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A scale-adjusted measure of "Urban sprawl" using nighttime satellite imagery

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Abstract

"Urban Sprawl" is a growing concern of citizens, environmental organizations, and governments. Negative impacts often attributed to urban sprawl are traffic congestion, loss of open space, and increased pollutant runoff into natural waterways. Definitions of "Urban Sprawl" range from local patterns of land use and development to aggregate measures of per capita land consumption for given contiguous urban areas (UA). This research creates a measure of per capita land use consumption as an aggregate index for the spatially contiguous urban areas of the conterminous United States with population of 50,000 or greater. Nighttime satellite imagery obtained by the Defense Meteorological Satellite Program's Operational Linescan System (DMSP OLS) is used as a proxy measure of urban extent. The corresponding population of these urban areas is derived from a grid of the block group level data from the 1990 U.S. Census. These numbers are used to develop a regression equation between Ln(Urban Area) and Ln(Urban Population). The 'scale-adjustment' mentioned in the title characterizes the "Urban Sprawl" of each of the urban areas by how far above or below they are on the "Sprawl Line" determined by this regression. This "Sprawl Line" allows for a more fair comparison of "Urban Sprawl" between larger and smaller metropolitan areas because a simple measure of per capita land consumption or population density does not account for the natural increase in aggregate population density that occurs as cities grow in population. Cities that have more "Urban Sprawl" by this measure tended to be inland and Midwestern cities such as Minneapolis–St. Paul, Atlanta, Dallas–Ft. Worth, St. Louis, and Kansas City. Surprisingly, west coast cities including Los Angeles had some of the lowest levels of "Urban Sprawl" by this measure. There were many low light levels seen in the nighttime imagery around these major urban areas that were not included in either of the two definitions of urban extent used in this study. These areas may represent a growing commuter-shed of urban workers who do not live in the urban core but nonetheless contribute to many of the impacts typically attributed to "Urban Sprawl". "Urban Sprawl" is difficult to define precisely partly because public perception of sprawl is likely derived from local land use planning decisions, spatio-demographic change in growing urban areas, and changing values and social mores resulting from differential rates of international migration to the urban areas of the United States. Nonetheless, the aggregate measures derived here are somewhat different than similar previously used measures in that they are 'scale-adjusted'; also, the spatial patterns of "Urban Sprawl" shown here shed some insight and raise interesting questions about how the dynamics of "Urban Sprawl" are changing.

Keywords: Urban sprawl; Sprawl Line; Nighttime satellite imagery

1. Introduction

The issue of what is commonly referred to as "Urban sprawl" is gaining increasing attention and concern from citizens, environmental organizations, and governments (http://www.sierraclub.org/sprawl/; http://www.vtsprawl.org/index3.htm; (Benfield et al., 2001)). Concerns are raised about the impact urban sprawl has on the loss of open space, traffic congestion, and energy consumption. Nonetheless, specific, measurable, and generally accepted definitions of urban sprawl are difficult to find. William Whyte's 1958 definition of urban sprawl referred to *patterns* of urban development ("*...the leapfrog nature of urban growth...*") (Whyte, 1958). Others have defined "Urban Sprawl" based simply on the aggregate population density of a given urban area (Fulton et al., 2001; Kolankiewicz & Beck, 2001). It is very likely that "Urban Sprawl" happens to some extent in specific areas of most cities. It could be argued that "Urban Sprawl" is similar to pornography in that it is difficult to define but '*You know it when you see it*'. It could be argued that "Urban Sprawl" is a multi-dimensional phenomenon

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that needs to be characterized with several variables. Nonetheless, this research focuses on providing a single, scale-adjusted (population corrected), aggregate indicator of "Urban Sprawl" for all urban areas of population greater than 50,000 in the conterminous United States.

Studies using aggregate population density as an indicator of "Urban Sprawl" have typically used 'urban area' designations of the U.S. Census along with corresponding population figures to determine an average population density for urbanized areas within the US (Fulton et al., 2001; Kolankiewicz & Beck, 2001). These aggregate measures of sprawl suffer from two problems: (1) problems associated with measurements of the areal extent of an urban area, and (2) the nonlinear variation of the aggregate population density of urban areas as a function of total population. Remotely sensed images of urban environments have great potential for delineating urban areas. GIS coverages of urban environments suffer from arbitrary administrative boundaries used in conjunction with housing unit density or population density thresholds. Nighttime imagery has some advantages over daytime imagery in that it is measuring emitted rather than reflected radiation, this avoids some classification problems in separating developed vs. non-developed land cover. This research utilizes a 'scale-adjusted' measure of "Urban Sprawl" that addressees the nonlinearity problem and uses two 'thresholds' of nighttime satellite imagery as a means of measuring the areal extent of urban areas in the United States.

The urban extent of cities varies as a nonlinear function of their total population (Nordbeck, 1965; Stewart & Warntz, 1958; Tobler, 1969). This has also been demonstrated using nighttime satellite imagery as a proxy measure of urban areal extent both nationally and globally (Sutton et al., 1997, 2001). Typically, as cities grow their aggregate population density increases; consequently, the aggregate population density of large cities like Los Angeles and Chicago will be higher than the aggregate population density of smaller cities such as Portland and Kansas City. However, this does not imply that Los Angeles and Chicago suffer less from "Urban Sprawl" than Portland or Kansas City. Any aggregate measure of "Urban Sprawl" for an urban area should be scale-adjusted by the total population of that urban area.

The U.S. Census defines the urban area (UA) of a city each time a census takes place. A UA is designated for all central cities with a population in excess of 50,000. The urban areas designated by the census do not always correspond with land cover maps derived from satellite imagery (Vogelmann et al., 1998). This study uses nighttime satellite imagery provided by the Defense Meteorological Satellite Program's Operational Linescan System (DMSP OLS) to measure the areal extent of the urban areas of the conterminous United States. Imhoff et al. (1997) have used the DMSP OLS imagery in similar ways. The DMSP OLS imagery is compared to a gridded population density dataset derived from the 1990 U.S. Census (Meij, 1995). This comparison results in measures of both the areal extent and the population of all the urban areas in the conterminous United States. These numbers are then used to calculate improved aggregate measures of urban sprawl.

2. Data and methods

The data required to develop a 'scale-adjusted' measure of urban sprawl are simply: (1) the areal extent of urban areas, (2) the corresponding population of those urban areas, and (3) a formula describing the relationship between the population and areal extent of these urban areas. The data used to obtain areal extent and population are: (1) a radiance calibrated DMSP OLS image of the United States (Elvidge et al., 1998), and (2) a grid of population density derived from the U.S. Census (Meij, 1995). Both of these images have a spatial resolution of 1 km^2 (Fig. 1). The numbers derived from these datasets are used in a population weighted regression of the Ln(Urban Area km^2) vs. Ln(Urban Population) relationship. One problem associated with using the nighttime satellite imagery as a proxy measure of urban extent is the question of thresholding: (i.e. 'What light intensity should be used to characterize an area as urban?').

The Denver metropolitan area illustrates this problem (Fig. 2). Fig. 2 shows the Denver Metropolitan area as represented by a 30-m resolution USGS National Land Cover Data (NLCD) image (Vogelmann et al., 2001). This image was used as a check on setting urban 'thresholds' on the DMSP OLS nighttime image. Defining 'urban' is a difficult problem unto itself. Many people contend that the corridor from Denver to Boulder is urban whereas the NLCD image classifies much of it as agricultural (The image derived by Vogelmann et al. is based in 1992 Landsat images.) The conurbation represented by Denver and Boulder is happening to lesser and greater extents throughout the United States. Because of this problem of conurbation and the more general problem of answering the "What is Urban?" question, two thresholds were used and analyzed separately. The blue line in Figs. 1 and 2 represent the lower threshold (900 $\mu W/cm^2/sr/\mu m$) which measures larger urban extents. The red lines of Figs. 1 and 2 represent the higher threshold (2000 $\mu W/cm^2/sr/\mu m$) for classifying the DMSP OLS image as 'urban'. The high threshold separates Boulder from Denver and is a more accurate measure of strictly urban land cover. The lower threshold captures Boulder and Denver in one conurbation and is probably a better measure of urban areas as metropolitan areas. The 30-m resolution USGS NLCD dataset is probably one of the best measures of urban land cover available; however, the size of these datasets makes it very difficult to apply this analysis for an area the size of the conterminous United States. In addition, the spatial resolution of the NLCD data introduces a fuzzy 'fractal' boundary for urban areas that makes it difficult to define 'urban' systematically.

