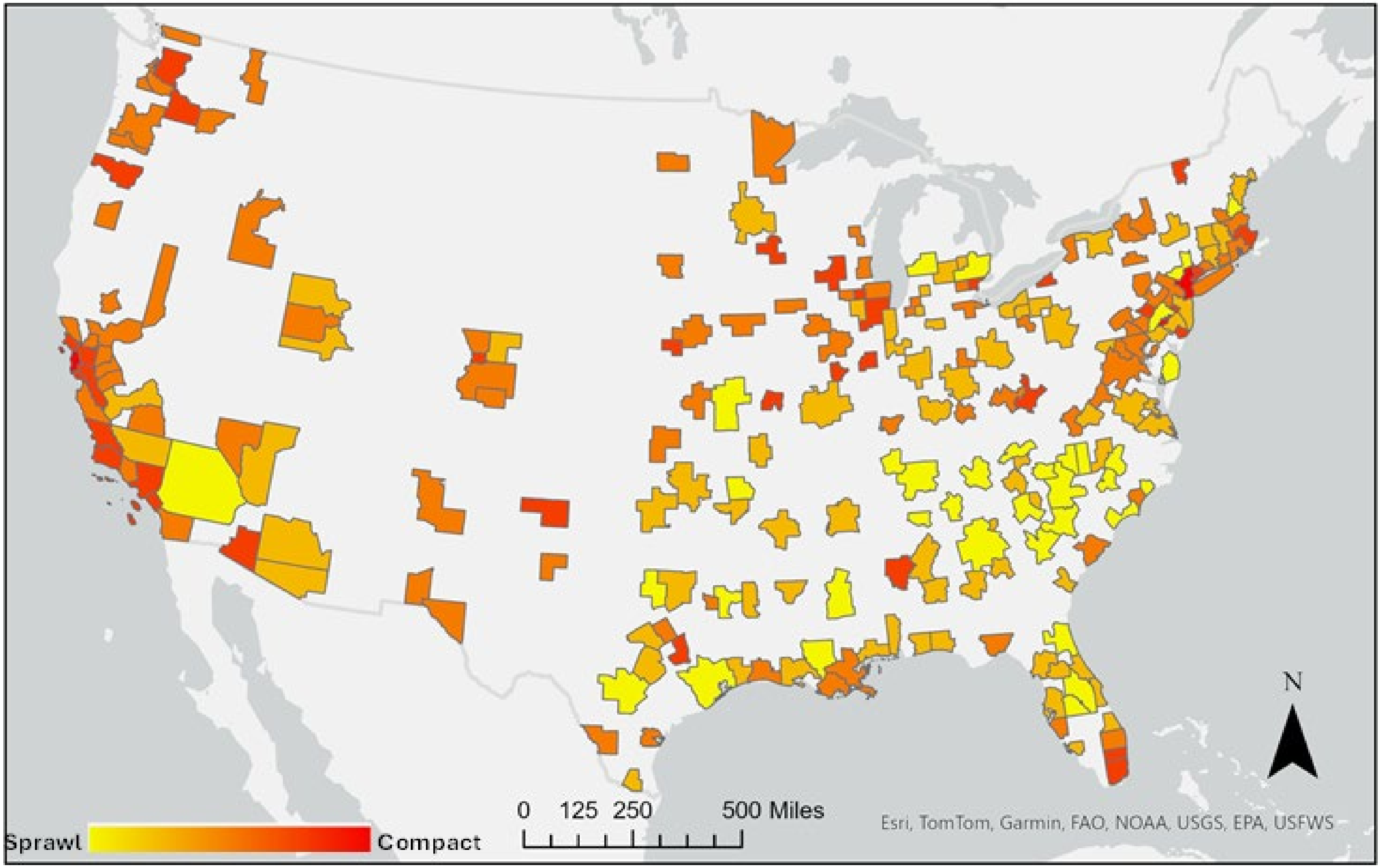

Figure 3.1. Map of compactness-sprawl scores for 233 U.S. metropolitan areas and divisions (ranging from sprawling (yellow color) to compact (red color)

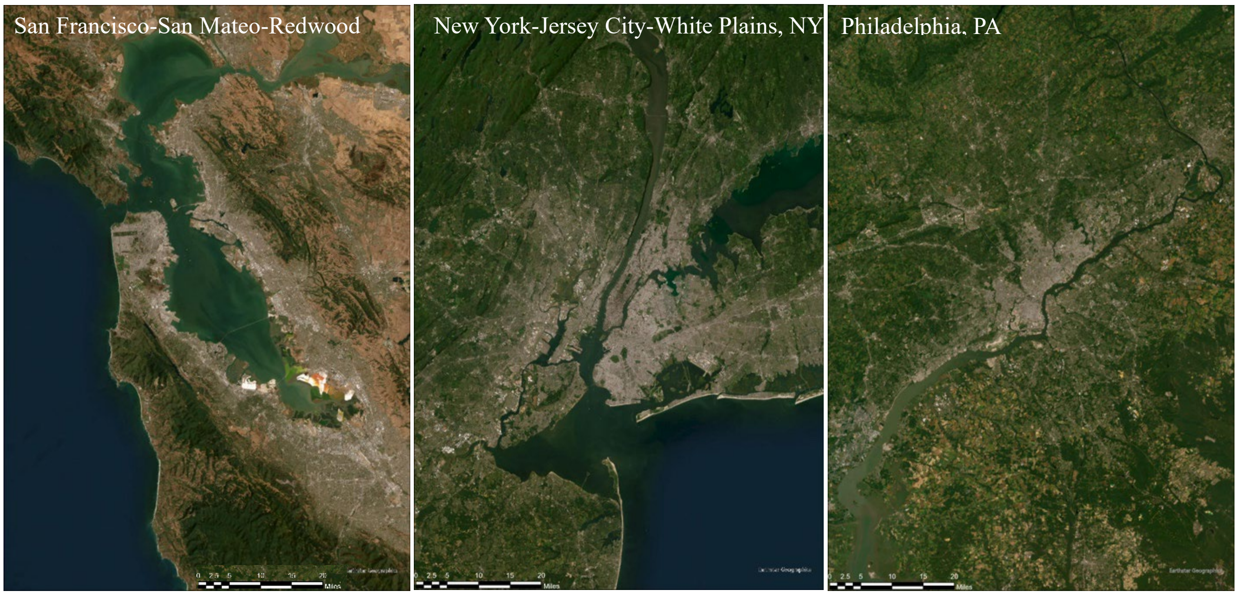

Figure 3.2. Areal imagery for the three most compact MSAs in 2020: San Francisco-San Mateo-Redwood City, CA; New York-Jersey City-White Plains, NY-NJ; Philadelphia, PA

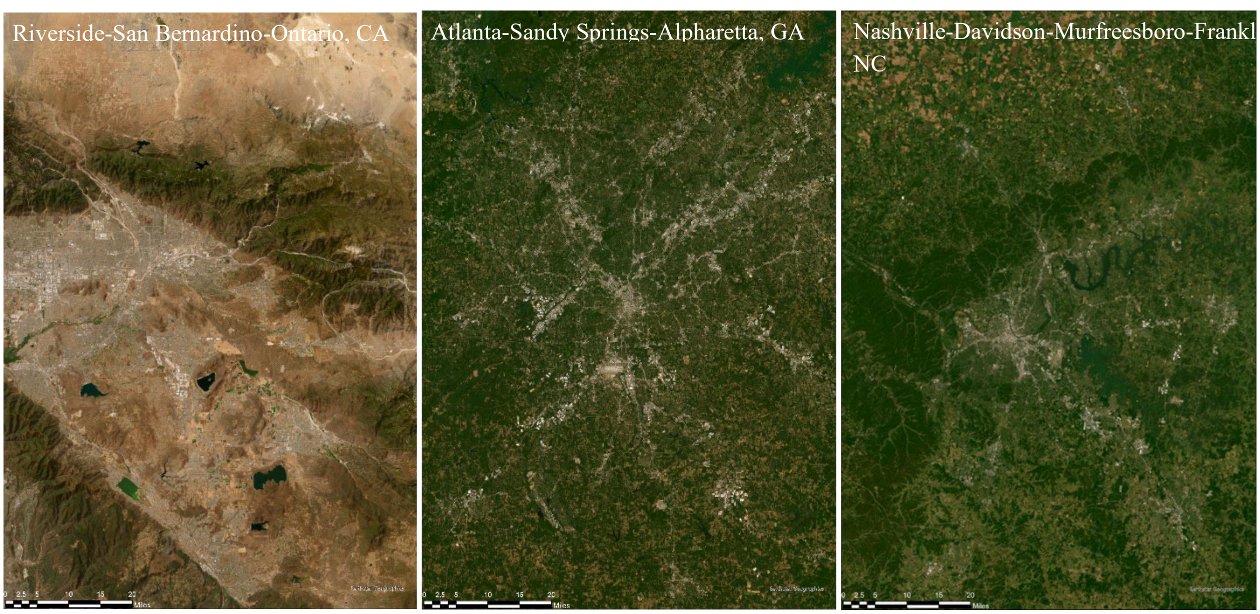

Figure 3.3. Areal imagery for the three most sprawling MSAs in 2020: Riverside-San Bernardino-Ontario, CA; Atlanta-Sandy Springs-Alpharetta, GA; Nashville-Davidson-Murfreesboro-Franklin, TN

Discussion of Key Findings

This study contributes to urban and transportation planning literature and practice in several key ways. First, it updates the overall compactness-sprawl index and its individual components to 2020 and validates these measures against transportation outcomes. Second, the analysis reveals shifts in the ranking of certain metropolitan areas along the compactness-sprawl continuum, highlighting changes in urban development patterns. Third, this study identifies the role of urban sprawl in influencing car dependency by estimating the elasticity of transportation outcomes in response to the compactness-sprawl index using an inferential approach, as well as determining the effective ranges in which these factors have the most remarkable impact using a machine-learning approach.

First, compared to the factor loadings of the individual compactness-sprawl components in the 2010 study by Hamidi and Ewing (2015b), several factors and indicators show improved performance in the 2020 update. For instance, the density factor in 2010 had an eigenvalue of approximately 5.8 and explained about 72% of the variance. In the 2020 analysis, these values increased to around 6.1 and 77%, respectively. Similarly, the street connectivity factor had an eigenvalue of about 2.5 and explained 50% of the variance in 2010, whereas in 2020 these values rose to approximately 3.3 and 67%. These improvements may be attributed to the use of updated and higher-resolution datasets, expanded variable coverage, and refined measurement techniques that better capture the complexity of urban form.

In addition, there are both similarities and differences in the compactness-sprawl rankings and scores of metropolitan areas between 2010 and 2020. For example, while the top two ranked metro areas remain the same in both years, the most compact urban form in 2020 is found in San Francisco, CA, whereas in 2010 it was New York, NY.

The shift toward San Francisco's increased compactness likely reflects several factors. First, the boundaries of the San Francisco metro division were redefined, resulting in a smaller metro division due to the separation of the San Rafael, CA, metro division. This boundary change alone may have concentrated development measures within a more compact urban core. Second, a series of development policy reforms implemented between 2010 and 2020—including zoning changes, transit-oriented development initiatives, and housing policies—have further supported a denser and more compact urban form. Throughout the last decade, San Francisco's Transit-First policy and continued investment in bicycle infrastructure have further reinforced walkable, transit-oriented development patterns that support a more compact urban form. Additionally, recent pro-housing reforms—including the removal of parking minimums and the introduction of mixed-use and transit-oriented developments under initiatives like the Family Zoning Plan—may have accelerated the city's densification by 2020.

Furthermore, the results show that Atlanta, GA, consistently ranks among the most sprawling metropolitan areas, maintaining its position as the second-most sprawling MSA in both 2010 and 2020. This finding aligns with previous studies highlighting Atlanta's low-density development, automobile dependence, and fragmented land-use patterns (Ewing et al., 2002; Glaeser & Kahn, 2004; Hamidi & Ewing, 2015b).

In the same line, some observed changes in compactness-sprawl scores and rankings are likely influenced by alterations to metropolitan area boundaries. For example, Philadelphia, PA, was ranked 33rd in 2010 with an overall compactness score of 122.42 (Density Factor: 141; Mix Factor: 142; Centering Factor: 115; and Street Factor: 122). However, by 2020, Philadelphia jumped to third place with a significantly higher score of 220 (Density: 229; Mix: 161; Centering: 168; Street: 199). This dramatic shift is largely attributed to the change in metro boundaries—Philadelphia's 2020 metropolitan division covers only about 15% of the area included in the 2010 delineation. A similar case is observed in San Rafael, CA, which ranked ninth in 2020 and emerged as one of the most compact metropolitan areas after being separated from the San Francisco metro division to form its own distinct region.

Finally, in the 2020 compactness-sprawl index rankings, several metropolitan areas stand out due to their distinct urban form characteristics. Los Angeles-Long Beach-Anaheim ranks surprisingly high (11th out of 233), reflecting its dense development pattern and strong concentration around multiple urban centers, despite being located in a region typically associated with sprawl. On the other end of the spectrum, the Atlanta-Sandy Springs-Alpharetta MSA ranks among the most sprawling, characterized by low density, poor connectivity, and a decentralized urban structure. Interestingly, Provo-Orem, UT, a relatively medium-sized metropolitan area, appears among the most compact regions, driven by strong street connectivity and mixed land use. These cases illustrate how both large and medium-sized metro areas can exhibit diverse spatial patterns.

This chapter underscores the importance of policy interventions and geographic delineations in shaping urban compactness. Metropolitan areas that implemented targeted zoning reforms, promoted transit-oriented development, and invested in multimodal transportation infrastructure—such as San Francisco and Los Angeles—demonstrated measurable gains in compactness scores. Conversely, consistent sprawl in regions like Atlanta highlights the persistent influence of automobile-oriented planning and low-density land-use patterns.

Chapter 4: Impacts of Sprawl on Quality-Of-Life Outcomes

In this chapter, we summarize a series of analyses on quality-of-life impacts of sprawl from social to transportation, housing and energy affordability, and the risk of heat-related and vector-borne disease. Our findings indicate that higher compactness scores are consistently associated with more travel options, lower vehicle miles traveled, substantially reduced traffic fatalities—particularly pedestrian-related deaths—and reduced car dependency and vehicle ownership. Compact urban form also promotes active modes of travel such as walking, cycling, and public transit and contributes significantly to better health outcomes. Beyond mobility and safety, compact development supports housing affordability by reducing transportation and energy costs. It also contributes to other improved public health, with reductions in COPD and heart attack hospitalizations, while fostering stronger social opportunities by reducing youth disconnection and increasing social capital. Together, these results reinforce the critical role of compact urban form in creating healthier, safer, and more sustainable urban environments. For more detailed information on data, measurements, and analytical methods, please contact the authors.

Sprawl and Traffic Fatalities

In 2023, approximately 41,000 individuals lost their lives in motor vehicle accidents (IIHS, 2023). When compared to other affluent nations, the U.S. exhibits some of the most concerning traffic safety statistics. In 2019, the country had the highest population-adjusted rate of motor vehicle crash fatalities among 29 high-income countries, with a rate of 11.1 deaths per 100,000 people. Additionally, between 2013 and 2022, the rate of traffic-related fatalities in the U.S. increased by 22.5%, rising from 10.41 to 12.76 per 100,000. In contrast, 27 other high-income countries experienced a decline in their traffic death rates during the same period. Moreover, pedestrian deaths surged sharply, placing the U.S. at the top for pedestrian fatality rates overall, as well as among those aged 15 to 24 and 25 to 64 (Naumann, 2025).

Addressing the issue of fatal motor vehicle accidents goes beyond simply saving lives; it also involves mitigating a substantial economic burden. In 2019, the financial costs associated with crashes in the United States were estimated to reach around $340 billion. This figure includes a range of expenses such as medical bills, lost productivity, legal and emergency services, insurance management, traffic congestion, property damage, and disruptions at work—averaging approximately $1,035 per person, which represents about 1.6% of the national GDP (Blincoe et al., 2023). These statistics highlight that decreasing fatalities is not just a public health concern but also a vital economic necessity for the country.

In this study, we applied the 2020 county compactness index along with fatal crash data to examine both the direct and indirect impacts of urban form on overall traffic fatality rates and pedestrian fatality rates at the county level in the U.S. using structural equation modeling (SEM). Table 1 shows the list of variables and data sources used in this analysis.

Table 4.1: List of variables and data sources

Variable name	Description	Data Sources
Outcome variables (county level)		
fatalities	Total fatal crashes 2017-2019	FARS (2017-2019)
PEDfataladj	Pedestrian involved fatalities adjusted by walking commute mode share from ACS (2017-2019)	FARS (2017-2019)
Endogenous variable (county level)		
VMT	Average household vehicle miles travel	StreetLight (January 2020)
Independent variables- exogenous - county level		
Compactness	Compactness index	Authors (2025)
HHsize	average household size	ACS (2015-19)
Lninc	Ln of Median household income in 1000s	ACS (2015-19)
lnMSApop	Ln of MSA population	Census (2020)
White	% of white population	ACS (2015-19)
AvgPrecpt	Mean precipitation rate	PRISM (2019)
Fuel	fuel price	OPIC (2010; adjusted with inflation rate)

Table 4.2 presents the direct, indirect, and total effects of the endogenous and exogenous variables on the overall traffic fatality rate. We begin with the variable of greatest interest in this study—compactness. The results indicate that, after controlling for confounding variables, compactness is significantly and negatively associated with county-level fatal crash rates, both directly and indirectly.

Table 4.2. The best SEM fitted model showing effects of variables on one another in the overall traffic fatality model

Variables			Coefficient (standard error)	Critical Ratio	*P*-value
lnVMT	<--------	Lninc	-0.047 (0.057)	-0.823	0.411
lnVMT	<--------	lncompact	-0.243 (0.061)	-3.978	<0.001
lnVMT	<--------	lnMSApop	0.007 (0.010)	0.659	0.510
lnVMT	<--------	lnHHsize	1.904 (0.144)	13.215	<0.001
lnVMT	<--------	Lnwhite	0.046 (0.053)	0.861	0.389
lnVMT	<--------	Fuel	-1.854 (0.089)	-20.819	<0.001
lnVMT	<--------	maxPrecpt	0.139 (0.027)	5.188	<0.001
lnfatal	<--------	lnVMT	0.418 (0.041)	10.158	<0.001
lnfatal	<--------	lncompact	-0.663 (0.091)	-7.309	<0.001
lnfatal	<--------	maxPrecpt	-0.008 (0.041)	-0.183	0.855
lnfatal	<--------	lnMSApop	-0.019 (0.016)	-1.247	0.213
lnfatal	<--------	Lninc	-1.178 (0.082)	-14.300	<0.001

Compactness also significantly reduces VMT directly (coefficient = -0.243, $p < 0.001$), suggesting that more compact counties generate less vehicle travel miles. Particularly, a 10% increase in compactness at the county level is associated with an overall 2.43% reduction in VMT. Since VMT itself is a strong predictor of fatalities, the reduction in travel partially mediates the beneficial effect of compactness on fatalities. In other words, compactness helps reduce fatalities not only by fostering safer urban forms but also by limiting the amount of travel that exposes residents to risk.

Tables 4.3 shows the direct, indirect, and total effects of the endogenous and exogenous variables on pedestrian fatality rates. The findings show that, after controlling for confounding factors, compactness is significantly and negatively associated with county-level pedestrian fatalities, both directly and indirectly. Specifically, a 10% increase in compactness at the county level corresponds to a 16.7 % direct reduction in pedestrian fatality rates, a 1.6% indirect reduction, and an overall 18.37 % reduction.

Table 4.3. The best SEM fitted model showing effects of variables on one another in the overall pedestrian fatality model

Variables			Coefficient (standard error)	Critical Ratio	*P*-value
lnVMT	<--------	Lninc	-0.048 (0.057)	-0.843	0.399
lnVMT	<--------	lncompact	-0.243 (0.061)	-3.965	<0.001
lnVMT	<--------	lnHHsize	1.923 (0.145)	13.285	<0.001
lnVMT	<--------	lnwhite	0.045 (0.053)	0.856	0.392
lnVMT	<--------	Fuel	-1.855 (0.089)	-20.769	<0.001
lnVMT	<--------	maxPrecpt	0.139 (0.027)	5.195	<0.001
lnVMT	<--------	lnMSApop	0.007 (0.010)	0.675	0.499
lnPEDfatal	<--------	lnVMT	0.686 (0.073)	9.355	<0.001
lnPEDfatal	<--------	lncompact	-1.670 (0.162)	-10.287	<0.001
lnPEDfatal	<--------	maxPrecpt	0.119 (0.070)	1.702	0.089
lnPEDfatal	<--------	lnMSApop	0.050 (0.028)	1.784	0.054
lnPEDfatal	<--------	Lninc	-1.030 (0.147)	-7.000	<0.001
lnPEDfatal	<--------	lnHHsize	1.477 (0.398)	3.709	<0.001
lnPEDfatal	<--------	lnwhite	-0.753 (0.140)	-5.366	<0.001

Overall, compactness emerges as a strong protective factor against pedestrian fatalities, operating both directly and indirectly through reductions in VMT. Household size increases risks substantially, while income and fuel price provide meaningful safety benefits. VMT itself remains a central mediator, amplifying the influence of several variables on pedestrian fatalities.

This analysis demonstrates that compact urban form plays a critical role in enhancing traffic safety in U.S. counties. By showing that greater compactness is directly and indirectly associated with lower overall fatality rates, fewer pedestrian deaths, and substantial reductions in VMT, the findings highlight the importance of land-use patterns as a determinant of roadway safety. These results suggest that dense, mixed-use, and well-connected urban development should be recognized not only as a planning and sustainability strategy but also as a public health and safety intervention. Integrating compactness into transportation and land-use policies offers a powerful pathway to reducing fatalities, improving pedestrian safety, and fostering healthier, more sustainable communities.

Urban Sprawl and Heat Exacerbated Health Outcomes

Urban sprawl, characterized by low-density and single-use development, often leads to an increase in impervious surfaces and a decrease in green spaces, which can elevate local temperatures (Artmann et al., 2019). Research has established links between urban form and extreme heat events, as well as increased hospitalizations due to cardiovascular and respiratory conditions, and heat-related deaths (Anderson et al., 2013; Milojevic et al., 2011). Nonetheless, many studies tend to focus on temperature, urban layout, or health outcomes in isolation, which limits our comprehension of the interrelated dynamics at play. This fragmented perspective can result in several significant issues: (1) neglecting critical mediating or moderating interactions between these elements; (2) producing piecemeal evidence that does not fully address the complexities of urban system; and (3) failing to recognize the cumulative effects on at-risk communities.

This section investigates how urban compactness influences local temperature conditions and, subsequently, population health outcomes. Specifically, it seeks to answer: (1) How does urban form—measured through a multidimensional 2020 compactness-sprawl index—affect intra-urban variation in heat exposure? and (2) What are the direct and indirect pathways through which urban form (compactness-sprawl index) impacts heat-related health outcomes, such as Asthma, COPD, and heart attack hospitalizations, via intermediate factors like the number of hot days, air pollution, and social vulnerability indicators? Using structural equation modeling (SEM), the study simultaneously models these complex relationships to identify key mediating mechanisms, including impervious surface coverage, vegetation (NDVI), humidity, and demographic risk factors (e.g., age, race, income, insurance, smoking). This comprehensive framework captures the interconnected nature of urban form, environmental stressors, and health burdens in a warming climate. Our sample includes 995 urban counties in the U.S.

As for outcomes, we used data on COPD, asthma, and heart attack hospitalizations from the CDC's National Environmental Public Health Tracking Network to analyze health outcomes across metropolitan areas. COPD was measured using the age-adjusted rate of hospitalizations among individuals aged 25 years or older per 10,000 population. Asthma hospitalizations were captured as the age-adjusted rate per 10,000 population, while heart attack hospitalizations reflected age-adjusted rates among individuals aged 35 and older per 10,000 population.

Additionally, we posit three mediating variables linking county sprawl to these health outcomes: extreme heat, air pollution, and smoking. The annual number of extreme heat days was obtained from the CDC National Environmental Public Health Tracking Network, defined as the number of days in which the daily maximum temperature exceeded the 90th percentile for that location. Air pollution was measured using levels of particulate matter (PM2.5) and nitrogen dioxide (NO_2) concentration at the county level, from Meng and Hankey's (2025) air quality maps. Smoking rates were operationalized using the age-adjusted percentage of adults who are current smokers, drawn from the CDC's Behavioral Risk Factor Surveillance System.

Tables 4.4, 4.5, and 4.6 show the relationships between compactness and hospitalization rates for COPD, asthma, and heart attacks, along with environmental mediators such as air pollution and hot summer days. These relationships are largely significant and consistent across models, indicating robust and significant impacts of sprawling development on hospitalization due to COPD, heart attack, and asthma.

