Computers, Environment and Urban Systems 44 (2014) 59–67

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/compenvurbsys

Comparing spatial metrics that quantify urban form

John H. Lowry [a], Michael B. Lowry [b,*]

[a] Department of Geography, Earth Science and Environment, University of the South Pacific, Suva, Fiji
[b] Department of Civil Engineering, University of Idaho, 875 Perimeter Drive MS 1022, Moscow, ID 83844, USA

ARTICLE INFO

Article history:
Received 4 July 2013
Received in revised form 19 November 2013
Accepted 22 November 2013

Keywords:
Urban form
Urban growth policy
Density
Street pattern
Accessibility
Urban sprawl

ABSTRACT

Measuring and characterizing urban form is an important task for planners and policy analysts. This paper compares eighteen metrics of urban form for 542 neighborhoods in Salt Lake County, Utah. The comparison was made in the context of characterizing three neighborhood types from different time periods: pre-suburban (1891–1944), suburban (1945–1990), and late-suburban (1990–2007). We used correlation analysis, within and across time periods, to assess each metric's ability to uniquely characterize urban form; and we used linear regression to assess the ability to distinguish neighborhood type. Three of the metrics show redundancy and two did not capture differences in urban form for the case study. Based on our findings, we recommend thirteen of the eighteen metrics for planners and policy analysts who want to quantify urban form using spatial data that are commonly available. Furthermore, our case study shows that despite policy efforts to encourage "smart growth," urban neighborhoods in Salt Lake County continue to exhibit characteristics of "sprawl." These findings suggest the effectiveness of smart growth policies in Salt Lake County have had limited effect.

1. Introduction

The spatial structure of cities, also called "urban form," has changed dramatically over the last century (Garreau, 1991; Jackson, 1985). Cities at the beginning of the century were relatively compact and densely populated, with transportation primarily by foot, wagon, or trolley. By the end of the twentieth century the defining characteristic of most U.S. cities was, and still is, a heavy reliance on the automobile for transportation. The urban form of many modern cities can be characterized as low-density, sprawling development.

A wide variety of spatial metrics have been created to characterize and quantify urban form (Ewing, Pendall, & Chen, 2002; Frenkel & Ashkenazi, 2008; Galster et al., 2001; Glaser, Kahn, & Chu, 2001; Song & Knaap, 2004; Theobald, 2002; Torrens, 2000; Weston, 2002). Urban scientists use spatial metrics to gain understanding about the evolving landscape in which we live. Planners and policy analysts use spatial metrics to evaluate and promote policies concerning land use and urban development. The increased use and growing demand for spatial metrics is due in part because of the availability of commercial and open source computing tools, such geographic information systems (GIS) that can store and analyze large amounts of spatial data, and the increased availability of spatial data in the public domain (Kerski & Clark, 2012).

This paper presents a study comparing 18 spatial metrics that are simple to compute and require commonly available GIS data. Our aim was to evaluate the metrics' relative effectiveness in capturing four dimensions of urban form: density, centrality, accessibility, and neighborhood mix (Ewing et al., 2002). Using Salt Lake County, Utah as our study area we assigned each of 542 neighborhoods to one of three neighborhood types based on the era during which they were developed: pre-suburban era (1891–1945), suburban era (1945–1990), and late-suburban era (1990–2007). Given the recognized differences in neighborhood design following World War II and the subsequent era of suburbanization, we wished to evaluate the relative ability of these metrics to capture differences in the four dimensions of urban form. To evaluate possible redundancy among metrics we use linear regression and correlation analysis, within and across neighborhood types, to assess each metric's ability to uniquely characterize urban form. We include the late suburban era neighborhood type in order to compare our results in Salt Lake County with a similar case study carried out in Portland, Oregon (Song & Knapp, 2004).

The next section provides background on urban form research and introduces various spatial metrics. Section 3 describes the case study community and the data used for this project. Sections 4 and 5 present the analysis method and a discussion of the results, respectively. Section 6 provides conclusions about the particular case study and offers recommendations for practitioners and researchers.

* Corresponding author. Tel.: +1 208 885 0139.
E-mail addresses: lowry_j@usp.ac.fj (J.H. Lowry), mlowry@uidaho.edu (M.B. Lowry).

0198-9715/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.compenvurbsys.2013.11.005

2. Background

2.1. Urban form research

Often the motivation to quantify urban form is to evaluate policies and strategies aimed at managing urban sprawl (Herold, Couclelis, & Clarke, 2005). In the 1990s the American Planning Association (APA) began promoting the concept of "smart growth" as a strategy for controlling sprawl (Knapp, 2005). Smart growth principals include encouraging mixed land uses, developing walkable neighborhoods, promoting public transportation, and fostering communities with a strong sense of place. Related to smart growth, are the ideals espoused by the philosophy of "New Urbanism" (Leccese, McCormick, Davis, & Poticha, 2000). Proponents of New Urbanism advocate an urban form reminiscent of residential development before World War II—in other words, compact, pedestrian friendly neighborhoods, mixed land uses, and easy access to public transit and activity centers.

A number of studies have used spatial metrics to evaluate smart growth policies and measure urban sprawl. For example, recently in this journal Liu and Shen (2011) used spatial metrics to analyze the influence of urban form on household travel and energy consumption in Baltimore, Maryland. Early and influential studies of spatial metrics include Galster et al. (2001) who used eight spatial metrics to characterize the amount of sprawl for 13 U.S. Urban Areas, and Ewing et al. (2002) who used 22 sprawl metrics to derive "sprawl rankings" for 83 U.S. cities. Weston (2002) used four spatial metrics to characterize urban form in Austin, Texas to assess the feasibility of retrofitting current residential neighborhoods to New Urbanist ideals. An important conclusion from Weston's work is that if planners with New Urbanist ideals hope to encourage re-development of existing neighborhoods they must first know, in a quantitative fashion, how far off those neighborhoods are from the ideal.

Finally, an important study, relevant to our work, was carried out by Song and Knapp (2004) who sought to quantitatively measure urban form across three different time periods of development in Portland, Oregon. Song and Knaap's motivation was to determine whether spatial measures of urban form offer empirical evidence that urban form changes over time. They found that starting in the 1990s several measures of sprawl had changed. For example, on average newer residential neighborhoods were better connected and more pedestrian friendly (Song & Knapp, 2004).

2.2. Spatial metrics

We compared 18 spatial metrics that are simple, straightforward, and require commonly available GIS data. We selected these metrics from eight previous case studies (Ewing et al., 2002; Frenkel & Ashkenazi, 2008; Galster et al., 2001; Glaser et al., 2001; Song & Knapp, 2004; Theobald, 2002; Torrens & Alberti, 2000; Weston, 2002).