The lower threshold creates larger conurbations of cities which are consequently measured as one 'urban cluster'

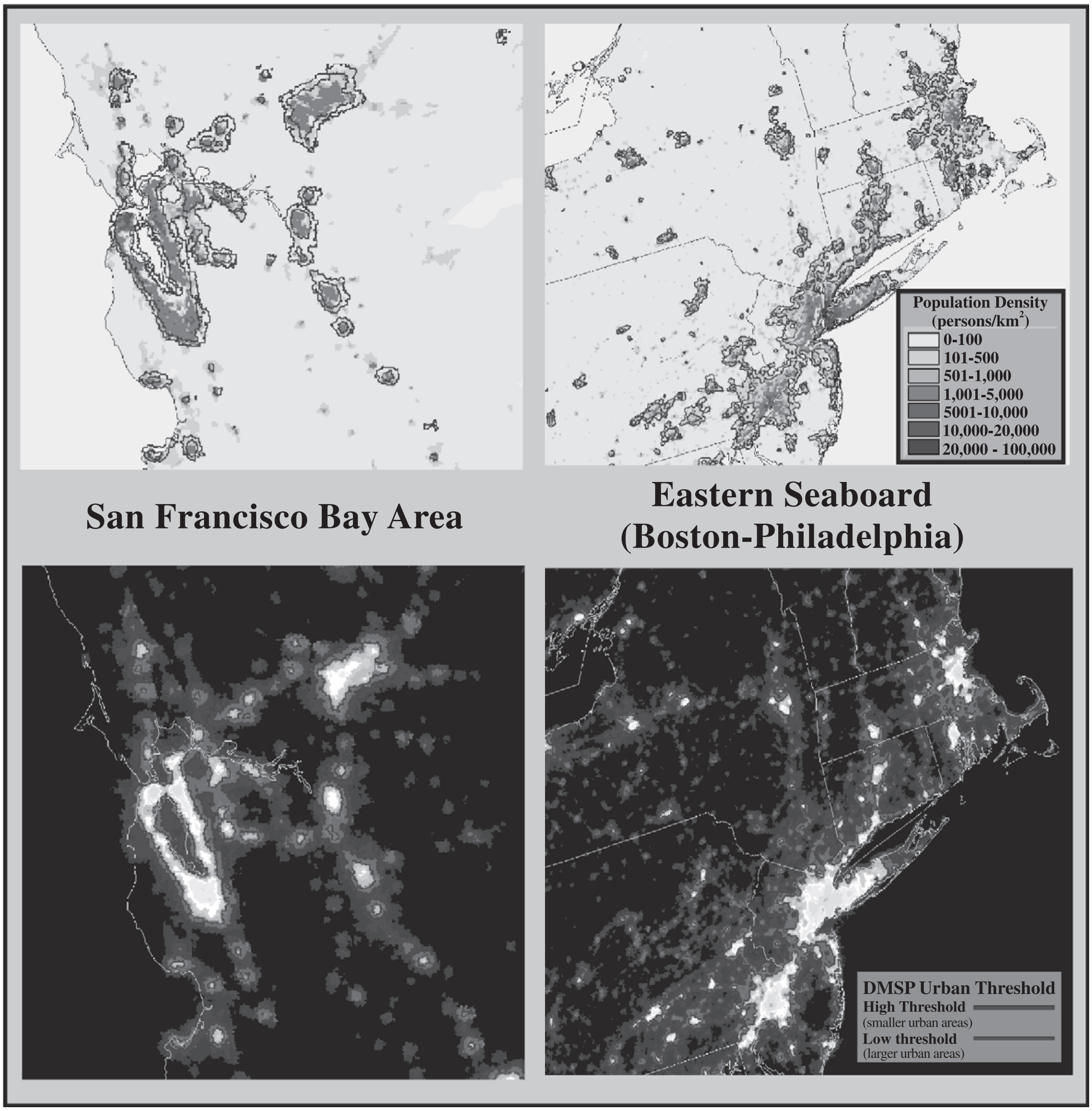

Fig. 1. Population density and DMSP OLS nighttime imagery used to calculate urban extent and population.

(e.g. Philadelphia, PA; Newark, NJ; New York, NY; Hartford, CT; and Springfield, MA are all measured as one giant conurbation with the low threshold but are all distinct clusters with the higher threshold (Fig. 1)). That same distinction holds with the Denver–Boulder conurbation (e.g. the low threshold captures Boulder and Denver in the same 'urban cluster' where the high threshold identifies them as separate urban areas (Fig. 2)). The DMSP OLS image was classified into a 'Low Threshold' urban image and a 'High Threshold' urban image. These two urban images were compared with the population density image to create the paired (Area (km^2), Population(total number of individuals)) points needed to derive the regression parameters for the following log–log relationship:

$$\mathrm{Ln}(\mathrm{Population}) = B_0 + B_1{*}\mathrm{Ln}(\mathrm{Area}) \tag{1}$$

This relationship shows a strong correlation for the (Area, Population) data using both the 'Low Threshold' ($R^2 = 0.97$, $N = 300$) and 'High Threshold' ($R^2 = 0.96$ $N = 244$) urban areas with population greater than or equal to 50,000.

3. Results and analysis

The regression line on the scatterplots of the Ln(Area) vs. Ln(Population) relationship represents a scale-adjusted ''Sprawl Line''. The line itself represents the average relationship between the areal extent and population of urban areas in the conterminous United States. It should be noted that the nature of this sprawl line is specific to the United States. A 'Sprawl Line' for other countries will generally have a higher intercept for countries with lower

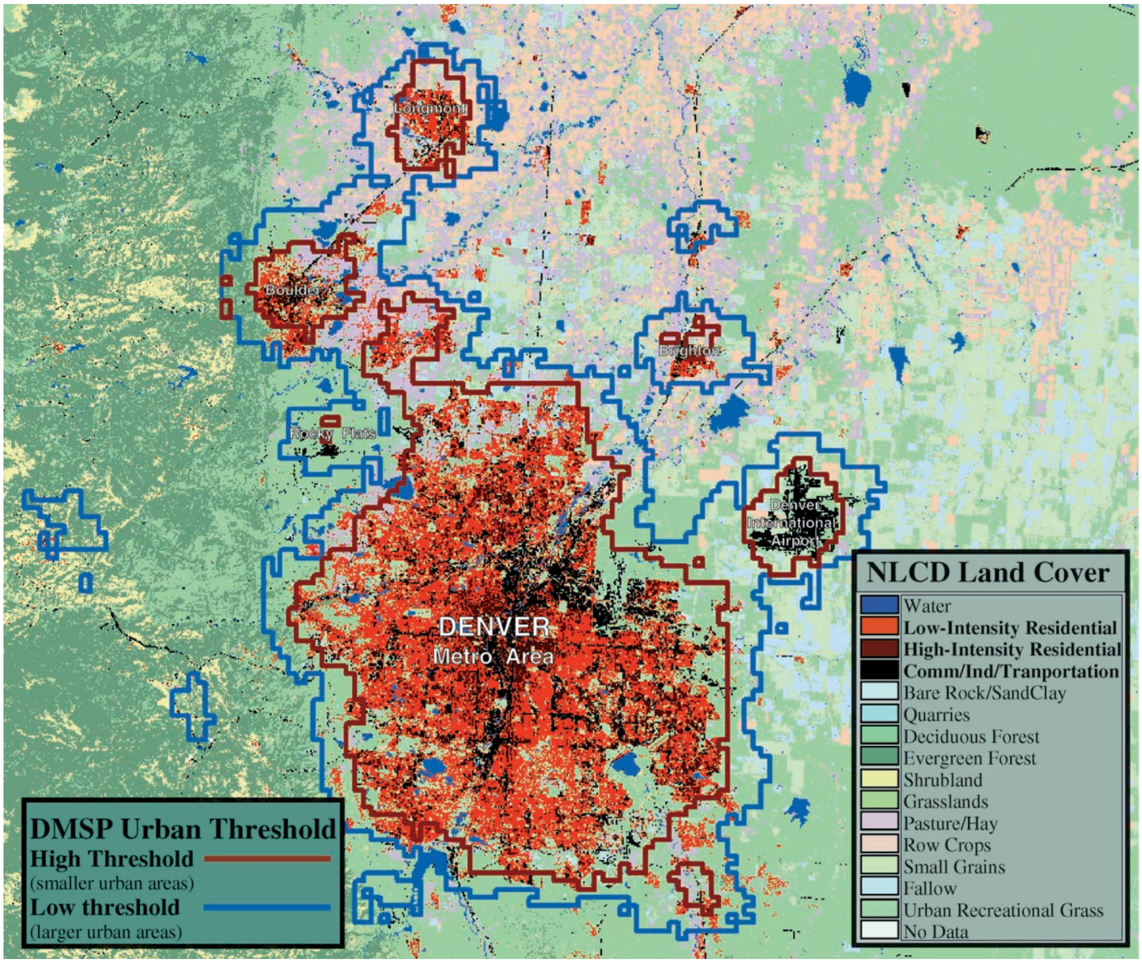

Fig. 2. Image of the Denver metro area using USGS National Land Cover Database (30 m) with both 'high' and 'low' DMSP urban thresholds.

GDP per capita (in general poorer countries have cities with higher population densities).

Each point in the scatterplot represents one of the urban areas of the US whose population is greater than 50,000. The points above the "Sprawl Line" represent urban areas with a higher than expected population, which implies lower land consumption per capita. These cities can be thought of as not suffering from "Urban Sprawl" as much as the urban areas that fall below the line. Points that fall below the "Sprawl Line" represent urban areas with lower than expected total populations and higher per capita land consumption. Scatterplots are provided for both the "High threshold" and "Low Threshold" definitions of urban (Figs. 3 and 4). The city name, state(s), areal extent, actual population, predicted population ('Sprawl Line' population), and percent difference are provided for both thresholds in Tables 1 and 2. The coding of the points in the scatter plots is based on the percent difference between the predicted population (i.e. on the 'Sprawl Line') and actual population of the urban areas in question. Images of the actual urban areas that the points in the scatterplots correspond to are provided for both the "Low Threshold" (Fig. 5) and the "High Threshold" (Fig. 6) data using the same coding.