Table 4.4. The best SEM fitted model showing effects of variables on one another in the COPD hospitalization model

Variables			Coefficient (standard error)	Critical Ratio	*P*-value
HotDays	<--------	Impervious	0.112 (0.031)	3.56	<0.001
AirP15N	<--------	Impervious	15.72 (0.815)	19.28	<0.001
HotDays	<--------	Compact	-0.636 (0.146)	-4.37	<0.001
AirP15N	<--------	Compact	30.78 (3.278)	9.39	<0.001
AirP15N	<--------	MSApop	2.53(0.563)	4.49	<0.001
Smoking	<--------	MSApop	0.025(0.006)	4.19	<0.001
Smoking	<--------	Income	-0.634 (0.028)	-22.6	<0.001
Smoking	<--------	age65plus	-0.053(0.026)	-2.05	0.040
AirP15N	<--------	meanNDVI	-27.55(3.699)	-7.45	<0.001
AirP15N	<--------	Humidity	25.9 (5.487)	4.71	<0.001
AirP15N	<--------	heat_humid	4.23(0.737)	5.74	<0.001
HotDays	<--------	Humidity	-1.0 (0.196)	-5.11	<0.001
AirP15N	<--------	Pctblack	1.45 (0.529)	2.73	0.006
Smoking	<--------	Pctblack	0.007 (0.005)	1.46	0.14
copdHospital	<--------	Compact	-0.202 (0.100)	-2.03	0.042
copdHospital	<--------	age65plus	0.434(0.077)	5.64	<0.001
copdHospital	<--------	Income	-0.348(0.114)	-3.04	0.002
copdHospital	<--------	Pctblack	0.061(0.016)	3.76	<0.001
copdHospital	<--------	NO insurance	-0.150 (0.046)	-3.27	0.001
copdHospital	<--------	Humidity	-0.211(0.145)	-1.45	0.147
copdHospital	<--------	lnHdaysum19plus	-0.002(0.025)	-.084	0.93
copdHospital	<--------	AirP15N	0.004 (0.001)	5.08	<0.001
copdHospital	<--------	Smoking	1.54 (0.126)	12.2	<0.001
copdHospital	<--------	heat_humid	0.104 (0.021)	4.96	<0.001

Table 4.5. The best SEM fitted model showing effects of variables on one another in the heart attack hospitalization model

Variables			Coefficient (standard error)	Critical Ratio	*P*-value
HotDays	<--------	Impervious	0.114(0.032)	3.61	<0.001
AirP15N	<--------	Impervious	16.94 (0.732)	23.15	<0.001
HotDays	<--------	Compact	-0.65 (0.147)	-4.43	<0.001
AirP15N	<--------	Compact	28.89 (3.270)	8.84	<0.001
AirP15N	<--------	MSApop	2.49(0.560)	4.46	<0.001
smoking	<--------	pctblack	0.008(0.005)	1.57	0.117
Smoking	<--------	MSApop	0.024(0.006)	4.07	<0.001
Smoking	<--------	Income	-0.632 (0.029)	-21.97	<0.001
Smoking	<--------	age65plus	-0.053(0.026)	-2.06	0.039
AirP15N	<--------	meanNDVI	-24.98(3.64)	-6.86	<0.001
AirP15N	<--------	Humidity	24.29 (5.430)	4.47	<0.001
AirP15N	<--------	heat_humid	4.11(0.734)	5.59	<0.001
HotDays	<--------	Humidity	-1.00 (0.197)	-5.08	<0.001
HeartAttack.Hosp	<--------	Compact	-0.132 (0.065)	-2.01	0.044
HeartAttack.Hosp	<--------	age65plus	0.90(0.050)	1.81	0.071
HeartAttack.Hosp	<--------	Income	-0.461(0.082)	-5.64	<0.001
HeartAttack.Hosp	<--------	pctblack	-0.022(0.010)	-2.09	0.037
HeartAttack.Hosp	<--------	NO insurance	-0.007 (0.030)	-0.23	0.819
HeartAttack.Hosp	<--------	Humidity	-0.069(0.094)	-0.73	0.465
HeartAttack.Hosp	<--------	HotDays	-0.015(0.016)	-0.92	0.358
HeartAttack.Hosp	<--------	AirP15N	0.002 (0.001)	3.57	<0.001
HeartAttack.Hosp	<--------	Smoking	0.47 (0.083)	5.68	<0.001
HeartAttack.Hosp	<--------	heat_humid	0.023 (0.014)	1.71	0.087
HeartAttack.Hosp	<--------	MSApop	-0.008(0.012)	-0.71	0.483

Table 4.6. The best SEM fitted model showing effects of variables on one another in the asthma hospitalization model

Variables			Coefficient (standard error)	Critical Ratio	*P*-value
HotDays	<--------	Impervious	0.065 (0.024)	2.77	0.006
AirP15N	<--------	Impervious	16.616 (0.766)	21.71	<0.001
HotDays	<--------	Compact	-0.426 (0.110)	-3.869	<0.001
AirP15N	<--------	Compact	29.93 (3.378)	8.86	<0.001
AirP15N	<--------	MSApop	2.69(0.573)	4.69	<0.001
smoking	<--------	pctblack	0.009(0.005)	1.61	0.109
Smoking	<--------	MSApop	0.022(0.006)	3.69	<0.001
Smoking	<--------	Income	-0.635 (0.028)	-22.42	<0.001
Smoking	<--------	age65plus	-0.089(0.025)	-3.61	<0.001
AirP15N	<--------	meanNDVI	-26.81(3.737)	-7.17	<0.001
AirP15N	<--------	Humidity	29.96 (5.479)	5.47	<0.001
AirP15N	<--------	heat_humid	3.97(0.746)	5.32	<0.001
HotDays	<--------	Humidity	-0.79 (0.145)	-5.43	<0.001
AsthmaHospital	<--------	Compact	-0.049 (0.135)	-0.36	0.719
AsthmaHospital	<--------	age65plus	0.40(0.086)	4.64	<0.001
AsthmaHospital	<--------	Income	-0.524(0.140)	-3.75	<0.001
AsthmaHospital	<--------	pctblack	0.135(0.020)	6.74	<0.001
AsthmaHospital	<--------	NO insurance	-0.165 (0.051)	-3.21	0.001
AsthmaHospital	<--------	Humidity	-0.99(0.205)	-4.86	<0.001
AsthmaHospital	<--------	HotDays	0.09(0.040)	2.27	0.023
AsthmaHospital	<--------	AirP15N	0.008 (0.002)	4.93	<0.001
AsthmaHospital	<--------	Smoking	0.41 (0.140)	2.92	0.004
AsthmaHospital	<--------	heat_humid	0.21 (0.025)	0.84	0.402
AsthmaHospital	<--------	meanNDVI	0.11(0.131)	0.82	0.410
AsthmaHospital	<--------	MSApop	0.067(0.021)	3.14	0.002

The findings of this study reveal important policy implications at the intersection of urban planning, transportation, climate resilience, and public health. Urban sprawl and car dependency emerge as significant contributors to heat-exacerbated health outcomes, particularly chronic respiratory and cardiovascular conditions. In contrast, compact urban form—characterized by higher density, mixed land use, and better connectivity—offers substantial public health benefits. Our analysis finds that more compact counties experience significantly lower rates of COPD and heart attack hospitalizations, likely due to greater accessibility to primary healthcare services, opportunities for active transportation, and reduced distances to daily destinations. These results highlight the value of designing cities that bring people closer to essential services while promoting walkability and transit access.

Sprawl and Lyme Disease Incidences

The incidence of Lyme disease, the most prevalent vector-borne disease in North America, has increased significantly over the past few decades (Little & Bowman, 2013). This rise coincides with the ongoing expansion of suburban and exurban development, making it critical to understand the interplay between land use, transportation systems, and Lyme disease risk (Treash, 2022). However, there is a notable gap in how the built environment-particularly suburban land-use patterns and urban form (compactness or sprawl)—shapes human exposure to vector-borne disease. Few studies systematically assess the spatial and structural drivers of Lyme disease at the intersection of public health and planning.

This section empirically investigates the relationship between county-level sprawl and Lyme disease incidence, with a focus on the role of urban sprawl. By using a quasi-experimental design with propensity score matching across urban, suburban, and exurban typologies in the Northeastern, Mid-Atlantic, and Midwestern U.S., we aim to provide novel evidence on how sprawl-linked built environments may increase public health vulnerabilities to Lyme disease. We selected 15 U.S. states and Washington, DC, which had endemic Lyme disease in the year 2018, for inclusion in the study. These states have sustained incidence rates (IR) of over 10 cases per 100,000 residents for over three consecutive years: Connecticut, Delaware, Maine , Maryland, Massachusetts, Minnesota, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, Virginia, West Virginia, Wisconsin, and Washington, DC.

Next, we divided the sample into three categories based on their compactness level: 1) compact (urban) counties with a compactness score above 110; 2) moderately compact (suburban) counties with compactness scores between 90 and 110; 3) sprawling (exurban) counties with compactness scores below 90. These categories will be referred to hereafter as urban, suburban, and exurban. We used Propensity Score Matching (PSM) to deal with the nonrandom assignment of counties. PSM resolves the selection bias by matching pairs from compact and sprawling counties which are balanced on all covariates except on level of compactness. Propensity scores can be estimated using a logit or probit model. We used the urban counties as the reference group and we performed two analyses for suburban and exurban counties in two steps: First, we ran the PSM to create the matching pair for the treatment category relative to the reference group and we investigated the balance between the two. Second, we performed a t-test to identify whether the differences were significant. Table 4.7 shows the list of variables and descriptive statistics.

Table 4.7. Variables, data sources, and descriptive statistics

	Variable	Data Source	Mean (SD)
Lyme disease	Lyme incidence rate	US Centers for Disease Control (CDC) National Notifiable Diseases Surveillance System, with US Census Bureau population estimates	43 (55)
Tick presence	*I. Scapularis* presence status	ArboNET Tick Module, CDC	n/a
Geography	State and county TIGER/Line boundary shapefiles	US Census Bureau	n/a
	percent water area	National Land Cover Database (NLCD)	11.1 (17.5)
	percent shrubland area		0.8 (1.1)
	percent forest area		36.1 (23.8)
	percent wetlands area		7.5 (8.4)
	Percent cultivated area		20.3 (19.3)
	Percent forest-developed edge		40.5 (21.5)
	Mean time-integrated normalized difference vegetation index (NDVI)	US Geological Survey (USGS) eMODIS Remote Sensing Phenology	47.2 (14.6)
	Majority soil type	Web Soil Survey (WSS) STATSGO2 database	n/a
Meteorology	Annual mean temperature (°F)	National Oceanic and Armospheric Administration's (NOAA) US Climate Divisional Database (nClimDiv)	51.7 (5.4)
	Annual mean dew point temperature (°F)	PRISM Northwest Alliance for Computational Science & Engineering at Oregon State University	42.7 (36.9)
Urban development	Sprawl index	Ewing et al., 2003, Ewing & Hamidi, 2014, Hamidi et al., 2025	108.3 (35.5)
Demographics	Population	US Census Bureau	263,507 (360692)
	Median household income (2018 USD)	US Census Bureau's ACS 5-Year Estimates	67,470 (18,251)
	Unemployment (%)	US Census Bureau's ACS 5-Year Estimates	5.2 (1.7)

The results of PSM analysis are shown in Table 4.8. Our findings indicate that compared with urban counties, suburban counties had a statistically significantly higher incidence rate of Lyme Disease, with 20 more cases per 100,000 per year ($p<0.01$). This suggests that there is an association between suburban development patterns and Lyme Disease incidence, where moderate sprawl may provide better conditions for pathogen transmission. The comparison between urban and exurban counties did not yield significant results, with a difference in Lyme Disease incidence rate of 13 more cases per 100,000 per year ($p=0.14$) in the exurban counties. This suggests that exurban and urban counties do not have significant differences in their Lyme Disease incidence rates.

Table 4.8. The results of PSM analysis comparing urban, suburban, and exurban counties

Comparison group – reference group	Difference in mean IR (cases/100,000/year)	p-value	Number of matched pairs
Suburban – urban	20	<0.01**	94
Exurban – urban	13	0.14	84
Exurban – suburban	-5	0.59	84

Overall, there is a nonlinear relationship between the degree of sprawl and Lyme Disease incidence. Suburban counties had significantly higher Lyme Disease incidence rates than urban counties, while no significant differences were observed between urban and exurban counties or between suburban and exurban counties. Suburban counties have a unique mix of habitat fragmentation with sufficient human-tick interactions to produce Lyme Disease. In contrast, urban settings harbor many humans and impervious surfaces which are not suitable for ticks, and exurban settings are thought to dilute transmission risk by spreading humans over larger areas with less frequent contact with tick habitats.

The Impacts of Urban Sprawl on Disconnected Youth in U.S. Counties

In the United States, approximately 11% of individuals aged 16 to 24 are considered "disconnected," meaning they are neither employed nor attending school, as highlighted in the Measure of America report (MoA, 2025). This rate is more than double that of several European nations, including the Netherlands and Sweden, where the percentage of disconnected youth is around 5% (Eurostat, 2025). The economic impact of this disconnection is significant, costing American taxpayers roughly $94 billion annually due to lost productivity, reduced tax income, and increased public expenditures (Shannon, 2012). Despite these substantial costs, the U.S. continues to face much higher levels of youth disconnection compared to other developed nations.

Compactness can affect disconnected youth both directly and indirectly through mediating mechanisms. Compact urban form directly improves accessibility to education and jobs, while also indirectly reducing disconnection through its effects on social segregation, social capital, and internet access. Conversely, sprawling forms amplify segregation, weaken social networks, and hinder digital connectivity, thereby heightening the risk of disconnection.

Table 4.9. List of variables, data sources, and descriptive statistics

Variables	Description	Source	Descriptive statistics	
			Mean	SD
Endogenous Variables				
disconect	% young people aged 16 to 24 who are neither in school nor employed (Disconnected Youth Rate)	MoA, 2016-2020	12.16	4.93
ressegregate	The dissimilarity index measures the degree of residential separation between African American and White residents in a county, with higher scores reflecting greater segregation	HDPulse Data Portal, NIH 2019	0.38	0.17
socicapConnect	The extent of social connections or friendships between low-income and high-income individuals	(Chetty et al., 2022)	0.82	0.15
socioCapCivic	Levels of volunteer activity and involvement in community organizations	(Chetty et al., 2022)	0.15	0.01
internet	It indicates the presence of fixed broadband service at the county level	HDPulse Data Portal, NIH 2019	0.89	0.09
Exogenous Variables				
compact	It measures the compactness-sprawl index at county level	Hamidi, et al., 2020	98.96	24.23
pop	Total population in county	Census, 2020	302176	57147[illegible]
redpopCD	Total population in Redlined C and D neighborhoods (definitely declining + hazardous)	(Breen, 2019)	12023	71355
povertyall	% of households below the poverty line in county	ACS, 2016-2020	8.83	3.71
singleparent	% single parents in county	ACS, 2016-2020	16.57	3.59
gdpChange	% change in county GDP from 2016 to 2019	BEA, 2016-2019	2.06	2.82
stdteacherration	Student-to-teacher ratio in county's schools	NCES, 2019	15.24	4.85

Accordingly, this study investigates the direct and indirect impacts of compact urban form on disconnected youth by employing Structural Equation Modeling (SEM) and using county-level data across the U.S. Table 4.9 presents the list of variables along with descriptive statistics. The outcome variable, the percentage of disconnected youth, was obtained from Measure of America for 2016–2020. This variable represents the proportion of young people aged 16 to 24 who were neither in school nor employed.

Table 4.10. Effects of variables on one another in the best-fitted disconnected youth model

			Coefficient	Standard error	P-value
lnressegregate	<---	lncompact	0.291	0.092	0.002
lnressegregate	<---	lnpop	0.064	0.014	<0.001
lnressegregate	<---	redpopCD	0.000	0.000	0.242
lnressegregate	<---	povertyall	0.036	0.016	0.022
lnsocicapConnect	<---	lncompact	0.179	0.020	<0.001
lnsocioCapCivic	<---	lncompact	0.286	0.052	<0.001
lnsocioCapCivic	<---	lnpop	-0.037	0.010	<0.001
lnsocioCapCivic	<---	redpopCD	0.000	0.000	0.146
lninternet	<---	lnpop	0.019	0.001	<0.001
lnsocicapConnect	<---	lnsingleparent	-0.233	0.028	<0.001
lninternet	<---	lncompact	0.011	0.006	0.058
lnsocioCapCivic	<---	lnsingleparent	-0.551	0.046	<0.001
lninternet	<---	gdpChange	0.002	0.000	<0.001
lninternet	<---	povertyall	-0.007	0.000	<0.001
lnsocicapConnect	<---	povertyall	-0.033	0.002	<0.001
lninternet	<---	lnressegregate	-0.020	0.004	<0.001
lninternet	<---	redpopCD	0.000	0.000	0.001
lnsocioCapCivic	<---	gdpChange	-0.023	0.004	<0.001
lndisconect	<---	lnressegregate	0.037	0.039	0.338
lndisconect	<---	lnsocicapConnect	-0.508	0.095	<0.001
lndisconect	<---	lnsocioCapCivic	-0.203	0.038	<0.001
lndisconect	<---	lncompact	-0.197	0.058	<0.001
lndisconect	<---	lnstdteacherration	0.141	0.048	0.003
lndisconect	<---	lnsingleparent	0.395	0.079	<0.001
lndisconect	<---	gdpChange	-0.001	0.004	0.858
lndisconect	<---	povertyall	0.006	0.006	0.287
lndisconect	<---	lnpop	-0.100	0.012	<0.001
lndisconect	<---	redpopCD	0.000	0.000	0.006
lndisconect	<---	lninternet	-1.345	0.366	<0.001

We included four mediating variables in our analysis. Social segregation was measured using the dissimilarity index, which quantified the degree of residential separation between Black and white residents in a county; higher values indicated greater segregation. Data for this variable were obtained from County Health Rankings & Roadmaps (2016–2019). To capture social capital, we used two indicators: social connectedness, defined as the extent of social connections between low- and high-income individuals (based on Chetty et al., 2022), and civic engagement, measured as the level of volunteer activity and participation in community organizations. Finally, internet accessibility was measured as the presence of fixed broadband service at the county level.

Overall, the results indicate a statistically significant negative association between compactness and disconnected youth: counties with higher levels of compactness tend to have lower levels of youth disconnection (Table 4.10). Beyond this direct effect, compactness also exerts indirect influences by reducing disconnected youth through mediating factors. The results also show that compactness has a significant positive impact on social capital. Specifically, a 10% increase in county-level compactness is directly associated with an estimated 1.79% increase in social connectedness and a 2.86% increase in civic engagement.

In summary, the findings of this study highlight a striking link between urban form and youth disconnection: more compact and connected urban environments are associated with lower levels of disconnected youth across U.S. counties. This suggests that beyond traditional, social, and economic interventions, thoughtful urban design can play a direct role in promoting youth engagement and opportunity. These results provide a compelling argument for promoting compact, well-connected, and accessible urban development as a strategy to reduce youth disconnection and enhance broader social well-being.

Impacts of Sprawl on Housing, Transportation, and Energy Costs and Affordability

The housing crisis has drawn significant attention in recent years, particularly in the aftermath of the presidential election. Many critics point to compact urban development and its restrictive policies as a key driver of the crisis, arguing that efforts to limit outward growth have constrained housing supply and driven up costs. Advocates of sprawl contend that expanding outward provides cheaper land for large-scale home construction, making housing more attainable for middle- and working-class families. Sprawling regions have been able to absorb much of the nation's housing demand, while strict anti-sprawl regulations have suppressed supply and worsened affordability. On the other hand, others argue that sprawl is incompatible with affordable, low-carbon housing goals, as it overlooks transportation-related emissions, environmental impacts, and infrastructure costs.

This section performs one of the most comprehensive analyses of sprawl and affordability to date, accounting for all major household expenditures associated with location: housing, transportation, and energy. Our hypothesis is that urban sprawl can affect housing affordability in three ways. The first one is directly through availability and price of land; the second is indirectly through the availability of transportation choices and costs; and the third is indirectly though costs associated with residential energy consumption patterns and costs. In this section we account for all three factors to explore the effects of urban sprawl on housing affordability.

This national study aims to examine the relationship between urban sprawl and housing, transportation, and energy burden individually and the combined housing + transportation + energy affordability. Using Multi-level Linear Modeling (MLM), we account for the degree of compactness at both neighborhood and county levels. Our sample includes 35,748 census tracts within 787 counties. Table 4.11. shows the full list of variables, description, and data sources.

Table 4.11. List of variables, definition, and data sources

Variable name	Description	Data Sources
Level1- Dependent Variables - Census Tract Level		
Ecost	Average annual household energy cost	LEAD2022
lnEaffordability	Ln of energy cost as percentage of income	LAI 2016, LEAD2022
lnH+Eaffordability	Ln of energy + housing cost as percentage of income	LAI2016, LEAD2022
lnH+Taffordability	Ln of housing + transportation cost as percentage of income	LAI2016, LEAD2022
lnH+T+Eaffordability	Ln of housing + transportation + energy cost as percentage of income	LAI2016, LEAD2022
Level1- Independent Variables - Census Tract Level		
compactnessCT	Compactness index	Authors (2025)
Hhsize	average household size	ACS 2015-19 (5-year estimates)
hhinc000	Median household income in 1000s	ACS 2015-19 (5-year estimates)
Pctblack	% of black population	ACS 2015-19 (5-year estimates)
Pctimmig	% of immigrant population	ACS 2015-19 (5-year estimates)
Pctfemwork	% of working females	ACS 2015-19 (5-year estimates)
Pctmulti	% of multi-family housing units	ACS 2015-19 (5-year estimates)
Avgroom	Average number of rooms in housing units	ACS 2015-19 (5-year estimates)
Pct30old	% of 30 or more-year-old housing units	ACS 2015-19 (5-year estimates)
personRoom1more	% of households with 1-or-more-person per room	ACS 2015-19 (5-year estimates)
Pctvacant	% of vacant housing units	ACS 2015-19 (5-year estimates)
Pctrent	% of households renting a home	ACS 2015-19 (5-year estimates)
Cdd	Cooling degree days	NREL, SLOPE 2020 estimates
Hdd	Heating degree days	NREL, SLOPE 2020 estimates
Level 2 – Independent Variables – County		
Compactness C	Compactness index	Authors (2025)
lnMSApop	Ln of MSA population	Census 2020
Erate000	Energy rate (dollar per kw) in 1000s	NREL, U.S. Electric Utility Companies & Rates 2020
AvgPrecept	Average precipitation	PRISM 2019
Hdays	Number of hot days	PRISM 2019
RealGDP	County Real GDP per capita	US-BEA 2019

Table 4.12. The best-fitted HLM models for Housing (**H**), Transportation (**T**), & Energy (**E**) burden

Variable	H	E	T	H + T	H + T +E
Intercept	2.55***	3.028***	7.49***	5.73***	5.52***
Level 1: Census tract level					
lncompact	0.0749***	-0.0544***	-0.185***	-0.0502***	-0.048***
pct30old	-0.00025***	0.00293***	-0.00019***	-0.00029***	-0.00018***
pctpov	-0.00139***	0.0097***	-0.00021***	-0.00088***	-0.000098***
Hhsize	-0.0055***	0.164***	0.036***	0.0124***	0.0257***
avgroom	0.00456***	-0.0625***	0.0121***	0.00696***	0.00376***
pctrent	-0.00065***	0.00371***	-0.00282***	-0.00166***	-0.00135***
pctvac	0.00046***	0.00857***	-0.00096***	-0.000055	0.00058***
pctblack	-0.00036***	0.00495***	0.00041***	-0.000063***	0.00018***
PersonRoom1+		-0.00124***			-0.00146***
pctfemwork		-0.00332***			-0.000102***
pctmulti		-0.00645***			-0.000298***
cdd85		0.00014***			0.0000019
hdd85		0.00012***			0.0000031***
Level 2: County level					
lncompact	0.0462 ***	-0.217***	-0.214***	-0.077***	-0.0569***
lnMSApop	0.0162***	-0.0601***	-0.099***	-0.0414***	-0.0401***
RealGDP	-0.00032	-0.0144***	-0.0099***	-0.00561***	-0.0051***
Erate000		0.00184***			-0.00025***
AvgPrecept		0.00013***			0.000041***
Hdays		0.00221***			0.00115***

Table 4.12 presents the results of best-fitted HLM models for housing, transportation, and energy burden and their combinations, where H denotes housing affordability, E denotes energy affordability, and T denotes transportation affordability. Our analysis indicates a significant negative relationship between compactness and energy burden at both the census tract and county levels. After controlling for confounding variables, a greater compactness score is associated with lower energy burden (percentage of income spent on energy).

As for the combined affordability of housing, transportation, and energy (H + T + E), the results indicate a statistically significant negative relationship between compactness and H + T + E costs relative to income at both the census tract and county levels. After controlling for confounding variables, a greater compactness score is associated with a lower H + T + E burden (costs relative to income).

In summary, the findings of this study highlight a striking link between urban form and housing affordability, showing that compact urban development offers a more affordable alternative for U.S. households compared to sprawling patterns of growth. When housing affordability is examined through a comprehensive lens that combines housing, transportation, and energy (H + T + E) costs, the advantages of compactness become clear: households in denser, more connected communities face lower overall cost burdens relative to income. These results underscore the importance of moving beyond narrow definitions of affordability that focus solely on housing prices and instead recognize the cumulative financial impacts of housing, transportation, and energy together. By demonstrating that compact urban form can ease the affordability crisis, this study provides critical evidence to inform housing, land-use, and transportation policies aimed at fostering more sustainable and equitable urban futures.

Chapter 5: Policy Recommendations and Conclusion

This study updates the compactness-sprawl indices originally developed in 2003 and refined in 2014. We incorporated updated data sources and refined key components—such as centering—through additional methodological steps. The revised indices combine four core dimensions of urban sprawl: development density, land-use mix, activity centering, and street connectivity. We developed indices at multiple geographic scales, including metropolitan areas, divisions, counties, and census tracts (representing neighborhood-level urban form) across the U.S. Measures, presented in the appendices, are immediately available to study the costs and benefits of different urban forms. They will be posted and available for download on the Center for Climate Smart Transportation website.