Following Ewing et al. (2002) we organize the metrics into four urban form categories: *density*, *centrality*, *accessibility*, and *neighborhood mix* (see Table 1). Churchman (1999) suggests *density* is the most intuitive characteristic of urban form and it is often considered the most indicative of "sprawl" (Galster et al., 2001). Smart growth advocates argue that living in low-density neighborhoods increases dependence on automobiles with potentially adverse health and environmental effects (Johnson, 2001). *Centrality* metrics seek to quantify the separation between where people live and where they must go for common daily activities (Song & Knapp, 2004). These measure the strength of activity centers, such as the central business district or other commercial centers (Ewing et al., 2002). *Accessibility* is a related concept, but with greater focus on the ability to access destinations (a neighborhood might have high centrality, i.e. near key activity centers, but poor accessibility because of missing street connections to the activity centers). Critics of sprawling suburban development contend that neighborhoods with winding dendritic streets, large residential blocks, and cul-de-sacs are not pedestrian friendly (Jin and White, 2012). Consequently, accessibility metrics seek to quantify street pattern and network connectivity (Ewing et al., 2002; Song & Knapp, 2004). *Neighborhood mix* refers to land use and demographic heterogeneity. It has been argued that zoning restrictions following World War II encouraged segregating residential subdivisions from commercial activities, and also encouraged (either intentionally or unintentionally) social and economic segregation (Lindsrom & Bartling, 2003). We include three metrics aimed at quantifying land use heterogeneity and two concerned with demographic heterogeneity. Unlike the other sixteen metrics, these three involve calculating an index (see Appendix A).

Table 1
Selected spatial metrics that use commonly-available GIS data.

Urban form category	Spatial metric (units)	GIS data	Earlier case study[a]
Density	1. Median single family residential lot size (acres)	Parcels	4, 7
	2. Housing density (housing units/sq. km.)	Census, Parcels	2, 5, 7
	3. Median number of rooms (#)	Census	7
	4. Population density (pop./sq. km.)	Census, Parcels	4, 8
	5. Average household size (people/housing unit)	Census	7
Centrality	6. Mean distance to commercial zone (km)	Streets, Parcels	2, 7
	7. Mean distance to public parks (km)	Streets, Parcels	7
	8. Mean distance to K-12 schools (km)	Streets, Parcels	
	9. Mean distance to transit bus stops (km)	Streets, Bus Stops	6, 7
Accessibility	10. Street connectivity (ratio streets to intersections)	Streets, Parcels	6, 7
	11. Median perimeter of residential blocks (m)	Parcels	7
	12. Dendritic street pattern (ratio cul-de-sacs to streets)	Streets, Parcels	6
	13. Median length of cul-de-sacs (m)	Streets, Parcels	7
Neighbor-hood mix	14. Land use contiguity (Juxtapose Interspersion Index)	Parcels	1
	15. Land use richness (Patch Richness)	Parcels	8
	16. Land use diversity (Simpsons Diversity Index)	Parcels	6, 8
	17. Pop. working outside city of residence (proportion)	Census	4, 3
	18. Renter–owner balance (ratio renters to owners)	Census	1

[a] 1 – Torrens and Alberti (2000), 2 – Galster et al. (2001), 3 – Glaser et al. (2001), 4 – Ewing et al. (2002), 5 – Theobald (2002), 6 – Weston (2002), 7 – Song and Knapp (2004), 8 – Frenkel and Ashkenazi (2008).

3. Study area

3.1. Salt Lake County, Utah

Approximately 1 million people live in the 16 cities that comprise Salt Lake County, Utah (U.S. Census., 2009). Nearly all of the county's population resides in a valley bounded by the Oquirrh Mountains to the west, Wasatch Range to the east, and Great Salt Lake to the north. In many respects urban expansion is limited by a natural growth boundary created by the physical features of the landscape. The areal extent of the valley bottom is approximately 310 square miles (800 km^2). While a significant portion of the valley bottom remains undeveloped as agriculture and rangeland, the county has witnessed tremendous growth in the last 30 years. We calculate that between 1977 and 2006 approximately 50% of agricultural lands had converted to suburban land uses (GIS calculation using UDNR-DWR. (2006) data), with population growth acting as the major driver of land use change.

Interest in growth issues for Salt Lake County can be traced to 1988 with the formation of the non-profit *Coalition for Utah's Future* which eventually became the current public/private partnership called *Envision Utah* (Envision Utah., 2009). Comprised of business leaders, community members, and a representative from the Governor's Office of Planning and Budget, *Envision Utah* has focused on ways to encourage economic growth and improve quality of life throughout the state. During the 1990s, *Envision Utah* actively researched and advocated for smart growth strategies that were already underway in California, Denver, and Portland. Hundreds of workshops were organized throughout Salt Lake County aimed at presenting different growth scenarios to local leaders and community members to help visualize and shape the urban form of new development (Envision Utah, 2009).

3.2. Three neighborhood types

What constitutes a residential neighborhood has been debated by urban planners and scholars for much of the last century. Neighborhoods have been variously defined as spatial units with relatively homogenous social and economic characteristics, residential areas with little through traffic, or as catchment areas for the local elementary school (Lynch, 1984). Because neighborhoods are considered the basic building block of urban form (Lynch, 1984) we sought a spatial unit that met the general conditions of relative spatial and demographic homogeneity.

Despite limitations, spatial census data offer an objective framework for delineating residential neighborhoods in urban and suburban areas (Song & Knapp, 2004). In the geographic hierarchy of the U.S. Census, census block groups (smaller than tracts yet larger than blocks) offer an appropriate geographical unit considered representative of neighborhoods with similar social, economic, and demographic characteristics (Peters & MacDonald, 2004). The population size for urban/suburban census block groups is approximately 1500 people (Peters & MacDonald, 2004). Because our study focuses on residential neighborhoods we identified neighborhoods as the residential portion of each census block group, thereby excluding census units predominated by commercial and industrial land uses. In total there were 542 residential neighborhoods defined from the census block groups in this manner (Fig. 1).

