

Quantifying the Spatiotemporal Trends of Urban Sprawl Among Large U.S. Metropolitan Areas Via Spatial Metrics

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Abstract Spatial metrics have emerged as a widely utilized tool to quantify urban morphologies and monitor urban sprawl. Since previous applications of spatial metrics have typically considered only a single urban class, this study evaluates how deriving spatial metrics from multiple land use/land cover (LULC) classification schemes can help elucidate the spatiotemporal trends of urban sprawl. Specifically, the urban morphologies of the fifty most populous metropolitan areas in the U.S. were quantified in 2001 and 2011 using spatial metrics derived from two LULC classification schemes: the more common urban/non-urban binary and a non-binary that considered four urban classes individually. The results indicated that many of the spatial metrics were significantly correlated with existing sprawl indices, suggesting that they accurately quantified components of urban form associated with urban sprawl. More sprawl-like morphologies were typically located in the Eastern region of the U.S. although the regional variability of select spatial metrics was dependent on the LULC classification scheme. Over the 10-year study period, spatial metric-based sprawl indices that compared the relative abundance of low and high intensity urban development suggested that sprawl attributable to low-density single family residential suburbs generally decreased among most metropolitan areas. However, detailed case studies revealed that sprawling development was still likely increasing within particular metros in the form of strip commercial development. Overall, the findings highlight the importance of considering multiple classification schemes to maximize the utility of spatial metrics for urban morphological analysis and urban planning.

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Introduction

Due to a multitude of social, governmental, technological, and economic forces, urban morphologies in the U.S. have been profoundly altered by urban sprawl since the mid-20th Century (Muller 2004; Bruegmann 2005). Specifically, urban sprawl has been attributed to the “flight from blight” (Mieszkowski and Mills 1993), increased affluence and political democratization (Bruegmann 2005), federal housing policies (Jackson 1985), federal highway subsidies (Su and DeSalvo 2008), the proliferation of personal automobiles (Muller 2004), ineffective local land use regulations (Carruthers and Ulfarsson 2002), and the natural evolution of cities (Mieszkowski and Mills 1993). The individual causes of sprawl are of course intricately interrelated since they generally occurred contemporaneously, prompting numerous studies to analyze the relative importance of each factor (Burchfield et al. 2006; Wassmer 2008).

Although the characteristics often associated with urban sprawl have occurred throughout urban history and across the world (Bruegmann 2005), the exceptional pace and magnitude of modern-day sprawl in the U.S. are key differentiating factors (Fulton et al. 2001). Unfortunately, the term “urban sprawl”, despite its ubiquitous usage, has not facilitated a particularly nuanced understanding of urban form because it has no unanimous definition (Galster et al. 2001; Bruegmann 2005; Jaeger et al. 2010). The word sprawl has been instilled with negative connotations (Bruegmann 2005) and come to embody a variety of meanings. Sprawl can refer to the spatial patterning of urban development, the underlying causes of urban expansion, the process of urban growth itself, and even the consequences associated with ever-expanding urban footprints (Galster et al. 2001). This paper is guided by Galster et al.’s (2001, p. 685) definition of urban sprawl as:

A pattern of land use in a UA [urban area] that exhibits low levels of some combination of eight distinct dimensions: density, continuity, concentration, clustering, centrality, nuclearity, mixed uses, and proximity.

The contention regarding what constitutes “urban sprawl” as well as its specific causes, outcomes, and potential alternatives has motivated numerous empirical efforts to quantify urban morphology (Torrens 2008). Similar to how no single conceptual definition of sprawl exists (Galster et al. 2001), Bereitschaft and Debbage (2014) identified numerous quantitative techniques used to evaluate urban form, which have relied upon demographic data, land use/land cover (LULC) data, or a hybrid of both. Within the demographic-based approach, population density is the most widely utilized variable to evaluate urban morphology (Lopez and Hynes 2003; Sutton 2003; Tsai 2014), although housing density has also proven particularly useful (Paulsen 2014). A main strength of utilizing demographic data is the computational simplicity and replicability of the methodologies. The second technique, based on LULC data, often involves the use of spatial or landscape metrics to quantify urban continuity, fragmentation, polycentrism, and other components of urban form (Herold et al. 2002). Spatial

metrics derived from LULC data complement the demographic measures since they more directly evaluate the physical manifestation of urban development in terms of its composition and configuration. Hybrid techniques have also been developed, most commonly in the form of composite indices that combine land use data and demographic information (Ewing et al. 2002; Song and Knaap 2004; Jaeger and Schwick 2014).

Regardless of the specific approach utilized, the quantification of urban morphology is generally conducted to aid urban planners in monitoring urban growth, improving spatial planning policies, and enhancing the sustainability of cities. However, the immense variety of quantitative techniques that have emerged due to the multi-dimensionality of sprawl (Galster et al. 2001) can often produce contradictory results for the same city depending on the specific measure used (Torrens 2008; Orenstein et al. 2014), which may make it difficult to formulate and implement policy. These methodological discrepancies have proven particularly problematic recently, as some studies have suggested that sprawl among major U.S. metros has been increasing, while others have indicated the opposite. For example, Barrington-Leigh and Millard-Ball (2015) found that sprawl in the U.S. peaked in 1994 and actually decreased by 9 % from 1994 to 2012 through an analysis of street network connectivity. In contrast, Laidley (2015) constructed a sprawl index based on population density that suggested, on average, U.S. metros have yet to reverse the trend toward more sprawling urban morphologies, as the index increased by 2.52 % from 2000 to 2010.

Spatial metric-based measures of urban form may provide a means to clarify the current contradictions in the literature and determine if large U.S. metros have recently trended toward more or less sprawling morphologies. Although progress has been made generally in urban morphological analysis through the development of more sophisticated measures of sprawl (e.g. Feng et al. 2015), the sensitivity of spatial metric assessments of urban morphology to various LULC classification schemes remains largely unexplored. Studies using spatial metrics to quantify urban form have typically conceptualized the city as consisting of a single urban or built-up class. The one overarching urban class is often incorporated into an urban/non-urban binary classification (Herold et al. 2002; Makido et al. 2012; Bereitschaft and Debbage 2013) or complemented by numerous other non-urban categories (Luck and Wu 2002; Jat et al. 2008). Although using one aggregate urban class may be appropriate for certain applications, it risks overlooking the inherent heterogeneity that exists within the single urban category and could obscure elements of urban form that are relevant to monitoring changes in urban sprawl.

Since spatial metrics are inherently dependent upon the classification scheme of the LULC dataset from which they are derived (Li and Wu 2004; Herold et al. 2005), this study analyzes how calculating spatial metrics from two different classification schemes, one that includes multiple urban classes with varying levels of development intensity (i.e. the “non-binary” classification scheme), and one that consists of the more common urban/non-urban binary, can help elucidate the spatiotemporal trends of urban sprawl in the U.S. Three principle research questions are addressed: 1) how do the binary, non-binary, and spatial metric-based sprawl indices compare to existing sprawl indices, 2) what is the variability in urban morphologies between major U.S. regions and is this spatial variability dependent on the classification scheme used, and 3) do the

spatial metrics generally indicate a decrease or increase in urban sprawl among major U.S. metros during the first decade of the 21st century?

Methods

Study Area

The study area consisted of the 50 most populous Metropolitan Statistical Areas (MSAs) in the contiguous U.S. as of 2010 (U.S. Census Bureau 2012) (Fig. 1). A MSA includes one or more urbanized areas with a population of at least 50,000 and proximate counties that exhibit strong socio-economic ties with the core(s) as evaluated by commuting patterns. This study included only sizable MSAs since they have been a focus of previous sprawl indices (Galster et al. 2001; Ewing et al. 2002) and spatial metric-based evaluations of urban form (Bereitschaft and Debbage 2014). By considering 50 cities, the sample also included a wide range of morphological typologies that exhibited relatively high (e.g. Raleigh) to relatively low (e.g. Portland) levels of sprawl according to existing measures (Ewing et al. 2002). Additionally, the spatial distribution of the MSAs throughout the U.S. enabled an assessment of how regional variability in urban morphology may be influenced by the different urban classification schemes.