Actionable Planning Policies for Better Quality-of-Life

Strategies for encouraging compact development follow directly from our operational definition of sprawl. The 2020 compactness indices combine four core dimensions of compact urban form: development density, land-use mix, activity centering, and street connectivity. To achieve a more compact urban form, it is essential to build a coordinated policy framework that improves these dimensions across regional and local scales. This chapter offers a set of actionable policies for each of these dimensions.

Planning for Higher Density Development

Density plays a foundational role in shaping urban structure and the availability of transportation options. Density improves land-use efficiency by utilizing shared infrastructure and makes sustainable non-driving modes of transportation such as walking, cycling, and transit more viable. Operational guidance is provided in Ewing et al. (2022). The following are examples of policies and recommendations for planners to help achieve higher density development:

- ***Zoning Reform:*** Allow higher residential and mixed-use densities near transit corridors and employment centers (e.g., adopting form-based codes to encourage flexible, mixed-use growth would be an integrated zoning reform).
- ***Incentives For Infill Development:*** Provide tax breaks, density bonuses, and reduced parking minimum requirements to encourage infill and brownfield redevelopment rather than greenfield sprawl.
- ***Transit-Oriented Upzoning:*** Require higher densities within walking distance (e.g., 800 meters) of major transit stations, supported by transit investment.
- ***Affordable Housing Integration:*** Pair density increases with inclusionary zoning and affordable housing mandates to ensure equitable access to transit-rich, high-demand areas.
- ***Parking Reform:*** Reduce or eliminate minimum parking requirements and promote shared parking, freeing up land for more productive uses.

- ***Land Value Capture & TOD Financing:*** Use tools such as value capture, impact fees, or tax-increment financing to reinvest in transit and public amenities that support compact growth.
- ***Design Guidelines for Livability:*** Ensure that higher-density areas include green spaces, community facilities, and active transportation infrastructure so density contributes to livability, not overcrowding.

Planning for Mixed-Use Development

Land-use diversity is another critical component of compactness. When housing, jobs, retail, and public services are located close to one another, it reduces the need for long car trips, supports active travel, and makes public transit more efficient. Mixed-use environments also enhance neighborhood vibrancy, foster social interaction, and contribute to economic resilience by diversifying local activity patterns. To achieve greater land-use mix, urban planners and policymakers can implement the following strategies:

- ***Mixed-Use Zoning:*** Encourage developments that combine housing, retail, services, and jobs in close proximity, replacing rigid single-use zoning.
- ***15-Minute Neighborhoods:*** Adopt planning policies that ensure daily needs (schools, groceries, healthcare, recreation) are accessible within a 15-minute walk or bike ride.
- ***Incentivize Small Businesses:*** Reduce permitting costs, streamline approvals, or offer grants for local shops and services in residential areas to strengthen neighborhood self-sufficiency.
- ***Public Facility Integration:*** Co-locate schools, libraries, community centers, and health clinics within mixed-use developments to serve multiple needs at once.
- ***Adaptive Reuse Policies:*** Encourage the conversion of vacant or underutilized commercial and industrial properties into housing, cultural, or community spaces.
- ***Inclusionary Development Requirements:*** Pair new mixed-use projects with requirements for affordable housing so residents across income levels can access these vibrant neighborhoods.
- ***Transit-Supportive Land-Use Planning:*** Align new mixed-use developments with transit corridors to maximize ridership and reduce car dependency (e.g., TOD development).

Planning for Strong Urban Centers

Strong urban centers are regional hubs of activity and help direct growth into walkable hubs—such as downtowns, town centers, and transit station areas—where jobs, housing, and services cluster together. Evidence from polycentric metropolitan regions shows that when centers are well connected by high-capacity transit and supported by land-use policy, they can reduce car dependence, lower emissions, and improve access to jobs and services. At the same time, centering policies encourage economic vitality by concentrating employment and retail activity in vibrant, multimodal hubs. Operational guidance is provided in Ewing et al. (2024). To achieve a high centering score, urban planners and policymakers can consider the following strategies:

- ***Regional Planning for Strong Centers:*** Designate a hierarchy of centers (CBDs and subcenters) in regional plans, directing growth inward rather than to the periphery.
- ***Identify the Effective Population and Employment Thresholds Required to Sustain Strong Centers and Adjust Land-Use Policies Accordingly:*** A recent national study by authors (under review) shows that the share of population in centers relative to the MSA becomes effective once it exceeds 0.3, and the share of employment in centers relative to the MSA becomes effective once it exceeds 0.35. Likewise, the population ratio of subcenters to the central business district (CBD) is most effective between 0.25 and 0.5, while the employment ratio of subcenters to the CBD is most effective between 0.2 and 0.5.
- ***Transit–Land-Use Alignment in Centers:*** Prioritize transit investments that connect major centers and require upzoning in station areas.
- ***Employment Clustering:*** Offer incentives for universities, hospitals, and major employers to locate in or near designated centers.
- ***Retail and Service Concentration:*** Discourage strip commercial development; support walkable main-street developments within centers.
- ***Equitable TOD Tools:*** Pair center development with inclusionary zoning, community land trusts, and anti-displacement funds.
- ***Parking Reform in Centers:*** Replace minimum parking requirements in centers with maximums, unbundle parking from housing, and reinvest curb pricing revenues locally.

Planning for Interconnected and Accessible Streets

Street accessibility is a critical dimension of compact development because it determines how land uses are connected to one another and how easily people can move within neighborhoods and across regions. Highly connected street networks with small block sizes shorten travel distances, disperse traffic, and make walking, cycling, and public transit more practical and attractive. In contrast, disconnected networks with cul-de-sacs, large blocks, and oversized arterials increase car dependency by forcing circuitous routes and discouraging active travel. Research consistently shows that fine-grained networks with smaller blocks are associated with lower vehicle miles traveled, higher walking and cycling rates, and improved traffic safety outcomes. To achieve a higher street accessibility score, urban planners and policymakers can consider the following strategies:

- ***Connected Street Grids:*** Require new developments to follow connected grid or semi-grid patterns, limiting cul-de-sacs and gated subdivisions.
- ***Small Block Standards:*** Identify and update the maximum block length standards in subdivision regulations to ensure permeability and walkability.
- ***Complete Streets Policies:*** Adopt and enforce Complete Streets design standards to ensure roads safely accommodate all users—pedestrians, cyclists, public transit, and vehicles.
- ***Traffic Calming and Safety Design:*** Implement narrower lanes, raised intersections, curb extensions, and road diets to reduce vehicle speeds and improve walkability.
- ***Retrofitting Existing Suburbs:*** Break up superblocks by adding pedestrian and cycling cut-throughs, secondary streets, or mid-block crossings.
- ***Green Mobility Corridors:*** Integrate linear parks, greenways, and cycle highways that connect neighborhoods and centers through safe, continuous routes.
- ***Transit-Supportive Street Design:*** Prioritize bus rapid transit (BRT) lanes, queue jumps, and signal priority along highly connected corridors.

Conclusions

How we build and develop affects everyone's day-to-day lives. How much we pay for housing, transportation, and energy, how long we spend commuting home, how likely we are to have a fatal car crash, how we advance opportunities for our children, our social life, the economic opportunities in our communities, and even our personal health are all connected to how our neighborhoods and surrounding areas are built. These factors are better in compact, connected neighborhoods and worse in sprawling ones.

As residents and their elected leaders recognize the health, safety, and economic benefits of better development strategies, many choose to encourage this type of growth through changes to public regulations and incentives. Local elected officials, state leaders, and federal lawmakers can all help communities grow in ways that support these improved outcomes.

Planning toward this type of growth requires a coordinated, multi-scalar approach that integrates density, land-use diversity, centering, and street connectivity. Each dimension reinforces the others: higher densities support mixed-use development; diverse land uses strengthen urban centers; and fine-grained, connected street networks knit these elements together. Evidence shows that such environments not only reduce car dependence and traffic fatalities but also promote healthier, more equitable, and economically vibrant communities. Moving forward, implementing supportive compact urban form policies at regional and local scales will be critical for achieving safer, more sustainable, and more resilient urban futures.

References

Abdollahpour Razkenari, S. S. (2024). A Multidimensional Study of Transit Ridership and Station Mode Shares in the United States: Nonlinear Effects, Data Aggregation, and Post-Pandemic Changes.

Abdollahpour, S. S., Qi, M., Le, H. T., & Hankey, S. (2024). Urban spatial structure and air quality in the United States: Evidence from a longitudinal approach. Environment International, 190, 108871.

Abdollahpour, S. S., Buehler, R., Le, H. T., Nasri, A., & Hankey, S. (2024). Built environment's nonlinear effects on mode shares around BRT and rail stations. *Transportation Research Part D: Transport and Environment*, *129*, 104143.

Abdollahpour, S. S., Le, H. T., Buehler, R., & Hankey, S. (2025). Data aggregation impacts on built environment-mode share models around public transit stations. *Journal of Transport and Land Use*, *18*(1), 397-424.

Abdollahpour, S. S., Le, H. T., & Hankey, S. (2025). Changes in the predictors of transit ridership in post-COVID-19 US metropolitan areas. *Travel behaviour and society*, *40*, 101002.

Aghaabbasi, M., & Chalermpong, S. (2023). Machine learning techniques for evaluating the nonlinear link between built-environment characteristics and travel behaviors: A systematic review. *Travel behaviour and society*, *33*, e100640-e100640.

Ahlfeldt, G., Pietrostefani, E., Schumann, A., & Matsumoto, T. (2018). Demystifying compact urban growth: Evidence from 300 studies from across the world.

Aithal, S. S., Sachdeva, I., & Kurmi, O. P. (2023). Air quality and respiratory health in children. Breathe, 19(2).

Allan BF, Keesing F, Ostfeld RS. Effect of Forest Fragmentation on Lyme Disease Risk. Conserv Biol. 2003 Feb;17(1):267–72.

Alidadi, M., & Sharifi, A. (2022). Effects of the built environment and human factors on the spread of COVID-19: A systematic literature review. *Science of the total environment*, *850*, 158056.

Anderson, G. B., Dominici, F., Wang, Y., McCormack, M. C., Bell, M. L., & Peng, R. D. (2013). Heat-related emergency hospitalizations for respiratory diseases in the Medicare population. American journal of respiratory and critical care medicine, 187(10), 1098-1103.

Anthony, J. (2004). Do state growth management regulations reduce sprawl? *Urban Affairs Review*, *39*(3), 376-397.

Arefi, M., & Nasser, N. (2021). Urban design, safety, livability, & accessibility. Urban design international, 26(1), 1-2.

Artmann, M., Inostroza, L., & Fan, P. (2019). Urban sprawl, compact urban development and green cities. How much do we know, how much do we agree? In (Vol. 96, pp. 3-9): Elsevier.

Aurand, A. (2013). Does sprawl induce affordable housing? *Growth and change*, *44*(4), 631-649.

Banai, R., & DePriest, T. (2014). Urban sprawl: Definitions, data, methods of measurement, and environmental consequences. *The Journal of Sustainability Education*.

Bardhan, R., Kurisu, K., & Hanaki, K. (2015). Does compact urban forms relate to good quality of life in high density cities of India? Case of Kolkata. *Cities*, *48*, 55-65.
Barman, S., Roy, D., Chandra Sarkar, B., Almohamad, H., & Abdo, H. G. (2024). Assessment of urban growth in relation to urban sprawl using landscape metrics and Shannon's entropy model in Jalpaiguri urban agglomeration, West Bengal, India. *Geocarto International*, *39*(1), 2306258.
Barns, S., Cosgrave, E., Acuto, M., & Mcneill, D. (2017). Digital infrastructures and urban governance. Urban Policy and research, 35(1), 20-31.
Behnisch, M., Krüger, T., & Jaeger, J. A. (2022). Rapid rise in urban sprawl: Global hotspots and trends since 1990. *PLOS Sustainability and Transformation*, *1*(11), e0000034.
Bereitschaft, B. (2022). Older adult population and neighborhood walkability by metropolitan area size and degree of urban sprawl. *Papers in Applied Geography*, *8*(3), 249-267.
Boeing, G. (2017). Street network shapefiles, node/edge lists, and graphml files. *Comput Environ Urban Syst*, *65*, 126-139.
Bobb, J. F., Peng, R. D., Bell, M. L., & Dominici, F. (2014). Heat-related mortality and adaptation to heat in the United States. Environmental health perspectives, 122(8), 811-816.
Bourdin A, Dokhelar T, Bord S, Van Halder I, Stemmelen A, Scherer-Lorenzen M, et al. Forests harbor more ticks than other habitats: A meta-analysis. For Ecol Manag. 2023 Aug;541:121081.
Breen, D. (2019). Mapping Inequality: Redlining in New Deal America; Renewing Inequality: Family Displacements through Urban Renewal. In: Oxford University Press Oxford, UK.
Breiner, H., Stroud, C., & Bonnie, R. J. (2015). Investing in the health and well-being of young adults.
Brueckner, J. K., & Largey, A. G. (2008). Social interaction and urban sprawl. *Journal of urban economics*, *64*(1), 18-34.
Cao, J., & Tao, T. (2023). Using machine-learning models to understand nonlinear relationships between land use and travel. *Transportation Research Part D: Transport and Environment*, *123*, 103930.
Cervero, R. (2009). Transport infrastructure and global competitiveness: Balancing mobility and livability. *The Annals of the American Academy of Political and Social Science*, *626*(1), 210-225.
Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining,
Chen, E., Brody, G. H., & Miller, G. E. (2022). What are the health consequences of upward mobility? Annual review of psychology, 73(1), 599-628.
Cheng, Y., He, K.-b., Du, Z.-y., Zheng, M., Duan, F.-k., & Ma, Y.-l. (2015). Humidity plays an important role in the PM2. 5 pollution in Beijing. Environmental pollution, 197, 68-75.

Chetty, R., Jackson, M. O., Kuchler, T., Stroebel, J., Hendren, N., Fluegge, R. B., Gong, S., Gonzalez, F., Grondin, A., & Jacob, M. (2022). Social capital I: measurement and associations with economic mobility. Nature, 608(7921), 108-121.

Chettry, V. (2023). A critical review of urban sprawl studies. *Journal of Geovisualization and Spatial Analysis*, *7*(2), 28.

Cheung, E. S. L., Curtis, D. S., Grineski, S., Wei, Y. D., & Wen, M. (2025). Spatial Social Polarization and Cardiometabolic Disease Prevalence and Incidence: What Is the Role of the Neighborhood Environment? *Journal of Health and Social Behavior*, 00221465251349818.

Cho, H.-S., & Choi, M. J. (2014). Effects of compact urban development on air pollution: Empirical evidence from Korea. Sustainability, 6(9), 5968-5982.

Choi, D.-a., & Ewing, R. (2021). Effect of street network design on traffic congestion and traffic safety. *Journal of transport geography*, *96*, 103200.

Cleland, S. E. (2023). The Human Health Impacts of Short-Term Exposure to Climate Change-Influenced Environmental Hazards The University of North Carolina at Chapel Hill.

Clear, T. R., & Montagnet, C. L. (2021). Impact of incarceration on community public safety and public health. In Public health behind bars: From prisons to communities (pp. 13-29). Springer.

Cohen, M. A., Rust, R. T., & Steen, S. (2006). Prevention, crime control or cash? Public preferences towards criminal justice spending priorities. Justice Quarterly, 23(3), 317-335.

Cutsinger, J., Galster, G., Wolman, H., Hanson, R., & Towns, D. (2005). Verifying the multi-dimensional nature of metropolitan land use: Advancing the understanding and measurement of sprawl. *Journal of Urban Affairs*, *27*(3), 235-259.

Danziger, S., & Ratner, D. (2010). Labor market outcomes and the transition to adulthood. The Future of Children, 133-158.

Davis, R. E., McGregor, G. R., & Enfield, K. B. (2016). Humidity: A review and primer on atmospheric moisture and human health. Environmental research, 144, 106-116.

Diuk-Wasser MA, VanAcker MC, Fernandez MP. Impact of Land Use Changes and Habitat Fragmentation on the Eco-epidemiology of Tick-Borne Diseases. J Med Entomol. 2021 Jul 16;58(4):1546–64.

D'Agata, A., Quaranta, G., Salvia, R., Carlucci, M., & Salvati, L. (2023). Mixed Land Use as an Intrinsic Feature of Sprawl: A Short-Term Analysis of Settlement Growth and Population Distribution Using European Urban Atlas. *Land*, *12*(5), 972.

Dougherty, C. (2025). *Why America Should Sprawl* https://www.nytimes.com/2025/04/10/magazine/suburban-sprawl-texas.html

Duke, N. N., Skay, C. L., Pettingell, S. L., & Borowsky, I. W. (2009). From adolescent connections to social capital: Predictors of civic engagement in young adulthood. Journal of adolescent health, 44(2), 161-168.

Eldafrawi, M., Varghese, K. K., Afsari, M., Babapourdijojin, M., & Gentile, G. (2024). Machine Learning-Enhanced Conformal Prediction Approach for Road Traffic Accident Severity Assessment: A Case Study of Rome. *Available at SSRN 4679159*.

Eldeeb, S., & Masoumi, H. (2023). Investigating walkability and bikeability in compact vs. new extensions: the case of Greater Cairo. Frontiers in Built Environment, 9, 1165996.

Enwin, A. D., & Ikiriko, T. D. (2023). Balancing urban development: Literature on the nexus between affordable housing and urban sprawl. *Int. J. Res. Rev*, *10*, 560-572. Eurostat. (2025). Drop in youths neither working nor studying. Eurostat. Retrieved 2025

Ewing, R. (1997). Is Los Angeles-style sprawl desirable? *Journal of the American planning association*, *63*(1), 107-126.

Ewing, R., & Cervero, R. (2010). Travel and the built environment: A meta-analysis. *Journal of the American planning association*, *76*(3), 265-294.

Ewing, R., & Hamidi, S. (2014). Measuring urban sprawl and validating sprawl measures. *Washington, DC: National Institutes of Health and Smart Growth America*.

Ewing, R., & Hamidi, S. (2015a). Compactness versus sprawl: A review of recent evidence from the United States. *Journal of planning literature*, *30*(4), 413-432.

Ewing, R., & Hamidi, S. (2015b). Urban sprawl as a risk factor in motor vehicle occupant and pedestrian fatalities: Update and refinement. *Transportation research record*, *2513*(1), 40-47.

Ewing, R., & Hamidi, S. (2017). *Costs of sprawl*. Routledge.

Ewing, R., Hamidi, S., Gallivan, F., Nelson, A. C., & Grace, J. B. (2014). Structural equation models of VMT growth in US urbanised areas. *Urban Studies*, *51*(14), 3079-3096.

Ewing, R., Hamidi, S., Grace, J. B., & Wei, Y. D. (2016). Does urban sprawl hold down upward mobility? *Landscape and Urban Planning*, *148*, 80-88.

Ewing, R., Lyons, T., Ameli, S.H., Hersey, J., & Kaniewska, J. (2024) Regional Policies, Practices, Tools, and Strategies to Implement Polycentric Development: Comparative Case Studies of Portland, Seattle, and Denver, *Land*, 13, 238.

Ewing, R., Lyons, T., Siddiq, F., Sabouri, S., Kiani, F., Hamidi, S., ... & Ameli, H. (2022). Growth Management Effectiveness: A Literature Review. *Journal of Planning Literature,* 08854122221077457.

Ewing, R., Pendall, R., & Chen, D. (2002). Measuring sprawl and its impact.

Ewing, R., Pendall, R., & Chen, D. (2003). Measuring sprawl and its transportation impacts. *Transportation research record*, *1831*(1), 175-183.

Ewing, R., & Rong, F. (2008). The impact of urban form on US residential energy use. Housing policy debate, 19(1), 1-30.

Ewing, R., Schieber, R. A., & Zegeer, C. V. (2003). Urban sprawl as a risk factor in motor vehicle occupant and pedestrian fatalities. American journal of public health, 93(9), 1541-1545.

Fan, Z., Zhan, Q., Wang, Y., Shao, Z., Fan, Y., & Zhang, Y. (2024). Investigating the effect of spatial patterns of artificial impervious surface on PM2. 5 at the intra-urban scale. Geo-Spatial Information Science, 1-20.

Faurie, C., Varghese, B. M., Liu, J., & Bi, P. (2022). Association between high temperature and heatwaves with heat-related illnesses: a systematic review and meta-analysis. Science of the Total Environment, 852, 158332.

Feng, Q., & Gauthier, P. (2021). Untangling urban sprawl and climate change: a review of the literature on physical planning and transportation drivers. *Atmosphere*, *12*(5), 547.

Feng, J., & Qi, S. (2024). Digital infrastructure expansion and economic growth in Asian countries. Journal of Business and Economic Options, 7(2), 27-32.

Fernandes, A. L. (2009). Disconnected youth: A look at 16-to 24-year olds who are not working or in school. Diane Publishing.

Frenkel, A., & Ashkenazi, M. (2008). Measuring urban sprawl: how can we deal with it? *Environment and Planning B: Planning and Design*, *35*(1), 56-79.

Fischhoff IR, Bowden SE, Keesing F, Ostfeld RS. Systematic review and meta-analysis of tick-borne disease risk factors in residential yards, neighborhoods, and beyond. BMC Infect Dis. 2019 Oct 17;19:861.

Fulton, W. B., Pendall, R., Nguyˆẽn, M., & Harrison, A. (2001). *Who sprawls most?: How growth patterns differ across the US*. Brookings Institution, Center on Urban and Metropolitan Policy Washington, DC.

Gainza, X., & Livert, F. (2013). Urban form and the environmental impact of commuting in a segregated city, Santiago de Chile. Environment and Planning B: Planning and Design, 40(3), 507-522.

Galster, G., Hanson, R., Ratcliffe, M. R., Wolman, H., Coleman, S., & Freihage, J. (2001). Wrestling sprawl to the ground: defining and measuring an elusive concept. *Housing Policy Debate*, *12*(4), 681-717.

Garrido-Cumbrera, M., Ruiz, D. G., Braçe, O., & Lara, E. L. (2018). Exploring the association between urban sprawl and mental health. *Journal of Transport & Health*, *10*, 381-390.

Genovese, D., Candiloro, S., D'Anna, A., Dettori, M., Restivo, V., Amodio, E., & Casuccio, A. (2023). Urban sprawl and health: A review of the scientific literature. *Environmental Research Letters*, *18*(8), 083004.

Glaeser, E., & Vigdor, J. (2012). The end of the segregated century: Racial separation in America's neighborhoods, 1890-2010. Manhattan Institute for Policy Research New York.

Glaeser, E. L., & Kahn, M. E. (2004). Sprawl and urban growth. In *Handbook of regional and urban economics* (Vol. 4, pp. 2481-2527). Elsevier.

Godtfredsen, N. S., & Prescott, E. (2011). Benefits of smoking cessation with focus on cardiovascular and respiratory comorbidities. The clinical respiratory journal, 5(4), 187-194.

Gordon, P., & Richardson, H. W. (1997). Are compact cities a desirable planning goal? *Journal of the American planning association*, *63*(1), 95-106.

Gould LH, Fee R, White J, Webb N, Carlyle M, Dick L, et al. Risk factors for Lyme disease among residents of rural, suburban, and urban areas in the United States: a case-control study. Am J Epidemiol. 2024 Sep 20;kwae368.

Granpayehvaghei, T., Bonakdar, A., Zandiatashbar, A., & Hamidi, S. (2019). The quest for creative industries: A multilevel national study of the impacts of urban form on the geography of creative industries. *Transportation research record*, *2673*(8), 157-168.

Grigorieva, E., & Lukyanets, A. (2021). Combined effect of hot weather and outdoor air pollution on respiratory health: literature review. Atmosphere, 12(6), 790.

Green, A. (2017). The crisis for young people: Generational inequalities in education, work, housing and welfare. Springer Nature.

Grengs, J. (2010). Job accessibility and the modal mismatch in Detroit. Journal of transport geography, 18(1), 42-54.

Gu, W., Xie, D., Li, Q., Feng, H., Xue, Y., Chen, Y., Tang, J., Zhou, Y., Wang, D., & Tong, S. (2024). Association of humidity and precipitation with asthma: a systematic review and meta-analysis. Frontiers in Allergy, 5, 1483430.

Guerra M, Walker E, Jones C, Paskewitz S, Cortinas MR, Stancil A, et al. Predicting the Risk of Lyme Disease: Habitat Suitability for Ixodes scapularis in the North Central United States. Emerg Infect Dis. 2002 Mar;8(3):289–97.

Guo L, Di L, Zhang C, Lin L, Di Y. Influence of urban expansion on Lyme disease risk: A case study in the U.S. I-95 Northeastern corridor. Cities. 2022 Jun 1;125:103633.

Ha, J., Lee, S., & Kwon, S. M. (2021). Revisiting the relationship between urban form and excess commuting in US metropolitan areas. *Journal of Planning Education and Research*, *41*(3), 294-311.

Hair, E. C., Moore, K. A., Ling, T. J., McPhee-Baker, C., & Brown, B. V. (2009). Youth who are “disconnected” and those who then reconnect: Assessing the influence of family, programs, peers and communities. Child Trends, 37, 1-8.

Hamidi, S. (2020). Urban sprawl and the emergence of food deserts in the USA. *Urban Studies*, *57*(8), 1660-1675.

Hamidi, S., & Ewing, R. (2014). A longitudinal study of changes in urban sprawl between 2000 and 2010 in the United States. *Landscape and Urban Planning*, *128*, 72-82.