We categorized the 542 neighborhoods into one of three neighborhood types based on the era during which they were developed. Neighborhood types were *pre-suburban* (developed between 1891 and 1944), *suburban* (developed from 1945 to 1990) and *late-suburban* (developed after 1991 to 2007). Neighborhood age was determined by calculating the median age of all residential buildings in the neighborhood using county parcel data. Suburban neighborhoods are most common, comprising 68% of the neighborhoods and 65% of the 2007 population. Pre-suburban neighborhoods constitute 18% of the neighborhoods and 14% of the 2007 population, with the remaining 14% of the neighborhoods and 21% of the population in the post-suburban category. Fig. 2 presents examples of the three neighborhood types depicted at the same map scale with high resolution digital aerial orthophotography. In these three examples, the median year-built for residential homes in photo (a) is 1920, in photo (b) is 1960, and in photo (c) is 1996.

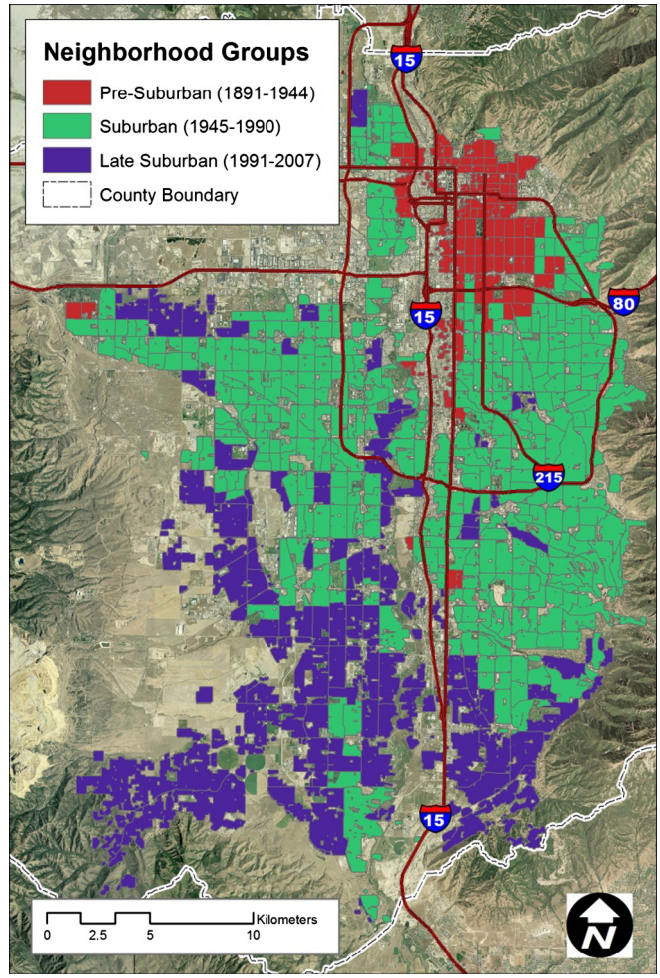

Fig. 1. Geographic distribution of the 542 neighborhoods.

4. Analysis methods and results

4.1. Statistical analysis of neighborhood types

While Analysis of Variance (ANOVA) is often used to test for differences between and among means of two or more groups, it is sometimes advantageous to consider ANOVA as a special case of the linear regression model (Hamilton, 1992; Lattin, Carrol, & Green, 2003). Using a regression model with encoded indicator variables for the neighborhood types allowed us to estimate regression coefficients from which inferences could be made concerning group (i.e. neighborhood type) means. From the regression equation:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \varepsilon_i \quad (1)$$

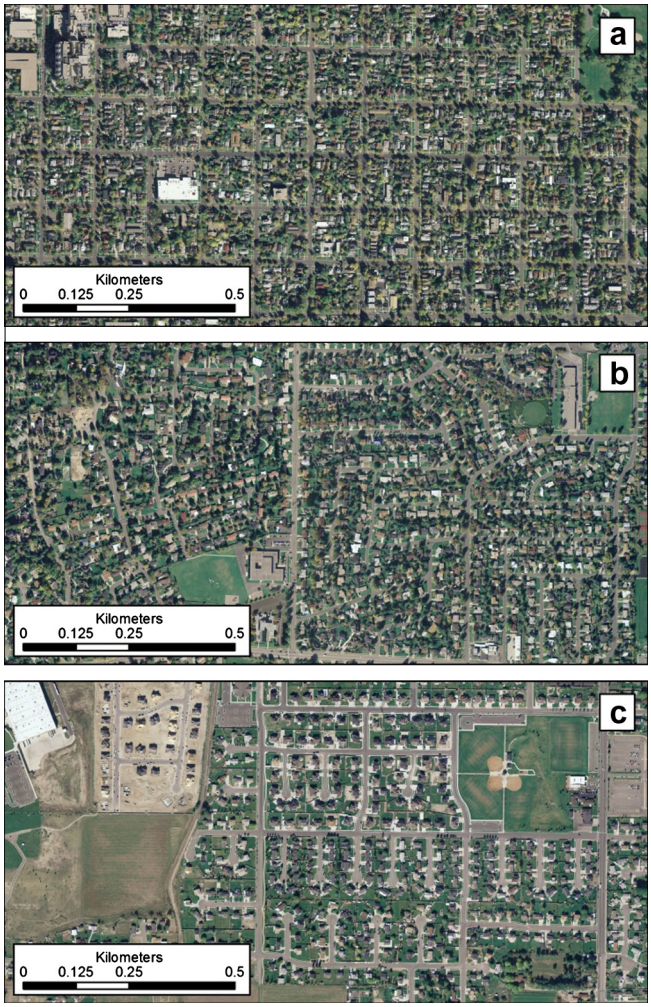

Fig. 2. Example neighborhood from neighborhood type (a) pre-suburban, (b) suburban, and (c) late-suburban.

Y_i represents the continuous variable for the urban form metric i and X_{i1} and X_{i2} are indicator variables (0 or 1) for the pre-suburban and suburban neighborhood types. The late-suburban neighborhood type is considered the omitted type, such that for the fitted model β_0 equals the mean for the late-suburban type when $\beta_1 = 0$ and $\beta_2 = 0$. It follows that, for the fitted model $\beta_0 + \beta_1$ equals the mean for the pre-suburban type and the mean for the suburban type is $\beta_0 + \beta_2$.

Because inference concerning model parameters (e.g. regression coefficients, group means) relies on assumptions of independence, we employed a spatial form of the linear regression model (Simultaneous Autoregressive model (Bailey & Gatrell, 1995; Bivand, Pebesma, & Gomez-Rubio, 2008)) to account for spatial dependence in model residuals.[1]

Table 2 compares population means of the three neighborhood types for the 18 urban form metrics. Population means are estimated using the methods described above, and a z-test used to test for equality of means. Larger z-scores indicate greater difference between two group means, with statistically significant differences denoted at $\alpha = 0.10$, 0.05, and 0.01 levels by asterisks.