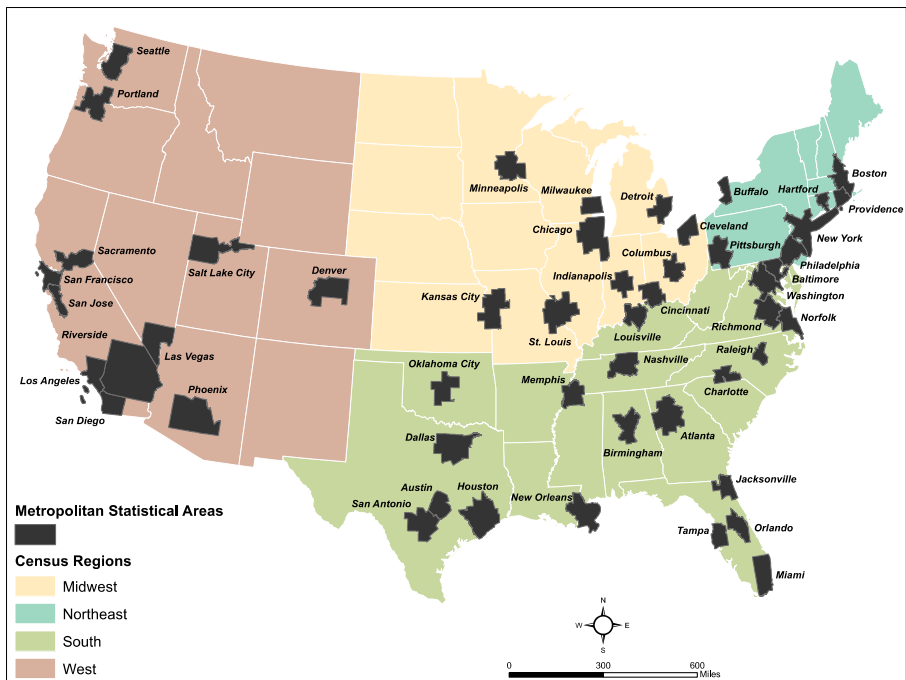


Fig. 1 The study area included the fifty most populous Metropolitan Statistical Areas (MSAs) in the U.S. as of 2010. The Census Regions used for the ANOVA are also depicted

Spatial Metric Calculations

The spatial metrics were calculated for 2001 and 2011 using the most recent edition of the National Land Cover Database (NLCD) available for each year (Fry et al. 2011). Developed primarily from the unsupervised classification of remotely sensed imagery collected by Landsat, the NLCD has a 30-m spatial resolution and an overall accuracy approaching 80 % for the more detailed Level II classification scheme used to derive the non-binary spatial metrics (Wickham et al. 2013). The NLCD Level II classification scheme is a slight modification of the Anderson Land Cover Classification System (Anderson et al. 1976) and includes 20 different LULC categories.

The 2001 and 2011 NLCD datasets were first reclassified into an urban/non-urban binary. The four developed land use classes were collapsed into one urban category and the remaining classes were combined into one non-urban category. The four developed classes of the NLCD are differentiated by the relative abundance of impervious surfaces: developed open space (Class 21) pixels have less than 20 % impervious surface coverage; low-intensity (Class 22) and medium-intensity development (Class 23) pixels have between 20–49 % and 50–79 % impervious surface coverage, respectively; and high-intensity development (Class 24) pixels have greater than 79 % impervious surface coverage.

The imperviousness thresholds produce substantive differences between the four urban categories (Fry et al. 2011). Developed open space commonly includes single-family housing units located within large lots and vegetation planted within urban settings. Low- and medium-intensity development typically encompass areas of denser single-family housing. Finally, high-intensity development encapsulates the urban core and other highly urbanized areas where people live and/or work in large numbers.

Landscape extent is an additional concept that must be considered when employing spatial metrics to quantify urban form (Li and Wu 2004). Only one landscape extent was utilized in order to focus on the importance of the classification schemes when characterizing changes in urban sprawl via spatial metrics. A sensitivity analysis revealed that considering the LULC data within an entire MSA boundary would be inappropriate because the large rural expanses located along the fringes of many MSA counties biased several of the spatial metrics (Galster et al. 2001). A more suitable landscape extent for the spatial metric calculations was obtained when analyzing only the NLCD data included within the 2010 U.S. Census Urbanized Areas and Urban Clusters (UA/UC) of each MSA. Similar to Laidley's (2015) treatment of MSA boundaries, the most recent UA/UC delineations were used for both the 2001 and 2011 metric calculations to better capture how sprawl has changed in the urban areas as they are currently defined. Figure 2 provides an example of how the NLCD 2011 data were extracted using the Census UA/UC within the Atlanta MSA to establish a more appropriate landscape extent.

The public domain software FRAGSTATS was used to calculate the spatial metrics (McGarigal et al. 2012). A single universal suite of spatial metrics for analyzing urban environments has not been established since the research objectives and characteristics of the city under investigation often inform metric selection for a given study (Herold et al. 2005). To elucidate how LULC classification schemes influence spatial metric results when analyzing urban form, the spatial metrics most frequently utilized for urban morphological analysis were identified through an extensive literature review

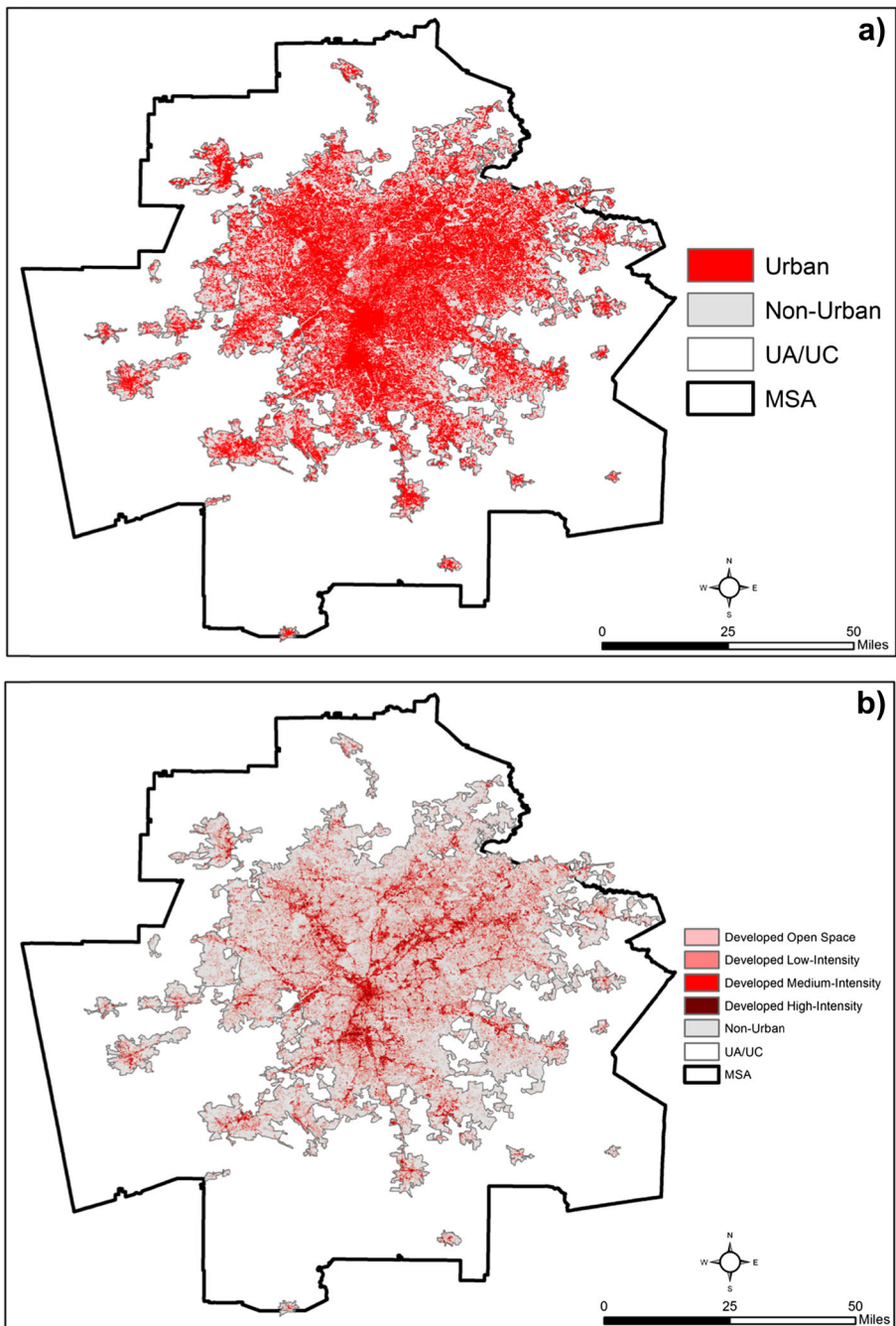


Fig. 2 The **a)** binary and **b)** non-binary urban classification schemes applied to the NLCD 2011 for the Atlanta, Georgia urbanized area

(Herold et al. 2002; Herold et al. 2003; Ji et al. 2006; Huang et al. 2007; Jat et al. 2008; Liu and Weng 2008; Makido et al. 2012; Bereitschaft and Debbage 2013; Connors

et al. 2013; Bereitschaft and Debbage 2014). Six spatial metrics were selected for analysis to evaluate several distinct aspects of urban form: percentage of landscape (PLAND), largest patch index (LPI), patch density (PD), edge density (ED), area-weighted mean patch fractal dimension (AWMPFD), and percentage of like adjacencies (PLADJ) (Tables 1 and 2).

