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Urban Centrality: A Simple Index

Rafael Henrique Moraes Pereira[1], Vanessa Nadalin[1], Leonardo Monasterio[1,2], Pedro H. M. Albuquerque[1,3]

[1]Division of Regional, Urban and Environmental Studies, Institute for Applied Economic Research (Ipea), Brasília, Brazil, [2]Catholic University of Brasilia, Brasília, Brazil, [3]Department of Management, University of Brasília, Brasília, Brazil

This study introduces a new measure of urban centrality. The proposed urban centrality index (UCI) constitutes an extension to the spatial separation index. Urban structure should be more accurately analyzed when considering a centrality scale (varying from extreme monocentricity to extreme polycentricity) than when considering a binary variable (monocentric or polycentric). The proposed index controls for differences in size and shape of the geographic areas for which data are available, and can be calculated using different variables such as employment and population densities, or trip generation rates. The properties of the index are illustrated with simulated artificial data sets and are compared with other similar measures proposed in the existing literature. The index is then applied to the urban structure of four metropolitan areas: Pittsburgh and Los Angeles in the United States; São Paulo, Brazil; and Paris, France. The index is compared with other traditional spatial agglomeration measures, such as global and local Moran's I, and density gradient estimations.

Introduction

A long list of studies relates urban centrality to other important urban issues: efficiency of transport systems and commuting patterns (Giuliano and Narayan 2003; Bertaud 2004; Schwanen, Dieleman, and Dijst 2004; Aguilera 2005), pollution (Bertaud, Lefèvre, and Yuen 2009), and energy consumption and urban structure in general (Shim et al. 2006). A proper measure of urban centrality is essential to make sound empirical claims about such matters. However, these studies do not use similar ways of quantifying urban spatial structure.

The problem seems to be that the concept of urban centrality does not have a widely accepted definition and measure. Can one single index number summarize the centrality degree of urban agglomerations? Such a measure could be important for the comparison of cities, linking their urban form to their performance in terms of the urban issues mentioned in the preceding paragraph.

Correspondence: Rafael Henrique Moraes Pereira, Division of Regional, Urban and Environmental Studies, Institute for Applied Economic Research (Ipea), SBS Quadra 1 Edifício BNDES, Sala 326, CEP 70.076-900 Brasília, Brazil.
e-mail: rafael.pereira@ipea.gov.br

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This article seeks to fill this gap, introducing a new measure of urban centrality. It is an extension of the spatial separation index (Midelfart-Knarvik et al. 2000) originally proposed to measure the spatial distribution of industries in the European Union. The proposed urban centrality index (UCI) identifies distinct urban structures from different spatial patterns of employment activities with regard to the degree of monocentricity or polycentricity that an urban area can assume. Urban structure should be more accurately analyzed by considering such a centrality scale (varying from extreme monocentricity to extreme polycentricity) rather than by a binary variable (monocentric or polycentric). The proposed index can be applied to urban areas of different shapes and sizes, making their comparison feasible.

Theoretical background: Monocentricity and polycentricity

Within the framework of urban studies, the issue of urban centrality has been addressed mainly through the analysis of the spatial patterns of jobs and residential population locations. Traditionally, these patterns have been captured by density functions (Anas, Arnott, and Small 1998). These functions collapse the available information into two variables: the density and the distance of different values of densities from the central business district (CBD).[1]

Furthermore, the spatial pattern of a polycentric city can be captured through the inclusion of distances to subcenters in the estimated density functions. Estimating these functions is a two-step procedure. The first is identification of potential subcenters. Once identified, these locations are included in the estimated equation, and those with significant coefficients are considered to be subcenters. This is the strategy used by Griffith and Wong (2007).

Another feature of a subcenter is that the amount of employment or population in the unit of analysis is higher than its neighbors. To determine how high is high enough, Giuliano and Small (1991) establish an arbitrary cutoff point of density. Anas, Arnott, and Small (1998) warn that cutoff points may be arbitrary. McMillen (2001) also adds that this method relies too much on local knowledge.

Another way of identifying subcenters is to use spatial statistics. Baumont, Ertur, and Le Gallo (2004), for instance, apply exploratory spatial data analysis to deal with the spatial autocorrelation and spatial heterogeneity of data. They use the local Moran or local G-statistics—Getis and Ord (1992)—to detect clusters of employment and employment density, as do Griffith and Wong (2007). However, these studies do not aim to find a summary measure for quantifying the degree of centrality of urban agglomerations. Still, the issue of urban polycentricity has been gathering more attention within other methodological approaches that propose to deconstruct the concept of urban form into different dimensions.