The utility of estimated beta coefficients and standard errors was that they allowed us to infer confidence intervals around the spatial metric means using Monte-Carlo simulation. We ran 1000 Monte-Carlo simulations using the estimated beta coefficients and standard errors to produce the strip-charts in Figs. 3 and 4. Error bars mark positions 1 and 2 standard deviations from the mean which is marked with X. Strip charts are useful because they visually graph differences in means and convey the variability of urban form metrics by neighborhood type. As an example, while there is little difference in means for *median block perimeter size* between the suburban era and the late-suburban era neighborhoods, the variance around the mean in the late-suburban era neighborhoods is nearly double the variance of the suburban era neighborhoods—in other words, there is a greater variety of neighborhood block sizes in late-suburban neighborhoods (after 1990) than in neighborhoods built during the suburban era (1945–1990).

4.2. Correlation analysis

We used Pearson's Moment correlation to identify possible redundancies between metrics. Fig. 5 shows correlations for each urban form category within neighborhood type and across all types. Fig. 6 shows correlations across all metrics. In general, we found most of the metrics to have correlations less than $\rho = 0.50$. However, a few metrics exhibit high correlation the implications of which are discussed below.

5. Discussion

The following discussion elaborates on the results presented above. First, we synthesize the findings with the intent to provide guidance for planners and policy analysts seeking to select and use spatial metrics to quantify urban form, and discuss the metrics within each urban form category: *density*, *centrality*, *accessibility*, and *neighborhood mix*. Second, we discuss the findings in terms of the lessons learned from the particular results of the case study.

5.1. Spatial metrics

The density metrics produced the highest correlations of all the categories, suggesting not all five may be necessary to characterize this dimension of urban form, or that information provided is only marginally different and may therefore be more suitable under specific circumstances depending on the aspect of urban form one is trying to measure (see Fig. 5). For example, while *population density* is a common density metric used in practice, Galster et al. (2001) and Theobald (2002) argue that *housing density* is a better measure of the physical condition of land use, and therefore urban form. We concur, and suggest *housing density* be coupled with *average household size* or *median number of rooms* to measure both the physical condition of land use and living density. In addition, we found that *median size of residential lots* is useful because it sheds light on societal values and affluence of neighborhoods. For our case study, this metric showed practical and statistical significance when comparing mean differences across the neighborhood types (Table 2 and Fig. 3).

It should be noted that centrality metrics measure characteristics of urban form in the present-day for neighborhoods developed at different time periods in the past. For example, *mean distance to commercial zones* is the mean distance of neighborhoods to present-day commercial areas. This type of metric, while not a measure of how the neighborhood was developed, is useful because it provides an assessment of urban form across the landscape as it is

[1] With spatial data, model residuals are frequently spatially autocorrelated. In our study, for example, we could expect two adjacent neighbourhoods to be similar, even after accounting for a particular measure, such as housing density. These additional forms of dependence often manifest themselves in the model residuals, thus violating a key assumption of the conventional independent error model (i.e. Ordinary Least Squares) resulting in a biased estimation of regression coefficients (Bivand et al., 2008).

Table 2
Mean values and statistical comparison of means by neighborhood type.

Spatial metric	Mean[a]			Z-score[b]		
	(a) Pre-suburb	(b) Suburb	(c) Late-suburb	(a) & (b)	(b) & (c)	(a) & (c)
1. Median single fam. res. lot size	0.13	0.25	0.30	8.78***	−3.60***	−9.44***
2. Housing density	40.88	16.14	12.93	−10.56***	1.39	9.22***
3. Median number of rooms	5.15	6.50	6.60	7.10***	−0.60	−6.01***
4. Population density	78.94	44.20	35.25	−9.53***	2.50**	9.26***
5. Average household size	2.38	2.91	3.09	6.34***	−2.45**	−6.72***
6. Mean dist. to com. zone	3400.88	3681.01	3837.95	2.81**	−2.13	−3.54***
7. Mean dist. to public parks	628.74	701.60	731.55	1.57	−0.79	−1.77
8. Mean dist. to K-12 schools	2113.99	2136.25	2779.44	0.18	−5.61***	−4.15***
9. Mean dist. to transit bus stops	322.08	411.31	530.06	2.22*	−3.81***	−4.18***
10. Street connectivity	2.24	1.92	1.80	−7.21***	2.70**	7.61***
11. Median perimeter of blocks	356.69	593.49	588.42	8.14***	0.17	−6.06***
12. Dendritic street pattern	21.70	11.08	7.09	−5.73**	2.08	−6.02***
13. Median length of cul-de-sacs	76.63	68.24	80.61	−1.97	−2.76**	−0.71
14. Land use contiguity	52.17	44.06	51.95	−4.06***	−3.88***	0.08
15. Land use richness	5.32	5.12	5.67	−1.80	−4.81***	−2.45**
16. Land use diversity	0.54	0.53	0.50	−1.31	1.67	2.34*
17. Pop. working outside city	0.62	0.73	0.75	6.00***	−1.98	−6.07***
18. Renter–owner balance	2.67	0.62	0.29	−5.79***	0.93	5.17***

[a] See Table 1 for units.
[b] Standardized difference between the means. Probability of equal means denoted by: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. *P*-values corrected for multiple testing using Bonferroni method (Dalgaard, 2002).