Common patterns shown in Figs. 5 and 6 are the fact that the west coast urban areas such as the Los Angeles metropolitan area, the San Francisco Bay area, San Diego, Portland, and Seattle all fall above the "Sprawl Line". In addition, several mid-western and inland urban areas such as Dallas–Ft. Worth, Oklahoma City, Saint Louis, Minneapolis–St. Paul, Atlanta, and Indianapolis fall below the "Sprawl Line". Some interesting changes that resulted from different thresholds are the breakup of the Philadelphia–Newark–New York–Hartford–Springfield conurbation and the breakup of the Boston–Providence–Fall River conurbation. The Boston breakup resulted in a transition from below the "Sprawl Line" (red) to neutral (white) and above (sage) the "Sprawl Line". The New York breakup resulted in a transition from neutral (White) to both above and below the "Sprawl Line" (New York, Hartford, Springfield went above (sage and green), Philadelphia went below

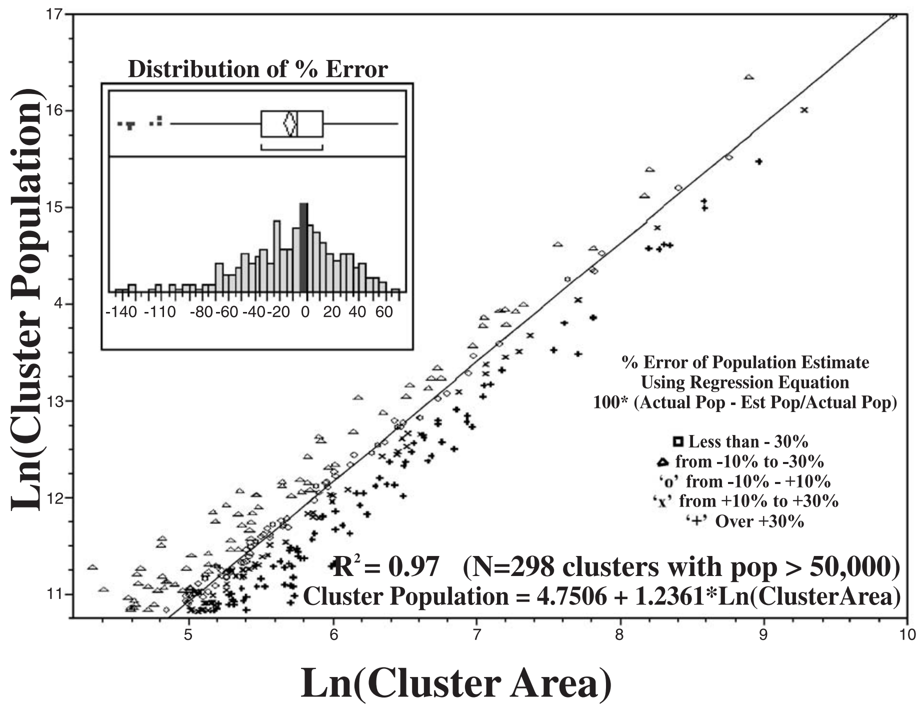

Fig. 3. 'The low threshold sprawl line', a regression of the urban clusters identified by the DMSP imagery with population greater than 50,000. Urban areas below the line suffer from 'sprawl' more than points above the line. Color coding of points represents the percent difference between the actual population and the population predicted by this regression equation.

(orange)). The overall variability of per capita land use as suggested by the distribution of percent error in Figs. 3 and 4 is also of interest.

Figs. 3 and 4 show that the aggregate measures of urban sprawl for urban areas in the US have wide variability of per capita land use consumption. Large

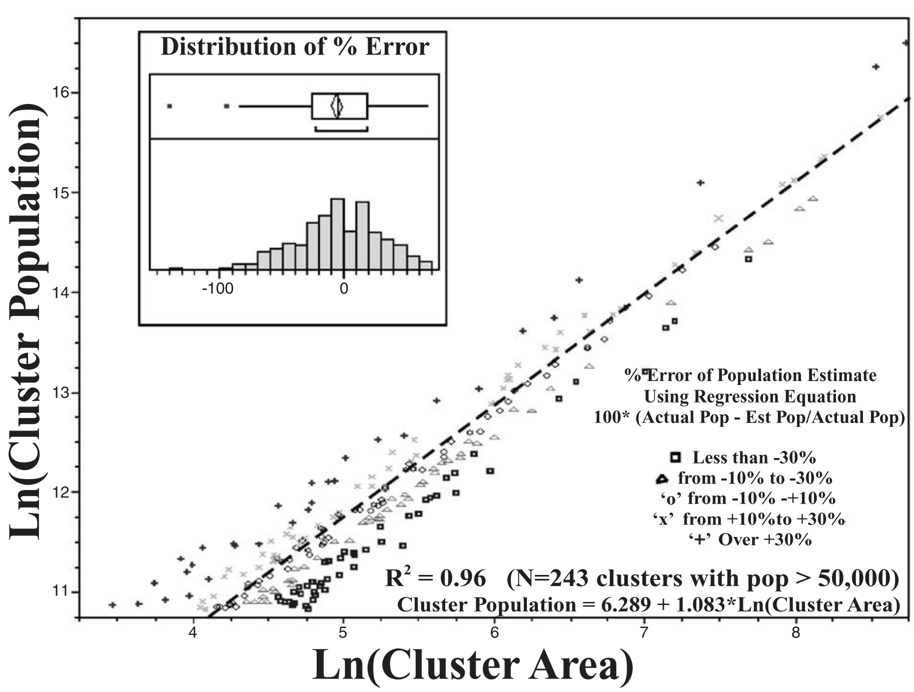

Fig. 4. 'The high threshold sprawl line', a regression of the urban clusters identified by the DMSP imagery with population greater than 50,000. Urban areas below the line suffer from 'sprawl' more than points above the line. Color coding of points represents the percent difference between the actual population and the population predicted by this regression equation.

Table 1
Urban clusters of population greater than 50,000 identified using the low threshold ($N = 300$)

City name	State(s)	Urban area (km^2)	Actual population	Estimated population	Percent difference	City name	State(s)	Urban area (km^2)	Actual population	Estimated population	Percent difference	City name	State(s)	Urban area (km^2)	Actual population	Estimated population	Percent difference
Abilene	TX	228	101,553	94,507	7	Gainesville	FL	215	121,496	87,896	28	PENSACOLA (metro)	FL	321	194,057	144,199	26
Albany	GA	197	75,940	78,899	–4	Grand Forks	ND	201	56,363	80,882	–44	PEORIA (metro)	IL	798	249,945	444,063	–78
ALBANY (metro)	NY	168	587,739	707,098	–20	Grand Junction	CO	150	55,788	56,346	–1	PHOENIX (metro)	AZ	2620	2,033,818	1,928,098	5
ALBUQUERQUE (metro)	NM	669	459,947	357,161	22	GRAND RAPIDS (metro)	MI	841	454,125	473,802	–4	Pine Bluff	ArKS	148	54,288	55,420	–2
Allentown–Bethlehem	PA	894	477,187	510,950	–7	Great Falls	MT	156	60,083	59,143	2	Pineville–Alexandria	LA	187	72,068	73,982	–3
Altoona	PA	146	77,767	54,496	30	Greeley	CO	194	70,500	77,418	–10	PITTSBURGH (metro)	PA	2498	1,673,087	1,817,822	–9
Amarillo	TX	356	157,343	163,860	–4	GREEN BAY (metro)	WI	496	168,983	246,813	–46	Pittsfield	MA	149	53,834	55,883	–4
Anderson	IN	316	88,208	141,430	–60	GREENSBORO (metro)	NC	1210	524,493	742,558	–42	Pocatello	ID	164	51,256	62,911	–23
Apple Valley–Victorville	CA	262	110,822	112,207	–1	Greenville	NC	146	55,554	54,496	2	Port Charlotte–Punta Gorda	FL	195	59,133	77,911	–32
Asheville	NC	511	135,749	256,065	–89	GREENVILLE (metro)	SC	1026	378,150	605,689	–60	Port Huron	MI	165	54,286	63,385	–17
Ashland–Ironton–Huntington	KY/OH/WV	614	183,795	321,253	–75	Hagerstown	MD	279	83,223	121,267	–46	PORT ST LUCIE (metro)	FL	471	170,064	231,541	–36
Athens	GA	188	75,822	74,471	2	Haines City–Winterhaven–Lakeland	FL	856	287,812	484,261	–68	Portland	ME	250	110,246	105,894	4
ATLANTA (metro)	GA	4016	2,223,195	3,267,625	–47	Hattiesburg	MS	176	55,408	68,645	–24	PORTLAND (metro)	OR/WA	1522	1,188,245	985,788	17
ATLANTIC CITY (metro)	NJ	399	156,833	188,643	–20	Hershey–Harrisburg	PA	950	401,723	550,767	–37	POUGHKEEPSIE (metro)	NY	388	190,521	182,240	4
Auburn–Opelika	AL	176	50,443	68,645	–36	Hickory	NC	199	59,804	79,889	–34	PROVO (metro)	UT	391	220,444	183,982	17
AUGUSTA (metro)	GA	595	233,713	309,019	–32	Holland	MI	175	59,485	68,164	–15	Pueblo	CO	237	103,183	99,135	4
AUSTIN (metro)	TX	1047	589,208	621,038	–5	Houma–Bayou Cane	LA	128	50,926	46,322	9	Rapid City	SD	287	65,798	125,576	–91
Bakersfield	CA	372	291,951	173,004	41	HOUSTON (metro)	TX	5358	3,234,428	4,665,292	–44	Reading	PA	339	189,032	154,251	18
BALTIMORE–WASHINGTON (metro)	MD/VA/DC	6374	5,422,658	5,781,194	–7	Huntsville–Madison	AL	539	181,947	273,505	–50	Redding	CA	111	50,622	38,847	23
BATON ROUGE (metro)	LA	744	371,327	407,249	–10	Idaho Falls	ID	99	52,013	33,727	35	Reno–Sparks–Sun Valley	NV	407	212,234	193,325	9
Battle Creek	MI	201	78,072	80,882	–4	INDIANAPOLIS (metro)	IN	2450	1,044,946	1,774,777	–70	Richland–Pasco–Kennewick	WA	229	97,760	95,019	3
BAY AREA (metro)	CA	3645	4,832,995	2,898,937	40	INDIO (metro)	CA	582	185,470	300,702	–62	RICHMOND (metro)	VA	1336	691,410	839,202	–21
BEAUMONT (metro)	TX	935	267,891	540,046	–102	Iowa City	IA	217	71,893	88,907	–24	ROANOKE (metro)	VA	344	176,007	157,066	11
Belton	TX	220	58,063	90,428	–56	Jackson	MI	215	82,415	87,896	–7	Rochester	MN	303	79,737	134,279	–68
Benton Harbor	MI	116	53,652	41,019	24	Jackson	TN	307	58,961	136,472	–131	ROCHESTER (metro)	NY	834	619,440	468,936	24
Billings	MT	226	88,493	93,484	–6	JACKSON (metro)	MS	669	275,668	357,161	–30	ROCK ISLAND (metro)	Il/IW	632	263,436	332,925	–26
BILOXI (metro)	MS	350	139,221	160,456	–15	Jacksonville	NC	143	61,676	53,117	14	ROCKFORD (metro)	IL/WI	1022	354,937	602,774	–70
BINGHAMTON (metro)	NY	241	146,405	101,206	31	JACKSONVILLE (metro)	FL	1170	645,880	712,359	–10	SACRAMENTO (metro)	CA	1289	1,112,795	802,890	28