Hamidi, S., & Ewing, R. (2015a). Is sprawl affordable for Americans? Exploring the association between housing and transportation affordability and urban sprawl. *Transportation research record*, *2500*(1), 75-79.

Hamidi, S., & Ewing, R. (2015b). *Measuring Sprawl and Its Transportation Impacts: Update*.

Hamidi, S., Ewing, R., Preuss, I., & Dodds, A. (2015). Measuring sprawl and its impacts: An update. *Journal of Planning Education and Research*, *35*(1), 35-50.

Hamidi, S., Ewing, R., & Sabouri, S. (2020). Longitudinal analyses of the relationship between development density and the COVID-19 morbidity and mortality rates: Early evidence from 1,165 metropolitan counties in the United States. *Health & place*, *64*, 102378.

Hamidi, S., Ewing, R., Tatalovich, Z., Grace, J. B., & Berrigan, D. (2018). Associations between urban sprawl and life expectancy in the United States. *International journal of environmental research and public health*, *15*(5), 861.

Hamidi, S., & Hamidi, I. (2021). Subway ridership, crowding, or population density: determinants of COVID-19 infection rates in New York City. *American journal of preventive medicine*, *60*(5), 614-620.

Hamidi, S., Sabouri, S., & Ewing, R. (2020). Does density aggravate the COVID-19 pandemic? Early findings and lessons for planners. *Journal of the American planning association*, *86*(4), 495-509.

Hamidi, S., & Zandiatashbar, A. (2019). Does urban form matter for innovation productivity? A national multi-level study of the association between neighbourhood innovation capacity and urban sprawl. Urban Studies, 56(8), 1576-1594.

Hamidi, S., Zandiatashbar, A., & Bonakdar, A. (2019). The relationship between regional compactness and regional innovation capacity (RIC): Empirical evidence from a national study. *Technological Forecasting and Social Change*, *142*, 394-402.

Hartell, A. M. (2018). Location Affordability and Regional Economic Resilience: Evidence from the US Foreclosure Crisis. *Transportation research record*, *2672*(3), 37-45.

Hastie, T., Tibshirani, R., Friedman, J. H., & Friedman, J. H. (2009). *The elements of statistical learning: data mining, inference, and prediction* (Vol. 2). Springer.

He, M., Li, N., He, Y., He, D., & Wang, K. (2017). Influences of temperature and humidity on perceived air quality with radiant panel workstation. Procedia Engineering, 205, 765-772.

Heindel, J. J., Skalla, L. A., Joubert, B. R., Dilworth, C. H., & Gray, K. A. (2017). Review of developmental origins of health and disease publications in environmental epidemiology. Reproductive toxicology, 68, 34-48.

Heylen D, Lasters R, Adriaensen F, Fonville M, Sprong H, Matthysen E. Ticks and tick-borne diseases in the city: Role of landscape connectivity and green space characteristics in a metropolitan area. Sci Total Environ. 2019 Jun 20;670:941–9.

Hoffman, J. S., Shandas, V., & Pendleton, N. (2020). The effects of historical housing policies on resident exposure to intra-urban heat: a study of 108 US urban areas. Climate, 8(1), 12.

Hook SA, Jeon S, Niesobecki SA, et al. Economic Burden of Reported Lyme Disease in High-Incidence Areas, United States, 2014–2016 - Volume 28, Number 6—June 2022 - Emerging Infectious Diseases journal - CDC. doi:10.3201/eid2806.211335

Huang, H., Hailin, Y., Xin, D., Peng, Z., Yong, L., Zhang, L., & Lei, Z. (2019). Influencing mechanisms of urban heat island on respiratory diseases. Iranian journal of public health, 48(9), 1636.

Irfeey, A. M. M., Chau, H.-W., Sumaiya, M. M. F., Wai, C. Y., Muttil, N., & Jamei, E. (2023). Sustainable mitigation strategies for urban heat island effects in urban areas. Sustainability, 15(14), 10767.

Jayamurugan, R., Kumaravel, B., Palanivelraja, S., & Chockalingam, M. (2013). Influence of temperature, relative humidity and seasonal variability on ambient air quality in a coastal urban area. International Journal of Atmospheric Sciences, 2013(1), 264046.

Jenerette, G. D., Harlan, S. L., Buyantuev, A., Stefanov, W. L., Declet-Barreto, J., Ruddell, B. L., Myint, S. W., Kaplan, S., & Li, X. (2016). Micro-scale urban surface temperatures are related to land-cover features and residential heat related health impacts in Phoenix, AZ USA. Landscape ecology, 31(4), 745-760.

Jiuwen, S., Xiaoxu, X., Qiangmin, X., & Weihao, S. (2024). Impact of urban form on housing affordability stress in Chinese cities: Does public service efficiency matter? *Cities*, *145*, 104682.

Kang, J. E., Yoon, D., & Bae, H.-J. (2019). Evaluating the effect of compact urban form on air quality in Korea. Environment and Planning B: Urban Analytics and City Science, 46(1), 179-200.

Khavarian-Garmsir, A. R., Sharifi, A., & Moradpour, N. (2021). Are high-density districts more vulnerable to the COVID-19 pandemic? *Sustainable Cities and Society*, *70*, 102911.

Killilea ME, Swei A, Lane RS, Briggs CJ, Ostfeld RS. Spatial dynamics of lyme disease: a review. EcoHealth. 2008 Jun;5(2):167–95.

Kirk, E. M. (2022). Community consequences of mass incarceration: Sparking neighborhood social problems and violent crime. Journal of Crime and Justice, 45(1), 103-119.

Kugeler KJ, Mead PS, Schwartz AM, Hinckley AF. Changing Trends in Age and Sex Distributions of Lyme Disease—United States, 1992-2016. Public Health Rep. 2021 Jun 29;137(4):655–9.

Kulsum, U., Moniruzzaman, M., & Kulsum, R. (2021). Quantifying the relationship of vegetation cover and air pollution: A spatiotemporal analysis of PM2. 5 and NDVI in Greater Dhaka, Bangladesh. Jagannath Univ. J. Sci, 7(2), 54-63.

Lambert, T. E., Catchen, J., & Vogelgesang, V. (2015). The impact of urban sprawl on disaster relief spending: An exploratory study. *Journal of Economic Issues*, *49*(3), 835-864.

Lan, T., Shao, G., Xu, Z., Tang, L., & Sun, L. (2021). Measuring urban compactness based on functional characterization and human activity intensity by integrating multiple geospatial data sources. *Ecological Indicators*, *121*, 107177.

Larkin, A., Van Donkelaar, A., Geddes, J. A., Martin, R. V., & Hystad, P. (2016). Relationships between changes in urban characteristics and air quality in East Asia from 2000 to 2010. Environmental science & technology, 50(17), 9142-9149.

Laurance WF, Nascimento HEM, Laurance SG, Andrade A, Ewers RM, Harms KE, et al. Habitat Fragmentation, Variable Edge Effects, and the Landscape-Divergence Hypothesis. Bennett P, editor. PLoS ONE. 2007 Oct 10;2(10):e1017.

Lee, C. (2019). Impacts of urban form on air quality in metropolitan areas in the United States. *Computers, Environment and Urban Systems*, *77*, 101362.

Leyden, K. M. (2003). Social capital and the built environment: the importance of walkable neighborhoods. American journal of public health, 93(9), 1546-1551.

Li, W. (2019). Mapping urban impervious surfaces by using spectral mixture analysis and spectral indices. Remote Sensing, 12(1), 94.

Lin, S., Luo, M., Walker, R. J., Liu, X., Hwang, S.-A., & Chinery, R. (2009). Extreme high temperatures and hospital admissions for respiratory and cardiovascular diseases. Epidemiology, 20(5), 738-746.

Little, S. E., & Bowman, D. D. (2013). Vector-borne diseases. Georgis' Parasitology for Veterinarians-E-Book: Georgis' Parasitology for Veterinarians-E-Book, 241.

Logan JJ. Local Landscape Change, Personal Practices, and Lyme Disease Risk in Ottawa, Ontario [Internet]. Université d’Ottawa / University of Ottawa; 2024 [cited 2025 Aug 1]. Available from: http://hdl.handle.net/10393/49908

Lopez, R., & Hynes, H. P. (2003). Sprawl in the 1990s: Measurement, distribution, and trends. *Urban Affairs Review*, *38*(3), 325-355.

Loprest, P., Spaulding, S., & Nightingale, D. S. (2019). Disconnected young adults: Increasing engagement and opportunity. RSF: The Russell Sage Foundation Journal of the Social Sciences, 5(5), 221-243.

Lyu, S., Huang, Y., & Sun, T. (2025). Urban sprawl, public transportation efficiency and carbon emissions. *Journal of Cleaner Production*, *489*, 144652.

Malpezzi, S., & Guo, W.-K. (2001). Measuring “sprawl”: alternative measures of urban form in US metropolitan areas. *Unpublished manuscript, Center for Urban Land Economics Research, University of Wisconsin, Madison*.

Malpezzi, S., & Guo, W. (2001). Measuring sprawl: alternative measures of urban from in US metropolitan areas. *The Center for Urban Land Economic Research, The University of Wisconsin*.

Martins-Filho, P. R. (2021). Relationship between population density and COVID-19 incidence and mortality estimates: A county-level analysis. *Journal of infection and public health*, *14*(8), 1087.

Mendelson, T., Mmari, K., Blum, R. W., Catalano, R. F., & Brindis, C. D. (2018). Opportunity youth: Insights and opportunities for a public health approach to reengage disconnected teenagers and young adults. Public Health Reports, 133(1_suppl), 54S-64S.

Milojevic, A., Wilkinson, P., Armstrong, B., Davis, M., Mavrogianni, A., Bohnenstengel, S., & Belcher, S. (2011). Impact of London's urban heat island on heat-related mortality. Epidemiology, 22(1), S182-S183.

MoA. (2025). YOUTH DISCONNECTION IN AMERICA. Measure of America.

Molnar, C. (2020). *Interpretable machine learning*. Lulu. com.

Moon KA, Pollak J, Poulsen MN, Hirsch AG, DeWalle J, Heaney CD, et al. Peridomestic and community-wide landscape risk factors for Lyme disease across a range of community contexts in Pennsylvania. Environ Res. 2019 Nov;178:108649.

Moon KA, Pollak JS, Poulsen MN, Heaney CD, Hirsch AG, Schwartz BS. Risk factors for Lyme disease stage and manifestation using electronic health records. BMC Infect Dis. 2021 Dec 20;21(1):1269.

Mouratidis, K. (2022). COVID-19 and the compact city: Implications for well-being and sustainable urban planning. *Science of the total environment*, *811*, 152332.

Muzayanah, I. F. U., Nazara, S., Mahi, B. R., & Hartono, D. (2020). Is there social capital in cities? The association of urban form and social capital formation in the metropolitan cities of Indonesia. International Journal of Urban Sciences, 24(4), 532-556.

Ong, P. M., & Miller, D. (2005). Spatial and transportation mismatch in Los Angeles. Journal of Planning Education and Research, 25(1), 43-56.

Pendall, R., & Carruthers, J. I. (2003). Does density exacerbate income segregation? Evidence from US metropolitan areas, 1980 to 2000. *Housing Policy Debate*, *14*(4), 541-589.

Pinkerton, K. E., & Joad, J. P. (2006). Influence of air pollution on respiratory health during perinatal development. Clinical and experimental pharmacology and physiology, 33(3), 269-272.

Qiu, H., Yu, I. T.-s., Tse, L. A., Chan, E. Y., Wong, T. W., & Tian, L. (2015). Greater temperature variation within a day associated with increased emergency hospital admissions for asthma. Science of the Total Environment, 505, 508-513.

Radeloff VC, Hammer RB, Stewart SI. Rural and Suburban Sprawl in the U.S. Midwest from 1940 to 2000 and Its Relation to Forest Fragmentation. Conserv Biol. 2005 Jun;19(3):793–805.

Rahman, M. H., & Antipova, A. (2024). Structural equation model in exploring urban sprawl and its impact on commuting time in 162 US urbanized areas. *Cities*, *148*, 104855.

Raman, S. (2010). Designing a liveable compact city: Physical forms of city and social life in urban neighbourhoods. *Built environment*, *36*(1), 63-80.

Robinson, L., Newell, J. P., & Marzluff, J. M. (2005). Twenty-five years of sprawl in the Seattle region: growth management responses and implications for conservation. *Landscape and Urban Planning*, *71*(1), 51-72.

Rodriguez, N. (2013). Concentrated disadvantage and the incarceration of youth: Examining how context affects juvenile justice. Journal of Research in Crime and Delinquency, 50(2), 189-215.

Roome A, Spathis R, Hill L, Darcy JM, Garruto RM. Lyme Disease Transmission Risk: Seasonal Variation in the Built Environment. Healthcare. 2018 Jul 19;6(3):84.

Sampson, R. J. (2012). *Great American city: Chicago and the enduring neighborhood effect*. University of Chicago press.

Sanchez-Ramirez, D. C., & Mackey, D. (2020). Underlying respiratory diseases, specifically COPD, and smoking are associated with severe COVID-19 outcomes: a systematic review and meta-analysis. Respiratory medicine, 171, 106096.

Sanderford, A. R., Keefe, M. J., Koebel, C. T., & McCoy, A. P. (2015). Factors influencing US homebuilders' adoption of green homebuilding products. *Journal of Sustainable Real Estate*, *7*(1), 60-82.

Seong, E. Y., Lee, N. H., & Choi, C. G. (2021). Relationship between land use mix and walking choice in high-density cities: A review of walking in Seoul, South Korea. *Sustainability*, *13*(2), 810.

Shannon, K. (2012). ‘Disconnected’ Youth Costing $93.7 Billion Annually. EducationWeek.

Schwaab, J. (2022). Sprawl or compactness? How urban form influences urban surface temperatures in Europe. City and Environment Interactions, 16, 100091.

Singer, M. E., Cohen-Zada, A. L., & Martens, K. (2024). Examining the performance of transit systems in large US metropolitan areas. *Transportation*, *51*(3), 1125-1147.

Sones, M., Holden, M., Kestens, Y., King, A. C., Rennie, M., & Winters, M. (2024). (Dis) connected by design? Using participatory citizen science to uncover environmental determinants of social connectedness for youth in under-resourced neighbourhoods. BMC Public Health, 24(1), 3104.

Springer YP, Johnson PTJ. Large-scale health disparities associated with Lyme disease and human monocytic ehrlichiosis in the United States, 2007–2013. PLoS ONE. 2018 Sep 27;13(9):e0204609.

Stacy, C., Su, Y., Noble, E., Stern, A., Blagg, K., Rainer, M., & Ezike, R. (2020). Access to Opportunity through Equitable Transportation. Washington, DC.

STATSGO2 Database | Natural Resources Conservation Service [Internet]. [cited 2025 Aug 1]. Available from: https://www.nrcs.usda.gov/resources/data-and-reports/description-of-statsgo2-database

Steurer, M., & Bayr, C. (2020). Measuring urban sprawl using land use data. *Land Use Policy*, *97*, 104799.

Stevenson, M., Thompson, J., De Sá, T. H., Ewing, R., Mohan, D., McClure, R., Roberts, I., Tiwari, G., Giles-Corti, B., & Sun, X. (2016). Land use, transport, and population health: estimating the health benefits of compact cities. The lancet, 388(10062), 2925-2935.

Stone Jr, B. (2008). Urban sprawl and air quality in large US cities. *Journal of environmental management*, *86*(4), 688-698.

Stone, B., Hess, J. J., & Frumkin, H. (2010). Urban form and extreme heat events: are sprawling cities more vulnerable to climate change than compact cities? Environmental health perspectives, 118(10), 1425-1428.

Su, W., Gu, C., Yang, G., Chen, S., & Zhen, F. (2010). Measuring the impact of urban sprawl on natural landscape pattern of the Western Taihu Lake watershed, China. *Landscape and Urban Planning*, *95*(1-2), 61-67.

Surya, B., Salim, A., Hernita, H., Suriani, S., Menne, F., & Rasyidi, E. S. (2021). Land use change, urban agglomeration, and urban sprawl: A sustainable development perspective of Makassar City, Indonesia. *Land*, *10*(6), 556.

Sy, K. T. L., White, L. F., & Nichols, B. E. (2021). Population density and basic reproductive number of COVID-19 across United States counties. *PloS one*, *16*(4), e0249271.

Tang, P., Yang, X., Sun, X., & Ye, H. (2023). Correlation between NDVI and PM2. 5 concentrations in a small-scale urban area.

Tagle, J. R. (2023). *Fighting sprawl and prioritizing affordable housing with GHG analysis*. U.S. Green Building Counci. https://www.usgbc.org/articles/fighting-sprawl-and-prioritizing-affordable-housing-ghg-analysis

Talen, E., & Koschinsky, J. (2014). Compact, walkable, diverse neighborhoods: Assessing effects on residents. *Housing Policy Debate*, *24*(4), 717-750.

Talen, E., & Koschinsky, J. (2013). The walkable neighborhood: A literature review. International journal of sustainable land use and urban planning, 1(1), 42-63.

Tatum R, Pearson-Shaver AL. Borrelia Burgdorferi. In: StatPearls. StatPearls Publishing; 2025. Accessed May 14, 2025. http://www.ncbi.nlm.nih.gov/books/NBK532894/

Tian, G., Kalantari, H. A., & Ewing, R. (2023). Are older adults living in compact development more active?–Evidence from 36 diverse regions of the United States. *Computational Urban Science*, *3*(1), 10.

Tong, C., & Wong, S. (1997). The advantages of a high density, mixed land use, linear urban development. *Transportation*, *24*(3), 295-307.

Torrens, P. M. (2008). A toolkit for measuring sprawl. *Applied Spatial Analysis and Policy*, *1*(1), 5-36.

Torrens, P. M., & Alberti, M. (2000). Measuring sprawl.

Treash, J. (2022). Bridging Urban Planning and Public Health: Investigating the Relationship Between Land Use Change and Vector-Borne Disease Risks in Ontario.

Trubka, R., Newman, P., & Bilsborough, D. (2010). The costs of urban sprawl–Infrastructure and transportation. *Environment design guide*, 1-6.

United States Geological Survey. Annual National Land Cover Database (NLCD) Collection 1 Products [Internet]. U.S. Geological Survey; [cited 2025 Mar 20]. Available from: https://www.sciencebase.gov/catalog/item/655ceb8ad34ee4b6e05cc51a

US EPA O. National Land-Cover Dataset (NLCD) Metadata | Landscape Ecology | US EPA [Internet]. [cited 2025 Aug 1]. Available from: https://www.gismanual.com/earthshelter/National%20Land-Cover%20Dataset%20(NLCD)%20Metadata%20%20US%20EPA.htm

Van Eenoo, E., Boussauw, K., & Fransen, K. (2022). Car dependency beyond land use. Journal of Transport and Land Use, 15(1), 117-136.

van Nes, A. (2021). Spatial configurations and walkability potentials. Measuring urban compactness with space syntax. *Sustainability*, *13*(11), 5785.

Van Niekerk, B. (2018). Housing as urbanism: A policy to discourage urban sprawl and provide well-located and affordable housing in South Africa. *Town and Regional Planning*, *73*, 68-82.

Wang, H.-C. (2022). Prioritizing compactness for a better quality of life: The case of US cities. *Cities*, *123*, 103566.

Wang, X., Shi, R., & Zhou, Y. (2020). Dynamics of urban sprawl and sustainable development in China. *Socio-Economic Planning Sciences*, *70*, 100736.

Wei, Y. D., & Ewing, R. (2018). Urban expansion, sprawl and inequality. In (Vol. 177, pp. 259-265): Elsevier.

Weitoft, G. R., Hjern, A., Batljan, I., & Vinnerljung, B. (2008). Health and social outcomes among children in low-income families and families receiving social assistance—a Swedish national cohort study. Social science & medicine, 66(1), 14-30.

Westra S, Goldberg MS, Didan K. The association between the incidence of Lyme disease in the USA and indicators of greenness and land cover. Curr Res Parasitol Vector-Borne Dis. 2023 Jul 7;4:100132.

Whitacre, B., Strover, S., & Gallardo, R. (2015). How much does broadband infrastructure matter? Decomposing the metro–non-metro adoption gap with the help of the National Broadband Map. Government Information Quarterly, 32(3), 261-269.

Whyte, W. H. (1993). *The exploding metropolis* (Vol. 1). Univ of California Press.

Wilby, R. L. (2007). A review of climate change impacts on the built environment. Built environment, 33(1), 31-45.

Wilson, B. (2020). Urban heat management and the legacy of redlining. Journal of the American Planning Association, 86(4), 443-457.

Xiong, N., Wei, Y. D., & Rey, S. J. (2024). Urban sprawl and racial inequality in intergenerational mobility. *Journal of Economic Geography*, *24*(2), 309-332.

Xue, W. A. N. G., Limin, J. I. A. O., & Ting, D. O. N. G. (2020). A comparative analysis of urban sprawl characteristics of high-density and low-density cities comparative analysis of large cities in China and America. Economic geography, 40(2), 70-78.

Yang, X., Liu, J., & Li, M. (2024). Transportation energy consumption decreases despite urban sprawl: Evidence from Chinese household survey. *Cities*, *146*, 104738.

Yannis, G., & Chaziris, A. (2022). Transport system and infrastructure. *Transportation research procedia*, *60*, 6-11.

Yasin, M. Y., Yusoff, M. M., Abdullah, J., & Noor, N. M. (2020). Is urban sprawl a threat to sustainable development? A review of characteristics and consequences. *Geografia*, *16*(4).

Young, D. R., Cradock, A. L., Eyler, A. A., Fenton, M., Pedroso, M., Sallis, J. F., Whitsel, L. P., & Committee, A. H. A. A. C. (2020). Creating built environments that expand active transportation and active living across the United States: a policy statement from the American heart association. *Circulation*, *142*(11), e167-e183.

Zhang, L., Shu, X., & Zhang, L. (2023). Urban sprawl and its multidimensional and multiscale measurement. *Land*, *12*(3), 630.

Zhao, P. (2010). Sustainable urban expansion and transportation in a growing megacity: Consequences of urban sprawl for mobility on the urban fringe of Beijing. *Habitat International*, *34*(2), 236-243.

Zhu, P., Ho, S. N., Jiang, Y., & Tan, X. (2020). Built environment, commuting behaviour and job accessibility in a rail-based dense urban context. *Transportation Research Part D: Transport and Environment*, *87*, 102438.

Zhu, Q., Zeng, M., Jia, P., Guo, M., Liang, X., & Guan, Q. (2024). Measuring the urban sprawl based on economic-dominated perspective: The case of 31 municipalities and provincial capitals. *Geo-Spatial Information Science*, *27*(4), 1272-1289.

Appendix A: Small Area (Census Tract) Sprawl Scores

The concept of sprawl naturally brings to mind large geographic areas. When we say Atlanta sprawls badly, we are referring to the Atlanta Metropolitan Area, or perhaps if we are a transportation planner, to the Atlanta Urbanized Area. From the earliest writings on sprawl, sprawl was said to occur primarily at the periphery of urbanized areas moving outward. An individual street or block may contribute to sprawl, but we would not say it is sprawl. This distinction seems particularly poignant when we talk about population and employment centering, which is defined by interrelationships among block groups. If one block group or a group of them has a significantly higher density than those surrounding it, we can say the former serves as a center for the block groups surrounding it.

Yet, we know from the travel and public health literatures that there is a demand in the research community for built environmental metrics at the sub-county level, what might be described as the community or neighborhood scale. Most of the built environment-travel studies, and most of the built environment-obesity studies, have related individual outcomes to such smaller areas. Therefore, we have derived sprawl-like metrics for census tracts within metropolitan areas, and posted them along with metropolitan area, and county sprawl metrics on the CST website. We have used the same type of variables as in larger area analyses, extracted principal components from multiple variables using principal component analysis, and once again, transformed the first principal component to an index with the mean of 100 and a standard deviation of 25. The variables contributing to the census tract compactness index are:

Table A1: Variable Loadings on the Census Tract Compactness Index for 2020

Variables	Data Sources	Factor Loadings
gross population density	Census 2020	0.72
gross employment density	LEHD 2019	0.28
net population density of urban lands	NLCD 2020	0.71
job-population balance	LEHD 2019	0.38
degree of job mixing (entropy)	LEHD 2019	0.62
weighted average Walk Score	Walk Score Inc.	0.85
percentage of small urban blocks	Census 2020	0.81
average block size	Census 2020	-0.69
intersection density	Boeing, 2017	0.82
percentage of 4-or-more-way intersections	Boeing, 2017	0.74
Eigenvalue		**4.7**
Explained variance		**46.9**

Appendix B. County Compactness Factors and Composite Indices for 2020

Below is the full list of compactness index scores for 995 metropolitan counties in the U.S. Table B1 also presents individual scores for each of the four dimensions of the index. Nonmetropolitan and rural metropolitan counties were excluded from the sample. More than 281 million Americans, nearly 85% of the U.S. population, lived in these 995 counties in 2020.