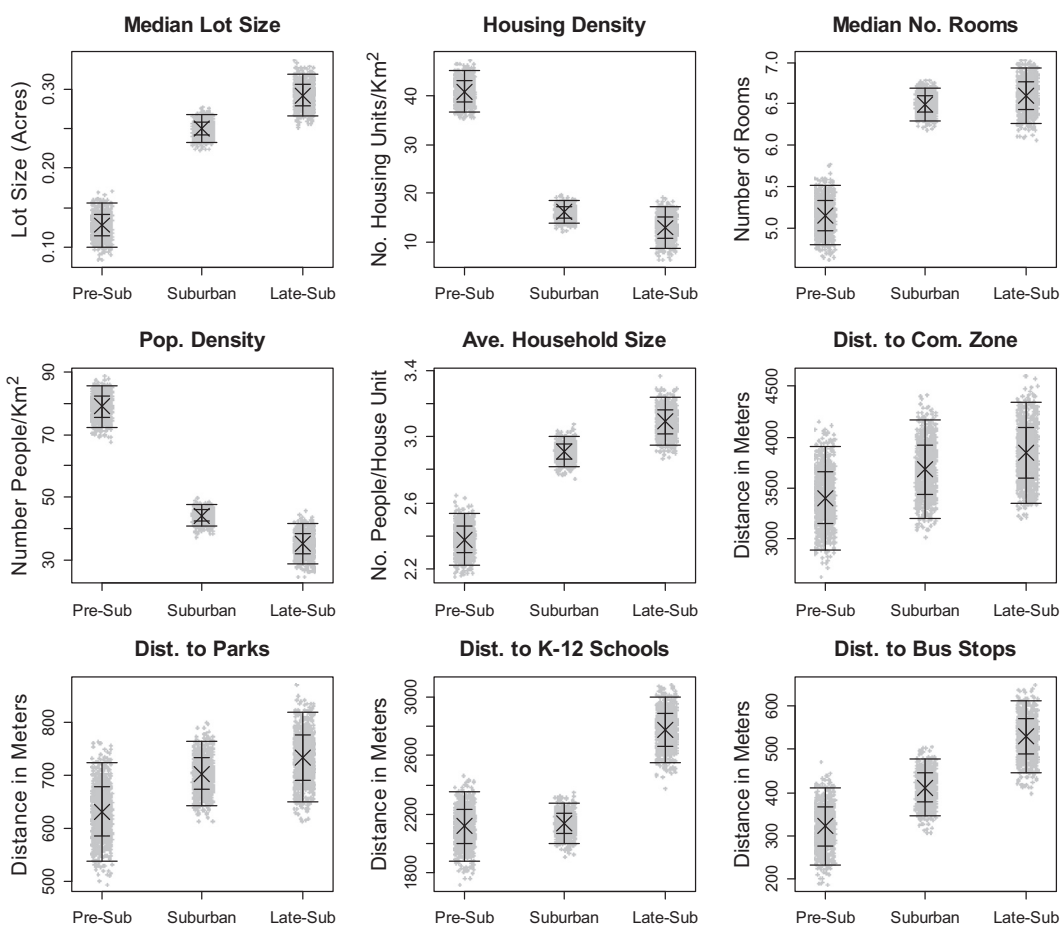

Fig. 3. Strip charts for density and centrality metrics.

today, and in the case of mean distance to commercial zones, tells us how much travel is required of people living in older pre-suburban neighborhoods as opposed to suburban neighborhoods.

What is striking about the centrality metrics is that we did not see major differences in mean values between neighborhood types. In fact, *mean distance to public parks* showed no statistically significant difference across any of the neighborhood types (Table 2 and Fig. 3). *Mean distance to transit bus stops* did show slight differences across neighborhoods; however it also exhibits high correlation with *mean distance to commercial zones* which

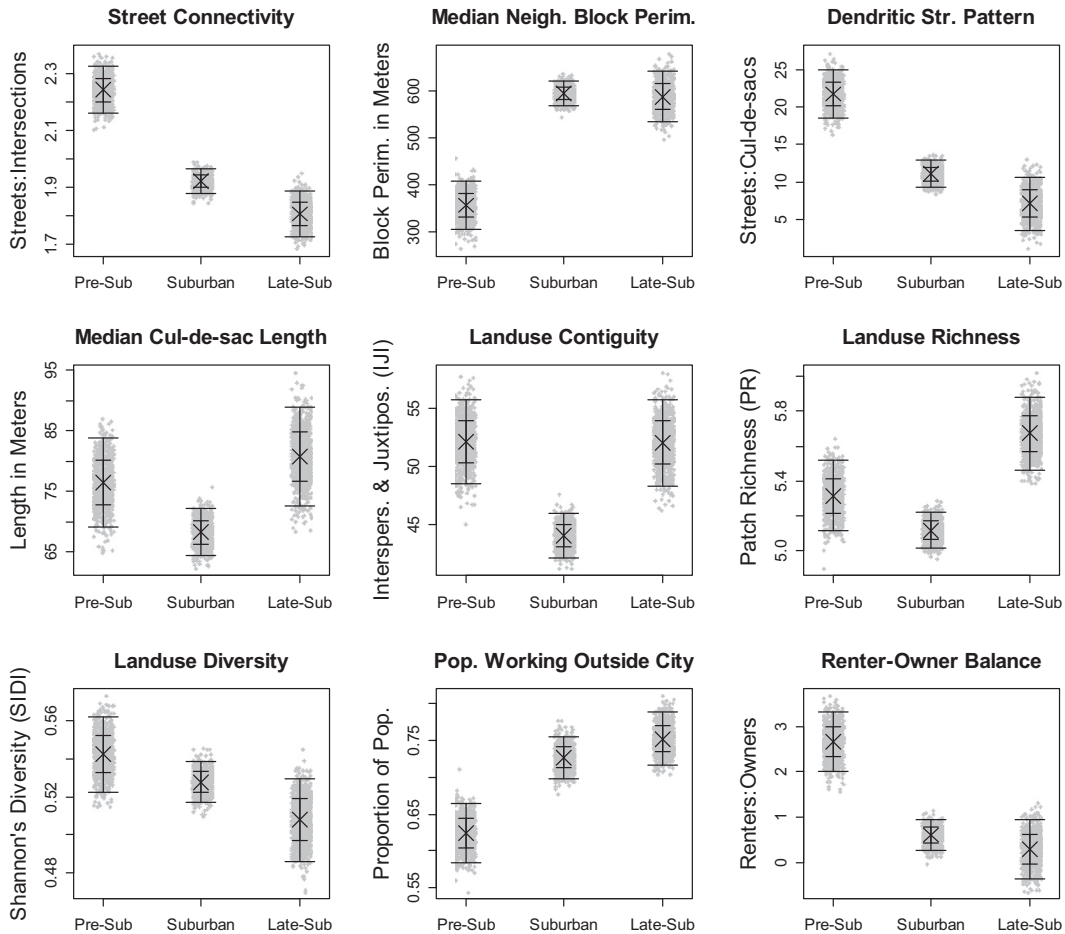

Fig. 4. Strip charts for accessibility and neighborhood mix metrics.

seemed to capture differences better. The observed correlation between these two metrics might be because there is often a high concentration of bus stops in commercial zones. For this reason, the metric *mean distance to transit bus stops* might be improved, and therefore more worthwhile, if it were to measure only the distance to bus stops located within a certain walkable radius. Another possible explanation could be that measures, such as *mean distance to transit bus stops*, are much more malleable once the neighborhood has been established. While some of the other measures, in contrast, are less subject to changes by governments or businesses once the main "shell" of the neighborhood has been put in place.