The six spatial metrics were calculated for each of the individual urban classes (i.e. NLCD Classes 21–24) and the one aggregate urban category (i.e. the binary classification scheme) in the years 2001 and 2011. Using Atlanta, Georgia as an example, Fig. 2 highlights the notable differences between the binary and non-binary urban classification schemes. In the case of Atlanta, the binary classification has an

Table 1 Equations and technical descriptions of the spatial metrics used to quantify urban form (McGarigal et al. 2012)

Spatial metric	Equation	Technical description
Area-Weighted Mean Patch Fractal Dimension (AWMPFD)	$AWMPFD = \sum_{j=1}^n \left[\left(\frac{2 \ln(0.25 p_{ij})}{\ln a_{ij}} \right) \left(\frac{a_{ij}}{\sum_{j=1}^n a_{ij}} \right) \right]$	Where p_{ij} is the perimeter of patch ij and a_{ij} is the area of patch ij (i = number of patch types, j = number of patches) Units: None
Edge Density (ED)	$ED = \frac{\sum_{k=1}^m e_{ik}}{A} * 10,000$	Where e_{ik} is the total edge length (m) of class i in the landscape and A is the total landscape area; the result is multiplied by 10,000 to convert to hectares Units: Meters per hectare
Largest Patch Index (LPI)	$LPI = \frac{\max_{j=1}^n(a_{ij})}{A} * 100$	Where $\max(a_{ij})$ is the area (m^2) of the largest patch of the corresponding class and A is the total landscape area (m^2); the result is multiplied by 100 to convert to a percentage Units: Percent
Patch Density (PD)	$PD = \frac{n_i}{A} * 10,000 * 100$	Where n_i is the number of patches in the landscape of patch type i and A is the total landscape area (m^2) Units: Number per 100 ha
Percentage Of Like Adjacencies (PLADJ)	$PLADJ = \left(\frac{g_{ii}}{\sum_{k=1}^m g_{ik}} \right) * 100$	Where g_{ii} is the number of like adjacencies between pixels of patch type i and g_{ik} is the number of adjacencies between pixels of patch types i and k Units: Percent
Percentage of Landscape (PLAND)	$PLAND = \frac{\sum_{j=1}^n a_{ij}}{A} * 100$	Where a_{ij} is the area (m^2) of patch ij and A is the total landscape area (m^2); the result is multiplied by 100 to convert to a percentage Units: Percent

Table 2 Shorthand names used to refer to the spatial metrics throughout the paper and descriptions of how they are expected to relate to urban sprawl

Shorthand name (Acronym)	General description	How non-binary potentially relates to urban sprawl	How binary potentially relates to urban sprawl
Shape Complexity (AWMPFD)	Measures shape complexity using a modified perimeter-area ratio. Higher values correspond to increasingly irregular and complex shapes.	More complexly shaped developed open space and low-intensity development are expected to correspond with more expansive urban morphologies since these classes form much of the urban edge, but it is unclear if such a relationship will exist for medium- and high-intensity development.	Higher values are typically indicative of more expansive urban spatial configurations within a binary classification scheme. Infill development can occur and subsequently reduce the shape complexity of expansive urban forms, which may complicate the interpretation.
Edginess (ED)	The total urban edge length divided by the city area. Higher values correspond to increasingly irregular and edgy shapes.	More edgy developed open space and low-intensity development are expected to correspond with more expansive urban morphologies since these classes form much of the urban edge, but it is unclear if such a relationship will exist for medium- and high-intensity development.	Higher values are typically indicative of more expansive urban spatial configurations within a binary classification scheme. Infill development can occur and subsequently reduce the edginess of expansive urban forms, which may complicate the interpretation.
Monocentrism (LPI)	Measures the nuclearity dimension of urban sprawl identified by Galster et al. (2001). It is calculated by dividing the area of the largest urban patch by the total city area.	When focusing solely on high-intensity development, the largest urban patch is often the Central Business District (CBD) or urban core, so lower values may be indicative of a less dominant urban center and/or a greater degree of polycentrism.	Since the values derived from the urban binary classification scheme evaluate the dominance of the largest continuously urbanized patch, which is unlikely to correspond directly with the urban core, it is expected to evaluate polycentrism at a more regional scale.
Fragmentation (PD)	Assesses the fragmentation of urban land use by quantifying the number of discrete urban patches relative to a city's total size.	Non-contiguous leapfrog development would increase PD. Therefore, higher PD values are typically representative of more fragmented urban morphologies.	Since the urban/non-urban binary will likely reduce the total number of urban patches within a city relative to the non-binary classification scheme, PD values derived from the binary are expected to be substantially lower.

Table 2 (continued)

Shorthand name (Acronym)	General description	How non-binary potentially relates to urban sprawl	How binary potentially relates to urban sprawl
Contiguity (PLADJ)	Utilizes adjacency matrices to measure the contiguity of urban development, another dimension included in the Galster et al. (2001) definition of sprawl. PLADJ is computed by comparing the number of like adjacencies between urban pixels to the total number of adjacencies involving urban pixels.	Larger PLADJ values represent higher levels of contiguity within the urban landscape. As observed by Galster et al. (2001), sprawl can either be continuous (i.e. continual suburban expansion) or discontinuous (i.e. leapfrog development) in nature.	These subtle differences may be more successfully revealed via the non-binary classification scheme since the contiguity of lower intensity development is evaluated independently of the higher intensity urban categories.
Relative Abundance (PLAND)	Simple composition metric, which calculates the total area of a given LULC category relative to the total city area. Standardizing by total area enabled fair comparisons since the sizes of the UA/UC varied considerably.	Less sprawling morphologies were expected to be characterized by a higher relative abundance of high-intensity development.	It was unclear if such a relationship would also exist for the urban binary since a higher proportion of the aggregate urban category could be attributable to an increase in either developed open space or high-intensity development.

amorphous appearance that obscures much of the detail revealed when the four urban classes are considered individually. Such dissimilarity in the conceptualization of the urban landscape will likely influence the spatial metric values and their potential applicability for assessing and monitoring changes in urban sprawl. Although spatial metrics may be sensitive to both physical and political impediments to urban growth, such as steep topography, bodies of water, and federally protected lands, by analyzing a suite of metrics derived from two separate classification schemes, we aim to tease apart the subtle morphological differences between cohesive, yet low density, metros and high-density metros that are spatially fragmented primarily due to their geographical context.

Finally, two second-order spatial metrics tailored specifically for urban morphological analysis were derived to serve as spatial metric-based sprawl indices. Firstly, the ratio between the relative abundance of developed open space (PLAND_21) and the relative abundance of high-intensity development (PLAND_24) was calculated (Eq. 1). Higher values for the Open/High Ratio would represent a more sprawling morphology since it quantifies the dominance of the least intense urban class relative to the most intense. For example, a city with a ratio value of 10 would contain ten times more developed open space than high-intensity development. The second derived metric, the Open & Low/Med. & High Ratio, has a similar interpretation. However, it compares the sum of the relative abundance of developed open space (PLAND_21) and the relative abundance of low-intensity development (PLAND_22) with the sum of the relative abundance of medium-intensity development (PLAND_23) and the relative abundance of high-intensity development (PLAND_24) (Eq. 2). These two spatial metric-based sprawl indices were calculated for both 2001 and 2011.

$$\text{Open} / \text{High Ratio} = \frac{\text{PLAND}_{21}}{\text{PLAND}_{24}} \quad (1)$$

$$\text{Open \& Low} / \text{Med. \& High Ratio} = \frac{(\text{PLAND}_{21} + \text{PLAND}_{22})}{(\text{PLAND}_{23} + \text{PLAND}_{24})} \quad (2)$$

Statistical Analyses

To address the first research question, the binary and non-binary spatial metrics as well as the spatial metric-based sprawl indices derived from the 2011 NLCD were compared to the 2010 Ewing and Hamidi (2014) sprawl index and the 2010 Lopez sprawl index, which is originally described in Lopez and Hynes (2003). This analysis was used to test whether the selected spatial metrics were capturing urban morphological patterns commonly associated with urban sprawl. The Ewing and Lopez sprawl indices were chosen because they are well-cited in the literature, employ fundamentally different methodologies, and were calculated for a majority of the cities included in this study. The Lopez Index was calculated for all 50 cities while the Ewing Index was available for all the cities except Boston, which was subsequently omitted from the comparative analysis that utilized the Ewing Index. The Fulton et al. (2001) and Sutton (2003)

indices were not incorporated since they combined cities that were considered independently in this analysis (i.e. Washington and Baltimore; San Jose and San Francisco), making direct comparisons difficult. Additionally, the Galster et al. (2001) index was not considered because values were only available for a limited set of 13 cities.

The Ewing Index combines multiple measures of urban form that evaluate density, land use mix, degree of centering, and street accessibility. The index has a mean of 100 where more compact cities have values above 100 and more sprawling cities have values below 100 (Ewing et al. 2002; Ewing and Hamidi 2014). In contrast, the Lopez Index quantifies sprawl by comparing the percentage of a city's population in high-density census tracts with the percentage in low-density census tracts. The index ranges from 0 to 100 with higher values indicative of more sprawling morphologies (Lopez and Hynes 2003).

The relationships between the spatial metrics and the sprawl indices were evaluated using both Pearson and Spearman correlations since the assumptions of parametric tests were often violated. Spearman coefficients were reported for the Ewing Index, because the violations clearly affected a number of the Pearson coefficients. Pearson correlations were reported for the Lopez Index, however, as the coefficients were similar for both measures. Although the spatial metrics and sprawl indices are not strictly comparable because they are derived using different urban extents (i.e. UA/UC versus MSA boundaries), significant correlations would generally suggest that the spatial metrics are successfully quantifying LULC patterns commonly associated with sprawl-like morphologies. Non-significant relationships, however, may indicate that the metrics represent unique components of urban morphology not captured by the sprawl indices, or are perhaps poor surrogates for measuring the complex spatial phenomenon of urban sprawl.