Dimensions and quantitative measures of urban centrality

The studies reviewed in this section separate urban morphology into different dimensions according to the key for understanding the specific phenomena they analyze. For the purpose of this article, we focus exclusively on the dimensions that relate to the proximity level of employment activities across space and its unequal distribution. Table 1 summarizes the morphological dimensions.

The morphological dimension of unequal distribution, also named the concentration dimension, "is defined as the degree to which development is concentrated in a few parts of a metropolitan area, regardless of high-density subareas being clustered or sparsely scattered" (Tsai 2005). Galster et al. (2001), Tsai (2005), and Lee (2006) use the Gini coefficient and the delta

Table 1 Morphological Dimensions Related to Urban Centrality

Dimension	Authors	Definitions	Measures
Unequal distribution/ concentration	Tsai (2005)	". . . the degree to which development* is concentrated in a few parts of a metropolitan area, regardless of high-density subareas being clustered or sparsely scattered" (p. 143).	Gini coefficient
	Lee (2006)	"How disproportionately jobs are clustered in a few locations" (p. 11).	Gini coefficient and delta index
	Galster et al. (2001)	"The degree to which housing units or jobs are disproportionately located in a relatively few areas or spread evenly in the urban area" (p. 700).	Delta/dissimilarity index (difference between employment share and the units' area share)
Centrality	Galster et al. (2001)	"The degree to which observations of a given urban land use are located close to the CBD of a urban area" (p. 701).	Average distance of a land use from the CBD (weighted by the number of observations). Centralization index
	Anas, Arnott, and Small (1998)	"At the city-wide level, activity may be relatively centralized or decentralized depending on how concentrated it is near a CBD" (p. 1431).	Monocentric density gradient
	Lee (2006)	"Centrality is the extent to which employment is concentrated with reference to the CBD" (p. 11).	Modified Wheaton index. Area-based centralization index. Ratio of weighted distance from the CBD to the urban radius
Clustering	Tsai (2005)	"The degree to which high-density subareas are clustered or randomly distributed" (p. 146).	Global Moran index
	Galster et al. (2001)	"The degree to which development within any one-mile square is clustered within one of the four one-half-mile squares contained within (as opposed to spread evenly throughout)." (p. 701).	"The average for all one-mile squares of the standard deviations of the density of a particular land use (e.g., housing units or employees) among the four squares of each one-mile grid with developable land, standardized by the average density across m-scale grids" (p. 701)
	Anas, Arnott, and Small (1998)	"At a more local level, activities may be clustered in a polycentric pattern or dispersed in a more regular pattern" (p. 1431).	Three different approaches: point pattern analysis; fractals; and subcenters' identification (polycentric density function, minimum density)

*Development denotes high density of employment or housing.

index to gauge the degree of inequality in the distribution of population or employment along the spatial units in a metropolitan area. However, both are nonspatial measures and therefore do not provide information about how densities are distributed in space (Tsai 2005), resulting in their being poor indicators.

Anas, Arnott, and Small (1998), Galster et al. (2001), and Lee (2006) also suggest two different morphology dimensions to address urban structure that help us better understand monocentricity and polycentricity patterns: centrality (centralized versus decentralized) and clustering (clustered versus dispersed). The centrality dimension is the extent to which employment is located close to the CBD. Galster et al. (2001) and Lee (2006) use the same intuitive procedure to capture centrality with an empirical measure. Both try to measure how quickly metropolitan employment spreads from the CBD to the urban edge. In contrast, the clustering dimension is the degree to which employment activities are concentrated in a few areas or are more dispersed in a more regular pattern. Tsai (2005) uses the global Moran index to gauge this dimension.