Our new metric for centrality, *mean distance to K-12 schools*, is not one that we found previously in the literature, but it proved to be very effective and easy to calculate. It exhibits low correlation with the other metrics, and demonstrates the ability to capture (with statistical significance) the trend toward longer school commute distances, a reality that has been well documented in the literature (McDonald, 2007). Therefore, we recommend two centrality metrics: *mean distance to commercial zones* and *mean distance to K-12 schools*.

Accessibility metrics provide information about residential design and street connectivity. Smart growth advocates argue that these qualities determine neighborhood "walkability" and "bikeability" (Lwin & Murayama, 2011). We found low correlation among all four accessibility metrics and each proved useful for quantifying urban form (Fig 5). For this reason, we recommend all four accessibility metrics in order to capture different dimensions of street design and connectivity. For example, *median cul-de-sac length* in the late-suburban era is about the same as the pre-suburban era, yet there are approximately three times as many cul-de-sacs.

Neighborhood mix metrics tell us about the spatial and demographic fabric of our urban landscape. All five neighborhood mix metrics showed low correlation within and across neighborhood types, suggesting the ability to uniquely quantify different aspects of neighborhood heterogeneity. However, *land use diversity* (Simpsons Diversity Index) did not convey differences in neighborhood type. It should be noted that this metric, like the other land use metrics, does not take into consideration land use quality. In other words, land use heterogeneity in one neighborhood is not qualitatively the same as the heterogeneity observed in another neighborhood. Therefore although *land use diversity*, which measures spatial evenness of land uses, is not statistically different across neighborhood types, this might be due to an interspersion of vacant or agricultural land.

Finally, the two metrics for demographic heterogeneity showed a statistically significant distinction between neighborhood types (Table 2 and Fig. 4) and effectively measure different aspects of the urban landscape. *Proportion of people working outside their city of residence* provides a measure of job decentralization while the *ratio of renters to owners* characterizes social and demographic heterogeneity. Consequently, we recommend all four neighborhood mix metrics: *land use contiguity*, *land use richness*, *population percentage working outside the city*, and *renter–owner balance*.

5.2. Case study findings

The findings of this case study are interesting and instructive for the broader debate on the natural and "planned" dynamics of

Density Metrics (1 to 5)

	Pre-suburban					Suburban					Late-suburban					All Neighborhoods			
2	0.10				2	-0.29				2	-0.43				2	-0.38			
3	-0.17	-0.54			3	0.31	-0.75			3	0.49	-0.49			3	0.46	-0.60		
4	0.19	0.94	-0.59		4	-0.29	0.86	-0.58		4	-0.48	0.92	-0.38		4	-0.42	0.91	-0.62	
5	-0.01	-0.61	0.42	-0.41	5	0.04	-0.31	0.42	0.16	5	0.19	-0.38	0.50	-0.19	5	0.33	-0.48	0.54	-0.28
	1	2	3	4		1	2	3	4		1	2	3	4		1	2	3	4

Centrality Metrics (6 to 9)

	Pre-suburban				Suburban				Late-suburban				All Neighborhoods			
7	-0.16			7	-0.06			7	0.18			7	-0.01			
8	-0.08	-0.08		8	0.11	0.05		8	0.24	0.34		8	0.23	0.07		
9	0.12	-0.11	0.25	9	0.29	-0.04	0.27	9	0.55	0.23	0.35	9	0.50	0.04	0.37	
	6	7	8		6	7	8		6	7	8		6	7	8	

Accessibility Metrics (10 to 13)

	Pre-suburban				Suburban				Late-suburban				All Neighborhoods			
11	-0.27			11	-0.06			11	-0.06			11	-0.20			
12	-0.23	0.18		12	0.00	-0.02		12	0.05	-0.26		12	0.06	-0.11		
13	0.09	-0.19	-0.05	13	-0.15	-0.07	-0.05	13	0.10	-0.13	0.16	13	-0.04	-0.11	-0.03	
	10	11	12		10	11	12		10	11	12		10	11	12	

Neighborhood Mix Metrics (14 to 18)

	Pre-suburban					Suburban					Late-suburban					All Neighborhoods				
15	0.33				15	0.37				15	0.02				15	0.32				
16	0.38	0.04			16	0.34	0.14			16	0.03	-0.04			16	0.28	0.07			
17	0.17	0.47	-0.05		17	0.01	0.00	0.09		17	-0.06	-0.14	0.16		17	-0.07	0.02	-0.01		
18	0.40	0.20	-0.09	-0.02	18	0.37	0.08	0.12	0.00	18	0.47	0.06	0.18	0.04	18	0.34	0.08	0.04	-0.21	
	14	15	16	17		14	15	16	17		14	15	16	17		14	15	16	17	

Fig. 5. Pearson's moment correlation for spatial metrics within and across neighborhood types. *Note: The metric number 1–18 is shown; see* Table 1 *for metric names, units, and GIS data required.*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1.00																	
2	-0.38	1.00																
3	0.46	-0.60	1.00															
4	-0.42	0.91	-0.62	1.00														
5	0.33	-0.48	0.54	-0.28	1.00													
6	0.43	-0.39	0.45	-0.36	0.60	1.00												
7	0.19	-0.05	0.01	-0.17	-0.23	-0.01	1.00											
8	0.36	-0.06	0.05	-0.10	0.15	0.23	0.07	1.00										
9	0.49	-0.30	0.42	-0.35	0.38	0.50	0.04	0.37	1.00									
10	-0.20	0.40	-0.25	0.32	-0.33	-0.39	-0.01	0.02	-0.10	1.00								
11	0.31	-0.30	0.37	-0.25	0.31	0.24	-0.10	-0.10	0.14	-0.20	1.00							
12	-0.28	0.06	-0.16	0.07	-0.18	-0.16	-0.10	-0.14	-0.18	0.06	-0.11	1.00						
13	0.20	0.03	-0.01	0.02	0.02	0.01	0.17	0.18	0.16	-0.04	-0.11	-0.03	1.00					
14	0.03	0.37	-0.44	0.33	-0.22	-0.17	0.06	0.22	0.03	0.23	-0.34	-0.16	0.25	1.00				
15	0.07	0.00	-0.21	-0.03	0.00	-0.03	0.02	0.22	0.03	0.01	-0.25	-0.14	0.16	0.32	1.00			
16	-0.17	0.22	-0.21	0.23	-0.16	-0.23	-0.03	-0.31	-0.32	-0.03	-0.12	-0.07	0.04	0.28	0.07	1.00		
17	0.46	-0.43	0.32	-0.40	0.35	0.43	0.15	0.15	0.20	-0.51	0.26	-0.31	0.08	-0.07	0.02	-0.01	1.00	
18	-0.14	0.44	-0.43	0.42	-0.29	-0.24	-0.01	0.08	-0.15	0.27	-0.15	0.00	0.07	0.34	0.08	0.04	-0.21	1.00
	Denisty (1-5)					Centrality (6-9)				Accessibilty (10-13)				Neighborhood Mix (14-18)				

Fig. 6. Pearson's moment correlation across all metrics. *Note: The metric number 1–18 is shown; see Table 1 for metric names, units, and GIS data required.*

urban form. A comparison of pre-suburban and suburban neighborhoods lends empirical evidence to the hypothesis that the spatial structure of urban neighborhoods experienced significant changes following World War II. Historians have documented that for almost five decades, economic conditions, societal values, and inexpensive automobiles pushed Americans into sprawling, low-density suburbs with segregated land uses and dendritic street networks (Jackson, 1985). We found 11 of the 18 urban form metrics confirmed this story with statistically significant differences in mean values.