Table B1: 2020 Metropolitan Compactness Score rankings

Rank	County	Density score	Mixed land use score	Activity centering score	Street connectivity score	**Composite (total) score**
1	New York County, NY	641.44	150.53	403.64	211.16	**460.29**
2	San Francisco County, CA	255.35	155.41	242.25	210.45	**252.58**
3	Kings County, NY	355.52	164.49	110.82	230.02	**232.00**
4	Bronx County, NY	337.53	155.56	83.20	221.32	**214.63**
5	Suffolk County, MA	224.43	146.87	175.50	198.63	**207.18**
6	District of Columbia, DC	199.26	136.97	207.47	187.66	**203.87**
7	Philadelphia County, PA	206.33	150.24	184.12	207.43	**197.87**
8	Charlottesville city, VA	129.45	148.21	175.69	153.78	**197.37**
9	Alexandria city, VA	176.83	156.97	127.93	175.66	**193.75**
10	Queens County, NY	267.08	161.52	99.67	216.98	**190.00**
11	Arlington County, VA	180.21	151.60	134.08	181.81	**187.38**
12	Falls Church city, VA	134.62	175.20	64.19	154.89	**185.68**
13	Hudson County, NJ	216.14	158.78	88.09	129.62	**183.60**
14	Baltimore City, MD	154.25	146.50	176.30	190.24	**181.42**
15	City of St. Louis MO	125.18	137.09	176.07	183.45	**174.84**
16	Richmond city, VA	124.37	132.02	174.28	174.18	**171.99**
17	Denver County, CO	135.58	142.34	182.18	186.38	**169.91**
18	Winchester city, VA	114.62	140.99	110.93	146.86	**169.15**
19	Orleans Parish, LA	122.84	138.39	140.71	211.69	**167.98**
20	Hopewell city, VA	109.39	120.23	78.59	185.28	**166.89**
21	Fredericksburg city, VA	112.95	129.14	96.98	155.63	**164.65**
22	Salem city, VA	105.17	125.18	109.44	139.15	**162.64**
23	Norfolk city, VA	119.58	129.87	151.74	178.48	**161.54**
24	Manassas Park city, VA	126.90	128.64	78.22	124.23	**160.40**
25	Harrisonburg city, VA	112.79	137.48	134.91	127.46	**159.68**
26	Waynesboro city, VA	103.43	131.71	80.48	147.48	**154.76**
27	Fairfax city, VA	118.81	139.16	64.10	138.77	**152.58**
28	Bristol city, VA	97.68	123.46	81.14	148.28	**152.49**
29	Asotin County, WA	105.69	143.81	76.07	134.54	**152.34**
30	Roanoke city, VA	107.75	123.76	122.92	160.88	**150.11**

31	Radford city, VA	102.92	114.30	69.48	154.74	**149.95**
32	Williamsburg city, VA	104.93	131.28	72.29	126.01	**149.44**
33	Franklin city, VA	98.25	117.51	63.89	132.53	**149.26**
34	Richmond County, NY	177.04	143.20	79.62	175.56	**148.00**
35	Staunton city, VA	100.84	129.51	91.73	127.52	**147.22**
36	Colonial Heights city, VA	107.24	117.90	67.33	142.35	**146.55**
37	Boone County, IA	94.78	152.89	64.14	135.69	**144.20**
38	Cabell County, WV	97.13	114.25	166.90	116.55	**142.85**
39	Manassas city, VA	119.61	128.84	70.78	134.12	**142.67**
40	Multnomah County, OR	124.18	142.22	147.85	166.59	**142.15**
41	Portsmouth city, VA	110.95	123.12	94.55	164.42	**141.27**
42	Essex County, NJ	163.83	149.22	117.74	150.30	**140.91**
43	Cascade County, MT	97.34	129.79	129.72	127.50	**140.38**
44	Lynchburg city, VA	103.61	118.98	126.55	129.89	**139.95**
45	Warren County, NY	95.72	119.65	165.15	88.82	**138.17**
46	Bristol County, RI	107.54	139.65	82.34	126.19	**137.45**
47	Monroe County, IN	104.02	120.57	168.48	102.73	**136.85**
48	Ohio County, WV	95.44	104.64	125.24	123.97	**136.28**
49	Brooke County, WV	91.59	78.49	143.65	117.41	**135.64**
50	Petersburg city, VA	101.08	106.77	78.80	143.26	**135.29**
51	Chattahoochee County, GA	89.73	125.30	69.09	100.87	**134.84**
52	Cook County, IL	149.58	141.12	179.55	166.67	**134.58**
53	Potter County, TX	99.67	109.67	131.35	140.68	**133.82**
54	Milwaukee County, WI	125.15	139.64	136.12	163.74	**133.80**
55	Laramie County, WY	100.71	121.25	125.69	126.77	**133.69**
56	Wabasha County, MN	88.94	126.78	84.34	109.92	**133.02**
57	Unicoi County, TN	94.43	114.90	85.09	106.84	**132.69**
58	Montour County, PA	96.70	121.30	76.19	106.26	**132.64**
59	Falls County, TX	89.45	114.87	77.90	117.29	**132.55**
60	Johnson County, IA	105.13	116.09	171.13	95.72	**132.38**
61	Dakota County, NE	98.38	112.01	72.90	115.32	**132.27**
62	Union County, NJ	141.81	153.79	92.75	151.32	**131.81**
63	Lincoln County, WI	92.39	139.32	78.89	104.56	**130.51**
64	Chelan County, WA	98.99	129.66	129.14	98.85	**130.47**
65	Carson City, NV	104.61	136.00	78.33	125.24	**130.22**
66	Macoupin County, IL	91.91	142.19	76.53	122.14	**130.12**
67	Cape May County, NJ	95.18	120.86	101.54	144.05	**129.98**
68	Bourbon County, KY	97.26	141.67	72.76	86.94	**129.38**
69	Bannock County, ID	101.50	122.95	116.14	117.01	**129.36**
70	Natrona County, WY	98.69	116.97	122.09	116.27	**129.31**
71	Douglas County, WI	94.73	126.21	94.69	113.93	**129.15**

72	Monongalia County, WV	100.16	110.90	148.11	105.43	**129.08**
73	Clay County, IN	90.51	145.77	66.88	104.31	**128.45**
74	Victoria County, TX	100.02	124.21	114.71	117.85	**128.27**
75	Benton County, OR	102.53	121.85	133.69	100.24	**128.26**
76	Sullivan County, IN	89.16	147.43	66.99	92.84	**128.10**
77	St. Bernard Parish, LA	100.96	115.00	82.30	123.33	**128.01**
78	Napa County, CA	102.38	131.94	124.22	113.47	**127.65**
79	Woodbury County, IA	100.11	124.13	107.12	131.31	**127.50**
80	Houston County, MN	89.16	131.26	72.23	97.60	**127.24**
81	Vigo County, IN	96.31	112.79	118.24	132.13	**126.98**
82	Nez Perce County, ID	99.38	119.97	82.58	120.30	**126.91**
83	Boyd County, KY	95.74	98.35	121.28	112.25	**126.87**
84	Providence County, RI	121.49	144.80	133.79	133.09	**126.83**
85	Buchanan County, MO	100.13	117.39	96.26	135.93	**126.75**
86	Passaic County, NJ	144.22	146.11	98.32	135.61	**126.37**
87	Chemung County, NY	96.87	122.58	124.32	104.41	**126.30**
88	Alameda County, CA	142.54	143.27	133.56	149.82	**126.09**
89	Marshall County, WV	93.04	125.08	77.67	111.91	**125.65**
90	Fayette County, KY	112.16	119.06	145.71	124.31	**125.61**
91	Champaign County, IL	106.63	125.96	144.26	105.76	**125.50**
92	Blair County, PA	97.40	125.99	108.42	129.48	**125.27**
93	Geary County, KS	95.78	104.56	88.21	121.51	**124.82**
94	Fulton County, IL	92.76	127.17	87.75	99.61	**124.78**
95	Broomfield County, CO	107.65	111.85	81.69	127.03	**124.31**
96	Jasper County, IA	100.19	143.50	76.23	90.92	**124.23**
97	Hall County, NE	97.11	118.14	81.74	134.25	**124.17**
98	Wichita County, TX	96.88	112.08	128.79	121.86	**123.85**
99	Grand Forks County, ND	104.58	142.19	92.20	96.82	**123.84**
100	Nicollet County, MN	97.41	135.83	68.94	104.22	**123.72**
101	Mercer County, NJ	114.68	122.64	142.78	120.50	**123.20**
102	Hampton city, VA	110.15	112.17	97.71	143.25	**123.08**
103	Dubuque County, IA	96.85	125.79	116.27	107.19	**122.89**
104	Kanawha County, WV	96.88	104.08	150.77	118.35	**122.66**
105	Green County, WI	89.68	136.72	76.32	102.59	**122.54**
106	Peoria County, IL	100.53	115.13	134.55	119.61	**122.44**
107	Albany County, NY	108.12	124.80	156.03	100.94	**121.86**
108	Lackawanna County, PA	99.60	126.52	125.88	121.91	**121.85**
109	Story County, IA	101.70	109.33	132.48	99.15	**121.52**
110	Jefferson County, AR	92.91	102.19	113.18	118.61	**121.42**
111	Jones County, IA	89.26	130.54	73.65	85.58	**121.40**
112	Schenectady County, NY	106.07	131.17	109.08	114.78	**121.32**

113	Ramsey County, MN	117.26	136.38	105.79	152.67	**121.32**
114	Newport News city, VA	111.32	118.48	105.68	130.46	**121.13**
115	Washington County, IA	88.71	124.86	74.74	93.47	**121.06**
116	Missoula County, MT	97.09	125.53	109.32	115.90	**120.64**
117	Newport County, RI	97.51	129.84	98.73	107.97	**120.38**
118	Miami-Dade County, FL	138.30	130.72	145.28	159.39	**120.29**
119	St. Louis County, MN	95.34	122.76	145.12	105.00	**120.28**
120	Eau Claire County, WI	98.53	122.22	115.10	106.27	**120.24**
121	Wood County, WV	95.93	118.98	104.23	114.17	**120.15**
122	Clinton County, MO	89.06	102.96	83.05	101.20	**119.92**
123	Lafayette County, MO	89.20	127.82	78.66	98.20	**119.92**
124	Vanderburgh County, IN	101.14	114.49	121.95	124.59	**119.92**
125	Olmsted County, MN	99.19	101.45	157.65	100.62	**119.90**
126	Sumner County, KS	87.94	131.17	71.15	87.94	**119.81**
127	Morehouse Parish, LA	94.09	120.66	65.51	102.47	**119.62**
128	Sangamon County, IL	96.86	105.36	150.49	112.88	**119.56**
129	Santa Barbara County, CA	118.91	139.02	115.73	124.43	**119.56**
130	Yellowstone County, MT	100.76	120.98	116.63	120.04	**119.51**
131	Hennepin County, MN	116.64	124.45	163.62	136.83	**119.44**
132	Nassau County, NY	130.29	148.61	106.77	159.07	**119.33**
133	Teller County, CO	90.69	118.34	71.82	99.99	**119.24**
134	Carroll County, IN	88.67	119.65	85.59	77.39	**119.20**
135	Yazoo County, MS	90.34	127.61	66.96	99.07	**119.20**
136	Douglas County, NE	108.88	124.30	132.88	143.21	**119.09**
137	Daviess County, KY	97.69	116.06	119.36	104.49	**118.89**
138	Allegany County, MD	92.63	104.07	112.25	110.69	**118.43**
139	Wicomico County, MD	94.69	109.17	134.65	98.11	**118.37**
140	Cowlitz County, WA	97.10	110.28	130.21	101.47	**118.18**
141	Dauphin County, PA	103.65	120.66	125.21	127.81	**118.00**
142	Dougherty County, GA	96.61	103.29	117.00	110.83	**117.86**
143	Jefferson Parish, LA	112.66	130.31	99.53	152.28	**117.64**
144	Hancock County, WV	93.86	98.83	79.14	115.28	**117.56**
145	Boulder County, CO	108.39	123.09	132.33	117.53	**117.56**
146	Colbert County, AL	94.79	117.24	77.47	120.72	**117.48**
147	Howard County, IN	97.63	115.69	96.43	115.01	**117.14**
148	Pawnee County, OK	88.33	113.00	61.47	93.24	**116.90**
149	Lehigh County, PA	110.24	125.91	113.99	132.94	**116.86**
150	West Baton Rouge Parish, LA	91.75	87.01	86.55	111.36	**116.74**
151	Washington County, NE	89.14	115.78	68.55	93.43	**116.49**
152	Walla Walla County, WA	97.95	125.75	78.64	108.99	**116.44**

153	Tom Green County, TX	98.47	112.41	104.92	121.87	**116.41**
154	Okmulgee County, OK	89.15	110.26	70.43	119.56	**116.30**
155	Shelby County, IN	97.13	111.94	99.31	88.74	**116.07**
156	La Crosse County, WI	98.89	127.36	86.32	123.76	**115.85**
157	Cooper County, MO	88.96	124.01	69.95	73.41	**115.82**
158	Garfield County, OK	97.56	129.53	80.84	101.95	**115.80**
159	Clay County, MN	101.48	132.60	79.61	96.42	**115.80**
160	Lancaster County, NE	105.63	130.97	114.70	124.46	**115.65**
161	Greenup County, KY	94.47	108.71	74.60	112.33	**115.62**
162	Saunders County, NE	88.35	125.03	64.73	89.84	**115.61**
163	Ray County, MO	89.21	128.51	70.71	79.87	**115.34**
164	Sutter County, CA	99.67	126.95	107.80	93.24	**115.33**
165	Black Hawk County, IA	98.39	127.87	89.45	122.41	**115.08**
166	Douglas County, WA	97.10	98.91	116.64	80.94	**114.91**
167	Franklin County, WA	103.40	114.88	88.00	118.10	**114.90**
168	Brazos County, TX	104.64	111.03	126.16	118.78	**114.86**
169	Mills County, IA	89.45	105.32	68.46	84.77	**114.86**
170	Taylor County, TX	99.03	120.58	102.00	119.22	**114.84**
171	Poquoson city, VA	96.79	91.55	82.28	69.44	**114.74**
172	Pottawattamie County, IA	97.15	118.91	101.07	101.57	**114.61**
173	Lycoming County, PA	94.97	123.15	103.56	109.77	**114.60**
174	Posey County, IN	91.50	109.81	78.88	88.62	**114.56**
175	Pueblo County, CO	100.15	114.62	102.24	129.38	**114.48**
176	Rock Island County, IL	100.71	129.31	86.91	122.83	**114.37**
177	Atlantic County, NJ	101.99	106.22	140.52	117.11	**114.36**
178	Camden County, NJ	113.29	135.21	101.44	142.80	**114.33**
179	Chittenden County, VT	99.93	117.83	148.76	79.47	**114.33**
180	Erie County, PA	100.88	131.16	125.69	107.51	**114.32**
181	Bibb County, GA	96.60	109.44	125.67	111.55	**114.30**
182	Miller County, AR	94.80	108.29	80.13	107.10	**114.30**
183	Ector County, TX	99.62	117.60	103.65	124.31	**114.28**
184	Marin County, CA	108.49	139.43	105.79	110.11	**114.27**
185	Androscoggin County, ME	97.10	102.10	143.45	86.12	**114.16**
186	Hamilton County, OH	109.37	125.47	158.65	116.42	**114.11**
187	Fulton County, GA	112.59	116.43	176.19	115.31	**114.05**
188	De Soto Parish, LA	87.97	65.00	140.98	76.90	**113.95**
189	Scott County, IA	100.70	124.47	93.42	127.86	**113.85**
190	Jefferson County, TX	101.06	110.21	114.95	135.44	**113.73**
191	San Luis Obispo County, CA	100.48	136.28	116.94	111.73	**113.72**
192	Sequoyah County, OK	91.38	108.75	95.66	89.75	**113.69**
193	Acadia Parish, LA	92.06	111.83	78.45	117.90	**113.65**

194	Madison County, IN	95.45	103.94	116.26	117.68	**113.43**
195	Kankakee County, IL	95.37	123.24	100.93	105.95	**113.38**
196	Douglas County, KS	104.02	129.66	95.33	100.37	**113.33**
197	Jackson County, IL	93.19	108.21	96.38	98.87	**113.31**
198	Charleston County, SC	101.42	110.49	151.07	117.35	**113.22**
199	Tompkins County, NY	100.03	100.97	147.07	76.30	**113.19**
200	Bay County, MI	95.88	116.64	100.48	110.37	**113.10**
201	Macon County, IL	95.25	111.39	107.45	109.33	**113.10**
202	Dane County, WI	107.68	120.31	150.07	113.63	**113.06**
203	Chesapeake city, VA	104.11	100.44	140.54	113.44	**112.89**
204	Fond du Lac County, WI	95.44	111.83	123.26	92.39	**112.86**
205	Mille Lacs County, MN	88.90	104.40	80.77	92.86	**112.71**
206	Riley County, KS	102.14	113.48	85.74	105.40	**112.68**
207	Mesa County, CO	100.34	106.27	115.68	116.14	**112.57**
208	Liberty County, GA	97.49	107.61	115.47	83.39	**112.56**
209	Virginia Beach city, VA	112.70	121.70	110.92	137.08	**112.55**
210	Benton County, MN	98.68	112.71	77.23	94.74	**112.41**
211	Allen County, OH	95.46	107.44	110.64	108.73	**112.35**
212	Richmond County, GA	101.57	105.12	132.81	109.88	**112.33**
213	Cambria County, PA	94.11	104.96	111.54	120.90	**112.31**
214	Kenosha County, WI	99.59	114.28	104.61	122.42	**112.21**
215	Butler County, KS	94.39	116.13	109.84	83.21	**112.20**
216	Midland County, TX	98.64	111.26	107.56	123.50	**112.17**
217	Kendall County, TX	91.96	96.61	121.26	76.53	**112.16**
218	St. Joseph County, IN	101.00	115.20	113.86	129.95	**112.12**
219	Cape Girardeau County, MO	95.53	97.70	123.59	94.27	**112.12**
220	Vermilion County, IL	91.09	91.81	110.51	113.75	**112.08**
221	Ingham County, MI	106.65	116.11	131.13	107.57	**112.02**
222	Box Elder County, UT	96.46	140.32	81.84	77.96	**111.89**
223	Bartholomew County, IN	95.19	100.53	113.27	101.51	**111.78**
224	Yamhill County, OR	98.81	130.54	85.39	106.56	**111.71**
225	Terrebonne Parish, LA	96.79	108.21	109.83	108.26	**111.63**
226	Centre County, PA	105.98	115.60	115.81	99.93	**111.60**
227	Benton County, IA	88.63	99.86	76.77	97.41	**111.53**
228	Durham County, NC	103.39	104.30	153.44	103.88	**111.34**
229	Tuscaloosa County, AL	95.10	104.94	142.58	107.68	**111.23**
230	Linn County, IA	100.26	115.86	127.73	106.91	**111.19**
231	McLean County, IL	101.77	113.42	118.17	104.52	**110.88**
232	Henry County, IL	90.36	108.36	98.23	90.75	**110.88**
233	Pinellas County, FL	114.34	125.50	106.49	160.73	**110.85**
234	Boone County, MO	99.32	111.22	130.64	99.44	**110.80**

235	Jackson County, MO	105.23	118.34	142.15	129.73	**110.68**
236	Campbell County, KY	99.49	114.33	87.76	109.99	**110.66**
237	Wayne County, MI	113.62	123.75	141.34	153.62	**110.62**
238	Orleans County, NY	94.58	134.97	84.62	64.26	**110.59**
239	Henderson County, KY	97.21	120.07	75.89	89.82	**110.59**
240	Imperial County, CA	102.09	138.63	101.43	96.59	**110.48**
241	Delaware County, IN	97.10	115.07	95.20	112.23	**110.42**
242	Gem County, ID	90.39	100.93	71.36	84.90	**110.26**
243	Delaware County, PA	119.00	141.54	84.96	139.90	**110.18**
244	Yuma County, AZ	99.88	95.17	134.10	114.11	**110.11**
245	Grant County, AR	88.75	109.62	74.69	71.89	**110.10**
246	Marion County, IN	109.46	113.30	151.70	131.95	**110.05**
247	Stevens County, WA	88.81	114.40	81.14	96.94	**110.05**
248	Simpson County, MS	88.85	103.38	79.63	87.18	**110.02**
249	Bergen County, NJ	134.60	148.60	86.48	155.44	**109.96**
250	Cass County, ND	103.13	125.55	109.84	100.53	**109.93**
251	Muskegon County, MI	96.40	103.80	126.33	110.07	**109.92**
252	Lane County, OR	101.71	132.06	130.58	103.49	**109.81**
253	Jerome County, ID	95.63	99.93	86.07	75.92	**109.77**
254	Bernalillo County, NM	108.65	122.56	122.60	136.91	**109.71**
255	Santa Cruz County, CA	106.26	130.82	106.71	108.98	**109.64**
256	Jasper County, MO	94.77	116.49	86.49	123.55	**109.62**
257	Hamblen County, TN	94.14	74.97	132.53	93.88	**109.60**
258	Lincoln County, SD	97.94	107.96	106.73	82.96	**109.60**
259	Sheboygan County, WI	97.18	121.56	98.37	102.24	**109.53**
260	Yakima County, WA	98.45	122.76	130.32	99.38	**109.51**
261	San Mateo County, CA	132.58	137.68	90.45	133.67	**109.47**
262	Ada County, ID	105.79	118.30	133.91	119.16	**109.39**
263	Onondaga County, NY	103.59	118.13	152.91	100.72	**109.35**
264	Harvey County, KS	89.99	119.86	69.33	89.46	**109.35**
265	Cole County, MO	93.78	99.31	119.88	88.80	**109.34**
266	Washington County, IN	93.29	102.20	89.03	75.45	**109.04**
267	Miami County, KS	88.87	102.16	87.44	89.52	**109.01**
268	Lucas County, OH	104.35	125.06	119.15	121.68	**108.98**
269	Allegheny County, PA	108.52	125.57	146.92	131.82	**108.90**
270	Chester County, SC	93.20	106.68	74.75	91.11	**108.76**
271	Carter County, TN	92.49	68.76	131.93	93.98	**108.67**
272	Minnehaha County, SD	102.25	113.61	107.09	114.97	**108.60**
273	Comanche County, OK	97.57	110.26	94.75	115.60	**108.60**
274	Crittenden County, AR	98.51	115.73	76.03	90.48	**108.58**
275	Forrest County, MS	94.09	98.21	109.69	98.29	**108.55**

276	Chatham County, GA	99.62	105.76	124.86	123.55	**108.47**
277	Montgomery County, AL	100.72	113.68	121.95	107.25	**108.45**
278	St. John the Baptist Parish, LA	96.83	101.72	77.34	99.44	**108.42**
279	Worcester County, MD	93.59	103.52	83.95	101.15	**108.33**
280	Kootenai County, ID	97.70	110.61	117.92	105.23	**108.31**
281	Outagamie County, WI	97.93	117.92	112.84	106.79	**108.15**
282	Spokane County, WA	100.47	116.13	129.25	131.75	**108.13**
283	Columbia County, PA	94.98	118.05	87.10	93.08	**108.11**
284	Wyandotte County, KS	101.92	104.06	98.08	125.20	**108.03**
285	Lebanon County, PA	95.91	118.22	91.72	117.53	**107.92**
286	King County, WA	120.43	126.56	159.04	128.99	**107.87**
287	Morton County, ND	90.78	92.50	97.72	83.84	**107.80**
288	St. James Parish, LA	88.91	78.33	98.05	78.04	**107.79**
289	Shawnee County, KS	98.54	111.11	110.21	111.92	**107.74**
290	Middlesex County, NJ	118.83	131.06	114.35	131.94	**107.74**
291	Burleigh County, ND	95.11	103.97	118.33	89.67	**107.67**
292	Lafourche Parish, LA	93.44	96.27	119.97	95.58	**107.55**
293	Twin Falls County, ID	97.37	124.97	82.89	97.68	**107.53**
294	Floyd County, IN	97.49	108.55	95.88	99.50	**107.48**
295	Kent County, RI	103.05	116.82	92.82	116.93	**107.41**
296	Pointe Coupee Parish, LA	88.78	88.90	86.93	81.20	**107.39**
297	Pennington County, SD	94.67	101.07	113.23	101.65	**107.28**
298	Winnebago County, IL	100.17	117.25	109.07	122.57	**107.10**
299	Muscogee County, GA	103.69	109.55	111.71	110.12	**107.07**
300	Kings County, CA	100.51	119.52	99.54	103.84	**107.01**
301	Westchester County, NY	128.23	145.86	100.16	124.22	**106.97**
302	Sacramento County, CA	116.58	129.03	140.93	131.17	**106.93**
303	Lubbock County, TX	104.24	120.41	104.74	122.53	**106.88**
304	Mineral County, WV	90.25	94.69	71.56	97.44	**106.84**
305	Warren County, IA	93.30	111.66	83.57	91.00	**106.75**
306	Morgan County, WV	89.14	94.40	78.76	67.32	**106.70**
307	Pulaski County, AR	100.37	106.27	130.95	123.96	**106.65**
308	Martin County, FL	98.70	101.64	123.02	101.32	**106.60**
309	Webb County, TX	105.04	108.27	94.37	137.38	**106.58**
310	Plaquemines Parish, LA	90.15	99.44	85.02	87.46	**106.55**
311	Bremer County, IA	88.92	91.29	78.77	90.01	**106.54**
312	Clinton County, IL	88.84	108.45	61.76	105.20	**106.32**
313	Broome County, NY	99.65	121.44	119.15	92.04	**106.23**
314	Santa Fe County, NM	97.62	117.11	113.40	93.96	**106.15**
315	Monroe County, IL	91.63	97.53	80.68	90.84	**106.04**