With regard to the second research question, MSAs located within the same region of the U.S. were expected to share similar urban morphologies due to the comparable economic forces, governmental policies, cultural values, and topographic barriers influencing urban development patterns (Bereitschaft and Debbage 2014). It was hypothesized that MSAs with binary and non-binary spatial metric values indicative of more sprawling morphologies would be clustered in the Southeast, as generally indicated by the existing sprawl indices discussed above. Each MSA was assigned to its appropriate Census Region (West, Midwest, South, and Northeast) and analysis of variance (ANOVA) tests were conducted with Census Region as the grouping variable. ANOVA tests were performed for the binary and non-binary spatial metrics to determine if any observed regional variability in the urban morphologies was dependent upon the LULC classification scheme. If significant differences were indicated by the F-Value, Tukey's Honestly Significant Difference (HSD) test was used to identify the specific regions that exhibited significantly different metric values.

For the final research question, changes in urban form were evaluated by subtracting the 2001 metric values from their respective values in 2011. This analysis focused primarily on the changes exhibited by the spatial metric-based sprawl indices. However, to help elucidate if the urban morphologies of large U.S. metros have indeed become less sprawling, as suggested by Barrington-Leigh and Millard-Ball (2015), three cities (Providence, Raleigh, and Austin) were selected for detailed case studies. By analyzing the broader suite of spatial metrics collectively, these case studies enabled a more nuanced evaluation of any alterations in urban morphology observed over the

10-year study period. The case studies also offered an opportunity to highlight how the binary and non-binary spatial metrics, as well as extant sprawl indices, capture potential changes in urban form differently. Finally, the case studies provided a platform from which to explore the efficacy of urban policies enacted by the cities to influence urban form. For each city, urban LULC maps for 2001 and 2011 as well as aerial imagery were produced to aid in the interpretation of the change statistics.

Results and Discussion

Comparison of Spatial Metrics with Sprawl Indices

The binary and non-binary spatial metrics were first compared with the Ewing and Lopez sprawl indices to ensure that they were accurately quantifying LULC patterns commonly associated with sprawling urban morphologies. The correlation coefficients between the Ewing Index and the spatial metrics are displayed in Table 3. High- and medium-intensity development as well as the urban binary exhibited the highest number of significant ($p < 0.05$) correlations, as at least five of the six spatial metrics were significantly correlated with the Ewing Index for each of these urban categories. Only two significant ($p < 0.05$) correlations were observed for the spatial metrics calculated for developed open space, and the low-intensity development spatial metrics displayed no significant correlations with the Ewing Index. Therefore, spatial metric values derived from the lower urban intensity levels may be less capable of serving as proxies for urban sprawl as conceptualized by the Ewing Index.

The direction of the relationships between the high-intensity development metrics and the Ewing Index were often as expected, however, certain relationships ran contrary to what has been reported in the literature (Huang et al. 2007; Bereitschaft and Debbage 2014). Since higher Ewing Index values denote less urban sprawl, the positive correlations for the relative abundance and monocentrism of high-intensity development indicate that higher metric values are associated with lower levels of

Table 3 Spearman's ρ correlation coefficients calculated between the 2010 Ewing and Hamidi (2014) sprawl index and both the binary and non-binary metrics derived from the 2011 NLCD

Spatial metric	Urban binary	Developed open space	Low-intensity development	Medium-intensity development	High-intensity development
Relative Abundance	0.42**	-0.43**	0.08	0.45**	0.51**
Fragmentation	-0.35*	-0.12	0.10	0.09	0.33*
Monocentrism	0.33*	-0.16	0.06	0.52**	0.53**
Edginess	-0.36*	-0.50**	0.11	0.38**	0.43**
Shape Complexity	-0.17	-0.17	0.04	0.61**	0.57**
Contiguity	0.36*	-0.01	0.03	0.51**	0.35*

Significance levels: $\wedge = p < 0.10$; * = $p < 0.05$; ** $p < 0.01$

sprawl. This was expected given that higher scores for these metrics are associated with more intensely urbanized cities with dominant urban cores. Higher values for edginess, shape complexity, and fragmentation were expected to correspond with higher levels of sprawl since complex and fragmented shapes are generally indicative of expansive urban forms. However, when analyzing only high-intensity development, edginess, shape complexity, and fragmentation were positively correlated with the Ewing Index, meaning more complexly shaped and fragmented high-intensity patches were actually associated with lower levels of sprawl. This discrepancy highlights how spatial metric values may have different interpretations when focusing on a particular urban intensity level rather than a simplified urban binary.

The relationships between the spatial metrics and the Lopez Index were markedly different (Table 4). Firstly, the direction of the relationships was typically opposite of that observed for the Ewing Index since higher scores on the Lopez Index are associated with more sprawling morphologies. The most notable disparity, however, was that the binary, medium-, and high-intensity development metrics all exhibited much stronger correlations with the Lopez Index. Approximately 63 % of the relationships between the spatial metrics and the Lopez Index had a *p*-value less than 0.01 whereas this proportion was only 40 % for the Ewing Index. This discrepancy may be explained by how the two sprawl indices were calculated. The Lopez Index relies solely upon population density data while the Ewing Index incorporates population information and factors that are more explicitly related to urban form. For example, the Ewing Index includes the average lot size of single-family dwellings and average block length. Spatial metrics, which are themselves relatively simple measures of urban land use configuration, may therefore be more analogous to less complex measures of urban sprawl that are derived from population data.

The correlations between the Lopez Index and the binary metrics aligned well with previous studies. As expected, higher relative abundance, monocentrism and contiguity values were correlated with less urban sprawl since higher scores for these metrics typically indicate a more centralized and contiguous urban morphology. Conversely, higher values for edginess, fragmentation, and shape complexity were correlated with more urban sprawl as anticipated, given that fragmented and complex urban shapes are generally associated with more expansive urban morphologies. The metrics for

Table 4 Pearson's *r* correlation coefficients calculated between the 2010 Lopez sprawl index and both the binary and non-binary metrics derived from the 2011 NLCD

Spatial metric	Urban binary	Developed open space	Low-intensity development	Medium-intensity development	High-intensity development
Relative Abundance	-0.67**	0.62**	-0.21	-0.79**	-0.71**
Fragmentation	0.52**	-0.02	-0.37**	-0.14	-0.61**
Monocentrism	-0.47**	0.23	-0.08	-0.57**	-0.56**
Edginess	0.49**	0.64**	-0.38**	-0.72**	-0.72**
Shape Complexity	0.33*	0.25^	-0.09	-0.79**	-0.69**
Contiguity	-0.58**	0.27^	0.03	-0.71**	-0.20

Significance levels: ^ = $p < 0.10$; * = $p < 0.05$; ** $p < 0.01$

medium- and high-intensity development were all negatively correlated with the Lopez Index. The negative associations were expected for relative abundance, as larger percentages of medium- and high-intensity development should be indicative of less sprawling morphologies. However, negative relationships for fragmentation, shape complexity, and edginess again suggest that more complexly shaped and fragmented patches of high-intensity development are actually indicative of lower levels of urban sprawl. The unexpected relationships between both sprawl indices and the shape complexity and edginess metrics for high-intensity development may be explained by the fact that the shape complexity of a given patch generally increases with its size (Hargis et al. 1998). Thus, less sprawling metros may have exhibited higher shape complexity for high-intensity development in part because they often have larger patches of high-intensity development. Nevertheless, the results of the correlation analysis overall suggest that the spatial metrics performed reasonably well at capturing LULC patterns commonly associated with urban sprawl.

Regional Variations in Urban Morphology

ANOVA and Tukey's HSD tests were conducted to determine if the regional variability in urban morphology in 2011 was captured by the spatial metrics and whether it was dependent on the LULC classification scheme used. The ANOVA results were visualized using boxplots (Fig. 3) and the regions that were significantly different from one another were summarized in Table 5. For the relative abundance of urban development, the binary yielded much larger percentages when compared to the non-binary metrics since it combined the four urban categories (Fig. 3a). The percentage of urban development calculated using the binary classification was significantly higher ($p < 0.05$) in the Midwest and West regions when compared to the South and Northeast. However, the tails of the boxplots revealed important regional exceptions such as Miami, which had a relative abundance of 83 % for the urban binary. The regional variability was substantially different for developed open space, as the West exhibited a significantly ($p < 0.01$) lower percentage than the South and Midwest. The low relative abundance of developed open space in the West region was likely attributable to the prominent physical barriers confining urban expansion and lack of natural vegetation among the arid cities of the Southwest. Low-intensity development was most prevalent in Midwestern cities, where the percentage was significantly ($p < 0.01$) higher than that observed for Northeastern and Southern cities. The West also exhibited a significantly ($p < 0.05$) higher relative abundance of low-intensity development than the Northeast. The relative abundance of medium-intensity development was significantly higher ($p < 0.01$) in the West; its median value was approximately double that observed in all other regions. The regional differences in the relative abundance of urban land use were least pronounced for high-intensity development. The West had a significantly ($p < 0.01$) higher percentage than the South, but no other regions were statistically distinguishable. The binary relative abundance metric appeared to summarize the regional variability fairly accurately, as the Northeast and South generally had lower proportions of urban development than the Midwest and West for each individual intensity level except developed open space. Therefore, Southern and Northeastern cities appear to contain higher proportions of non-urban land use, which could be attributable