BIRMINGHAM (metro)	AL	1303	607,992	813,674	− 34
BLOOMINGDALE (metro)	TN	651	163,763	345,330	− 111
Bloomington	IL	300	96,564	132,639	− 37
Bloomington	IN	247	87,764	104,327	− 19
Boise	ID	368	170,657	170,709	0
BOSTON (metro)	MA/NH/RI	7755	5,213,817	7,365,654	− 41
Bowling Green	KY	220	50,720	90,428	− 78
Bristol	VA/TN	306	64,276	135,923	− 111
Brownsville	TX	257	117,724	109,568	7
BUFFALO (metro)	NY	1151	960,398	698,098	27
Burlington	VT	182	79,156	71,547	10
Burlington – Graham	NC	205	72,170	82,875	− 15
Caldwell – Nampa	ID	150	50,690	56,346	− 11
Carbondale – Marion	IL	216	55,567	88,402	− 59
Cedar Falls – Waterloo	IA	290	102,541	127,199	− 24
Cedar Rapids – Marion	IA	338	137,462	153,689	− 12
Champaign – Urbana	IL	226	115,996	93,484	19
CHARLESTON (metro)	SC	648	337,354	343,365	− 2
CHARLESTON (metro)	WV	485	149,342	240,071	− 61
CHARLOTTE (metro)	NC/SC	1867	748,605	1,268,745	− 69
Charlottesville	VA	104	66,369	35,844	46
CHATTANOOGA (metro)	TN	624	254,752	327,727	− 29
Cheyenne	WY	214	63,363	87,392	− 38
CHICAGO (metro)	Il/IN/WI	10,645	9,007,153	10,892,249	− 21
Chico	CA	125	63,812	44,985	30
CINCINATTI (metro)	OH/KY	3606	2,142,182	2,860,676	− 34
CLEVELAND (metro)	OH	3827	2,647,858	3,078,753	− 16
Cocoa Beach	FL	200	76,268	80,386	− 5
College Station	TX	262	107,631	112,207	− 4
Colorado Springs	CO	633	337,588	333,575	1
Columbia	MO	194	75,249	77,418	− 3
Columbus	GA/AL	284	183,402	123,957	32
Johnstown	PA	171	75,541	66,244	12
Joplin	MO	172	54,658	66,723	− 22
Kalamazoo – Portage	MI	302	163,898	133,732	18
Kankakee	IL	250	64,729	105,894	− 64
KANSAS CITY (metro)	MO/KS	2219	1,257,585	1,570,447	− 25
Killeen	TX	312	94,472	139,222	− 47
Knoxville	TN	1065	337,155	634,251	− 88
Kokomo	IN	164	61,066	62,911	− 3
Lafayette	IN	228	106,717	94,507	11
Lafayette	LA	295	131,150	129,914	1
Lake Charles – Sulphur	LA	428	121,355	205,719	− 70
Lancaster – Ephrata – Columbia	PA	694	261,180	373,718	− 43
Lancaster – Palmdale	CA	390	181,076	183,401	− 1
LANSING (metro)	MI	649	301,539	344,020	− 14
Laredo	TX	215	121,192	87,896	27
Las Cruces	NM	126	68,188	45,430	33
LAS VEGAS (metro)	NV	1079	700,406	644,565	8
Lawrence	KS	135	65,488	49,471	24
Lewiston – Auburn	ME	146	58,533	54,496	7
Lexington – Fayette	KY	409	226,953	194,499	14
Lima	OH	216	76,976	88,402	− 15
Lincoln	NE	284	189,582	123,957	35
Little Rock	ArKS	753	311,178	413,343	− 33
Lodi	CA	97	57,733	32,888	43
Longview	TX	287	78,529	125,576	− 60
Longview – Kelso	WA	101	51,679	34,571	33
LOS ANGELES (metro)	CA	7279	12,477,606	6,811,353	45
LOUISVILLE (metro)	KY/IL	1291	793,285	804,429	− 1
Lubbock	TX	385	187,790	180,502	4
Lynchburg – Madison Heights	VA	179	79,883	70,093	12
Macon	GA	267	122,862	114,858	7
Madison	WI	707	285,586	382,383	− 34
Saginaw – Bay City	MI	656	225,184	348,609	− 55
Saks – Anniston	AL	195	53,256	77,911	− 46
SALEM (metro)	OR	193	149,888	76,925	49
Salinas	CA	123	106,507	44,098	59
SALT LAKE CITY (metro)	UT	1072	777,267	639,404	18
San Angelo	TX	170	81,380	65,766	19
SAN ANTONIO (metro)	TX	1340	1,126,674	842,306	25
San Benito – Harlingen	TX	234	82,077	97,588	− 19
SAN DIEGO (metro)	CA	1931	2,229,601	1,322,677	41
San Jacinto – Hemet	CA	103	73,088	35,418	52
SAN JUAN (metro)	TX	758	299,739	416,735	− 39
Santa Barbara – IV – Goleta	CA	176	139,555	68,645	51
Santa Clarita	CA	297	119,555	131,002	− 10
Santa Crus – Live Oak – Capitola	CA	122	98,724	43,655	56
Santa Fe	NM	160	61,148	61,022	0
Santa Maria	CA	123	71,435	44,098	38
Santa Rosa – Rohnert Park	CA	236	166,460	98,619	41
SARASOTA (metro)	FL	742	371,982	405,898	− 9
Savannah	GA	394	168,046	185,727	− 11
Scranton – Wilkes – Barre	PA	621	359,071	325,782	9
SEATTLE (metro)	WA	2464	2,125,920	1,787,312	16
Seven Oaks (metro)	SC	677	318,302	362,444	− 14
Sheboygan	WI	154	59,596	58,208	2
Shreveport – Bossier City	LA	564	249,711	289,257	− 16
Sioux City	IA	314	95,492	140,325	− 47
Sioux Falls	SD	348	104,863	159,325	− 52
SOUTH BEND (metro)	IN/MI	837	349,510	471,020	− 35
South Yarmouth – Hyannis	MA	169	50,916	65,289	− 28
Spokane	WA	580	290,154	299,426	− 3
Spring Hill	FL	178	53,592	69,610	− 30
Springfield	IL	409	141,094	194,499	− 38
Springfield	MO	445	176,645	215,858	− 22

(continued on next page)

Table 1 (*continued*)