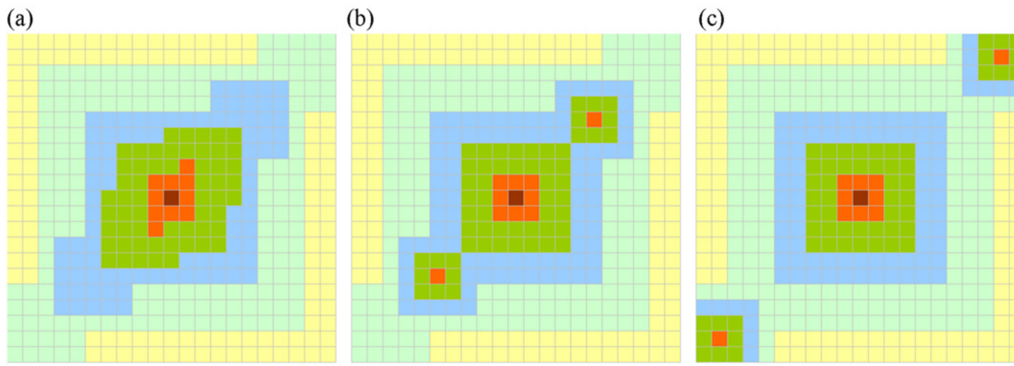
According to results reported in Table 1, the conceptual distinction between the morphological dimensions of centrality and clustering is rather vague, possibly because the proposed morphological dimensions are not fully independent. For instance, in extreme cases, an urban agglomeration with a very high centrality level (i.e., with a large number of employment activities located close to a CBD) would necessarily present a high cluster level, depicted by a monocentric pattern. Also, an urban agglomeration presenting a very low cluster level (with jobs spread evenly through space) would necessarily present a low centrality level, depicted by an acentric pattern. Accordingly, Anas, Arnott, and Small (1998) and Lee (2006, p. 11) state that "polycentric urban structure is a combined outcome of metro-wide decentralization and local level clustering." To deal with this conceptual overlap, we treated these two dimensions as one single dimension, namely proximity. This dimension addresses how clustered or dispersed jobs are in space by focusing on the degree to which employment activities are close to or distant from each other.

One important conclusion based on the review of these other studies is that centrality should be more accurately analyzed by considering a continuum scale. Low levels represent more monocentric urban structures, and high levels represent more polycentric ones. The need to understand urban centrality in this flexible way is illustrated by Bertaud (2004, p. 9), when he states that "No city is ever 100% monocentric, and it is seldom 100% polycentric (i.e., with no discernable 'downtown'). Some cities are dominantly monocentric, others are dominantly polycentric and many are in between." Using this more realistic understanding of urban centrality can supplement other studies in a quest to find more accurate results when investigating the implications of urban form on a series of urban issues, such as commuting patterns, pollution, and energy consumption.

A UCI

The starting point of our proposed index is the widely known location coefficient (LC) introduced by Florence (1948, p. 34) and is introduced here to measure the unequal distribution factor of jobs within an urban area.

$$LC = \frac{1}{2}\sum_{1}^{n}\left|s_i - \frac{1}{n}\right| \tag{1}$$



	(a)		(b)		(c)
Venables index	84.234	Venables index	70.287	Venables index	65.260
Gini	0.6219	Gini	0.6219	Gini	0.6219
LC	0.5039	LC	0.5039	LC	0.5039
UCI	0.2552	UCI	0.2964	UCI	0.3112
Global Moran	0.7025	Global Moran	0.6851	Global Moran	0.7309

Legend					
21.2	10	3	0.9	0.3	0.2

Figure 1. Varying degrees of urban centrality from monocentric (a) to polycentric (c).

where n = number of areas; $s_i = E_i/E$, that is, the share of employment in area i (E_i) of the total employment (E) of the city; and E = total number of jobs in a city.

The range of the LC is zero to $1 - 1/n$. If LC equals zero, then economic activity is evenly distributed, while values close to $(1 - 1/n)$ indicate that employment is concentrated in a few areas. In its conventional form, this coefficient captures only the nonspatial inequality of job distribution. In other words, LC fails to take into account distance or spatial patterns; therefore, cities with similar values of LC may have completely different spatial profiles (as illustrated in Fig. 1). The LC has the same mathematical intuition that lies behind the Gini coefficient. We chose to use the LC because it is easier to calculate and widely accepted in regional science studies (Hoover and Giarratani 1999).

The second term of our UCI is based on the spatial separation index originally proposed by Midelfart-Knarvik et al. (2000, 2002) to evaluate changes in the spatial distribution of economic activity across European regions. This index—the Venables index, V—is calculated as follows (Sousa 2002):

$$V = S' \times D \times S \tag{2}$$

where S = a column vector of S_i; and D = a distance matrix whose entry d_{ij} is the distance between the centroids of areas i and j. In the simplest version, the main diagonal of D is equal to zero.[2]

When all employment activity is concentrated in just one spatial unit, the minimum value of V is reached; that is, zero (no matter where this spatial unit is). However, the index has no maximum value and therefore cannot be compared across different spatial settings. To overcome this limitation, it is necessary to calculate the maximum attainable value of V.