To highlight a few prominent differences between pre-suburban and suburban neighborhoods, we note *median residential lot size* increased from nearly a tenth of an acre to a full quarter acre, *housing density* decreased drastically from 41 units/square km to only 16 units/square km, and *dendritic street pattern* nearly doubled. The neighborhood mix metrics showed more homogenous land uses in the suburban neighborhoods. Again, this metric is based on present-day land uses, so the more heterogeneous nature of pre-suburban neighborhoods may be a relict of how the neighborhoods were developed (i.e. non-residential land uses juxtaposed to residential land uses) or current zoning policies in older neighborhoods allowing mixed uses, or a combination of the two. The lower value for *land use contiguity* suggests less even interspersion and juxtaposition, or "clumping." In other words, the

suburban neighborhoods exhibit more discontinuous residential development, also known as "leap-frog" sprawl (Ji, Ma, Twibell, & Underhill, 2006).

Furthermore, compared to the pre-suburban neighborhoods, 10% more of the people living in neighborhoods built during the suburban period commute to work outside of their city of residence. They are also three times more likely to be homeowners in the suburbs compared to those living in neighborhoods built during the pre-suburban period.

Equally informative is the comparison between suburban and late-suburban neighborhoods, which were built during a period of active efforts to reverse, or at least decelerate, urban sprawl. However, despite efforts toward "smart growth," it seems many of the same trends continued, albeit not nearly as drastically – *median lot size* increased from a quarter to a third of an acre, *housing density* decreased again, but not nearly as much, from 16 units/square km to 13 units/square km, and street patterns showed even more dendritic qualities. Concerning urban sprawl in the 1990s Lopez and Hynes (2003) found that continued sprawling growth was not a universal phenomenon across the U.S. and in fact some metropolitan areas became more densely populated. However, they suggest that increased density is more likely to occur in cities where low-density growth is not an option, such as where there are physical barriers to suburban expansion.

Finally, considering that the "New Urbanist" philosophy seeks to shape development toward an urban form reminiscent of pre-World War II, it is constructive to compare pre-suburban and late-suburban neighborhoods. However, and perhaps lamentably for New Urbanists, our results show that across nearly all metrics urban form the late-suburban neighborhoods do not resemble pre-suburban neighborhoods. On the other hand, it should be noted that our analysis compared differences in neighborhoods types "on average," so it is all together possible that a few specific neighborhoods built during the late-suburban period may have successfully achieved some ideals of new urbanism.

6. Conclusion

This study compared 18 spatial metrics that are used by practicing planners and academics to quantify urban form. The results showed high correlation for a few of the metrics – an indication of possible redundancy in what they are measuring. Furthermore, some metrics proved more effective than others for characterizing urban form. Based on our findings, we recommend thirteen spatial metrics to quantify urban form: *median single family residential lot size*, *housing density*, *average household size*, *mean distance to commercial zones*, *mean distance to K-12 schools*, *street connectivity*, *median perimeter of blocks*, *dendritic street pattern*, *median length of cul-de-sacs*, *land use contiguity*, *land use richness*, *population percentage working outside the city*, and *renter–owner balance*.

Additionally, our analysis revealed significant differences in spatial and demographic characteristics of three residential neighborhood types. Spatial structure is very much a relict of the time period in which the development occurred. The differences we report between pre-suburban (1891–1944) and suburban (1945–1990) neighborhoods are not surprising given the widely recognized changes that occurred in U.S. cities across these two time periods (Lindsrom & Bartling, 2003; Mieszkowski & Mills, 1993). Of greater interest is what we find when we compare suburban and late-suburban (1990–2007) era neighborhoods.

Beginning in the 1990s, concern for uncontrolled urban growth reached the consciousness of professionals and laypersons alike. In a study similar to ours, Song and Knapp (2004) report that the city of Portland, OR appears to be winning the battle against urban sprawl. While they do not explicitly correlate the policies of Portland's growth management program to their observations of an urban form more characteristic of Smart Growth, they suggest that the changes observed after 1990 could very well be a result of such policies.

Our findings suggest that Salt Lake County is not doing as well in the battle against sprawling urban growth. Many factors might explain the lack of shift toward "smarter growth." Geographically the county has room to grow. As of 2006, 65 square miles (165 km^2) or 20% of the valley bottom was still in agricultural production (GIS calculation with UDWR (2006) data) and in prime position for residential expansion. Utah's population is young and growing, fueling demand for additional homes (U.S. Dept. of HUD, 2009). Generally the political climate is conservative, favoring local control of land use planning rather than planning on a regional scale (Envision Utah, 2009). The strategies employed by Envision Utah are not enforceable regulations, but are rather guiding principles, offered to local decision makers based on information obtained from the public through informal workshops. Finally, Utah experienced high economic growth during the 1990s and early 2000s (U.S. Dept. of HUD, 2009) as did much of the nation. These combined factors greatly influence the spatial and demographic pattern of residential neighborhoods observed in this study.

Acknowledgements

This research was funded by the Intermountain Digital Image Archive Center, Utah State University under a grant from NASA (NNX06AF56G). We gratefully acknowledge Dr. Douglas Ramsey (Utah State University) and Dr. Mevin Hooten (formerly of Utah State University, now Colorado State University) for their insightful contributions. We also acknowledge the helpful critique of earlier drafts by two anonymous reviewers.

Appendix A

Because the three neighborhood mix metrics are expressed as an index value rather than a common unit of measure (as are the other spatial metrics) we provide the equations for these metrics for the interested reader. These metrics are drawn from discipline of landscape ecology (McGarigal, Cushman, Neel, & Ene, 2002) and may be unfamiliar to some urban planners. For each of these indices a higher value corresponds to greater land use heterogeneity.