316	Lawrence County, OH	93.68	94.45	90.17	101.68	**105.94**
317	San Patricio County, TX	93.09	103.43	74.63	116.79	**105.90**
318	Williamson County, IL	92.36	96.00	85.52	113.51	**105.90**
319	Montgomery County, MD	116.83	128.16	133.17	120.76	**105.86**
320	San Benito County, CA	99.73	108.12	81.92	95.06	**105.84**
321	Hampden County, MA	105.07	127.19	124.58	108.90	**105.77**
322	Washington County, MD	96.71	113.03	118.69	92.63	**105.72**
323	Carbon County, PA	93.20	94.79	98.89	98.28	**105.66**
324	Northampton County, PA	102.76	122.10	102.05	124.69	**105.63**
325	Glynn County, GA	92.75	103.65	88.60	110.96	**105.61**
326	Pulaski County, VA	91.35	93.63	80.65	93.72	**105.60**
327	Manatee County, FL	102.06	108.97	123.70	124.05	**105.58**
328	Jefferson County, OH	94.52	106.45	84.11	92.60	**105.49**
329	Lafayette Parish, LA	99.30	106.51	116.83	115.31	**105.47**
330	Marion County, OR	101.43	124.69	122.65	104.08	**105.45**
331	Berkshire County, MA	93.39	115.33	121.47	82.46	**105.41**
332	Racine County, WI	99.26	122.40	95.25	112.61	**105.30**
333	Oneida County, NY	99.20	115.66	131.85	88.80	**105.26**
334	Blue Earth County, MN	96.82	114.84	87.37	87.50	**105.24**
335	Bonneville County, ID	98.92	114.88	94.25	102.32	**105.18**
336	Poinsett County, AR	89.18	110.15	70.48	71.96	**105.08**
337	Nueces County, TX	105.07	119.67	103.96	123.88	**105.06**
338	Lampasas County, TX	88.60	69.94	78.20	102.64	**104.93**
339	Sebastian County, AR	97.28	111.37	88.44	113.21	**104.75**
340	Indian River County, FL	98.01	95.13	102.95	123.27	**104.73**
341	Vermilion Parish, LA	91.57	92.46	96.84	97.97	**104.71**
342	Broward County, FL	124.31	127.15	115.66	153.28	**104.69**
343	Cumberland County, NJ	100.81	107.78	111.50	97.75	**104.64**
344	Edgecombe County, NC	90.15	95.77	82.33	102.17	**104.64**
345	Iberia Parish, LA	95.22	101.29	88.60	100.49	**104.62**
346	Los Angeles County, CA	150.98	146.37	147.98	141.17	**104.48**
347	Woodford County, KY	93.06	95.05	73.58	85.73	**104.42**
348	Jackson County, MS	94.54	90.54	129.08	102.16	**104.37**
349	Hinds County, MS	98.15	99.36	133.77	101.51	**104.29**
350	Cache County, UT	98.78	112.16	112.40	87.59	**104.26**
351	Garland County, AR	91.05	101.01	110.94	96.59	**104.26**
352	Berks County, PA	107.25	121.54	121.44	108.03	**104.25**
353	LaPorte County, IN	94.29	108.95	97.28	103.46	**104.22**
354	Boone County, IL	97.13	98.12	88.09	90.38	**104.15**
355	Floyd County, GA	93.60	89.49	121.72	93.23	**104.09**
356	Schoharie County, NY	90.65	119.37	87.61	51.58	**104.09**

357	Livingston County, NY	92.25	130.38	97.51	58.88	**104.07**
358	Ottawa County, OH	91.50	89.84	91.51	88.94	**104.00**
359	Columbia County, OR	93.49	102.35	90.57	86.28	**103.99**
360	Mecklenburg County, NC	108.77	109.83	166.38	111.33	**103.95**
361	Somerset County, MD	89.46	103.44	67.75	81.27	**103.91**
362	Carlton County, MN	89.27	103.73	77.84	86.29	**103.82**
363	Warren County, KY	96.48	105.42	116.69	91.62	**103.76**
364	Herkimer County, NY	94.60	132.82	72.09	78.48	**103.63**
365	Arapahoe County, CO	113.62	116.84	112.85	130.48	**103.63**
366	New Hanover County, NC	102.12	114.15	95.72	115.08	**103.63**
367	Belmont County, OH	91.43	99.35	88.66	98.49	**103.62**
368	Randall County, TX	100.98	117.93	76.34	116.35	**103.60**
369	Meade County, SD	88.35	75.64	86.27	98.43	**103.59**
370	Winnebago County, WI	99.61	124.46	83.29	112.10	**103.55**
371	Monterey County, CA	112.79	130.71	105.53	107.97	**103.50**
372	Charlotte County, FL	95.67	92.42	119.31	114.54	**103.28**
373	Seward County, NE	88.76	80.57	71.26	85.71	**103.19**
374	Harrison County, MS	96.80	98.84	124.17	104.91	**103.17**
375	Butte County, CA	98.30	125.19	107.72	95.53	**103.09**
376	Hardin County, KY	93.90	86.31	124.80	95.49	**103.05**
377	Polk County, IA	103.41	120.79	119.95	117.28	**103.00**
378	Polk County, OR	98.78	111.41	83.23	96.20	**102.96**
379	Orange County, NC	98.41	97.51	134.86	81.61	**102.95**
380	Calhoun County, AL	90.22	82.55	125.04	104.33	**102.94**
381	Lamar County, GA	89.38	92.51	73.83	72.54	**102.90**
382	Wayne County, WV	93.90	85.55	80.43	101.21	**102.88**
383	Polk County, MN	89.23	120.19	68.36	72.38	**102.83**
384	Christian County, KY	96.52	105.25	82.02	98.98	**102.80**
385	Jones County, TX	95.38	37.67	72.49	124.18	**102.78**
386	Davidson County, TN	105.24	107.69	147.51	114.76	**102.76**
387	Dallas County, IA	100.52	106.85	81.57	102.79	**102.75**
388	Weber County, UT	105.36	115.90	102.97	111.11	**102.72**
389	Stearns County, MN	96.57	107.66	115.86	94.30	**102.70**
390	Santa Clara County, CA	134.88	134.06	112.81	133.47	**102.58**
391	Buncombe County, NC	95.32	101.07	146.98	92.20	**102.52**
392	Oklahoma County, OK	103.92	112.81	138.97	122.92	**102.40**
393	Do+¦a Ana County, NM	98.30	110.62	110.12	107.37	**102.36**
394	Jackson County, MI	94.00	98.86	136.53	84.26	**102.36**
395	Florence County, SC	93.78	90.18	131.52	91.93	**102.30**
396	Galveston County, TX	102.03	104.78	106.80	131.03	**102.18**
397	Yolo County, CA	104.74	130.54	83.93	107.29	**102.17**

398	Rock County, WI	96.38	108.68	106.24	102.67	**102.15**
399	Sedgwick County, KS	103.41	116.59	121.59	119.41	**102.13**
400	Clarke County, GA	101.50	109.84	94.71	97.83	**102.06**
401	Travis County, TX	108.20	116.41	160.24	112.17	**101.92**
402	Copiah County, MS	89.76	113.72	64.80	73.59	**101.90**
403	Grayson County, TX	92.52	100.93	106.01	106.15	**101.88**
404	Bay County, FL	98.35	109.45	84.41	123.82	**101.88**
405	New Castle County, DE	107.81	119.46	108.85	127.37	**101.87**
406	Franklin County, OH	112.66	120.77	136.11	128.57	**101.86**
407	Tippecanoe County, IN	103.64	109.31	101.62	103.45	**101.69**
408	Dallas County, TX	117.84	113.09	150.67	143.24	**101.63**
409	Fulton County, OH	89.84	121.01	75.61	71.70	**101.63**
410	Warren County, VA	93.00	82.35	97.35	83.73	**101.63**
411	Lauderdale County, AL	93.15	87.39	124.78	84.62	**101.57**
412	Escambia County, FL	99.45	95.99	124.88	119.09	**101.55**
413	DeKalb County, IL	98.06	107.60	89.98	96.65	**101.42**
414	Jefferson County, KY	108.31	113.25	129.30	124.26	**101.38**
415	Leon County, FL	102.63	101.86	125.24	105.64	**101.29**
416	Leavenworth County, KS	94.86	101.06	93.79	94.03	**101.28**
417	Kenton County, KY	102.75	106.97	89.62	114.12	**101.05**
418	Skagit County, WA	95.86	109.31	99.19	96.79	**101.01**
419	Rockland County, NY	121.06	129.53	84.67	104.53	**100.78**
420	Washington County, OR	112.21	130.81	98.63	121.09	**100.73**
421	Marathon County, WI	94.17	117.95	95.97	95.12	**100.66**
422	Gregg County, TX	95.65	104.46	98.19	100.65	**100.54**
423	Etowah County, AL	91.53	88.05	112.19	98.98	**100.52**
424	Anson County, NC	91.51	99.75	78.25	59.02	**100.50**
425	Scott County, KY	96.34	93.28	84.40	92.74	**100.49**
426	Madison County, OH	90.79	83.37	95.67	86.12	**100.48**
427	Raleigh County, WV	92.53	100.79	86.63	97.76	**100.46**
428	Montgomery County, OH	102.74	118.72	115.26	121.09	**100.45**
429	Richland County, SC	101.03	102.80	133.25	110.27	**100.34**
430	Grady County, OK	91.77	89.50	83.07	100.78	**100.33**
431	Jefferson County, AL	98.61	104.81	133.20	130.30	**100.33**
432	Sarasota County, FL	102.40	108.24	111.59	126.10	**100.22**
433	Montgomery County, VA	97.01	106.54	91.48	93.84	**100.21**
434	Mercer County, PA	94.87	118.33	90.10	89.55	**100.14**
435	Jefferson County, WV	91.98	77.11	96.84	100.63	**100.11**
436	Jackson County, OR	97.89	120.94	111.02	91.47	**100.10**
437	Luzerne County, PA	100.38	119.52	101.80	115.28	**100.06**
438	Cumberland County, ME	97.68	108.61	141.55	85.24	**100.02**

439	Okaloosa County, FL	99.83	107.75	104.14	106.77	**99.89**
440	Franklin County, MA	93.71	111.68	96.28	73.74	**99.86**
441	Benton County, WA	99.23	106.96	109.21	102.44	**99.82**
442	Fayette County, WV	90.77	72.70	92.83	94.97	**99.67**
443	Greene County, OH	97.24	105.81	110.71	94.72	**99.64**
444	Houston County, AL	93.43	98.30	107.29	90.96	**99.62**
445	Jackson County, WV	89.00	102.08	65.74	79.73	**99.56**
446	Warren County, NJ	94.71	109.52	91.92	93.25	**99.54**
447	Caddo Parish, LA	97.50	105.54	101.50	117.22	**99.46**
448	Merced County, CA	102.06	120.99	108.60	97.33	**99.44**
449	Whatcom County, WA	96.29	105.51	123.75	94.34	**99.41**
450	New Haven County, CT	107.47	124.31	138.64	103.38	**99.36**
451	Henrico County, VA	105.89	105.71	101.07	121.82	**99.29**
452	Cuyahoga County, OH	111.74	128.79	129.89	118.55	**99.28**
453	Coconino County, AZ	95.62	118.81	123.19	63.93	**99.20**
454	Osage County, OK	92.80	81.91	79.87	99.68	**99.08**
455	Orange County, CA	134.19	138.51	113.38	140.17	**99.07**
456	Washoe County, NV	104.04	106.55	129.67	109.68	**98.95**
457	Rensselaer County, NY	98.62	114.16	101.40	92.79	**98.81**
458	Ouachita Parish, LA	94.53	82.43	120.83	106.93	**98.80**
459	Sagadahoc County, ME	90.59	86.79	89.13	78.14	**98.68**
460	Yuba County, CA	98.35	99.59	80.16	98.37	**98.65**
461	Stanislaus County, CA	109.64	138.16	90.65	115.76	**98.58**
462	Isanti County, MN	92.12	95.41	85.60	75.74	**98.55**
463	Morgan County, AL	95.31	93.27	104.42	100.32	**98.54**
464	Stark County, OH	98.21	112.30	105.01	122.08	**98.49**
465	Delaware County, OH	98.96	100.15	122.84	93.34	**98.39**
466	Suffolk city, VA	96.84	99.94	92.42	91.54	**98.31**
467	Salem County, NJ	94.15	94.72	91.65	86.75	**98.27**
468	Autauga County, AL	96.51	103.79	79.98	82.21	**98.25**
469	Thurston County, WA	98.53	98.25	135.30	95.35	**98.25**
470	Haywood County, NC	91.07	88.54	88.33	96.55	**98.18**
471	Cass County, NE	88.56	84.49	63.73	92.22	**98.03**
472	Alachua County, FL	101.48	100.34	114.03	109.05	**98.00**
473	Fairfield County, CT	110.92	128.76	134.08	100.93	**97.94**
474	Shasta County, CA	95.25	110.10	115.77	86.42	**97.92**
475	Whitley County, IN	91.34	86.75	94.37	65.71	**97.88**
476	Perry County, OH	89.40	95.09	76.48	79.96	**97.86**
477	Adams County, CO	111.53	116.80	89.60	132.11	**97.72**
478	McLennan County, TX	98.20	100.67	106.48	116.16	**97.72**
479	Clark County, OH	96.55	107.40	85.48	105.66	**97.67**

480	Monroe County, NY	104.28	116.26	145.34	98.57	**97.61**
481	Mahoning County, OH	98.09	111.73	104.58	102.09	**97.61**
482	Ozaukee County, WI	93.80	110.89	82.75	91.29	**97.58**
483	Le Sueur County, MN	89.24	84.72	76.93	80.51	**97.43**
484	Russell County, AL	93.31	86.85	82.80	95.88	**97.43**
485	Jessamine County, KY	95.01	95.95	78.09	86.90	**97.41**
486	Calumet County, WI	94.40	92.89	86.23	82.14	**97.36**
487	Cochise County, AZ	95.91	109.72	82.37	102.81	**97.29**
488	San Juan County, NM	92.95	95.12	124.58	76.88	**97.27**
489	Peach County, GA	89.95	81.26	80.00	87.19	**97.26**
490	Howard County, MD	104.25	119.78	116.57	89.55	**97.24**
491	Shiawassee County, MI	92.84	93.99	94.71	84.28	**97.14**
492	Calhoun County, MI	95.14	106.02	95.14	96.85	**97.11**
493	Fairfax County, VA	117.02	118.50	127.64	117.35	**97.06**
494	Fayette County, PA	92.35	94.90	97.70	104.94	**97.04**
495	Upshur County, TX	89.89	92.22	82.21	80.30	**97.03**
496	Hancock County, MS	91.19	79.11	79.70	99.52	**96.99**
497	Rapides Parish, LA	92.32	90.73	103.03	105.04	**96.87**
498	DeKalb County, GA	112.02	113.55	129.64	108.09	**96.85**
499	Sullivan County, TN	92.66	82.41	125.97	97.85	**96.81**
500	Washtenaw County, MI	104.02	108.50	132.05	89.02	**96.76**
501	Pitt County, NC	98.02	98.64	108.60	96.31	**96.66**
502	Contra Costa County, CA	113.55	123.31	119.86	122.54	**96.63**
503	Bowie County, TX	93.34	103.38	81.27	98.82	**96.57**
504	Sarpy County, NE	102.37	106.81	78.27	118.36	**96.51**
505	Sumter County, SC	91.67	87.21	112.81	89.56	**96.36**
506	Deschutes County, OR	96.80	105.06	112.60	92.51	**96.36**
507	Summit County, OH	101.18	117.12	110.88	118.79	**96.36**
508	Putnam County, WV	94.22	99.34	79.55	84.13	**96.34**
509	Saginaw County, MI	96.13	97.44	104.18	107.18	**96.23**
510	Grundy County, IL	92.51	85.08	82.31	92.82	**96.19**
511	Beaver County, PA	95.41	104.41	85.19	115.55	**96.11**
512	Hillsborough County, NH	102.20	112.51	125.34	96.55	**96.11**
513	Middlesex County, MA	122.50	136.33	114.33	119.30	**96.06**
514	Sonoma County, CA	100.86	132.55	108.37	100.92	**96.04**
515	Shelby County, KY	93.02	90.11	92.50	72.45	**96.03**
516	Iberville Parish, LA	92.30	59.16	81.71	96.57	**95.91**
517	Putnam County, IN	89.81	92.54	78.44	76.58	**95.87**
518	Clark County, KY	93.08	62.39	82.79	99.33	**95.83**
519	Clark County, IN	95.66	95.96	90.46	101.09	**95.78**
520	Atascosa County, TX	88.93	73.26	89.94	96.53	**95.70**

521	Pickaway County, OH	93.68	89.78	86.70	85.26	**95.62**
522	Norfolk County, MA	110.79	128.96	102.43	112.18	**95.53**
523	Larimer County, CO	99.93	111.50	111.48	105.92	**95.50**
524	Tioga County, NY	92.12	112.52	79.27	64.18	**95.49**
525	Roanoke County, VA	96.58	96.64	98.79	86.43	**95.27**
526	Calcasieu Parish, LA	95.83	104.26	108.78	99.06	**95.26**
527	Morgan County, IN	92.26	85.30	94.50	90.87	**95.21**
528	San Joaquin County, CA	107.33	129.85	100.81	121.48	**95.16**
529	Smith County, TX	94.97	93.21	120.53	101.72	**95.12**
530	New London County, CT	95.15	100.17	139.27	80.77	**95.09**
531	Pierce County, WA	105.01	108.18	132.96	119.79	**95.04**
532	Lamar County, MS	91.02	82.98	112.57	71.19	**94.98**
533	Craighead County, AR	95.27	93.15	112.09	79.53	**94.96**
534	Essex County, MA	117.15	132.89	94.83	115.36	**94.95**
535	Ulster County, NY	93.44	100.89	127.37	77.66	**94.91**
536	York County, VA	96.11	81.05	87.18	92.28	**94.86**
537	St. Lucie County, FL	102.09	95.16	110.14	116.34	**94.84**
538	Tazewell County, IL	95.23	100.08	81.83	109.20	**94.83**
539	Lowndes County, GA	94.48	92.13	101.05	94.52	**94.79**
540	Hillsborough County, FL	108.14	106.27	138.56	130.63	**94.69**
541	Boone County, IN	94.39	103.96	80.57	82.09	**94.68**
542	Hardin County, TX	90.60	86.87	90.96	83.14	**94.65**
543	Washington County, AR	99.01	104.33	115.16	92.57	**94.62**
544	Lancaster County, PA	101.31	114.22	132.48	96.11	**94.61**
545	Tulare County, CA	100.96	126.80	106.56	103.39	**94.59**
546	Frederick County, MD	97.21	103.85	121.63	92.63	**94.56**
547	Solano County, CA	107.00	119.34	94.69	115.41	**94.56**
548	Newton County, MO	91.21	98.64	79.61	83.57	**94.55**
549	Lake County, IN	101.57	119.76	88.14	130.22	**94.54**
550	Greene County, MO	100.32	110.77	101.47	106.39	**94.53**
551	Penobscot County, ME	92.03	95.72	134.10	69.76	**94.52**
552	El Paso County, TX	107.50	108.48	112.60	133.29	**94.51**
553	Porter County, IN	96.21	101.23	103.79	95.54	**94.50**
554	Creek County, OK	91.43	81.08	88.52	99.76	**94.38**
555	Rusk County, TX	89.25	110.93	74.12	72.94	**94.38**
556	Pierce County, WI	93.97	85.00	83.80	72.39	**94.36**
557	Josephine County, OR	95.04	103.22	83.56	87.15	**94.34**
558	Shelby County, TN	104.96	104.38	138.30	116.64	**94.28**
559	Wayne County, NC	91.78	73.11	123.89	90.98	**94.27**
560	Lake County, OH	100.88	112.38	104.05	90.30	**94.19**
561	Hocking County, OH	89.28	82.61	63.89	86.20	**94.17**

562	Armstrong County, PA	92.55	89.49	88.60	88.68	**94.16**
563	Knox County, TN	99.80	96.87	141.18	99.34	**94.15**
564	Hampshire County, MA	101.45	110.82	103.20	77.15	**94.15**
565	Bristol County, MA	108.59	122.71	99.40	114.28	**94.14**
566	Crawford County, AR	92.38	80.63	96.55	83.89	**94.08**
567	Caldwell County, NC	91.28	83.88	109.25	80.61	**94.01**
568	Whitfield County, GA	95.07	83.65	107.27	87.54	**93.94**
569	Washington County, PA	94.40	106.48	99.11	102.17	**93.90**
570	Ventura County, CA	111.66	128.84	102.86	115.80	**93.86**
571	Forsyth County, NC	99.06	98.59	131.50	98.54	**93.86**
572	Berrien County, MI	93.56	107.65	88.87	100.17	**93.84**
573	Weld County, CO	97.05	107.65	113.46	101.89	**93.73**
574	Anderson County, TN	91.94	76.10	103.46	89.54	**93.67**
575	Logan County, OK	90.38	73.34	95.46	84.61	**93.59**
576	Greene County, VA	90.46	81.03	77.12	59.34	**93.58**
577	Richland County, OH	94.12	99.69	98.32	88.92	**93.53**
578	Linn County, OR	96.26	112.12	86.86	86.88	**93.43**
579	Rockwall County, TX	99.16	86.26	88.13	101.31	**93.42**
580	Gaston County, NC	95.81	95.18	114.48	99.13	**93.30**
581	Highlands County, FL	91.76	82.55	87.52	109.92	**93.18**
582	Cumberland County, PA	98.15	111.39	96.12	102.60	**93.05**
583	Monmouth County, NJ	103.79	131.08	93.51	116.13	**92.94**
584	St. Clair County, IL	95.45	104.32	92.34	116.73	**92.90**
585	Madison County, IL	96.72	108.05	88.99	116.13	**92.83**
586	York County, PA	98.71	106.70	125.84	101.04	**92.81**
587	Bradley County, TN	93.72	75.66	118.33	85.98	**92.80**
588	Salt Lake County, UT	113.32	122.14	111.27	122.91	**92.51**
589	Strafford County, NH	96.35	107.29	94.72	82.12	**92.46**
590	St. Charles Parish, LA	92.79	73.16	83.82	93.78	**92.41**
591	Chippewa County, WI	91.68	89.55	80.54	90.73	**92.29**
592	Cass County, MO	94.66	106.04	76.86	95.16	**92.28**
593	Mathews County, VA	89.27	54.02	74.29	50.41	**92.26**
594	Darlington County, SC	90.33	91.78	87.90	78.92	**92.10**
595	Tulsa County, OK	103.12	111.15	113.01	118.10	**92.07**
596	Kitsap County, WA	97.69	103.40	116.25	92.14	**92.06**
597	Allen County, IN	99.64	105.66	113.01	104.61	**92.00**
598	Valencia County, NM	92.72	85.91	88.32	90.13	**91.97**
599	Nash County, NC	91.89	85.53	101.45	87.31	**91.92**
600	Davis County, UT	106.25	117.46	87.26	108.27	**91.89**
601	Seminole County, FL	106.11	107.53	95.57	121.65	**91.71**
602	Niagara County, NY	97.63	113.77	85.58	100.91	**91.64**

603	Warrick County, IN	95.71	92.26	79.51	83.66	**91.57**
604	Walton County, FL	89.98	69.72	108.77	86.69	**91.40**
605	Appomattox County, VA	88.60	77.11	74.25	53.10	**91.21**
606	Berkeley County, WV	93.56	85.23	103.68	91.66	**91.20**
607	Kent County, DE	94.89	85.88	114.14	95.25	**91.14**
608	St. Clair County, MI	94.07	102.30	96.94	91.81	**91.12**
609	Woodford County, IL	89.04	79.36	68.16	91.10	**91.10**
610	Kent County, MI	100.21	111.31	132.43	97.99	**91.00**
611	Adams County, PA	92.52	94.22	100.64	80.05	**90.99**
612	Gibson County, TN	89.10	87.45	85.12	76.10	**90.92**
613	Hartford County, CT	106.81	117.92	134.22	95.63	**90.89**
614	Placer County, CA	100.75	112.70	104.13	104.28	**90.83**
615	Waller County, TX	91.26	57.89	95.04	98.31	**90.81**
616	St. Charles County, MO	104.13	108.26	93.00	116.17	**90.76**
617	Cobb County, GA	107.84	107.05	122.13	110.73	**90.72**
618	Palm Beach County, FL	108.54	118.15	121.09	126.34	**90.68**
619	Somerset County, NJ	101.76	113.75	95.29	104.08	**90.57**
620	Washington County, RI	92.93	105.29	89.82	85.66	**90.54**
621	Middlesex County, CT	94.47	101.66	112.78	76.00	**90.53**
622	Morris County, NJ	101.84	118.52	109.78	99.89	**90.51**
623	Erie County, NY	108.78	127.94	119.24	99.72	**90.49**
624	Albemarle County, VA	96.12	101.33	99.03	71.71	**90.45**
625	Jefferson County, ID	88.80	80.11	84.34	63.33	**90.43**
626	Sumter County, FL	99.08	75.96	82.25	117.48	**90.43**
627	Lee County, AL	97.02	90.71	114.56	85.68	**90.38**
628	Gloucester County, NJ	99.99	116.85	85.18	105.10	**90.38**
629	Kalamazoo County, MI	97.27	104.71	107.52	93.43	**90.35**
630	Bossier Parish, LA	94.31	84.68	101.61	94.48	**90.35**
631	Ocean County, NJ	107.72	108.66	95.57	127.78	**90.30**
632	Caldwell County, TX	89.62	68.46	81.45	92.01	**90.26**
633	Madison County, TN	94.84	99.02	82.05	87.32	**90.26**
634	DuPage County, IL	111.44	124.80	88.64	129.24	**90.24**
635	Hamilton County, IN	100.95	96.74	111.22	104.73	**90.21**
636	East Baton Rouge Parish, LA	102.71	102.58	101.74	118.04	**90.21**
637	Alamance County, NC	95.54	102.51	93.19	93.64	**90.17**
638	Columbia County, WI	89.18	90.44	76.79	85.36	**90.12**
639	Cecil County, MD	92.38	87.53	101.46	84.15	**90.11**
640	Duval County, FL	105.70	103.18	121.00	126.55	**90.03**
641	Kane County, IL	102.83	114.24	95.79	116.59	**89.95**
642	Miami County, OH	92.14	98.98	77.34	97.79	**89.90**
643	Guadalupe County, TX	98.48	85.77	101.42	98.80	**89.89**