The created proximity index (PI) solves the normalization issue with V and changes its interpretation to suit our needs:

$$P = 1 - \frac{V}{V_{max}} \quad (3)$$

where V_{max} = the maximum attainable value of the spatial separation index.

The interpretation of PI is the opposite of V, with its theoretical range being (0, 1). Values of PI closer to one mean that employment is clustered in one single center (this economic center does not necessarily match the geometric center). If PI is zero, employment is as spatially separated as possible. In other words, employment activities are distributed in a way that maximizes the distances between them.[3]

Our proposed UCI is the product of the LC and the PI:

$$UCI = LC \times PI \quad (4)$$

One advantage of this UCI is that its calculation circumvents the identification of centers and subcenters. The application of this UCI to hypothetical spatial patterns and actual data sets shows its other advantages vis-à-vis other traditional measures of urban centrality.

The estimation of V_{max} is not trivial, because it has no closed-form solution. In the very simple square grids presented in the next section, V_{max} is obtained when each corner has one-fourth of the total employment. In a region forming a perfect circle, the maximum value of V occurs when all employment is evenly distributed along the external edge.

However, in real cities, V_{max} can be calculated only with a constrained optimization algorithm that depends on a distance matrix (D). We still have not coded this, but an approximation of V_{max} can be estimated by analogy to the circle shape. Thus, we have chosen to consider the "opposite of maximum proximity" as a homogeneous distribution of values along the edge of a map. Although this solution is not the global maximum of V, it may be considered a satisfactory solution for two reasons: (1) intuitively, it is the opposite of a completely monocentric city with all employment in the center, and (2) it is easy to calculate and does not require a specific algorithm. This normalization procedure makes comparisons of urban areas of different shapes and sizes possible.

Our UCI does not satisfy all of the criteria stated by Combes and Overman (2004). It is subjected to the modifiable areal unit problem (Haining 2003), it has no direct connection with theory, and it has no sampling distribution to statistical hypothesis testing (yet).[4] However, these shortcomings are shared by other measures of urban form, such as rank–order tests and measures of employment distribution.

Experiments using artificial data sets describing hypothetical metropolitan forms

This section presents several experiments using artificial data sets describing hypothetical metropolitan forms. The aim of this simulation was to verify whether or not our UCI distinguishes between theoretical urban structures along the centrality scale. All calculations were done using R (R Development Core Team 2011) and *spdep* (Bivand 2011). In the theoretical examples that follow, the chart tones represent the number of jobs in each cell on a 21×21 square tessellation territory. The total number of jobs is fixed at 441 for every hypothesized metropolitan form, providing a constant urban density at the metropolitan scale.[5]

On the one hand, the highest possible monocentricity level is found in an urban structure that concentrates all jobs at a single center. In this situation, there is, simultaneously, the highest possible level of (1) inequality in the distribution of employment among spatial units and of (2) proximity in the localization of jobs, because this spatial pattern is fully concentrated at a single point. Our UCI assumes its maximum value equal to one for this structure.

On the other hand, the definition of the highest level of polycentricity is not so straightforward. Which is the most polycentric city? One possible answer would be the urban structure where the number of centers is as large as possible. In a city whose territory is divided into discrete polygons, this occurs when the number of centers equals the number of polygons. The result is an acentric urban structure with a perfectly even spatial distribution of jobs. But this structure could also be classified as the least monocentric city, because no true centers exist. A second possible answer would be the urban structure with the largest number of centers that maximizes the distances between them. In the case of a regular squared grid shape, this situation occurs when each corner has one-fourth of the total employment. In both situations, our UCI assumes its lowest value (equal to zero).[6]

Our UCI calculated for all other urban structure patterns varies between these two extreme monocentric and polycentric patterns. Thus, one advantage of our UCI is its ability to distinguish among varying degrees of urban monocentricity or polycentricity in situations where other indices do not. Fig. 1 shows two urban areas easily recognized as polycentric and a third one easily recognized as monocentric. One of the polycentric structures has closer subcenters to the CBD than the other. The closer the subcenters are, the more the urban structure approximates a monocentric pattern. As the distances approach zero, all subcenters merge into one big CBD, as illustrated in Fig. 1a. Although they share the same distribution of jobs among their spatial units, they are clearly different in their spatial distributions. Thus, although the Gini coefficient and LC remain the same, our UCI and the Moran index do not. Our UCI increases monotonically as the subcenters get closer to the CBD. In contrast, the Moran index does not vary in a systematic way. Initially, it falls when subcenters get closer to the CBD; later, however, it increases when subcenters merge into a single large CBD.