City name	State(s)	Urban area (km^2)	Actual population	Estimated population	Percent difference	City name	State(s)	Urban area (km^2)	Actual population	Estimated population	Percent difference	City name	State(s)	Urban area (km^2)	Actual population	Estimated population	Percent difference
COLUMBUS (metro)	OH	1345	970,904	846,190	13	Mandan – Bismark	ND	237	64,437	99,135	– 54	Springfield	OH	170	91,156	65,766	28
Corpus Christi	TX	467	252,731	229,114	9	Mansfield	OH	215	76,612	87,896	– 15	St. Cloud	MN	296	82,005	130,458	– 59
CYPRESS LAKE (metro)	FL	662	235,274	352,551	– 50	Marysville – Yuba City	CA	101	55,466	34,571	38	St. Joseph	MO	200	74,878	80,386	– 7
DALLAS – FT WORTH (metro)	TX	5316	3,467,946	4,620,166	– 33	Medford	OR	150	63,537	56,346	11	ST. LOUIS (metro)	IL/MO	3877	2,116,728	3,128,510	– 48
Danbury	CT	247	108,759	104,327	4	Melbourne	FL	283	128,557	123,418	4	State College	PA	150	62,984	56,346	11
DAYTONA BEACH (metro)	FL	210	136,524	85,379	37	MEMPHIS (TN)	TN/MS/AK	1585	875,665	1,036,429	– 18	Stockton – Manteca	CA	463	320,045	226,693	29
De Land – Deltona	FL	198	76,117	79,394	– 4	Merced	CA	111	64,216	38,847	40	Syracuse – Fairmount	NY	571	390,528	293,698	25
Decatur	IL	297	94,048	131,002	– 39	MIAMI (metro)	FL	3506	3,676,239	2,763,015	25	Tallahassee	FL	231	137,828	96,045	30
Denison – Sherman	TX	300	54,757	132,639	– 142	Midland	TX	151	89,118	56,811	36	TAMPA (metro)	FL	2076	1,552,746	1,446,411	7
DENVER (metro)	CO	2456	1,721,453	1,780,147	– 3	MINNEAPOLIS – ST. PAUL (metro)	MN	4195	2,193,189	3,448,442	– 57	Terre Haute	IN	321	86,058	144,199	– 68
Derby	KS	656	351,952	348,609	1	Missoula	MT	180	51,334	70,577	– 37	Texarkana	TX/AK	193	66,284	76,925	– 16
DES MOINES (metro)	IA	738	314,031	403,197	– 28	MOBILE (metro)	AL	552	278,531	281,675	– 1	TOLEDO (metro)	OH	785	500,986	435,145	13
DETROIT (metro)	MI	4511	4,002,492	3,772,066	6	Modesto – Ceres	CA	339	246,740	154,251	37	Topeka	KS	229	125,196	95,019	24
Dothan	AL	162	50,606	61,965	– 22	Monroe	LA	209	94,966	84,877	11	Tucson – Flowing Wells	AZ	803	558,465	447,502	20
Dubuque	IA	180	65,137	70,577	– 8	MONTEREY (metro)	CA	76	78,265	24,331	69	TULSA (metro)	OK	968	486,450	563,685	– 16
Duluth – Superior	MN/WI	354	111,452	162,724	– 46	Montgomery	AL	360	182,291	166,137	9	Turlock	CA	99	50,474	33,727	33
Durham – Chapel Hill – Raleigh	NC	1152	517,449	698,847	– 35	Muncie	IN	228	91,087	94,507	– 4	Tuscaloosa – Northport	AL	259	100,269	110,623	– 10
Eau Claire – Chippewa Falls	WI	330	86,084	149,209	– 73	Muskegon – Grand Haven	MI	286	120,472	125,036	– 4	Tyler	TX	218	82,955	89,414	– 8
EL PASO (metro)	TX	685	516,816	367,741	29	Myrtle Beach	SC	397	79,716	187,476	– 135	Utica	NY	288	123,059	126,117	– 2
Elmira	NY	119	61,672	42,333	31	Napa	CA	82	62,516	26,725	57	Vacaville – Fairfield – Suisun City	CA	325	170,924	146,422	14
Erie	PA	212	173,743	86,384	50	NAPLES (metro)	FL	409	116,202	194,499	– 67	Van Buren – Ft Smith	ArKS	256	89,946	109,042	– 21

Eugene – Santa Clara – Springfield	OR	238	166,162	99,652	40	NASHVILLE (metro)	TN	2214	717,456	1,566,078	– 118	Ventura – Oxnard	CA	366	305,541	169,564	45
Eustis – Leesburg	FL	203	54,995	81,877	– 49	New Bedford	MA	179	126,519	70,093	45	Vero Beach	FL	151	51,456	56,811	– 10
Evansville – Henderson	IN/ KY	556	198,373	284,198	– 43	NEW ORLEANS (metro)	LA	1161	1,042,244	705,597	32	Victoria	TX	174	55,010	67,683	– 23
Fargo – Moorhead	ND/ MN	365	132,534	168,992	– 28	NEW YORK (metro)	NY/NJ/ CT/MA	20,095	23,586,830	23,874,604	– 1	Vienna – Parkersburg	WV	165	58,307	63,385	– 9
Farragut	TN	1065	337,155	634,251	– 88	Newark	OH	192	62,458	76,433	– 22	Vineland – Millville	NJ	240	81,074	100,688	– 24
FAYETTEVILLE (metro)	ArKS	450	111,816	218,858	– 96	Niceville – Wright – Ft Walton Beach	FL	159	66,139	60,551	8	Visalia	CA	106	77,372	36,697	53
Flint – Beecher – Burton	MI	837	359,086	471,020	– 31	NORFOLK (metro)	VA	1439	1,109,425	919,822	17	Waco	TX	350	132,967	160,456	– 21
Florence	SC	158	50,264	60,081	– 20	Norwich – New London	CT	375	134,140	174,729	– 30	Warner Robins	GA	159	60,623	60,551	0
Florence – Sheffield	AL	305	70,626	135,374	– 92	Ocala	FL	214	71,179	87,392	– 23	Wausau	WI	299	64,874	132,093	– 104
Forest Park	GA	4016	2,223,195	3,267,625	– 47	Odessa	TX	199	94,964	79,889	6	Weirton – Steubenville	WV/OH	194	71,836	77,418	– 8
Fort Bragg – Fayetteville	NC	412	202,180	196,263	3	OGDEN (metro)	UT	456	226,220	222,467	2	Wheeling	WV	150	59,353	56,346	5
Fort Campbell – Clarkesville	KY/TN	404	81,657	191,567	– 135	OKLAHOMA CITY (metro)	OK	1470	736,454	944,358	– 28	Wichita	KS	656	351,952	348,609	1
Fort Collins	CO	199	104,326	79,889	23	Olympia	WA	128	67,983	46,322	32	Wichita Falls	TX	316	93,261	141,430	– 52
Fort Sill – Lawton	OK	233	79,727	97,073	– 22	OMAHA (metro)	NE/ IW	855	554,748	483,562	13	Williamsport	PA	102	53,661	34,994	35
Fort Wayne	IN	529	257,074	267,251	– 4	Onalaska – La Crosse	WI	266	79,609	114,327	– 44	Wilmington	NC	223	84,022	91,953	– 9
Frederick	MD	245	69,916	103,285	– 48	ORLANDO (metro)	FL	2012	982,151	1,391,538	– 42	Yakima	WA	222	94,734	91,444	3
Fredericksburg	VA	182	54,241	71,547	– 32	OSHKOSH (metro)	WI	778	235,690	430,358	– 83	York	PA	402	165,405	190,396	– 15
Fresno – Clovis	CA	479	455,151	236,408	48	Owensboro	KY	171	60,944	66,244	– 9	YOUNGSTOWN (metro)	OH/PA	1144	459,426	692,858	– 51
Gadsden	AL	202	53,435	81,380	– 52	Panama City – Callaway	FL	225	77,441	92,973	– 20	Yuma	AZ	167	69,793	64,3368	

Table 2
Urban clusters of population greater than 50,000 identified using the high threshold ($N = 244$)

City name	State(s)	Urban area (km^2)	Actual population	Estimated population	Percent error	City name	State(s)	Urban area (km^2)	Actual population	Estimated population	Percent error	City name	State(s)	Urban area (km^2)	Actual population	Estimated population	Percent error
Abilene	TX	96	83,952	75,685	10	Gainesville	FL	93	86,934	73,126	16	Oshkosh	WI	123	58,084	98,999	− 70
Albany	GA	89	53,972	69,725	− 29	Grand Forks	ND	106	53,517	84,263	− 57	PENSACOLA (metro)	FL	161	135,861	132,528	2
ALBANY (metro)	NY	404	400,010	359,096	10	GRAND RAPIDS (metro)	MI	419	369,739	373,564	− 1	Peoria	IL	256	151,051	219,044	− 45
Albuquerque	NM	394	396,534	349,476	12	Great Falls	MT	82	54,072	63,803	− 18	Phenix City	AL	138	126,760	112,143	12
ALLENTOWN (metro)	PA	388	348,419	343,713	1	Greeley	CO	79	63,249	61,278	3	PHILADELPHIA (metro)	PA/NJ/DE	3505	4,559,644	3,731,034	18
Altoona	PA	53	57,400	39,763	31	Green Bay	WI	274	156,516	235,779	− 51	PHOENIX (metro)	AZ	1758	1,888,278	1,766,646	6
Amarillo	TX	187	142,487	155,866	− 9	Greensboro	NC	248	175,157	211,638	− 21	PITTSBURGG (metro)	PA	484	810,791	436,740	46
Anderson	IN	110	63,085	87,714	− 39	Greenville–Wade Hampton	SC	176	125,993	145,957	− 16	Portland	ME	119	87,092	95,515	− 10
APPLETON (metro)	WI	313	162,269	272,347	− 68	Harrisburg	PA	270	206,057	232,052	− 13	PORTLAND (metro)	OR/WA	881	965,815	835,727	13
ATLANTA (metro)	GA	2159	1,677,477	2,207,144	− 32	HARTFORD (metro)	CT	443	509,477	396,802	22	PROVIDENCE (metro)	MA	470	584,849	423,070	28
Atlantic City	NJ	131	81,413	105,993	− 30	High Point	NC	77	57,724	59,599	− 3	Provo–Orem	UT	120	145,990	96,385	34
AUGUSTA (metro)	GA/SC	224	159,296	189,540	− 19	HOUSTON (metro)	TX	3045	2,782,568	3,203,531	− 15	Pueblo	CO	93	82,805	73,126	12
AUSTIN (metro)	TX	503	481,620	455,346	5	Huntsville	AL	176	120,430	145,957	− 21	Racine	WI	131	112,132	105,993	5
Bakersfield	CA	204	243,805	171,274	30	INDIANAPOLIS (metro)	IN	1333	903,648	1,308,970	− 45	Raleigh–Cary	NC	290	231,556	250,732	− 8
BALTIMORE–WASHINGTON DC (metro)	MD/DC/VA/DE	3588	4,723,738	3,826,854	19	INDIO (metro)	CA	243	131,705	207,019	− 57	Reading	PA	117	136,076	93,777	31
Baton Rouge–Merrydale	LA	340	270,711	297,891	− 10	Iowa City	IA	87	60,958	68,029	− 12	Reno–Sparks	NV	178	173,200	147,754	15
BAY AREA (metro)	CA	1586	3,589,205	1,580,162	56	Jackson	MI	86	54,250	67,182	− 24	RICHMOND (metro)	VA	443	402,315	396,802	1
Bay City	MI	70	52,421	53,751	− 3	Jackson	MS	252	181,661	215,339	− 19	Roanoke–Salem–Hollins	VA	178	134,906	147,754	− 10
BEAUMONT (metro)	TX	390	201,166	345,633	− 72	Jacksonville	FL	585	458,550	536,295	− 17	Rochester	MN	127	63,852	102,491	− 61