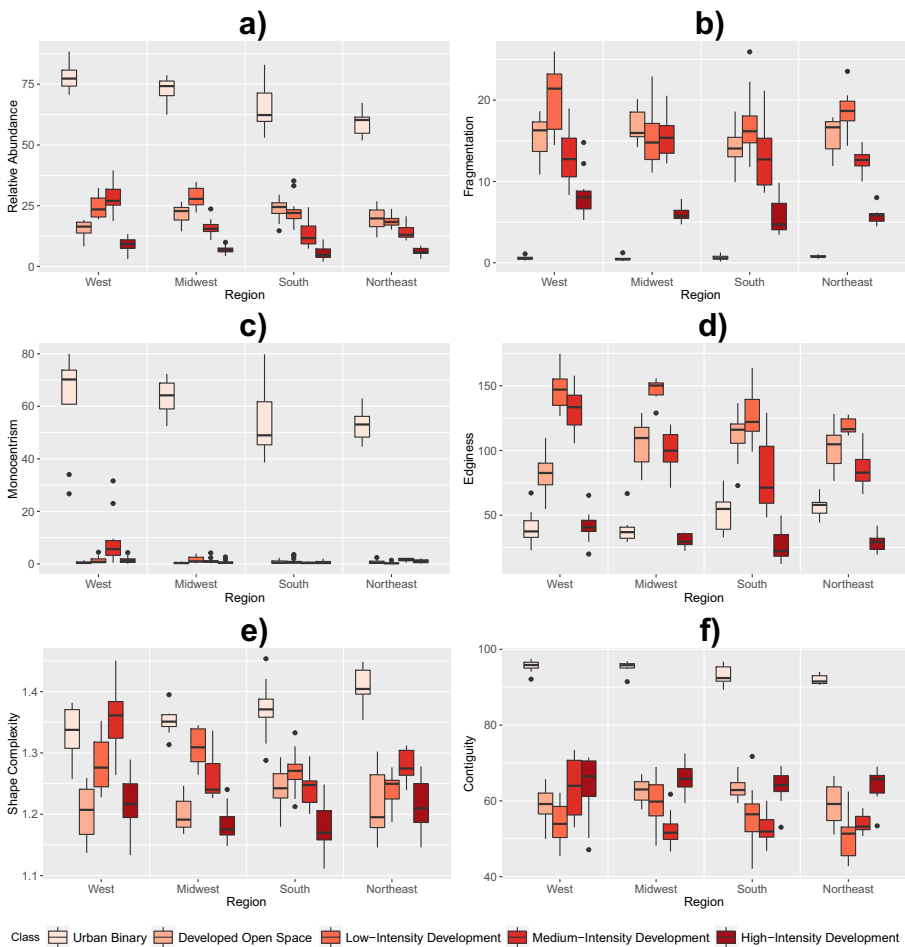


Fig. 3 Regional variability of the binary and non-binary spatial metrics in 2011 by Census Region for **a**) relative abundance (PLAND), **b**) fragmentation (PD), **c**) monocentrism (LPI), **d**) edginess (ED), **e**) shape complexity (AWMPFD), and **f**) contiguity (PLADJ)

to more fragmented urban forms and/or the increased presence of natural vegetation.

The fragmentation values for the urban binary were substantially lower than those observed for the non-binary metrics because aggregating the urban classes into one category reduced the number of distinct urban patches (Fig. 3b). Additionally, the binary fragmentation metric exhibited no significant regional variation. Significant regional variability was observed, however, for two of the four individual urban intensity levels. The West exhibited a significantly ($p < 0.05$) higher degree of fragmentation for low-intensity development than the Midwest, as well as significantly ($p < 0.05$) more fragmented high-intensity development than all other regions. Regional variations in fragmentation were therefore sensitive to how the urban landscape was classified. This suggests that the differences between a binary and non-binary classification can influence urban morphology results and a metric’s potential applicability for monitoring changes in urban sprawl. This may be particularly true for patch-based

Table 5 Summary of the urban morphology regional variability results

Spatial metric	Urban class	Region			
		West	Midwest	South	Northeast
Relative Abundance	Developed Open Space	a	b	b	ab
	Low-Intensity	ac	a	bc	b
	Medium-Intensity	a	b	b	b
	High-Intensity	a	ab	b	ab
	Urban Binary	a	a	b	b
Fragmentation	Developed Open Space	a	a	a	a
	Low-Intensity	a	b	ab	ab
	Medium-Intensity	a	a	a	a
	High-Intensity	a	b	b	b
	Urban Binary	a	a	a	a
Monocentrism	Developed Open Space	a	a	a	a
	Low-Intensity	a	a	a	a
	Medium-Intensity	a	b	b	b
	High-Intensity	a	ab	b	ab
	Urban Binary	a	ab	b	ab
Edginess	Developed Open Space	a	b	b	ab
	Low-Intensity	a	a	b	b
	Medium-Intensity	a	b	b	b
	High-Intensity	a	b	b	b
	Urban Binary	a	a	b	b
Shape Complexity	Developed Open Space	a	a	b	ab
	Low-Intensity	ac	a	bc	b
	Medium-Intensity	a	b	b	b
	High-Intensity	a	a	a	a
	Urban Binary	a	ab	bc	c
Contiguity	Developed Open Space	a	ab	b	ab
	Low-Intensity	ab	a	ab	b
	Medium-Intensity	a	b	b	b
	High-Intensity	a	a	a	a
	Urban Binary	a	a	b	b

Regions that do not share a common letter are significantly (p -value < 0.05) different from one another according to Tukey's HSD test

metrics since the number of urban patches is highly dependent on the classification scheme. In contrast to relative abundance, the binary metric for fragmentation failed to summarize the regional variability identified by several of the non-binary metrics.

Monocentrism was much higher for the binary since combining the urban categories produced a small number of large urban patches. The binary exhibited significant ($p < 0.05$) regional variability (Fig. 3c), in contrast to Bereitschaft and Debbage

(2014). This disparity was potentially due to the differences in the landscape extents used and the sample of cities analyzed. The South exhibited significantly ($p < 0.05$) lower levels of monocentrism than the West when analyzing the urban binary. There was no significant regional variability in monocentrism for either developed open space or low-intensity development. The West exhibited a significantly ($p < 0.05$) higher degree of monocentrism with respect to medium-intensity development than all other regions and significantly higher values than the South for high-intensity development. The low monocentrism values for the South across most of the intensity levels, particularly high-intensity development, were indicative of the polycentric and low-density morphologies common to the region. For example, in Orlando the largest high-intensity urban patch was responsible for less than 0.04 % of the city's total area. Miami was again a notable exception, however, with a binary monocentrism value of 80 %. There were also notable outliers in the West, as San Francisco and Riverside exhibited the two lowest levels of monocentrism according to the urban binary. Although the results were more nuanced when considering the individual urban intensity levels, the binary monocentrism metric appeared to capture much of the regional variability.

Smaller numerical differences were observed between the binary and non-binary edginess metrics (Fig. 3d). The regional variations in edginess according to the binary metric were similar to those observed by Bereitschaft and Debbage (2014); urban development in the Northeast and South was significantly ($p < 0.05$) more edgy than in the West and Midwest. Regional variability was also observed among the individual urban intensity levels, with significantly ($p < 0.01$) higher edginess values for developed open space in the South and Midwest relative to the West. Opposite the regional pattern displayed by the binary, the edginess of low-intensity development was significantly ($p < 0.01$) lower in the Northeast and South than in the West and Midwest. For medium-intensity development, edginess was significantly ($p < 0.01$) higher for Western cities than those located in all other regions. The West also exhibited significantly ($p < 0.05$) higher levels of edginess for high-intensity development than all other regions. The binary edginess metric appeared to capture the main differences between the South/Northeast and the West/Midwest regions, but the specific direction and magnitude of the regional differences varied for each urban intensity level.

As observed for edginess, the binary and non-binary metrics for shape complexity were numerically similar (Fig. 3e). The binary results again agreed with Bereitschaft and Debbage (2014), as shape complexity was significantly ($p < 0.01$) higher in the Northeast than in the West and Midwest as well as significantly ($p < 0.05$) higher in the South than in the West. Southern cities exhibited significantly ($p < 0.05$) higher shape complexity values than Midwestern and Western cities for developed open space. Low-intensity development was significantly ($p < 0.05$) more complex in the Midwest than in the Northeast and South as well as more complex in the West than in the Northeast. Western cities were the most dissimilar with respect to the shape complexity of medium-intensity development, as they exhibited significantly ($p < 0.01$) higher values than all other regions. Notably, the shape complexity of high-intensity development did not exhibit significant regional variability. Overall, the regional division in urban shape complexity between the Northeast/South and West/Midwest observed when using the binary metric was not fully supported by the non-binary metrics, suggesting that the binary classification may provide an overly broad assessment of urban shape complexity.

The binary contiguity median values were above 90 % for each region and higher than the non-binary median values since combining the urban intensity levels into one aggregate urban category substantially increased the number of like adjacencies (Fig. 3f). In agreement with Bereitschaft and Debbage (2014), the binary results indicated that urban contiguity was significantly ($p < 0.05$) higher in the West and Midwest relative to the South and Northeast. The regional variations for each urban intensity level were more nuanced. Developed open space was significantly ($p < 0.05$) more contiguous for Southern cities than Western cities, while low-intensity development was significantly ($p < 0.05$) more contiguous in the Midwest than in the Northeast. Cities in the West exhibited significantly ($p < 0.01$) higher levels of contiguity for medium-intensity development than cities in all other regions. Notably, there was no significant regional variation in the contiguity of high-intensity development. It appears that the Northeast/South—West/Midwest division indicated by the binary contiguity metric may be overly simplistic when considering particular types of urban land use.