Case studies: Pittsburgh, Los Angeles, São Paulo, and Paris

For empirically testing our UCI, we have chosen cities in the United States (Pittsburgh and Los Angeles), France (Paris), and Brazil (São Paulo) that represent four different urbanization processes. Paris is the oldest of the four cities we examine and one that did not have a car-oriented development. São Paulo is located in a less-developed country, with very poor mass transportation and urban infrastructure. We chose two cities in the United States to measure urban centrality. Los Angeles is widely recognized as a leading example of a decentralized, sprawling city (Giuliano and Small 1991); Pittsburgh is a former industrial city with one clear CBD (Quinlan 2006) and is representative of a more monocentric city.

We use employment density data for metropolitan areas. For the U.S. cities, we used a data set with employment aggregated to census tracts for the year 2000, obtained from the National Historical Geographic Information System (NHGIS) website.[7] For the São Paulo metropolitan area, we used data for the year 1997 from the Origin–Destination Survey (Pesquisa Origem–Destino) produced by the Companhia do Metropolitano de São Paulo—Metrô, the firm that runs the city's subway system.[8] For Paris, we used data from the population census of 1999, aggregated to "communes," available at the website of France's National Institute of Statistics and Economic Studies (INSEE).

Table 2 Metropolitan Areas Features

Features		Metropolitan area			
		Los Angeles*	Pittsburgh*	São Paulo†	Paris‡
Year		2000	2000	1997	1999
Total area (km^2)		12,317	13,839	7,954	12,069
Total employment		5,169,266	1,086,842	6,959,394	5,038,730
Population		12,365,627	2,358,695	16,792,406	10,947,510
Average employment density		420	79	875	417
Number of polygons		2,629	721	389	1,300
Average area of polygons (km^2)		4,68	19,19	20,45	9,28
Number of jobs per polygon	Maximum	5,649	4,711	108,059	170,748
	Average	1,966	1,507	17,890	3,876
	Standard deviation	846	819,92	16,371	12,613
Employment density per polygon (km^2)	Maximum	16,466	5,544	131,922	62,586
	Average	1,746	605	5,854	819
	Standard deviation	1,462	689	11,508	3,582

Sources: *NHGIS, population census of 2000; †SP-Metrô, Origin-Destination Survey of 1997; ‡INSEE, population census of 1999.

Table 2 presents descriptive statistics for these metropolitan areas.[9] Los Angeles, Pittsburgh, and Paris are quite similar in terms of total area. In total population and employment, however, Pittsburgh is smaller, leading to the smallest average employment density. São Paulo has the smallest area and the highest total employment, leading to the highest average employment density (almost twice the density of Los Angeles and Paris).

Area units vary in number and average size across these four cities. For São Paulo, the spatial information is not very refined; this city has a small number of polygons with a high average area. The information per polygon reveals that Paris and São Paulo have much higher densities and total employment, indicating a greater concentration of jobs. A comparison between Los Angeles and Pittsburgh polygons reveals a similar distribution of total number of jobs, but a considerably higher job density in Los Angeles, a surprise because it is known as being a sprawled area. Also surprising is that Los Angeles has an average employment density per polygon (1,746 per km^2) greater than Paris (819 per km^2).

These first descriptive statistics portray a complex and wide range of spatial patterns of employment distributions. Fig. 2 displays employment density maps for the four cities.

São Paulo and Paris exhibit similar geographic patterns, where just a few polygons have very high densities. In contrast, the U.S. cities have few, if any, polygons in the upper-density classes. The distribution of jobs in Los Angeles looks spread out over the territory, but in Pittsburgh, even though it has relatively low employment densities, jobs look much more spatially concentrated.