644	James City County, VA	95.53	86.85	79.82	92.77	**89.86**
645	Bell County, TX	99.36	97.84	105.96	112.50	**89.82**
646	Elkhart County, IN	95.80	96.59	94.71	104.95	**89.80**
647	Hamilton County, TN	97.79	93.90	117.44	105.94	**89.77**
648	Goochland County, VA	89.68	90.76	70.86	59.38	**89.74**
649	Monroe County, MI	92.71	92.19	114.32	80.65	**89.71**
650	Wood County, OH	94.77	103.71	90.89	85.05	**89.63**
651	Jefferson County, CO	106.64	121.15	88.34	118.05	**89.57**
652	Washington County, MN	99.78	105.62	91.42	104.95	**89.46**
653	Franklin County, MO	90.84	90.85	92.67	89.20	**89.46**
654	Platte County, MO	97.42	95.73	77.78	93.35	**89.45**
655	Carver County, MN	94.84	93.52	85.79	90.11	**89.37**
656	Coryell County, TX	96.77	83.35	84.56	89.25	**89.35**
657	St. Louis County, MO	107.20	113.91	111.36	122.91	**89.30**
658	Boone County, KY	99.11	90.76	94.41	89.95	**89.29**
659	Pima County, AZ	102.97	107.32	132.36	113.60	**89.29**
660	Clark County, NV	119.51	109.31	128.14	130.75	**89.25**
661	Madera County, CA	96.50	105.56	94.18	83.93	**89.23**
662	Dearborn County, IN	90.17	72.88	88.79	81.60	**89.20**
663	Campbell County, TN	89.16	70.31	79.38	84.09	**89.11**
664	McClain County, OK	89.52	79.19	68.30	88.50	**89.02**
665	El Paso County, CO	104.52	112.81	101.57	121.81	**88.86**
666	Montgomery County, TN	97.78	76.95	133.80	83.39	**88.79**
667	Lake County, IL	103.80	111.40	106.92	117.49	**88.78**
668	Carroll County, OH	88.75	82.49	68.29	66.95	**88.74**
669	Clark County, WA	104.53	112.36	94.64	113.64	**88.69**
670	Johnson County, IN	98.04	106.32	81.98	92.86	**88.67**
671	Brown County, WI	98.42	115.55	86.09	99.44	**88.63**
672	Eaton County, MI	93.55	104.40	84.83	80.37	**88.57**
673	Clay County, MO	100.06	101.89	90.70	104.10	**88.51**
674	Montgomery County, PA	106.89	127.80	97.95	116.33	**88.44**
675	Spalding County, GA	93.26	77.83	80.55	90.63	**88.43**
676	Scott County, MN	97.92	101.51	79.79	97.21	**88.40**
677	Washington County, UT	97.70	96.34	88.75	100.03	**88.38**
678	Butler County, OH	101.55	106.41	99.82	106.60	**88.37**
679	Washington County, TN	94.29	82.78	97.30	96.33	**88.36**
680	Madison County, MS	93.80	85.36	96.37	86.91	**88.35**
681	Dutchess County, NY	95.73	107.96	118.59	80.11	**88.34**
682	Loudoun County, VA	103.80	113.96	84.66	114.46	**88.27**
683	Clackamas County, OR	100.46	122.41	92.64	101.57	**88.25**
684	Rowan County, NC	92.22	88.46	101.57	91.62	**88.24**

685	Barnstable County, MA	91.90	108.85	85.90	105.40	**88.22**
686	Jefferson County, NY	93.62	90.93	97.86	82.35	**88.20**
687	Dakota County, MN	105.32	110.58	87.22	114.85	**88.16**
688	Jasper County, IN	88.76	94.11	70.66	59.66	**88.15**
689	Trumbull County, OH	95.06	106.08	86.80	98.88	**88.14**
690	Canyon County, ID	98.57	109.44	83.60	101.05	**88.12**
691	Hancock County, IN	92.89	82.93	87.27	87.66	**88.11**
692	Fairfield County, OH	96.16	93.37	92.26	94.70	**88.11**
693	Burlington County, NJ	100.70	112.27	104.44	102.81	**88.07**
694	Anne Arundel County, MD	105.12	108.98	101.63	114.45	**87.96**
695	Culpeper County, VA	90.59	78.04	90.66	71.87	**87.88**
696	Catoosa County, GA	93.00	81.32	81.64	86.46	**87.79**
697	Craven County, NC	92.25	83.02	90.67	90.90	**87.72**
698	Prince George's County, MD	113.90	119.36	95.60	120.13	**87.52**
699	Baltimore County, MD	109.26	123.40	102.24	108.38	**87.51**
700	Faulkner County, AR	94.05	87.31	104.54	79.43	**87.49**
701	Cleveland County, OK	101.18	103.81	96.46	98.96	**87.44**
702	Westmoreland County, PA	95.31	107.66	95.20	111.91	**87.40**
703	Ionia County, MI	93.20	78.46	92.02	76.31	**87.34**
704	Tooele County, UT	97.98	91.70	76.50	77.06	**87.27**
705	Rogers County, OK	91.54	77.63	92.98	91.88	**87.26**
706	Oswego County, NY	93.49	89.56	106.95	72.68	**87.17**
707	Dorchester County, SC	103.26	98.61	76.39	97.25	**87.12**
708	Henderson County, NC	91.68	90.53	86.50	91.65	**87.07**
709	Lincoln County, MO	91.10	60.60	107.15	76.49	**86.99**
710	Sequatchie County, TN	88.99	51.74	75.56	64.33	**86.81**
711	Guilford County, NC	99.94	107.13	115.90	100.32	**86.75**
712	Pottawatomie County, KS	88.97	68.04	59.78	85.76	**86.75**
713	Clayton County, GA	106.72	93.07	92.43	104.82	**86.49**
714	Utah County, UT	106.91	119.66	95.85	108.09	**86.44**
715	Houston County, GA	97.93	97.11	79.77	97.47	**86.40**
716	Greenville County, SC	99.34	100.24	125.49	96.17	**86.38**
717	Marion County, FL	93.86	81.96	125.60	106.07	**86.38**
718	Volusia County, FL	99.12	101.57	101.54	120.75	**86.33**
719	Madison County, NY	91.60	103.11	80.46	65.32	**86.27**
720	Marion County, TN	89.01	70.61	60.28	82.79	**86.13**
721	Harrison County, TX	89.00	75.49	84.33	89.04	**86.10**
722	Butler County, PA	93.88	98.82	105.88	81.35	**86.09**
723	Johnson County, KS	105.60	114.53	94.01	112.44	**86.07**
724	Orange County, FL	109.63	99.52	124.55	126.86	**86.03**
725	Lee County, FL	101.01	97.96	113.95	122.01	**85.91**

726	Windham County, CT	93.23	94.90	104.01	66.91	**85.77**
727	Catawba County, NC	92.81	79.93	108.25	90.24	**85.66**
728	St. Croix County, WI	91.93	91.88	90.07	75.33	**85.63**
729	Rockdale County, GA	96.37	85.23	83.74	84.68	**85.62**
730	Bryan County, GA	91.94	66.34	93.13	67.95	**85.58**
731	Putnam County, NY	93.49	92.56	80.24	84.53	**85.54**
732	Callaway County, MO	89.21	83.92	75.96	69.47	**85.54**
733	Washington County, WI	93.46	99.25	91.40	80.09	**85.44**
734	Hunt County, TX	91.12	68.61	100.10	91.56	**85.41**
735	St. Tammany Parish, LA	96.26	91.62	98.05	104.87	**85.40**
736	Hall County, GA	94.35	81.74	114.00	90.07	**85.39**
737	Brown County, OH	89.21	80.31	71.19	76.79	**85.28**
738	Genesee County, MI	96.15	99.36	103.25	109.04	**85.28**
739	Washington County, VA	89.58	78.67	86.18	71.42	**85.21**
740	Christian County, MO	91.66	87.40	83.18	83.49	**85.17**
741	Washington County, NY	92.14	87.55	88.68	62.01	**85.11**
742	Licking County, OH	94.63	91.69	96.03	91.14	**84.96**
743	Worcester County, MA	103.58	117.60	125.82	90.48	**84.89**
744	Williamson County, TN	95.94	78.16	124.61	88.59	**84.86**
745	Kendall County, IL	98.08	81.94	84.66	96.40	**84.80**
746	Carter County, KY	88.74	48.62	75.07	84.43	**84.78**
747	Pike County, PA	90.55	40.43	113.42	82.23	**84.74**
748	Oconee County, GA	90.59	79.27	74.37	70.03	**84.66**
749	Mohave County, AZ	96.14	94.41	96.69	91.43	**84.65**
750	Lancaster County, SC	92.43	86.03	82.87	85.28	**84.64**
751	Shelby County, AL	94.41	76.21	120.26	90.54	**84.57**
752	San Diego County, CA	120.30	125.70	126.41	118.32	**84.53**
753	Sandoval County, NM	100.38	92.10	80.23	91.97	**84.43**
754	Campbell County, VA	90.82	85.78	81.05	68.97	**84.37**
755	Botetourt County, VA	89.14	67.06	80.33	68.03	**84.37**
756	Person County, NC	89.20	78.13	84.54	58.83	**84.36**
757	Levy County, FL	88.21	65.11	71.37	90.07	**84.31**
758	Loudon County, TN	90.60	62.06	84.93	87.14	**84.30**
759	Tolland County, CT	94.45	82.32	123.41	62.95	**84.28**
760	Hawkins County, TN	89.48	73.49	86.68	75.91	**84.25**
761	Midland County, MI	95.99	86.00	84.68	74.14	**84.14**
762	Wyoming County, PA	88.81	76.61	69.71	59.84	**84.08**
763	Osceola County, FL	101.90	84.94	95.76	120.58	**84.08**
764	Clay County, FL	98.29	84.77	108.58	87.87	**84.02**
765	Pickens County, SC	91.91	82.82	101.36	82.28	**83.91**
766	St. Martin Parish, LA	89.75	68.27	80.16	83.42	**83.91**

767	Ontario County, NY	93.68	98.90	93.70	65.39	**83.89**
768	Collin County, TX	106.89	102.91	110.56	122.92	**83.87**
769	Webster County, MO	89.17	81.66	68.83	69.71	**83.82**
770	McDuffie County, GA	88.92	52.33	73.98	69.77	**83.77**
771	Canadian County, OK	98.33	96.80	80.24	89.58	**83.77**
772	Franklin County, VT	92.36	76.39	88.52	61.72	**83.71**
773	Saline County, AR	91.89	75.53	108.15	79.83	**83.71**
774	Meade County, KY	89.56	50.76	91.78	66.00	**83.69**
775	Fresno County, CA	104.74	127.80	100.70	107.21	**83.67**
776	Dawson County, GA	89.71	57.09	81.02	65.39	**83.54**
777	Franklin County, PA	93.12	94.81	93.25	83.28	**83.54**
778	Madison County, AL	96.79	88.58	118.67	97.30	**83.44**
779	Tarrant County, TX	109.92	113.17	112.49	134.18	**83.38**
780	Anoka County, MN	100.60	107.65	86.12	103.90	**83.31**
781	Saratoga County, NY	94.00	93.77	111.11	81.29	**83.28**
782	Isle of Wight County, VA	90.69	79.99	70.65	65.19	**83.20**
783	Murray County, GA	89.95	62.24	83.86	72.93	**83.18**
784	Fort Bend County, TX	106.12	89.57	117.35	117.97	**83.15**
785	Gadsden County, FL	89.21	59.16	73.55	90.32	**83.14**
786	Marshall County, MS	88.83	74.76	70.01	67.98	**83.11**
787	Cumberland County, NC	98.83	96.01	102.32	96.83	**83.10**
788	Warren County, OH	98.29	90.48	102.35	89.67	**82.97**
789	Nassau County, FL	91.65	73.74	85.40	89.99	**82.88**
790	Harris County, TX	115.57	115.92	135.04	134.62	**82.85**
791	Mobile County, AL	97.14	99.82	104.36	100.08	**82.50**
792	Bullitt County, KY	93.87	75.75	84.37	83.14	**82.44**
793	Rockingham County, VA	91.13	80.84	89.64	75.68	**82.39**
794	Amherst County, VA	89.43	71.92	78.00	57.81	**82.33**
795	Spartanburg County, SC	93.58	87.55	117.00	93.51	**82.24**
796	Blount County, TN	93.20	70.50	105.74	86.05	**82.22**
797	Cameron County, TX	100.34	100.34	93.99	106.87	**82.22**
798	Anderson County, SC	91.58	75.10	123.12	81.87	**82.21**
799	Hunterdon County, NJ	92.11	93.26	97.61	70.20	**81.93**
800	Harrison County, IN	89.20	67.47	82.48	65.70	**81.90**
801	St. Johns County, FL	96.82	81.30	98.73	105.08	**81.72**
802	Plymouth County, MA	100.04	102.48	110.86	95.85	**81.72**
803	Lorain County, OH	98.22	109.34	84.62	95.83	**81.62**
804	Comal County, TX	93.80	74.45	101.88	90.73	**81.55**
805	Clinton County, MI	91.21	86.85	84.32	69.58	**81.50**
806	Hays County, TX	97.05	79.04	106.89	94.27	**81.50**
807	Orange County, TX	89.97	63.29	85.84	95.43	**81.43**

808	Robertson County, TN	91.50	80.27	91.64	66.20	**81.41**
809	Lee County, GA	89.74	56.49	79.91	70.35	**81.41**
810	Andrew County, MO	88.51	42.90	71.97	69.08	**81.39**
811	Fayette County, GA	93.24	93.46	82.08	81.09	**81.35**
812	Douglas County, CO	101.58	95.72	90.49	104.87	**81.32**
813	Brevard County, FL	102.10	98.65	97.53	115.45	**81.18**
814	Suffolk County, NY	105.01	121.42	104.68	119.76	**81.13**
815	Johnson County, TX	93.30	79.73	95.35	95.89	**81.11**
816	Medina County, TX	88.92	54.90	77.63	91.50	**81.10**
817	Monroe County, PA	92.42	78.00	108.80	82.70	**81.08**
818	Kern County, CA	103.58	125.83	99.17	101.05	**81.01**
819	Oakland County, MI	104.35	112.80	116.31	109.82	**81.00**
820	Walker County, GA	91.73	70.90	84.05	77.99	**80.99**
821	Ascension Parish, LA	94.20	85.76	80.30	89.44	**80.97**
822	Orange County, NY	102.24	110.99	97.17	86.37	**80.95**
823	Dinwiddie County, VA	89.20	73.80	79.25	46.10	**80.95**
824	Harford County, MD	99.66	101.30	88.82	89.12	**80.94**
825	Union County, OH	92.36	68.06	80.37	78.40	**80.90**
826	Fauquier County, VA	90.43	78.09	95.30	63.30	**80.89**
827	Flagler County, FL	97.36	77.68	78.72	90.60	**80.48**
828	Hendricks County, IN	96.62	88.97	80.50	95.24	**80.41**
829	Macomb County, MI	107.77	122.12	86.72	110.03	**80.34**
830	El Dorado County, CA	94.20	87.80	98.92	83.91	**80.20**
831	Prince George County, VA	91.10	65.15	74.03	78.87	**80.15**
832	Wagoner County, OK	93.14	61.85	79.82	94.57	**80.15**
833	Pickens County, GA	89.55	48.96	85.61	69.81	**80.07**
834	Wake County, NC	103.75	106.06	117.99	107.92	**79.99**
835	Queen Anne's County, MD	89.64	77.48	74.73	65.50	**79.87**
836	Gloucester County, VA	90.69	51.20	86.64	70.02	**79.84**
837	Roane County, TN	89.10	54.53	83.87	83.42	**79.82**
838	Sussex County, NJ	93.93	86.76	92.66	78.16	**79.82**
839	Bartow County, GA	92.01	75.09	91.41	81.81	**79.59**
840	Wise County, TX	88.93	54.43	95.72	82.28	**79.58**
841	Citrus County, FL	90.62	66.43	95.42	101.34	**79.51**
842	Alexander County, NC	89.50	72.78	77.84	55.08	**79.40**
843	Collier County, FL	99.33	97.07	86.61	106.05	**79.28**
844	Waukesha County, WI	96.44	105.83	89.24	101.13	**79.27**
845	Haralson County, GA	89.21	53.72	71.22	73.62	**79.27**
846	Benton County, AR	95.59	87.17	103.37	92.03	**79.23**
847	Lake County, FL	96.56	82.09	100.81	110.53	**79.15**
848	Chester County, PA	97.64	105.23	109.23	91.85	**79.08**

849	Perry County, PA	89.21	69.98	73.87	68.67	**79.08**
850	Prince William County, VA	107.80	97.58	81.96	111.95	**79.03**
851	Yavapai County, AZ	95.30	94.46	92.80	87.12	**78.90**
852	Spotsylvania County, VA	97.51	81.17	83.39	86.57	**78.87**
853	Stafford County, VA	98.66	82.73	82.17	90.21	**78.75**
854	Jones County, GA	89.38	51.10	77.14	64.10	**78.73**
855	Portage County, OH	93.99	83.00	98.74	78.17	**78.73**
856	Bexar County, TX	107.78	107.07	118.01	123.09	**78.71**
857	Burke County, NC	90.01	71.84	88.64	78.21	**78.66**
858	Hoke County, NC	92.29	58.28	87.89	72.44	**78.56**
859	Davie County, NC	89.78	63.73	80.03	66.76	**78.53**
860	Calvert County, MD	94.03	63.55	82.80	89.72	**78.46**
861	Kaufman County, TX	93.09	67.57	89.51	98.61	**78.42**
862	Chesterfield County, VA	100.40	84.44	107.00	94.59	**78.34**
863	Chilton County, AL	88.73	67.73	82.69	61.92	**78.22**
864	Laurens County, SC	89.31	58.04	90.70	78.58	**78.11**
865	Newton County, GA	93.40	58.25	103.78	79.90	**77.97**
866	Lawrence County, AL	88.48	60.96	76.84	61.34	**77.96**
867	Chisago County, MN	89.91	71.66	73.83	73.88	**77.96**
868	Yates County, NY	88.69	62.44	68.80	55.63	**77.90**
869	Cabarrus County, NC	97.40	89.29	79.68	99.00	**77.87**
870	Frederick County, VA	93.92	70.63	88.08	75.75	**77.81**
871	Monroe County, GA	88.77	56.91	70.68	63.21	**77.68**
872	Ottawa County, MI	97.03	96.61	94.44	87.51	**77.63**
873	Bibb County, AL	88.42	43.77	66.39	71.72	**77.62**
874	Hanover County, VA	93.79	85.04	81.15	76.07	**77.57**
875	Sherburne County, MN	91.28	67.35	89.85	81.23	**77.55**
876	Douglas County, GA	95.67	81.63	88.40	80.47	**77.55**
877	Lonoke County, AR	90.92	56.65	91.52	80.08	**77.54**
878	Bastrop County, TX	89.77	67.88	82.45	89.94	**77.44**
879	Carroll County, GA	91.15	68.27	109.54	68.95	**77.39**
880	Montcalm County, MI	89.34	65.35	79.07	80.74	**77.38**
881	Rankin County, MS	93.36	71.87	97.58	86.09	**77.25**
882	Hernando County, FL	96.92	74.19	80.10	106.32	**77.24**
883	Chatham County, NC	89.69	80.20	76.98	72.82	**77.21**
884	Maricopa County, AZ	111.77	113.59	134.39	124.22	**77.20**
885	Horry County, SC	95.12	84.84	96.26	105.12	**77.19**
886	Aiken County, SC	91.81	78.37	84.63	96.51	**77.14**
887	Polk County, FL	98.32	82.61	111.46	118.09	**77.12**
888	McHenry County, IL	97.89	96.67	81.83	99.64	**77.06**
889	Santa Rosa County, FL	93.50	78.37	101.00	83.57	**77.05**

890	Rockingham County, NC	90.47	73.24	84.48	77.75	**76.89**
891	Bucks County, PA	101.93	118.01	86.29	98.83	**76.84**
892	Ellis County, TX	92.73	76.37	92.65	94.22	**76.78**
893	Tangipahoa Parish, LA	91.70	72.39	88.92	87.90	**76.72**
894	Lapeer County, MI	91.17	64.09	107.38	61.68	**76.69**
895	Beaufort County, SC	93.17	82.60	79.34	98.28	**76.68**
896	Hidalgo County, TX	101.69	94.11	105.38	114.69	**76.29**
897	Williamson County, TX	102.12	99.54	91.30	108.36	**76.28**
898	Snohomish County, WA	104.65	109.38	99.17	100.45	**76.22**
899	Madison County, NC	88.69	38.73	68.13	69.22	**76.18**
900	Charles County, MD	96.90	74.63	91.50	84.53	**76.07**
901	Clarendon County, SC	89.41	39.29	92.62	59.08	**75.97**
902	Iredell County, NC	93.82	85.11	86.61	86.50	**75.77**
903	Maury County, TN	93.13	69.07	86.42	78.62	**75.71**
904	Brazoria County, TX	97.39	89.44	92.87	99.49	**75.62**
905	Morgan County, GA	88.68	49.48	63.40	60.05	**75.51**
906	Denton County, TX	104.67	99.42	92.48	117.98	**75.13**
907	Preston County, WV	88.99	55.80	76.60	59.85	**74.89**
908	Onslow County, NC	94.17	78.89	96.61	83.54	**74.75**
909	DeSoto County, MS	94.99	77.69	90.61	85.93	**74.72**
910	Clermont County, OH	96.84	90.53	80.95	85.34	**74.54**
911	York County, SC	96.44	86.08	94.26	89.23	**74.52**
912	Cass County, MI	89.16	60.70	72.27	74.57	**74.43**
913	Gwinnett County, GA	107.93	103.11	104.43	98.73	**74.37**
914	Columbia County, GA	96.55	83.81	79.62	80.86	**74.11**
915	Coweta County, GA	93.30	79.28	89.25	76.71	**74.10**
916	Wilson County, TX	89.13	43.07	86.75	75.11	**74.02**
917	Warren County, MO	89.53	48.49	72.61	69.69	**73.93**
918	Wright County, MN	91.20	86.35	80.05	77.45	**73.89**
919	Barrow County, GA	92.18	69.52	77.61	75.75	**73.81**
920	Carroll County, MD	93.10	82.76	87.97	79.85	**73.81**
921	Wakulla County, FL	88.97	32.75	87.23	68.10	**73.76**
922	Medina County, OH	95.27	95.59	82.00	73.28	**73.76**
923	St. Mary's County, MD	92.46	61.14	93.12	80.17	**73.75**
924	Rockingham County, NH	93.37	92.44	104.60	77.51	**73.61**
925	Wayne County, NY	90.36	80.09	87.03	59.85	**73.46**
926	Jefferson County, MO	94.36	81.08	85.97	92.06	**73.43**
927	York County, ME	92.09	88.11	97.61	73.57	**73.25**
928	Wilson County, TN	93.01	73.61	96.99	72.57	**73.15**
929	Bedford County, VA	89.64	75.33	88.73	55.83	**73.13**
930	Kershaw County, SC	89.32	70.55	73.24	69.65	**73.01**

931	Will County, IL	100.92	106.71	85.37	105.76	**72.92**
932	Pasco County, FL	99.70	87.48	80.81	121.36	**72.84**
933	Parker County, TX	90.54	66.88	95.22	82.54	**72.76**
934	Stokes County, NC	89.26	51.38	87.01	58.65	**72.71**
935	Butts County, GA	89.88	33.69	72.79	66.40	**72.69**
936	Cherokee County, GA	98.08	93.36	81.26	85.70	**72.68**
937	Davidson County, NC	91.56	79.73	86.15	81.25	**72.48**
938	Dade County, GA	88.93	12.25	78.00	64.55	**72.27**
939	Brunswick County, NC	90.19	71.13	77.35	97.48	**72.20**
940	Scott County, VA	88.57	31.56	63.04	72.35	**72.17**
941	Limestone County, AL	90.58	62.51	87.15	78.81	**72.14**
942	Cheatham County, TN	89.85	52.79	85.26	52.64	**72.10**
943	Jefferson County, TN	89.56	52.59	80.80	72.01	**71.93**
944	New Kent County, VA	89.37	33.81	64.60	67.86	**71.91**
945	Livingston County, MI	91.93	78.59	96.64	76.59	**71.88**
946	Oldham County, KY	91.36	69.08	71.88	71.63	**71.82**
947	Granville County, NC	89.84	58.60	84.79	63.58	**71.75**
948	Tipton County, TN	91.73	35.33	99.62	69.74	**71.74**
949	Pender County, NC	89.75	64.50	74.47	66.17	**71.70**
950	Montgomery County, TX	96.72	85.13	117.15	90.94	**71.51**
951	Union County, NC	94.15	80.21	88.10	88.30	**71.47**
952	Madison County, GA	89.36	50.22	69.76	58.34	**71.33**
953	Effingham County, GA	89.87	46.10	81.55	80.36	**71.26**
954	Lexington County, SC	93.88	86.38	93.29	84.85	**71.23**
955	Elmore County, AL	90.00	51.48	92.65	75.87	**71.17**
956	Sussex County, DE	91.28	75.59	88.50	94.64	**71.09**
957	Baker County, FL	88.62	23.98	80.31	71.02	**71.09**
958	Lincoln County, NC	91.02	62.62	87.70	67.46	**70.82**
959	Berkeley County, SC	96.91	80.53	78.90	89.32	**70.81**
960	Grainger County, TN	88.93	32.66	71.84	60.53	**70.80**
961	Dickson County, TN	89.42	55.94	75.41	68.46	**70.62**
962	Augusta County, VA	89.33	69.67	84.64	61.69	**70.40**
963	Grant County, KY	89.37	31.13	69.89	66.43	**70.36**
964	Baldwin County, AL	90.95	82.48	80.53	92.65	**70.20**
965	Henry County, GA	95.12	77.17	94.34	81.74	**70.14**
966	Geauga County, OH	89.99	84.22	85.07	52.27	**70.10**
967	Randolph County, NC	90.62	75.09	89.80	70.31	**69.52**
968	Franklin County, VA	89.00	48.96	96.56	51.45	**69.46**
969	Fluvanna County, VA	90.07	44.55	69.23	54.00	**69.42**
970	Sumner County, TN	95.51	76.08	89.38	75.61	**69.04**
971	Oconto County, WI	88.40	45.25	73.85	64.10	**68.99**