The ANOVA and Tukey's HSD tests employed in the regional analysis revealed several noteworthy trends (Fig. 3; Table 5). Firstly, with the exception of edginess and shape complexity, the metric values derived from the urban binary were markedly different from those calculated using the four individual urban intensity levels. These differences should be considered when choosing how to assess and monitor changes in urban sprawl with spatial metrics. The binary metrics also identified a clear distinction between the urban morphologies of Northeastern/Southern and Western/Midwestern cities, with more polycentric, complexly shaped, discontinuous and overall sprawl-like urban forms typically located in the East. However, this East–West division was not consistently present when analyzing the individual urban intensity levels. In particular, the morphologies of developed open space and high-intensity development exhibited weaker regional variability and were generally more similar throughout the U.S.

Spatial Metric-Based Sprawl Indices

The relationships between the two spatial metric-based sprawl indices and existing indices were examined to further evaluate the potential for spatial metrics to serve as surrogate measures of urban sprawl. The Open & Low/Med. & High Ratio was significantly ($p < 0.01$) correlated with the Lopez Index and exhibited a higher correlation coefficient ($r = 0.78$) than any of the individual binary or non-binary spatial metrics, with the exception of the relative abundance and shape complexity of medium-intensity development (Fig. 4). The Open/High Ratio also displayed a strong correlation with the Lopez Index ($r = 0.68$, $p < 0.01$) but was outperformed by the previous spatial metric-based sprawl index as well as several of the binary and non-binary spatial metrics. The spatial metric-based sprawl indices were also significantly correlated with the Ewing Index. However, for the Ewing Index, the Open/High Ratio ($\rho = -0.54$, $p < 0.01$) outperformed the Open & Low/Med. & High Ratio ($\rho = -0.49$, $p < 0.01$) as well as all the binary and non-binary spatial metrics with the exception of high- and medium-intensity development shape complexity.

Mapping the 2011 spatial metric-based sprawl indices revealed a clear East–West division in urban form, with the higher Open & Low/Med. & High Ratio values indicating that more sprawl-like morphologies were generally clustered in the Southeastern region of the U.S. (Fig. 5a). For example, Raleigh and Charlotte were

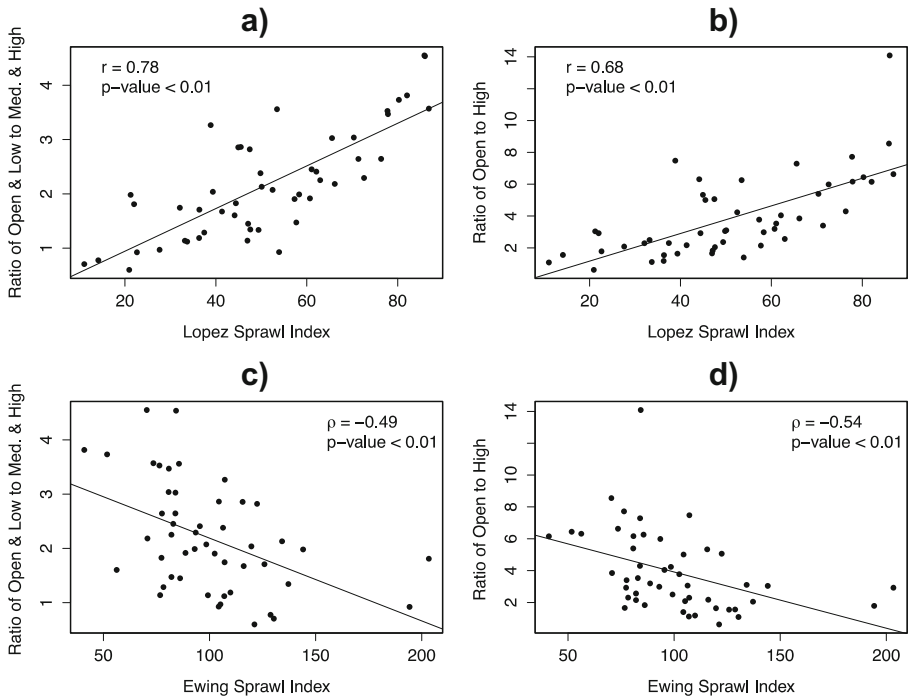


Fig. 4 Relationships between the 2011 spatial metric-based sprawl indices and the 2010 Lopez (a–b) and Ewing (c–d) sprawl indices. Pearson coefficients are reported in a and b while Spearman coefficients are reported in c and d

the only cities with an Open & Low/Med. & High Ratio greater than 4.5, indicating that they contained more than four and a half times as much developed open space and low-intensity development than medium- and high-intensity development. With the exception of Providence, all cities with an Open & Low/Med. & High Ratio less than one were located in the Western region (i.e. San Diego, San Francisco, San Jose, Los Angeles, and Las Vegas). Ratio values less than one signify that medium- and high-intensity development was more prevalent than developed open space and low-intensity development.

The Open/High Ratio exhibited a similar spatial pattern with more sprawling morphologies generally located in the Southeast (Fig. 5b). Among the metropolitan areas with the ten highest Open/High Ratios, only two, Riverside and Cleveland, were located outside of the South. By this measure, Raleigh was the most sprawling city in the study, containing over fourteen times as much developed open space as high-intensity development. On the opposite end of the spectrum, Las Vegas was the only city with an Open/High Ratio less than one, indicating particularly low levels of sprawl. Despite its popular reputation as a vast sprawling metropolis (Sutton 2003), Los Angeles exhibited the second lowest Open/High Ratio of 1.08. Finally, Riverside displayed the most marked difference between the Open/High and the Open & Low/Med. & High Ratio, as the metro's high relative abundance of medium-intensity development lowered its Open & Low/Med. & High Ratio substantially.

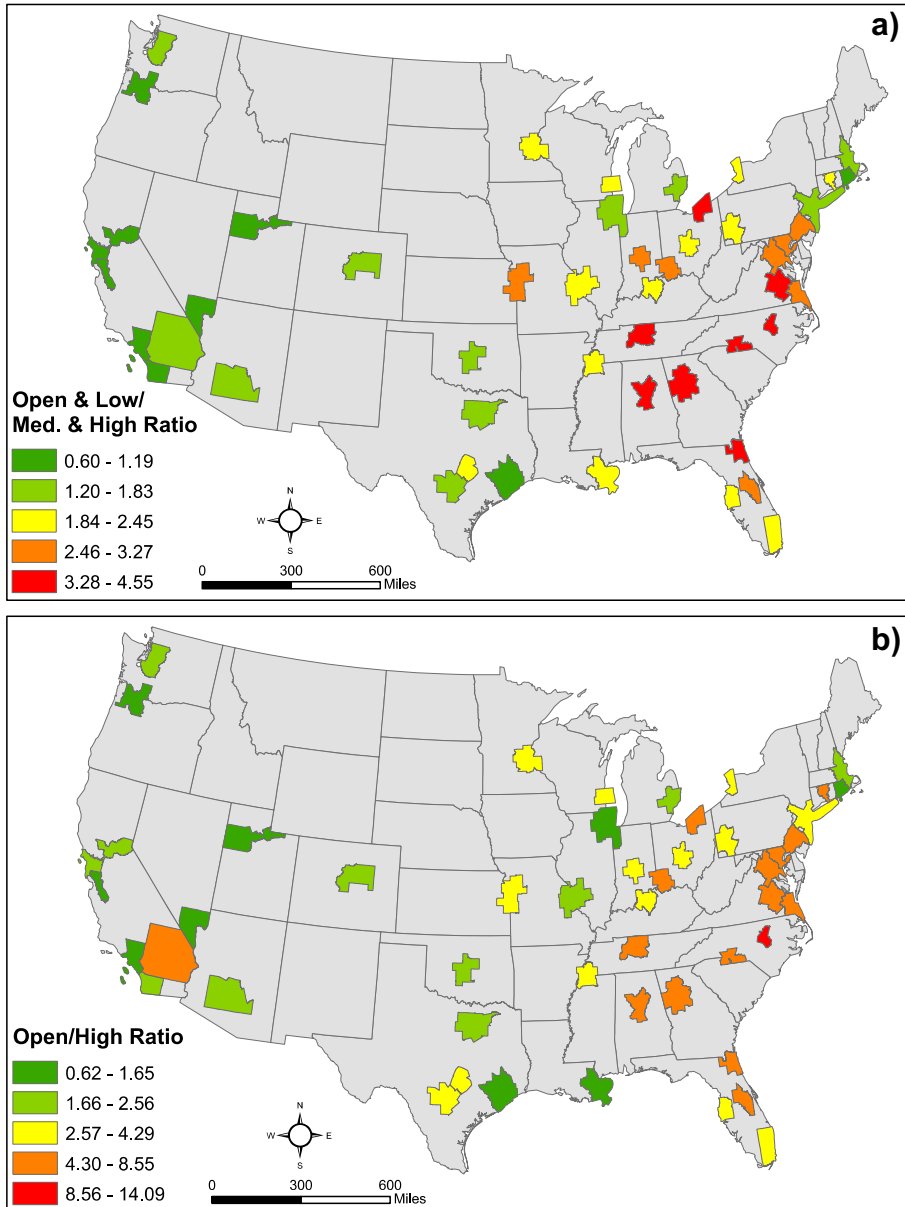


Fig. 5 The 2011 values for the a) Open & Low/Med. & High Ratio and b) Open/High Ratio

Changes were calculated between the 2011 spatial metric-based sprawl indices and their respective values in 2001 to determine if the urban morphologies of U.S. metros have become more sprawl-like in recent years. From 2001 to 2011, the Open & Low/Med. & High Ratio decreased by an average of 0.43 while the Open/High Ratio decreased by 0.90. These decreases suggest that higher intensity urban development outpaced lower intensity development during the study period. Therefore, low density single family housing commonly associated with developed open space and low-



Fig. 6 Changes from 2001 to 2011 for the **a)** Open & Low/Med. & High Ratio and **b)** the Open/High Ratio

intensity development generally became less dominant in the urban landscapes, which partially supports Barrington-Leigh and Millard-Ball's (2015) assessment that urban sprawl among large U.S. metros has recently declined.