Juxtaposition and Interspersion Index

$$= \frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}[(E_{ik}) * \ln(E_{ik})]}{\ln\left(\frac{m(m-1)}{2}\right)}, \tag{1}$$

$$\text{Patch Richness} = \frac{m}{100 \text{ hectares}}, \quad \text{and} \tag{2}$$

$$\text{Simpsons Diversity Index} = 1 - \frac{\sum_{i=1} mn_i(n_i - 1)}{N(N-1)} \tag{3}$$

where m is the number of land use types in the neighborhood, E_{ik} the length of the edge between land use type i and land use type k, n_i the number of parcels of a land use type i in the neighborhood, and N is the number of parcels in the neighborhood.

References

Bailey, T., & Gatrell, A. C. (1995). *Interactive spatial data analysis*. Harlow, Essex, England: Pearson Education Limited.

Bivand, R. S., Pebesma, E. J., & Gomez-Rubio, V. (2008). *Applied spatial data analysis with R*. New York): Springer Science+Business Media, LLC.

Churchman, A. (1999). Disentangling the concept of density. *Journal of Planning Literature, 13*, 389–411.

Dalgaard, P. (2002). *Introductory statistics with R*. New York: Springer.
Envision Utah. (2009). "The history of Envision Utah" About Envision Utah website <http://www.envisionutah.org/historyenvisonutahv5p1.pdf>.
Ewing, R., Pendall, R., & Chen, D. (2002). *Measuring sprawl and its impact*. Smart Growth America, Washington DC. <http://www.smartgrowthamerica.org/sprawlindex/MeasuringSprawl.PDF>.
Frenkel, A., & Ashkenazi, M. (2008). Measuring urban sprawl: How can we deal with it? *Environment and Planning B: Planning and Design, 35*, 56–79.
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.
Garreau, J. (1991). *Edge city*. New York: Doubleday.
Glaser, E. L., Kahn, M. E., & Chu, C. (2001). *Job sprawl: employment location in U.S. metropolitan areas*. Washington DC: The Brookings Institution, Center on Urban & Metropolitan Policy. <http://www.brookings.edu/es/urban/publications/glaeserjobsprawl.pdf>.
Hamilton, L. C. (1992). *Regression with graphics: A second course in applied statistics*. Belmont, CA: Duxbury Press.
Herold, M., Couclelis, H., & Clarke, K. C. (2005). The role of spatial metrics in the analysis and modeling of urban land use change. *Computers, Environment and Urban Systems, 29*(4), 369–399.
Jackson, K. T. (1985). *Crabgrass frontier: The suburbanization of the United States*. New York: Oxford University Press.
Ji, W., Ma, J., Twibell, R. W., & Underhill, K. (2006). Characterizing urban sprawl using multi-stage remote sensing images and landscape metrics. *Computers, Environment and Urban Systems, 30*(6), 861–879.
Jin, X., & White, R. (2012). An agent-based model of the influence of neighbourhood design on daily trip patterns. *Computers, Environment and Urban Systems, 36*(5), 398–411.
Johnson, M. P. (2001). Environmental impacts of urban sprawl: A survey of the literature and proposed research agenda. *Environment and Planning A, 33*, 717–735.
Kerski, J., & Clark, J. (2012). *The GIS guide to public domain data*. Redlands, CA: ESRI Press.
Knapp, G. J. (2005). A requiem for smart growth? In D. R. Mandelder (Ed.), *Planning reform in the new century*. Chicago, IL: American Planning Association.
Lattin, J. M., Carrol, J. D., & Green, P. E. (2003). *Analyzing multivariate data*. Pacific Grove, CA: Brooks/Cole–Thompson Learning.
Leccese, M., McCormick, K., Davis, R., & Poticha, S. R. (2000). *Charter for the new urbanism*. New York: McGraw-Hill.
Lindsrom, M. J., & Bartling, H. (2003). *Suburban sprawl: Culture, theory, and politics*. Lanham, Maryland: Rowman & Littlefield Publishers Inc.
Liu, C., & Shen, Q. (2011). An empirical analysis of the influence of urban form on household travel and energy consumption. *Computers, Environment and Urban Systems, 35*(5), 347–357.
Lopez, R., & Hynes, P. H. (2003). Sprawl in the 1990s: Measurement, distribution and trends. *Urban Affairs Review, 48*(3), 325–355.
Lwin, K. K., & Murayama, Y. (2011). Modelling of urban green space walkability: Eco-friendly walk score calculator. *Computers, Environment and Urban Systems, 35*(5), 408–420.
Lynch, K. (1984). *Good city form*. Cambridge, MA: The MIT Press.
Mcdonald, N. (2007). Active transportation to schooltrends among U.S. schoolchildren, 1969–2001. *American Journal of Preventive Medicine, 32*(6), 509–516.
McGarigal, K., Cushman, S. A., Neel, M. C., & Ene, E. (2002). *FRAGSTATS: Spatial Pattern Analysis Program for Catagorical Maps* Computer software program produced by the authors at the University of Massachusetts, Amherst www.umass.edu/landeco/research/fragstats/fragstats.html.
Mieszkowski, P., & Mills, E. (1993). The causes of metropolitan suburbanization. *Journal of Economic Perspectives, 7*(3), 135–147.
Peters, A., & MacDonald, H. (2004). *Unlocking the census with GIS*. Redlands, CA: ESRI.
Song, Y., & Knapp, G.-J. (2004). Measuring urban form. *Journal of the America Planning Association, 70*(2), 210–225.
Theobald, D. M. (2002). Land-use dynamics beyond the American urban fringe. *The Geographical Review, 91*(3), 544–564.
Torrens, P. M., & Alberti, M. (2000). *Measuring sprawl. Centre for advanced spatial analysis*. London: University College London. <www.casa.ucl.ac.uk/working_papers/Paper27.pdf>.
U.S. Census. (2009). *State and county quick facts*. <http://quickfacts.census.gov/qfd/index.html>. Retrieved 08.07.10
U.S. Dept. of HUD, 2009 *Salt lake consolidated plan*. <http://www.hud.gov/offices/cpd/about/conplan/local/ut/consolidatedplansaltlakecounty.cfm> Retrieved 08.07.10.
UDNR-DWR. (2006). GIS dataset of water-related land uses. *Utah Department of Natural Resources, Division of Water Resources* Salt Lake City, UT.
Weston, L. M. (2002). A methodology to evaluate neighborhood urban form. *Planning Forum, 8*, 64–77.