Billings	MT	134	81,886	108,626	– 33	Johnson City–Endwell	NY	105	104,603	83,402	20	ROCHESTER (metro)	NY	436	501,677	390,013	22
Biloxi–Orange Grove–Gulfport	MS	145	84,025	118,319	– 41	Kalamazoo–Portage	MI	144	130,429	117,436	10	ROCK ISLAND (metro)	IL/IA	353	238,573	310,251	– 30
Binghamton	NY	105	104,603	83,402	20	KANSAS CITY (metro)	MO/KS	1310	1,080,657	1,284,517	– 19	Rockford–Loves and Machesney Park	IL	273	198,644	234,847	– 18
BIRMINGHAM (metro)	AL	692	491,410	643,343	– 31	Kenosha	WI	125	84,476	100,744	– 19	SACRAMENTO (metro)	CA	732	957,634	683,729	29
Bismarck–Mandan	ND	122	59,855	98,127	– 64	Kingston–Wilkes–Barre	PA	54	78,946	40,577	49	Saginaw	MI	189	128,190	157,672	– 23
Bloomington	IN	105	67,728	83,402	– 23	Knoxville	TN	293	188,821	253,544	– 34	SALEM (metro)	OR	105	119,846	83,402	30
Bloomington–Normal	IL	158	88,288	129,855	– 47	Lafayette	IN	130	95,584	105,117	– 10	Salinas	CA	50	83,904	37,331	56
Boise	ID	144	134,035	117,436	12	Lafayette	LA	140	99,417	113,905	– 15	SALT LAKE CITY (metro)	UT	604	676,377	555,192	18
BOSTON (metro)	MA	1782	2,526,537	1,792,791	29	Lake Charles–Sulphur	LA	219	94,733	184,960	– 95	San Angelo	TX	62	57,756	47,129	18
Boulder	CO	60	68,210	45,484	33	Lakeland	FL	155	100,262	127,185	– 27	SAN ANTONIO (metro)	TX	932	1,030,870	888,269	14
Bourbonnais–Bradley–Kankakee	IL	103	54,321	81,682	– 50	Lancaster	PA	129	113,401	104,241	8	San Benito–Harlingen	TX	68	51,009	52,090	– 2
Brownsville	TX	114	103,085	91,175	12	Lancaster–Palmdale	CA	198	137,046	165,823	– 21	SAN DIEGO (metro)	CA	708	1,358,730	659,475	51
Bryan	TX	118	90,934	94,646	– 4	LANSING (metro)	MI	290	245,317	250,732	– 2	San Juan	TX	205	152,916	172,184	– 13
BUFFALO (metro)	NY	620	802,696	571,144	29	Laredo	TX	125	117,188	100,744	14	San Ramon–Dublin–Pleasanton	CA	99	80,966	78,251	3
Canton	OH	251	204,723	214,413	– 5	Las Cruces	NM	59	50,734	44,663	12	Santa Barbara	CA	38	52,939	27,729	48
Cedar Falls–Waterloo	IA	149	89,574	121,860	– 36	LAS VEGAS (metro)	NV	755	683,307	707,036	– 3	Santa Clarita	CA	91	70,596	71,424	– 1
Cedar Rapids–Marion	IA	187	124,368	155,866	– 25	Lawrence	KS	45	55,236	33,303	40	Santa Maria	CA	32	52,748	23,018	56
Champaign–Urbana	IL	129	104,373	104,241	0	Lawrence–Haverhill	MA	226	203,518	191,374	6	Santa Rosa	CA	52	73,103	38,951	47
Chapel Hill–Durham–Carrboro	NC	143	126,054	116,552	8	Lexington–Fayette	KY	178	191,007	147,754	23	SARASOTA (metro)	FL	305	270,460	264,814	2
Charleston	WV	120	66,021	96,385	– 46	Liberty	MO	1310	1,080,657	1,284,517	– 19	Savannah	GA	166	136,586	136,993	0

(continued on next page)

Table 2 (*continued*)

City name	State(s)	Urban area (km^2)	Actual population	Estimated population	Percent error	City name	State(s)	Urban area (km^2)	Actual population	Estimated population	Percent error	City name	State(s)	Urban area (km^2)	Actual population	Estimated population	Percent error
CHARLESTON (metro)	SC	192	151,599	160,386	−6	Lima	OH	116	63,553	92,909	−46	Scranton	PA	104	114,534	82,542	28
Charlotte–Matthews	NC	616	417,672	567,153	−36	Lincoln	NE	162	173,471	133,420	23	SEATTLE (metro)	WA	1334	1,599,991	1,310,034	18
Chattanooga–East Ridge	TN	263	153,309	225,541	−47	LITTLE ROCK (metro)	AR	298	223,399	258,235	−16	Shreveport–Bossier City	LA	310	198,149	269,520	−36
CHICAGO (metro)	IL	5204	6,979,378	5,725,381	18	Longview	TX	111	58,702	88,578	−51	Sioux City	IA	159	87,069	130,745	−50
CINCINNATI (metro)	OH	964	1,021,678	921,360	10	Lorain–Elyria	OH	91	99,948	71,424	29	Sioux Falls	SD	190	99,143	158,577	−60
CLEVELAND (metro)	OH	1537	1,798,996	1,527,337	15	LOS ANGELES (metro)	CA	5036	11,553,514	5,525,396	52	Somerset	MA	58	93,031	43,843	53
Cockeysville	MD	3588	4,723,738	3,826,854	19	LOUISVILLE (metro)	KY/IN	755	696,823	707,036	−1	South Bend	IN	197	172,048	164,916	4
Colorado Springs	CO	369	298,485	325,515	−9	Lubbock	TX	197	168,116	164,916	2	Spartanburg	SC	97	54,537	76,540	−40
Columbia	MO	87	56,936	68,029	−19	Macon	GA	104	82,636	82,542	0	Spokane	WA	232	223,184	196,885	12
COLUMBUS (metro)	OH	872	902,619	826,481	8	MADISON (metro)	WI	324	239,333	282,733	−18	Springfield	IL	189	123,427	157,672	−28
Concord–Walnut Creek	CA	139	183,495	113,024	38	Manchester	NH	84	96,579	65,491	32	Springfield	MO	182	143,191	151,355	−6
Crystal Lake–Cary–Algonquin	IL	121	55,483	97,256	−75	Martinez	GA	224	159,296	189,540	−19	Springfield	OH	67	70,367	51,260	27
Cypress Lake–Ft. Meyers	FL	229	153,004	194,128	−27	McAllen–Mission	TX	205	152,916	172,184	−13	Springfield (metro)	MA	221	285,636	186,791	35
DALLAS–FT. WORTH (metro)	TX	3324	3,057,197	3,522,738	−15	Melbourne	FL	103	66,785	81,682	−22	St. Cloud	MN	133	68,615	107,748	−57
Danbury	CT	70	53,013	53,751	−1	MEMPHIS (metro)	TN	844	750,349	797,767	−6	St. Joseph	MO	105	64,395	83,402	−30
DAYTON (metro)	OH	573	523,276	524,386	0	Meriden	CT	76	72,006	58,761	18	ST. LOUIS (metro)	MO/IL	2171	1,843,086	2,220,439	−20
DAYTONA BEACH (metro)	FL	95	85,968	74,832	13	MIAMI (metro)	FL	2708	3,554,887	2,821,233	21	ST. PETERSBURG (metro)	FL	757	817,089	709,065	13
Decatur	IL	158	77,052	129,855	−69	Midland	TX	69	75,376	52,920	30	Stockton	CA	150	229,223	122,746	46
Denton	TX	65	51,330	49,604	3	MILWAUKEE (metro)	WI	1128	1,158,171	1,092,335	6	Syracuse	NY	237	274,276	201,486	27
Dentsville–St. Andrews–Cayce	SC	285	218,858	246,052	−12	MINNEAPOLIS–ST. PAUL (metro)	MN	2473	1,998,783	2,556,960	−28	Tallahassee	FL	110	98,047	87,714	11