The spatial variability of the change calculations highlighted that cities in the Southeast, which generally exhibited the most sprawling morphologies, also typically underwent the most substantial reductions in urban sprawl from 2001 to 2011. In fact, the twelve cities with the most substantial reductions in the Open & Low/Med. & High

Ratio were all located in the South (Fig. 6a). This was likely due to two main reasons. Firstly, the general dearth of medium- and high-intensity urban development in these cities meant mathematically that even modest increases in the relative abundance of more intense development would substantially reduce the ratios. The relative abundance of high-intensity development in Raleigh, for example, only increased from 1.28 % in 2001 to 2.01 % in 2011, but produced the largest decrease in the Open & Low/Med. & High Ratio. Secondly, many of the most sprawling cities have recently attempted to combat the ill effects of low-density urban expansion by implementing policies that encourage denser land use patterns. For example, in the Charlotte MSA, the reduction of the Open & Low/Med. & High Ratio may be partly attributable to the success of the more stringent urban growth control policies outlined by the Cabarrus County land use plan (Cabarrus County 2008). Conversely, Providence was the only city that exhibited an increase in the Open & Low/Med. & High Ratio. The increase indicated that lower intensity development had become more dominant in the urban landscape of Providence, suggesting an expansion of urban sprawl due to low-density single family residential land use.

The changes in the Open/High Ratio displayed a similar spatial pattern, with Southern cities generally exhibiting greater reductions (Fig. 6b). A notable exception, however, was Riverside, which had the largest Open/High Ratio reduction of any city, suggesting a substantial decrease in sprawl. Interestingly, when considering only the 50 cities included in this study, Riverside exhibited the second, third, and third largest reduction in urban sprawl between 2000 and 2010 according to the Lopez, Ewing, and Laidley indices, respectively. Concerning cities that appeared to become more sprawling during the study period, both Providence and Chicago had positive Open/High Ratio change values. This finding was also supported by existing indices, as Chicago exhibited the fourth largest increase in sprawl among the cities considered in this study according to the Laidley Index.

Individual City Case Studies: Providence, Raleigh, and Austin

While positive change values for the spatial metric-based sprawl indices clearly suggest an increase in sprawl, as they indicate that lower intensity suburban development is becoming more dominant in the urban landscape, interpreting negative change values is not quite as straight-forward. Negative changes imply that sprawl attributable to low-density suburban development has decreased, but this does not necessarily preclude increases in other manifestations of urban sprawl. For example, urban growth in the form of strip developments and big-box shopping centers, which is often a prominent component of sprawling morphologies (Ewing 2008; Curran 2002), would increase the relative abundance of high-intensity land use and subsequently decrease the spatial metric-based sprawl indices. To tease apart these subtle differences, detailed case studies that examined the results of all six spatial metrics were conducted for Providence, Raleigh, and Austin. These three cities were selected based upon the changes in their spatial metric-based sprawl indices.

Providence was the only metro that exhibited increases in both spatial metric-based sprawl indices, suggesting that its urban morphology had become more sprawling over the study period (Fig. 7a). Of the metros included in this study, Providence also exhibited the largest decrease in the Ewing Index (i.e. the largest increase in sprawl).

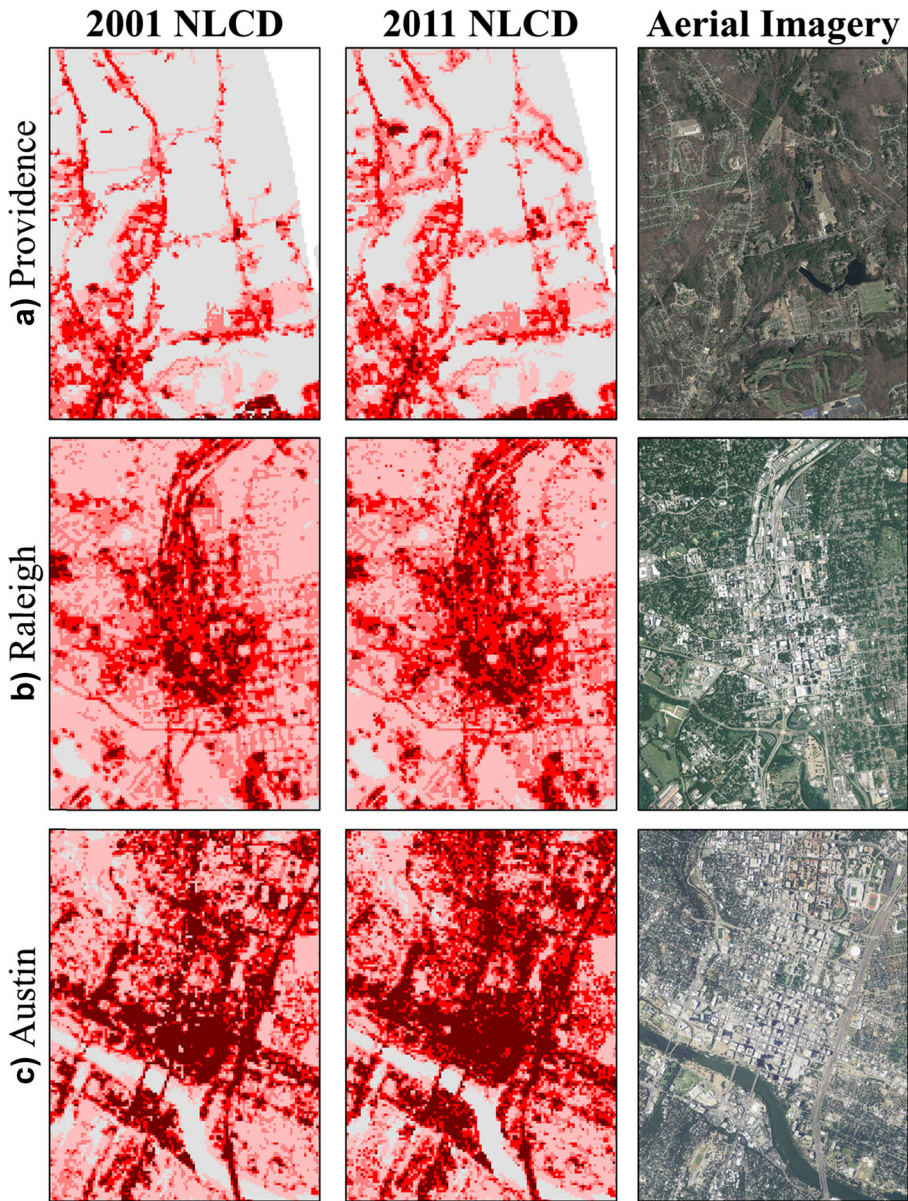


Fig. 7 The 2001 NLCD, 2011 NLCD, and aerial imagery for the three case study cities. Darker reds represent more intense urban development and gray represents non-urban land cover. All the maps are at 1:56,000 scale with north at the top

It should be noted, however, that Providence ranked as the 5th densest metro in 2011, even after undergoing the most substantial increase in sprawl from 2001 to 2011. Collectively, the individual metrics also suggested a transition to a more sprawling morphology. For example, there was an increase in the relative abundance, shape complexity, and edginess of developed open space, which was likely capturing the

expansion of low-density suburban development along the periphery of the metro. The residential suburbs constructed just north of Woonsocket, Rhode Island highlight one of many instances where the Providence urban morphology became more sprawl-like (Fig. 7a). At the opposite end of the urban intensity spectrum, there was only a modest increase in the relative abundance of high-intensity development. Simultaneously, the minimal increase in the monocentrism of high-intensity development suggests that the growth of intense urban land use was more likely occurring along the urban periphery as fragmented strip and big-box commercial developments rather than within or adjacent to the existing urban core. Overall, the spatial metric change calculations suggest that the vision for containing sprawl and protecting rural character via clustered developments outlined in the 2025 Rhode Island long-term land use plan has thus far been largely unfulfilled (Rhode Island Division of Planning 2006).