Fig. 3 portrays the clusters we uncovered when we calculated local Moran's I statistic (Anselin 1995) for the employment density data.[10]

São Paulo and Paris have a more similar spatial pattern, presenting a large contiguous central area with high employment concentration. Pittsburgh has a central area with two main clusters of high employment densities and a few more employment clusters nearby. Los Angeles has an even

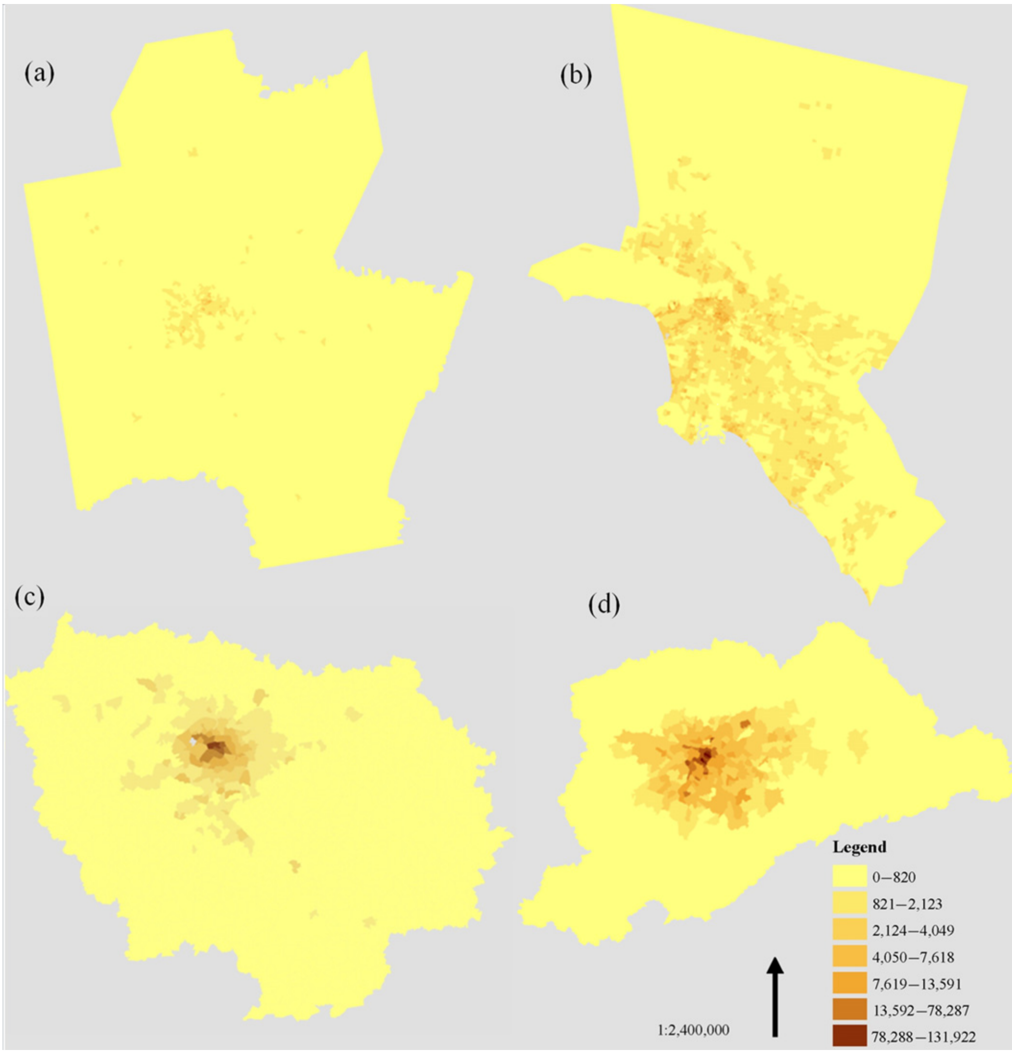


Figure 2. Employment density maps (jobs/km^2). (a) Pittsburgh, (b) Los Angeles, (c) Paris, and (d) São Paulo. Sources: NHGIS, population census of 2000 (U.S. cities); INSEE, population census of 1999 and LVMT (Laboratoire Ville Mobilité Transport) (Paris); SP-Metrô, Origin-Destination Survey, 1997 (São Paulo).

larger number of clusters, although they are more fragmented and dispersed throughout the metropolitan area. The bigger cluster (in terms of area) corresponds to the CBD region, but many other clusters exist that do not seem to focus on it. These patterns of clusters support a description of São Paulo and Paris as more monocentric and of Pittsburgh and Los Angeles as more polycentric urban structures.