DENVER (metro)	CO	1414	1,496,741	1,395,363	7	Mobile	AL	237	205,440	201,486	2	TAMPA (metro)	FL	608	583,155	559,177	4
DES MOINES (metro)	IA	404	282,097	359,096	– 27	Modesto – Ceres	CA	134	180,740	108,626	40	Terre Haute	IN	121	66,268	97,256	– 47
DETROIT (metro)	MI	2917	3,693,143	3,057,887	17	Monroe	LA	93	61,635	73,126	– 19	TOLEDO (metro)	OH	462	451,450	415,273	8
Dubuque	IA	71	53,550	54,584	– 2	Montgomery	AL	193	146,875	161,291	– 10	Topeka	KS	113	99,547	90,309	9
Duluth – Superior	MN/WI	171	91,674	141,469	– 54	Muncie	IN	107	75,866	85,125	– 12	Tucson – Flowing Wells	AZ	426	462,167	380,330	18
Eau Claire	WI	128	65,729	103,366	– 57	Muskegon	MI	84	64,512	65,491	– 2	Tulsa – Broken Arrow	OK	458	372,572	411,379	– 10
El Paso	TX	364	458,405	320,739	30	Naples	FL	131	60,958	105,993	– 74	Tuscaloosa – Northport	AL	114	76,872	91,175	– 19
Elkhart	IN	100	54,260	79,108	– 46	Nashua	NH	103	75,732	81,682	– 8	Tyler	TX	94	60,227	73,978	– 23
Erie	PA	96	141,595	75,685	47	NASHVILLE (metro)	TN	1098	543,210	1,060,894	– 95	Utica	NY	109	92,900	86,850	7
Eugene – Santa Clara	OR	101	107,032	79,965	25	New Bedford	MA	72	95,384	55,417	42	Ventura – Oxnard	CA	120	178,755	96,385	46
Evansville	IN	218	143,000	184,045	– 29	NEW HAVEN (metro)	CT	440	529,236	393,891	26	Waco	TX	135	103,479	109,504	– 6
Fargo – Moorhead	ND/MN	228	128,495	193,210	– 50	NEW ORLEANS (metro)	LA	598	928,119	549,219	41	Waterbury	CT	71	97,234	54,584	44
Fayetteville – Springdale	AR	131	61,092	105,993	– 73	NEW YORK (metro)	NY	6159	14,608,724	6,872,020	53	Wausau	WI	115	51,874	92,042	– 77
Fitchburg	MA	58	54,972	43,843	20	Niagara Falls	NY	85	66,691	66,336	1	Wichita	KS	345	295,839	302,640	– 2
FLINT (metro)	MI	361	264,215	317,876	– 20	Norfolk – Portsmouth	VA	562	693,279	513,488	26	Wichita Falls	TX	144	71,304	117,436	– 65
Florence – Sheffield	AL	117	50,740	93,777	– 85	Oceanside – Escondido	CA	186	275,653	154,963	44	Wilmington	NC	78	54,096	60,438	– 12
Fort Bragg – Fayetteville	NC	189	115,563	157,672	– 36	Odessa	TX	84	76,712	65,491	15	Winston – Salem	NC	169	119,621	139,678	– 17
Fort Collins	CO	86	88,132	67,182	24	Ogden	UT	93	82,166	73,126	11	Worcester – Hudson – Marlborough	MA	240	237,536	204,251	14
Fort Sill – Lawton	OK	96	56,916	75,685	– 33	OKLAHOMA CITY (metro)	OK	759	572,493	711,095	– 24	Yakima	WA	79	65,240	61,278	6
Fort Smith	AR	73	51,339	56,252	– 10	OMAHA (metro)	NE	572	526,167	523,395	1	York	PA	131	98,412	105,993	– 8
Fort Wayne	IN	322	229,100	280,842	– 23	Onalaska – La Crosse	WI	106	59,723	84,263	– 41	YOUNGSTOWN (metro)	OH	518	366,664	470,077	– 28
Frederick	MD	105	52,415	83,402	– 59	ORLANDO (metro)	FL	1259	839,650	1,230,425	– 47	Yuma	AZ	57	51,689	43,025	17
Fresno – Clovis	CA	275	408,376	236,712	42												

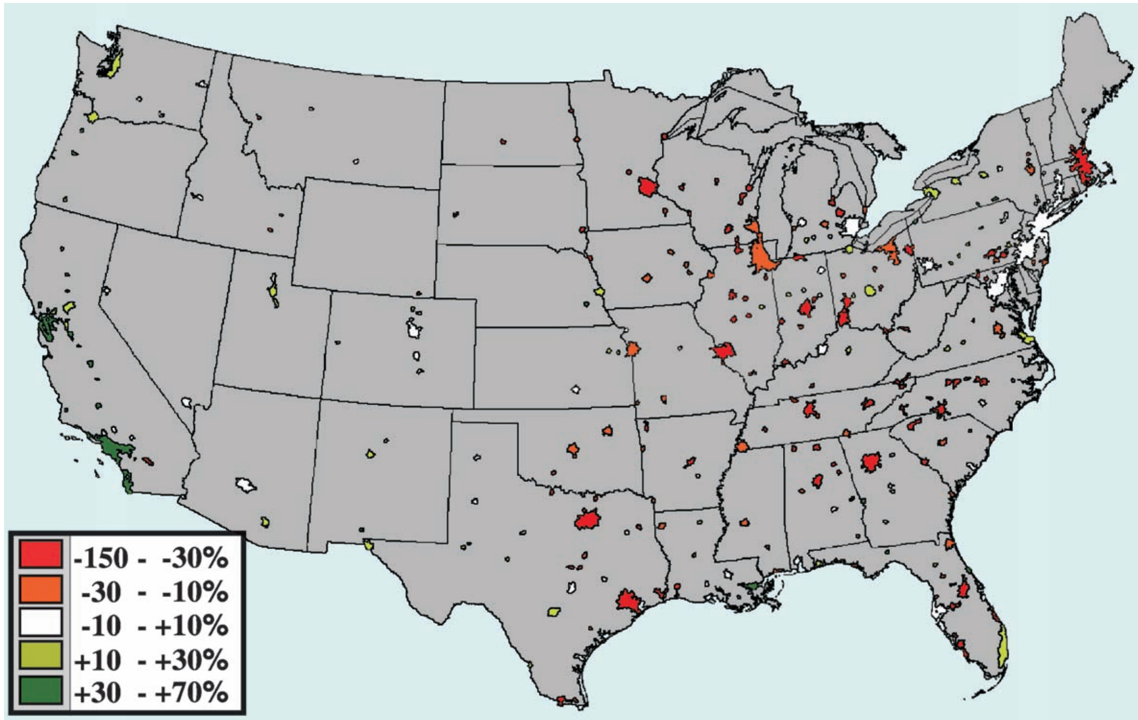

Fig. 5. Low threshold urban clusters with population greater than 50,000 classified based on Ln(Area) vs. Ln(Population) relationship. Cities with "sprawl" appear red and orange.

urban areas such as the Los Angeles metropolitan area and the Dallas–Ft. Worth metropolitan area have dramatically different per capita land use consumption. This variability is the fundamental basis of many questions regarding "Urban Sprawl".

4. Discussion

These aggregate indicators of "Urban Sprawl" for the urban areas of the United States do not suggest that there are

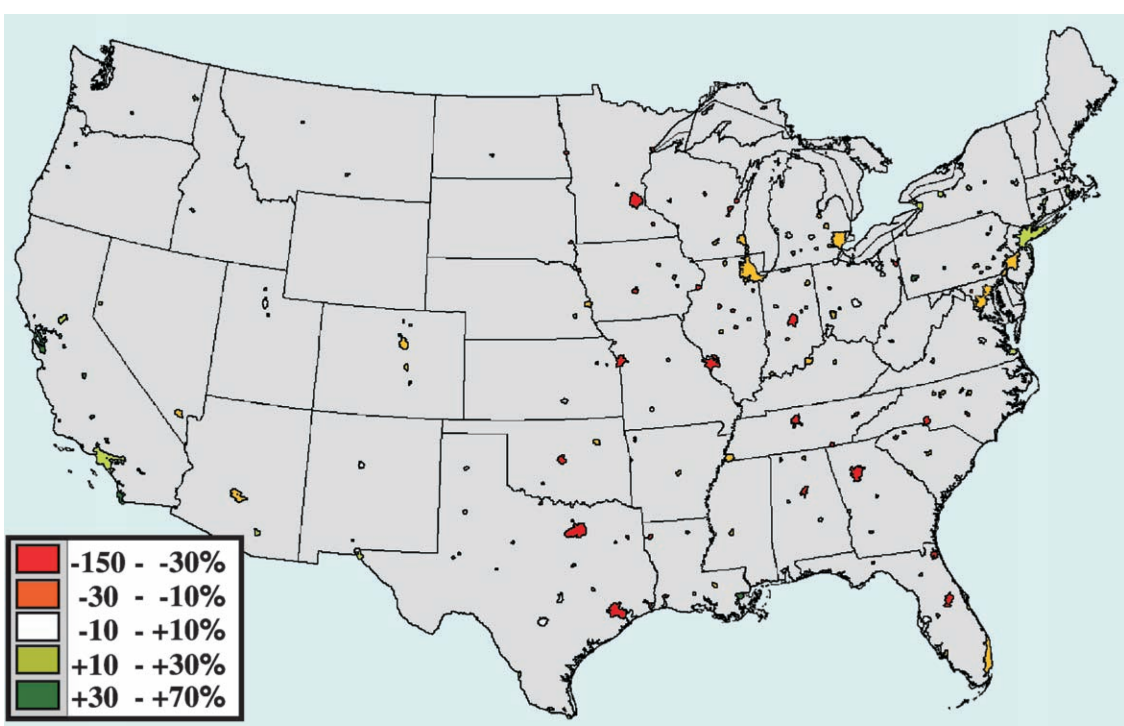

Fig. 6. High threshold urban clusters with population greater than 50,000 classified according to percent deviation from expected population based on Ln(Area) vs. Ln(Population) relationship. Cities with "sprawl" appear red and orange.

no areas of "Urban Sprawl" within urban areas above the "Sprawl Line"; however, these results are comparable yet different than previously determined aggregate numbers because they are scale-adjusted. It is very likely that the green urban areas in Figs. 5 and 6 that are well above the "Sprawl Line" contain smaller areas within them that most people would characterize as "Urban Sprawl". In order to identify these areas, finer spatial resolution data would be needed in addition to other metrics that accounted for mixed use zoning, availability of green-space, residential-employment based commuter-sheds, etc. It is very likely that larger urban areas have 'pockets of sprawl' within or around them that are not captured by these aggregate measures. Despite the coarse resolution of the indicators presented here, the patterns displayed are interesting. The majority of coastal urban areas (with the notable exception of Houston) had lower per capita land consumption (i.e. fall above the "Sprawl Line"). This may result from the higher costs of coastal land and the pressures to utilize coastal lands more intensively. Similar reasoning may explain why so many of the inland cities have high per capita land consumption (i.e. fall below the "Sprawl Line" because inland real estate is not influenced by coastal effects). Other geographic influences such as mountain ranges, deserts, and swamps may also influence urban areal extent. Nonetheless, this regional variability of "Urban Sprawl" conflicts with conventional wisdom in many ways (Fulton et al., 2001).