Raleigh, selected as the second case study, had the largest and second largest decrease in the Open & Low/Med. & High and Open/High Ratios, respectively (Fig. 7b). Existing sprawl indices were not in agreement whether the urban morphology of Raleigh had become more or less sprawling. Of the cities considered in this study, Raleigh exhibited the fourth largest decrease in sprawl according to the Ewing and Laidley indices while the Lopez Index suggested a modest increase in sprawl. Although low-density single family residential development became less prominent in the urban landscape, as indicated by the spatial metric-based sprawl indices, an analysis of the individual metrics revealed two trends that suggested other manifestations of sprawl increased in Raleigh over the decade. Firstly, even though the relative abundance of medium-intensity development increased, it became more fragmented and less contiguous. Secondly, the slight increase in the relative abundance of high-intensity development corresponded with a negligible increase in the monocentrism of the urban core. These changes imply that the expansion of intense urban land use most likely occurred along the periphery of the metro in the form of strip and/or big-box development rather than as infill development proximate to the urban core, which would result in a less polycentric form. The LULC changes within the urban core of Raleigh suggest that little densification has occurred (Fig. 7b). Therefore, the policies of the 2030 comprehensive plan appear to have curbed low-density residential sprawl in Raleigh to some degree, but the usage of zoning and parking standards to encourage mixed-use retail nodes and disincentivize auto-centric strip commercial and big-box development seem to have been less effective (City of Raleigh 2009).

Austin, which ranked 8th and 5th for sprawl reduction according to the Open & Low/Med. & High and Open/High Ratios, respectively, was chosen for the final case study (Fig. 7c). Changes in previously available sprawl indices were also not conclusive for Austin, as sprawl increased according to the Lopez and Ewing indices but a large reduction of sprawl was suggested by recent increases in street connectivity (Barrington-Leigh and Millard-Ball 2015). The complexity of Austin's urban morphology was highlighted in detail by Torrens (2008), who concluded that the urban core of Austin resisted sprawl between 1990 and 2000 while more fragmented suburban forms increased along the urban fringe. Yet, the individual spatial metrics analyzed here suggest that since 2001 Austin may have been more successful in reducing both residential and commercial forms of sprawl than Raleigh. The relative abundance of developed open space, for example, decreased in Austin. Since developed open space is unlikely to return to a natural LULC (i.e. forest, grassland, etc.), a decrease in relative

abundance suggests an intensification of existing urban land use. The relative abundance and contiguity of medium-intensity development also increased substantially with only a modest growth in fragmentation. This implies that medium-intensity development often occurred adjacent to existing medium-intensity land use, which may be indicative of the infill around Austin's urban core (Fig. 7c). It also suggests that new patches of medium-intensity development, likely associated with relatively dense single family suburbs along the urban periphery, were mostly contiguous. Finally, the monocentrism of high-intensity development in Austin increased more substantially than that of all the other cities exhibiting the ten greatest reductions in sprawl according to the spatial metric-based sprawl indices. This indicates that the increase in the relative abundance of high-intensity development in Austin was not predominately attributable to strip and big-box commercial development as in Raleigh, but was instead also due to the growth of the urban core. The LULC changes within the urban core of Austin illustrate that it has indeed become more dominant and intensely developed since 2001 (Fig. 7c). Additionally, within central Austin more broadly, several New Urbanist neighborhoods have emerged during the study period, such as the Domain, the Triangle, and the redevelopment of the Muller Municipal Airport. The changes in the spatial metric values collectively suggest that the urban land use policies outlined by the Austin Tomorrow Comprehensive Plan, specifically the Traditional Neighborhood Development ordinance and the Commercial Design Standards, have to some degree reduced both residential and commercial manifestations of sprawl (City of Austin 2008).

The discussions above focused primarily on the non-binary metrics because their binary counterparts were not as capable of distinguishing between the different urban forms. For example, the relative abundance, monocentrism, and contiguity of the urban binary increased for Providence, Raleigh, and Austin between 2001 and 2011 despite the crucial differences highlighted by the non-binary metrics. The binary classification scheme, therefore, appeared to obscure urban morphological details that were necessary to effectively distinguish changes in urban sprawl.

Conclusions

Although analyzing spatial metrics derived from two classification schemes was data intensive, it proved to be an effective method for uncovering the spatiotemporal patterns of urban sprawl among major U.S. metros. Concerning how the spatial metrics related to existing measures of sprawl, the majority of the metrics displayed significant correlations with the Ewing and Lopez sprawl indices. This suggests that both binary and non-binary spatial metrics are capable of accurately quantifying LULC patterns commonly associated with sprawl-like urban morphologies. The spatial metrics exhibited much stronger correlations with the Lopez Index, however, implying that they are most analogous to less complex measures of urban sprawl based only on population data rather than more complex composite indices like the Ewing Index. This is perhaps due to the resolution of the NLCD and/or the algorithms of the selected spatial metrics, which may be unable to resolve the detailed urban landscape characteristics included in the Ewing Index.

The ANOVA used to examine the regional variability of urban form indicated that metros with more sprawling urban land use morphologies were generally concentrated in the Eastern U.S. However, the regional variability of select spatial metrics varied according to the LULC classification scheme. The analysis also demonstrated that the composition and configuration of high-intensity development and developed open space was more similar throughout the U.S. than the low or medium urban intensity levels and the urban binary. Much of the regional variability in urban morphology was therefore likely due to differences in the configuration and composition of the intermediate urban intensity classes rather than differences amongst urban cores or peripheries.

Finally, two spatial metric-based sprawl indices were derived to determine whether sprawl increased or decreased during the first decade of the 21st Century. These sprawl indices were designed to follow many of the suitability criteria outlined by Jaeger et al. (2010) (e.g. intuitive interpretation, mathematical simplicity, modest data requirements, etc.) and are available from the corresponding author upon request. The two spatial metric-based sprawl indices were more strongly correlated with the Ewing and Lopez indices than many of the binary and non-binary metrics, and both suggested that Western cities generally exhibited lower levels of urban sprawl. This was likely a result of the stronger urban growth controls and more pronounced natural containment, such as topographic and hydrological barriers as well as the need for water supply infrastructure, common amongst Western cities (Nelson and Sanchez 2005). Miami was a notable exception in the Southeast. The metro's relatively low sprawl values likely reflected its stringent urban growth controls (an urban development boundary has been in place in Miami-Dade County since the 1970s), as well as the effectiveness of the Atlantic Ocean and Everglades National Park as natural physical barriers (Nelson and Sanchez 2005; EPA 2012).

The change calculations indicated that the spatial metric-based sprawl indices, on average, decreased from 2001 to 2011. This suggests that low density single family housing became less dominant within the urban landscapes. Therefore, urban sprawl, at least attributable to residential suburban development, appeared to decrease. The individual city case studies, however, revealed that decreases in the spatial metric-based sprawl indices, while indicative of less residential sprawl, do not necessarily preclude increases in other forms of sprawl. For example, Raleigh illustrated an interesting case where sprawl attributable to low-density residential development likely decreased while commercial sprawl, in the form of strip and big-box development, appeared to simultaneously increase. This notion that different manifestations of sprawl may be increasing and decreasing concurrently within the same metro may explain the contradictory findings present in the literature (e.g. Barrington-Leigh and Millard-Ball 2015; Laidley 2015). Depending on how sprawl is evaluated and quantified, these various manifestations might implicitly hold different weights within certain sprawl indices.

The measures of urban sprawl based more directly on urban land use patterns, such as the spatial metrics presented here, the street connectivity analysis of Barrington-Leigh and Millard-Ball (2015), and the Ewing Index when considering only the MSAs incorporated in this study, all generally indicate that sprawl has decreased in recent years. Conversely, population based measures, such as the Lopez and Laidley indices, reveal that sprawl on average has continued to increase. Evaluations of sprawl based on

urban land use patterns may therefore be more sensitive to ongoing changes due to a time lag between LULC change and subsequent population shifts. As several metros appear to be on the precipice of shifting from more to less sprawling urban morphologies, this lag, however slight, could potentially explain the different conclusions reached by population and urban form-based sprawl indices. Additionally, urban form-based sprawl indices are expected to be more sensitive to smaller changes in land use patterns due to the higher resolution of LULC data when compared to the census blocks and tracts commonly used in population-based measures.

With respect to the various classification schemes evaluated, it would be injudicious to conclude that the binary or non-binary is superior without a comprehensive understanding of the urban process under investigation (e.g. urban growth, air quality, urban heat island effect). Our findings emphasize that the nature of the LULC classification scheme, specifically the detail of the urban class, *does* influence the spatial metric results. Planners who rely on studies that use spatial metrics to quantify and monitor urban sprawl as well as explore the linkages between urban form and environmental processes need to be cognizant of this contingency. Careful consideration needs to be given to the LULC classification scheme and the individual spatial metrics that are utilized since analyzing either an urban binary or individual urban classes might be more suitable for certain metrics and applications. When monitoring changes in urban sprawl, the binary failed to reveal important urban morphological details that were subsequently captured by analyzing the four urban classes independently.

These results must be generalized with caution, however, as the spatial metrics were calculated for only one spatial resolution and landscape extent. The relationships between the spatial metrics and existing sprawl indices may also have been influenced by slight temporal discrepancies due to the different datasets used. Additional research that utilizes a collection of complementary sprawl measures rather than a single index or value is recommended to more comprehensively describe how urban morphologies have evolved. Continuing to monitor the temporal shifts in the spatial metric-based sprawl indices and interpreting these changes in conjunction with the broader suite of spatial metrics, for example, may prove valuable in assessing the efficacy of urban policies implemented to guide urban growth and curb urban sprawl. Overall, this detailed examination of the utility of spatial metrics should encourage their continued usage for urban morphological studies and urban planning while highlighting the importance of selecting both appropriate spatial metrics and LULC classification schemes.

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