972	Forsyth County, GA	99.41	85.01	79.85	81.66	**68.64**
973	Rutherford County, TN	98.34	75.44	95.52	88.58	**68.42**
974	Pinal County, AZ	99.71	71.61	93.82	100.34	**67.88**
975	St. Clair County, AL	89.79	47.82	87.25	76.79	**67.84**
976	Union County, TN	88.94	24.65	74.25	52.06	**66.99**
977	Spencer County, KY	89.57	19.87	66.12	61.46	**66.93**
978	Johnston County, NC	91.46	69.29	93.58	81.19	**66.84**
979	Harnett County, NC	90.50	57.96	81.05	85.56	**66.52**
980	Yadkin County, NC	89.13	49.29	73.18	51.77	**66.39**
981	Walton County, GA	90.77	65.30	81.20	63.39	**66.15**
982	San Bernardino County, CA	107.94	116.76	102.06	100.32	**65.91**
983	Liberty County, TX	88.98	34.02	89.76	85.46	**65.88**
984	Livingston Parish, LA	92.14	61.47	86.81	73.04	**64.80**
985	Franklin County, NC	89.96	47.71	77.81	70.02	**64.80**
986	Paulding County, GA	94.00	64.70	79.64	77.21	**63.18**
987	Fayette County, TN	89.02	45.44	69.57	54.20	**62.65**
988	Chambers County, TX	89.15	24.34	68.10	82.63	**62.19**
989	Blount County, AL	89.04	27.55	81.75	71.98	**62.02**
990	Currituck County, NC	89.34	14.78	71.02	64.81	**61.82**
991	Riverside County, CA	106.09	113.07	96.81	104.00	**61.77**
992	Powhatan County, VA	89.91	42.04	63.98	44.49	**60.82**
993	Grant Parish, LA	88.33	3.98	66.63	68.30	**60.55**
994	Pike County, GA	89.35	14.71	59.60	50.11	**56.76**
995	Harris County, GA	89.03	17.82	64.81	61.57	**55.30**

Appendix C. 2020 Metropolitan Indices

Below is the full list of compactness index scores for 202 medium-sized and large metropolitan areas and 13 metropolitan divisions in 11 largest metropolitan areas. The table also presents individual scores for each four dimensions of index. All regions are census-defined Metropolitan Statistical Areas unless marked with an asterisk (*). These are Metropolitan Divisions.

Table C1: 2020 Metropolitan Compactness Score rankings

Rank	Metro area	Density score	Mixed land use score	Activity centering score	Street connectivity score	**Composite (overall) score**
1	San Francisco-San Mateo-Redwood City, CA*	229.03	160.91	238.93	170.86	**242.91**
2	New York-Jersey City-White Plains, NY-NJ*	323.19	170.43	190.70	173.01	**227.38**
3	Philadelphia, PA*	229.05	161.07	168.18	199.64	**220.82**
4	Miami-Miami Beach-Kendall, FL*	173.35	133.51	127.33	177.35	**158.37**
5	Trenton-Princeton, NJ	132.91	120.01	122.02	128.79	**152.23**
6	Boston, MA*	158.16	133.56	150.39	125.17	**145.92**
7	Chicago-Naperville-Evanston, IL*	175.31	138.61	152.95	158.52	**145.10**
8	Santa Maria-Santa Barbara, CA	115.74	148.11	99.71	124.76	**143.32**
9	San Rafael, CA*	108.92	150.72	94.14	105.02	**141.74**
10	Boulder, CO	106.30	121.68	122.81	118.72	**141.66**
11	Los Angeles-Long Beach-Glendale, CA*	183.51	160.02	123.76	154.76	**137.69**
12	Champaign-Urbana, IL*	99.03	126.07	124.96	87.74	**136.47**
13	San Luis Obispo-Paso Robles, CA	94.51	143.17	104.53	104.26	**135.40**
14	Springfield, IL	88.72	87.53	151.06	104.32	**135.23**
15	Detroit-Dearborn-Livonia, MI*	120.86	123.18	117.95	169.90	**134.37**
16	Anaheim-Santa Ana-Irvine, CA*	154.26	148.59	96.81	155.45	**132.72**
17	Erie, PA	95.40	135.04	109.47	96.66	**132.24**
18	Charleston, WV	85.08	88.28	159.81	97.86	**130.89**
19	Santa Cruz-Watsonville, CA	103.19	132.50	85.30	110.83	**130.35**
20	Oakland-Berkeley-Livermore, CA*	140.41	142.37	110.03	148.80	**130.31**
21	Fort Lauderdale-Pompano Beach-Sunrise, FL*	139.41	130.19	86.81	169.14	**129.47**
22	Atlantic City-Hammonton, NJ	96.20	89.24	130.02	114.49	**129.35**
23	Lincoln, NE	104.71	132.15	90.10	112.28	**128.98**
24	Eugene-Springfield, OR	98.72	137.75	117.51	89.68	**128.50**
25	Yakima, WA	89.78	118.95	132.11	81.53	**127.60**
26	Madison, WI	112.72	114.17	147.95	90.81	**126.34**
27	Yuma, AZ	91.68	71.44	137.99	106.77	**126.19**
28	San Jose-Sunnyvale-Santa Clara, CA	145.93	139.07	91.03	139.26	**125.68**
29	Columbia, MO	94.40	102.44	142.55	65.65	**124.42**
30	Reading, PA	104.81	118.36	107.68	104.40	**122.99**

31	Seattle-Bellevue-Kent, WA*	140.56	120.24	140.84	125.85	**122.24**
32	Tuscaloosa, AL	83.41	90.09	156.42	78.78	**121.29**
33	College Station-Bryan, TX	96.87	98.53	104.50	107.95	**120.97**
34	Rochester, MN	97.14	85.87	143.03	72.28	**120.40**
35	Bridgeport-Stamford-Norwalk, CT	111.17	131.55	122.04	101.33	**120.11**
36	Burlington-South Burlington, VT	90.49	100.06	159.76	46.74	**119.95**
37	Amarillo, TX	90.61	105.20	96.01	113.04	**119.75**
38	Duluth, MN-WI	84.89	118.25	132.21	69.91	**118.40**
39	Laredo, TX	106.80	94.76	66.34	133.25	**118.38**
40	Cedar Rapids, IA	90.70	109.40	116.95	83.51	**117.49**
41	Spokane-Spokane Valley, WA	94.06	108.25	108.64	124.80	**117.28**
42	New Haven-Milford, CT	109.77	123.38	114.97	105.51	**117.01**
43	Salinas, CA	105.55	133.86	84.57	96.07	**116.48**
44	Las Cruces, NM	88.14	101.02	98.71	99.28	**116.34**
45	Denver-Aurora-Lakewood, CO	124.60	119.98	129.77	135.47	**116.03**
46	Reno, NV	102.63	91.87	123.36	105.96	**115.88**
47	Modesto, CA	108.91	147.67	58.31	114.10	**115.67**
48	Lexington-Fayette, KY	99.46	100.85	132.18	92.98	**115.55**
49	Fargo, ND-MN	102.93	126.39	87.61	72.20	**114.85**
50	Corpus Christi, TX	100.92	111.09	78.51	122.70	**114.66**
51	Rockford, IL	91.91	106.83	81.84	119.23	**113.33**
52	Salem, OR	95.74	121.29	100.89	91.61	**112.53**
53	Medford, OR	89.34	118.44	102.03	68.10	**112.52**
54	South Bend-Mishawaka, IN-MI	90.25	97.25	91.16	116.88	**112.46**
55	Santa Rosa-Petaluma, CA	94.28	138.03	86.95	94.80	**112.06**
56	Lubbock, TX	95.31	116.51	77.36	104.60	**111.93**
57	New Orleans-Metairie, LA	104.48	117.06	95.93	141.71	**111.92**
58	Chico, CA	90.47	124.41	80.79	77.47	**111.64**
59	Salt Lake City, UT	119.85	120.13	92.03	124.04	**110.86**
60	Portland-Vancouver-Hillsboro, OR-WA	117.21	133.58	112.00	125.51	**110.58**
61	Frederick-Gaithersburg-Rockville, MD*	116.02	123.28	108.34	109.01	**109.99**
62	Milwaukee-Waukesha, WI	109.77	125.72	104.04	124.23	**109.67**
63	Stockton, CA	107.36	133.35	67.60	121.86	**109.63**
64	Binghamton, NY	90.31	116.16	103.30	64.62	**109.18**
65	Nassau County-Suffolk County, NY*	117.18	141.73	86.08	146.76	**109.10**
66	Omaha-Council Bluffs, NE-IA	100.51	116.31	110.64	111.44	**108.99**
67	Oxnard-Thousand Oaks-Ventura, CA	106.68	131.78	74.13	118.32	**108.46**
68	Utica-Rome, NY	89.58	110.37	119.17	61.34	**108.42**
69	Las Vegas-Henderson-Paradise, NV	128.68	97.37	109.71	141.78	**108.26**
70	Merced, CA	95.39	118.38	87.20	76.84	**108.09**
71	Appleton, WI	87.68	105.69	90.25	86.96	**107.97**

72	Manchester-Nashua, NH	96.95	102.52	107.81	89.55	**107.94**
73	Scranton--Wilkes-Barre, PA	91.08	117.46	88.49	113.57	**107.84**
74	Bellingham, WA	88.34	90.41	105.46	80.53	**107.00**
75	Olympia-Lacey-Tumwater, WA	90.71	78.69	120.20	87.13	**106.77**
76	Providence-Warwick, RI-MA	107.18	133.18	95.52	123.47	**106.74**
77	Allentown-Bethlehem-Easton, PA-NJ	100.42	118.03	82.98	125.30	**106.35**
78	Washington-Arlington-Alexandria, DC-VA-MD-WV*	128.86	109.77	161.15	111.06	**106.32**
79	El Paso, TX	106.76	96.28	87.42	136.34	**106.26**
80	Albuquerque, NM	101.26	111.35	101.67	114.45	**105.97**
81	Cambridge-Newton-Framingham, MA*	129.31	141.99	78.58	125.45	**105.97**
82	Tacoma-Lakewood, WA*	106.50	95.99	102.66	123.73	**105.94**
83	Fort Collins, CO	93.55	101.57	88.90	99.16	**105.60**
84	Huntington-Ashland, WV-KY-OH	83.28	83.53	123.71	91.91	**105.24**
85	Charlottesville, VA	92.74	100.27	123.70	42.50	**105.21**
86	Lancaster, PA	98.69	105.45	110.64	87.92	**105.18**
87	Harrisburg-Carlisle, PA	93.81	106.68	96.35	108.83	**105.07**
88	Norwich-New London, CT	85.66	80.91	135.82	65.34	**104.96**
89	Vallejo, CA	105.00	114.51	60.42	111.64	**104.51**
90	Evansville, IN-KY	89.70	101.73	91.34	90.47	**104.17**
91	West Palm Beach-Boca Raton-Boynton Beach, FL*	111.90	114.90	88.43	131.39	**103.85**
92	North Port-Sarasota-Bradenton, FL	97.66	98.07	91.34	131.01	**103.54**
93	Davenport-Moline-Rock Island, IA-IL	89.95	124.28	59.42	107.23	**103.39**
94	Tyler, TX	83.68	68.91	109.52	94.68	**103.25**
95	Visalia, CA	93.50	128.49	76.93	90.68	**102.92**
96	Canton-Massillon, OH	87.18	102.33	76.12	116.05	**102.88**
97	Newark, NJ-PA*	124.84	140.51	87.97	110.14	**102.52**
98	Peoria, IL	86.53	96.42	103.24	94.39	**102.40**
99	Bremerton-Silverdale-Port Orchard, WA	88.61	87.76	98.49	87.33	**102.38**
100	Sioux Falls, SD	95.99	102.21	92.47	71.23	**102.05**
101	Baltimore-Columbia-Towson, MD	114.32	117.85	122.35	117.71	**101.83**
102	Roanoke, VA	88.05	89.17	101.99	87.62	**101.55**
103	Ann Arbor, MI	103.64	94.45	98.37	77.56	**101.26**
104	Syracuse, NY	96.38	103.99	132.67	68.06	**101.13**
105	Kennewick-Richland, WA	92.65	96.81	75.44	98.40	**100.85**
106	San Diego-Chula Vista-Carlsbad, CA	125.68	126.78	102.38	121.82	**100.78**
107	Sacramento-Roseville-Folsom, CA	108.92	123.35	114.55	114.15	**100.58**
108	Wichita, KS	95.37	110.43	100.07	92.28	**100.37**
109	York-Hanover, PA	90.13	93.02	103.28	94.12	**100.00**
110	Waco, TX	86.56	81.18	78.82	109.18	**99.54**

111	Lake County-Kenosha County, IL-WI*	97.08	103.60	87.32	122.54	**99.42**
112	Colorado Springs, CO	100.90	105.21	72.50	123.86	**99.18**
113	Charleston-North Charleston, SC	93.45	85.70	122.82	102.94	**99.07**
114	Houma-Thibodaux, LA	82.66	86.79	90.29	80.28	**98.83**
115	Boise City, ID	96.85	110.96	106.65	87.00	**98.54**
116	Tallahassee, FL	94.63	74.30	117.39	82.25	**98.49**
117	Wilmington, NC	91.44	98.62	66.75	96.99	**98.25**
118	Dayton-Kettering, OH	92.87	107.07	92.60	109.69	**97.66**
119	Buffalo-Cheektowaga, NY	104.86	126.36	93.51	94.58	**97.63**
120	Toledo, OH	91.93	115.95	87.83	95.03	**97.57**
121	Des Moines-West Des Moines, IA	98.83	115.95	90.83	89.45	**97.41**
122	Topeka, KS	86.92	100.90	84.46	69.48	**97.27**
123	Lake Charles, LA	84.71	88.67	88.51	77.60	**97.27**
124	Springfield, MA	98.22	118.57	90.93	84.47	**96.53**
125	Macon-Bibb County, GA	82.38	81.83	99.39	75.33	**96.10**
126	Tucson, AZ	102.63	93.23	99.78	114.28	**96.01**
127	Port St. Lucie, FL	92.26	79.13	92.86	109.41	**95.99**
128	Greeley, CO	87.21	93.89	85.42	88.31	**95.95**
129	Wilmington, DE-MD-NJ*	101.03	106.13	75.75	109.93	**95.74**
130	Lafayette-West Lafayette, IN	93.12	97.47	74.39	70.85	**95.71**
131	Savannah, GA	88.87	72.01	100.71	102.28	**95.63**
132	Beaumont-Port Arthur, TX	83.66	78.02	92.10	106.49	**94.53**
133	Kalamazoo-Portage, MI	89.70	88.14	80.21	82.12	**94.45**
134	Camden, NJ*	102.25	122.08	71.43	120.25	**94.44**
135	Albany-Schenectady-Troy, NY	96.20	110.20	113.76	77.47	**93.94**
136	Provo-Orem, UT	102.06	117.59	60.65	103.05	**93.79**
137	Gainesville, FL	90.46	78.45	91.14	90.04	**93.45**
138	Crestview-Fort Walton Beach-Destin, FL	87.50	80.74	88.58	84.63	**93.21**
139	Austin-Round Rock-Georgetown, TX	103.26	94.51	138.22	104.09	**93.17**
140	Fort Wayne, IN	91.57	90.62	88.29	88.51	**92.99**
141	Elkhart-Goshen, IN	84.69	75.11	65.95	98.08	**92.38**
142	Fresno, CA	104.13	130.04	66.75	96.71	**91.75**
143	Pittsburgh, PA	100.30	110.32	114.36	113.14	**91.68**
144	Hagerstown-Martinsburg, MD-WV	84.76	82.70	95.87	75.03	**91.53**
145	Virginia Beach-Norfolk-Newport News, VA-NC	101.54	103.52	102.23	117.05	**91.44**
146	Columbus, GA-AL	88.95	85.00	93.34	76.20	**91.44**
147	Cape Coral-Fort Myers, FL	93.80	79.55	84.46	125.50	**91.42**
148	Akron, OH	91.48	100.32	80.44	105.81	**90.82**
149	Monroe, LA	80.34	57.03	101.03	80.82	**90.54**
150	Lansing-East Lansing, MI	95.63	94.87	104.90	69.26	**90.42**

151	Asheville, NC	81.60	75.80	114.29	84.73	**89.85**
152	Montgomery, AL	86.97	86.71	97.41	75.68	**89.70**
153	Ogden-Clearfield, UT	99.04	114.35	62.01	99.35	**89.70**
154	New Brunswick-Lakewood, NJ*	106.40	123.52	74.63	129.88	**89.28**
155	Tampa-St. Petersburg-Clearwater, FL	106.61	95.91	99.39	143.42	**89.13**
156	Minneapolis-St. Paul-Bloomington, MN-WI	111.03	110.86	122.20	105.81	**87.97**
157	Lafayette, LA	83.53	84.48	90.15	93.99	**87.91**
158	Durham-Chapel Hill, NC	89.91	75.44	135.93	65.59	**87.83**
159	Palm Bay-Melbourne-Titusville, FL	94.52	80.00	68.64	118.93	**87.23**
160	Gulfport-Biloxi, MS	82.41	71.42	97.94	91.50	**86.98**
161	Flint, MI	84.67	80.72	71.85	104.67	**86.80**
162	Bakersfield, CA	97.83	127.11	67.99	86.79	**86.58**
163	Gary, IN*	92.68	108.16	55.48	112.07	**86.52**
164	Cleveland-Elyria, OH	103.23	117.18	100.57	97.70	**86.34**
165	Fort Smith, AR-OK	82.99	90.46	62.82	79.64	**86.07**
166	Pensacola-Ferry Pass-Brent, FL	86.61	64.64	103.33	96.10	**85.98**
167	Shreveport-Bossier City, LA	84.00	77.22	78.48	98.37	**85.87**
168	Phoenix-Mesa-Chandler, AZ	112.46	101.49	117.71	124.96	**85.48**
169	Ocala, FL	81.04	50.74	95.35	107.39	**85.34**
170	Richmond, VA	97.50	83.99	117.74	94.92	**85.34**
171	Hartford-East Hartford-Middletown, CT	98.88	102.85	110.57	77.87	**85.27**
172	Spartanburg, SC	79.83	60.69	101.62	85.33	**85.10**
173	Columbus, OH	100.53	103.02	113.64	98.80	**84.80**
174	Dallas-Plano-Irving, TX*	112.04	92.22	122.16	130.33	**84.45**
175	Oklahoma City, OK	101.62	95.90	100.81	96.89	**84.22**
176	Worcester, MA-CT	98.21	107.29	97.41	73.92	**84.03**
177	Gainesville, GA	82.55	50.26	92.08	76.59	**83.82**
178	Birmingham-Hoover, AL	86.25	70.35	115.10	110.48	**83.68**
179	Indianapolis-Carmel-Anderson, IN	96.26	91.98	121.90	101.87	**83.47**
180	Elgin, IL*	94.39	95.90	64.96	106.11	**82.94**
181	Portland-South Portland, ME	86.30	82.03	119.78	58.02	**82.84**
182	Louisville/Jefferson County, KY-IN	95.87	91.41	103.75	94.84	**82.46**
183	Little Rock-North Little Rock-Conway, AR	85.40	74.28	109.01	91.29	**82.41**
184	Deltona-Daytona Beach-Ormond Beach, FL	89.40	79.38	65.06	120.57	**82.32**
185	Rochester, NY	94.62	102.28	119.18	58.56	**81.11**
186	Johnson City, TN	81.02	47.49	77.58	89.49	**81.09**
187	Lake Havasu City-Kingman, AZ	84.00	71.57	64.47	76.51	**80.94**
188	Cincinnati, OH-KY-IN	97.77	99.46	121.03	89.59	**80.54**
189	Youngstown-Warren-Boardman, OH-PA	84.46	101.99	67.01	86.41	**80.53**
190	Mobile, AL	86.67	82.12	72.34	87.80	**80.53**
191	St. Louis, MO-IL	96.32	102.11	106.29	113.24	**80.34**

192	Lynchburg, VA	80.71	79.43	97.36	45.86	**79.76**
193	Springfield, MO	87.70	93.00	74.08	76.79	**79.68**
194	Memphis, TN-MS-AR	96.02	79.85	111.92	92.81	**79.60**
195	McAllen-Edinburg-Mission, TX	95.43	69.97	79.54	115.07	**79.54**
196	Killeen-Temple, TX	86.69	70.89	72.59	100.50	**79.33**
197	Tulsa, OK	90.09	89.09	88.02	98.27	**78.80**
198	Fort Worth-Arlington-Grapevine, TX*	102.19	96.34	84.65	123.65	**78.13**
199	Kansas City, MO-KS	98.14	103.70	95.21	102.25	**77.67**
200	Lakeland-Winter Haven, FL	89.21	51.21	82.15	120.37	**76.44**
201	Fayetteville-Springdale-Rogers, AR	86.16	73.45	90.70	78.33	**75.87**
202	Orlando-Kissimmee-Sanford, FL	105.15	77.91	95.60	125.02	**75.59**
203	Poughkeepsie-Newburgh-Middletown, NY	90.83	98.60	79.71	70.17	**75.50**
204	Clarksville, TN-KY	84.87	52.83	102.18	58.25	**73.83**
205	Columbia, SC	88.30	73.59	103.18	78.22	**73.79**
206	Grand Rapids-Kentwood, MI	92.49	90.39	98.83	73.74	**73.50**
207	Salisbury, MD-DE	77.74	61.27	88.29	81.69	**73.20**
208	Jacksonville, FL	95.88	75.49	91.95	109.50	**73.03**
209	Longview, TX	78.09	78.78	65.67	67.92	**72.92**
210	Greensboro-High Point, NC	86.32	80.44	91.92	79.10	**72.85**
211	Montgomery County-Bucks County-Chester County, PA*	97.05	116.91	68.51	100.74	**72.65**
212	Charlotte-Concord-Gastonia, NC-SC	93.65	79.06	138.10	85.06	**72.63**
213	Huntsville, AL	84.12	55.06	92.21	80.98	**71.39**
214	Chattanooga, TN-GA	85.60	61.23	89.40	82.41	**71.33**
215	Kingsport-Bristol, TN-VA	76.55	50.41	92.11	70.39	**71.15**
216	Raleigh-Cary, NC	95.21	82.78	91.62	92.06	**71.00**
217	San Antonio-New Braunfels, TX	98.96	85.33	95.42	109.39	**70.68**
218	Jackson, MS	82.84	64.88	100.59	69.93	**70.20**
219	Houston-The Woodlands-Sugar Land, TX	109.07	95.46	110.27	121.12	**69.92**
220	Knoxville, TN	84.92	55.89	120.41	74.97	**69.84**
221	Augusta-Richmond County, GA-SC	84.78	66.11	91.29	75.60	**69.42**
222	Winston-Salem, NC	83.20	63.05	105.08	69.08	**68.56**
223	Warren-Troy-Farmington Hills, MI*	96.01	103.42	81.25	95.47	**65.23**
224	Rockingham County-Strafford County, NH*	82.57	75.30	71.73	62.25	**65.11**
225	Jacksonville, NC	79.57	44.42	61.75	65.48	**63.65**
226	Greenville-Anderson, SC	84.31	66.52	94.73	76.89	**63.38**
227	Baton Rouge, LA	88.39	68.86	72.09	87.97	**62.51**
228	Myrtle Beach-Conway-North Myrtle Beach, SC-NC	79.83	48.62	63.65	91.41	**60.04**
229	Fayetteville, NC	83.15	54.83	70.33	78.28	**60.03**
230	Hickory-Lenoir-Morganton, NC	76.29	43.12	77.75	67.17	**57.87**

231	Nashville-Davidson--Murfreesboro--Franklin, TN	91.42	62.66	117.16	72.58	**57.39**
232	Atlanta-Sandy Springs-Alpharetta, GA	100.91	82.86	133.43	79.42	**57.22**
233	Riverside-San Bernardino-Ontario, CA	102.83	108.71	66.07	98.41	**54.32**