Conventional wisdom suggests that 'auto-oriented' western cities will suffer from "Urban Sprawl" more than older Northeastern and Midwestern cities because their initial development occurred prior to widespread automobile use. The results of this research and the conclusions of Fulton et al. counter conventional wisdom. Western cities, despite their 'automobile-oriented' development have less per capita land consumption than most Midwestern and many Northeastern cities. Some of the temporal dynamics that explain this counter-intuitive truth are described in: "*Who Sprawls Most? How Growth Patterns Differ Across the U.S.*" (Fulton et al., 2001). As cities grow in population, urban sprawl questions often come down to questions of per capita land use consumption.

This study provides a snap-shot of urban land use consumption utilizing a 'scale-adjustment' and a systematic measure of urban area. As urban areas grow, a key question regarding urban sprawl is whether it is a result of population growth or land use planning decisions. The relative contributions of increasing population and land use planning decisions complicate public perception of "Urban Sprawl". Per capita land use consumption as measured by scale-adjusted aggregate population density indicators show counter-intuitive results with respect to the issue of "Urban Sprawl".

Most residents of Denver, CO would claim that Denver is experiencing "Urban Sprawl". Yet these same people would be surprised to find that cities like Minneapolis–St. Paul have more "Urban Sprawl" than Denver. They would also claim that "Urban Sprawl" in Los Angeles is much worse than it is in Denver (despite evidence to the contrary). In many respects, the term "Urban Sprawl" may be a polite or 'politically correct' means of complaining about the negative consequences of population growth or the changing 'scale' of the total population of the city they live in. Future studies may show that absolute scale (i.e. total population of contiguous urban area) may have more influence on both public perception and practical assessments of the negative consequences of what is conventionally termed "Urban Sprawl".

"Urban Sprawl" is often blamed as the cause of traffic congestion, loss of open space, and other general problems in the urban environment. Rational Land Use Planning is often touted as the means of avoiding the negative consequences of "Urban Sprawl". In Denver, this rational planning has resulted in high-density developments on the urban fringe. The resulting high residential density on the urban periphery with traditional high-density employment in the core resulted in long commuting distances and traffic congestion. Subsequently, the following *unplanned* results were: (1) development of the "Tech Center" outside of the central business district (CBD) to the southeast, 2) 'Pop-tops' and 'Scrape-offs' resulting in increased housing density and cost just outside the CBD, and (3) an ever expanding 'commuter-shed' of people who work in Denver but live over 20 miles outside of the city in 'rural' or 'ex-urban' places like Conifer, Evergreen, Genesee, and Bailey.

The economics of real estate in many cities in the US is forcing the core 'middle class' citizens (e.g. Teachers, Police Officers, and Nurses) out of their midst because of the increasing cost of urban housing. Populations that live in the 'commuter-shed' but not in the 'urban' area represent a significant and growing fraction of the driving public of many urban areas in the United States. These populations raise significant questions about the meaning and legitimacy of measurements of urban sprawl based on contiguous urban areas (including this one). Important questions to ask are: (1) To what extent do 'ex-urbans' contribute to the negative consequences of "Urban Sprawl", (2) Why do 'ex-urbans' choose to live outside the urban area (cheaper housing, better schools, commune with nature, they like to drive, etc.), and (3) What mechanisms can city planners use to influence the areal extent and population of their 'ex-urban' commuter-shed?

The low light levels seen the DMSP OLS imagery that do not fall in either the "High Threshold" or "Low Threshold" definition of urban used here often represent this commuter-shed of middle and high income people who work in the urban core. This phenomenon is perhaps an ironic counter example of the "Spatial Mismatch" of low-income inner-city potential employees and the suburban employment opportunities that exist for them (Kasarda, 1988). It is interesting to note that cities like Los Angeles (often noted for urban sprawl) do not suffer from high per capita levels of land use consumption. Does this fact imply that Los

Angeles does not suffer from "Urban Sprawl?" These low light intensity areas that are measured by the DMSP OLS imagery but fall outside of both of the thresholds used here may be usefully incorporated into new measures of urban extent for characterizing more complex definitions of regions such as commuter-sheds and 'functional regions' for urban areas.

Measuring "Urban Sprawl" may be a red herring in that it is too difficult to provide a single number that characterizes "Urban Sprawl" for any meaningful areal extent. Los Angeles is developing in all the right ways to avoid "Urban Sprawl" as far as the experts are concerned; nonetheless, Los Angeles continues to suffer from traffic congestion, lack of open space, and high per capita expenditures of energy (Egan, 2002). There are many reasons that potentially explain why Los Angeles and other cities in the US perform well by aggregate indicators of "Urban Sprawl": (1) It may be due to the aforementioned reasons associated with coastal land and/or the local cost of real estate, (2) It may simply be a function of the absolute size of the city, or (3) It may be due to impacts that the forces of globalization have on 'global' cities like Los Angeles. Cities in less developed countries generally have much lower levels of per capita land consumption (Sutton et al., 2001). This is typically explained by the lower levels of economic development found in these cities and the implications that these levels of development imply with respect to fewer people driving cars (and the sprawl associated with a driving population).

Aggregate measures of "Urban Sprawl" as provided here do not provide much insight to planners for any given urban area. Intra-urban decisions about land-use planning and residence vs. employment intensive areas will have more impact on traffic congestion, green-space availability, and per capita energy consumption. In this respect, William Whyte's focus on 'patterns of development' regarding "Urban Sprawl" is more useful (Whyte, 1958). Nonetheless, the aggregate measures of "Urban Sprawl" described here do raise interesting questions about the dynamics of urban development. "Urban Sprawl" can be measured by aggregate measures of per capita land consumption; however, the negative attributes associated with "Urban Sprawl" are really a complex interaction of the total size of the urban area in question (scale), the intra-urban land use planning (i.e spatial 'match' or 'mis-match' of jobs and housing), and culturally defined tolerances associated with urban life (globalization). Remotely sensed datasets at a range of spatial and temporal scales nonetheless have great potential for informing the planning process and monitoring and characterizing many urban patterns and processes.

The patterns shown in Figs. 5 and 6 raise interesting questions about the dynamics of "Urban Sprawl" in the United States. Coastal cities as far apart as Boston and Los Angeles show lower aggregate levels of "Urban Sprawl" than inland cities such as Atlanta and Minneapolis–St. Paul. Conventional wisdom suggests that aggregate levels of "Urban Sprawl" would be more related to historical development than these measures indicate. Conventional wisdom may be ignoring the more recent 'historical' international migration to many of these cities with lower per capita land use consumption. This migration is differentially changing the demographics, social mores, and aggregate density of the cities of the United States. The spatial patterns shown in Figs. 5 and 6 suggest future research questions about the relative contributions of the impacts of globalization, land-use planning, and scale on "Urban Sprawl".

5. Conclusion

Clearly, measuring "Urban Sprawl" is a daunting task. Many people decide "Urban Sprawl" is happening in their backyard based on perceived negative experiences such as traffic congestion, changing demographics, or overall population growth that is correctly or incorrectly attributed to "Urban Sprawl". This investigation presents a measure of "Urban Sprawl" that is scale-adjusted to the total population of an urban area and uses nighttime satellite imagery as an objective and uniform measure of the areal extent of metropolitan areas with populations greater than 50,000. Aggregate measures of per capita land consumption using these methods show that western cities like Los Angeles and San Francisco have lower levels of "Urban Sprawl" than inland and Midwestern cities such as Atlanta, St. Louis, and Minneapolis. This total population or 'scale-adjusted' method of measuring sprawl produces an aggregate measure that allows for fair comparisons of the "Urban Sprawl" in large metropolitan areas to the "Urban Sprawl" in small metropolitan areas. Nonetheless, the nighttime imagery used to provide this measure of the areal extent of "urban" areas hints at problems with "Urban Sprawl" measures based on a single aggregate statistic derived solely from contiguous measures of areal extent. Most, if not all, of the low light levels *not* counted as "Urban" exist on the periphery of the areas that are counted as "Urban" (Fig. 1). These low light areas in the DMSP OLS imagery represent a growing population of 'ex-urban' citizens who drive to, and work in, urban environments and contribute to the negative consequences typically attributed to "Urban Sprawl". Thorough understanding of the problems presently attributed to "Urban Sprawl" will require more in-depth studies that address the inter-related issues of globalization, intra-urban land use planning, and total spatio-demographic extent of the urban areas in question.

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