Equation (4) defines our UCI as the product of the PI and the LC. Table 3 displays a comparison of these indices with the global Moran's I and our UCI. All indices are consistent with the same ranking of cities, from more monocentric to more polycentric: Paris, São Paulo, Pittsburgh, and Los Angeles.

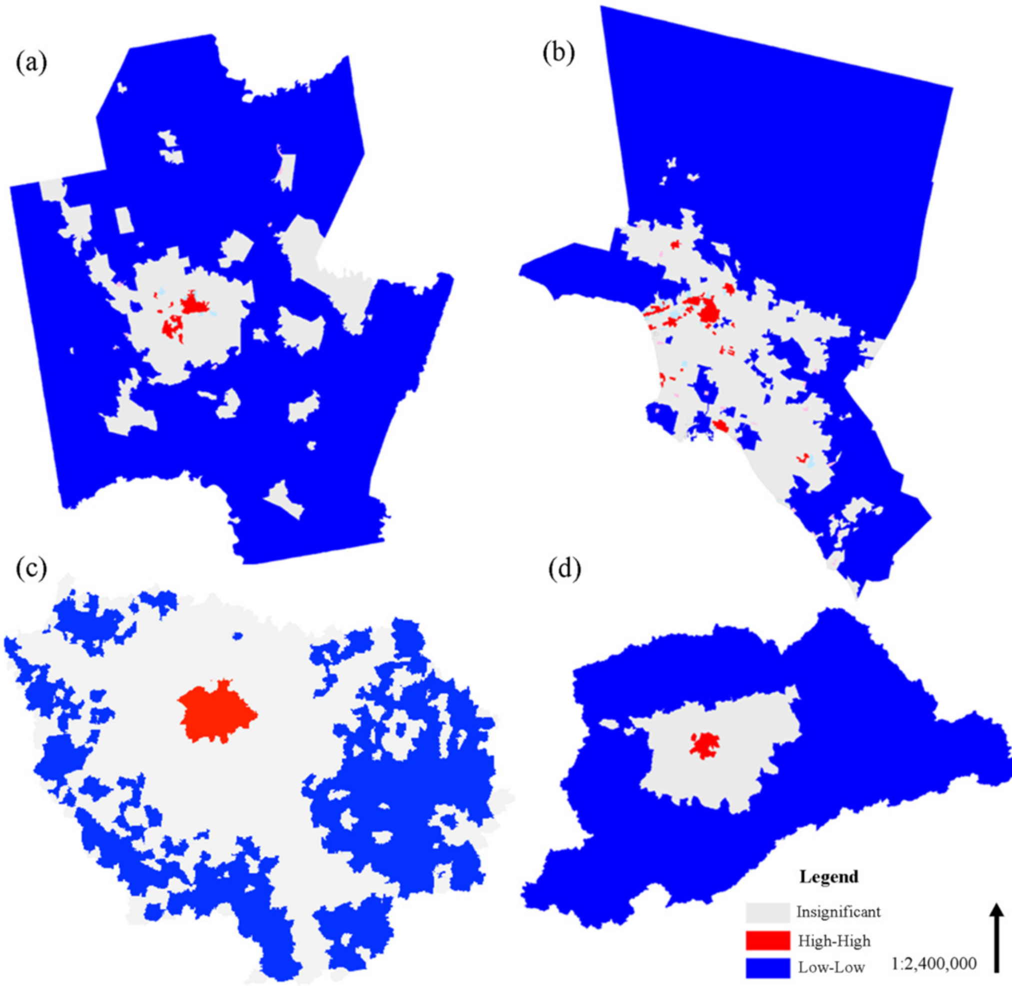


Figure 3. Local Moran's I clusters maps for employment densities: (a) Pittsburgh, (b) Los Angeles, (c) Paris, and (d) São Paulo. Sources: NHGIS, population census of 2000 (U.S. cities); INSEE, population census of 1999 and LVMT (Laboratoire Ville Mobilité Transport) (Paris); SP-Metrô, Origin–Destination Survey, 1997 (São Paulo).

Table 3 Concentration and Spatial Pattern Indexes

	LC	PI	Global Moran I	UCI
Paris	0.708	0.725	0.76	0.514
São Paulo	0.319	0.628	0.67	0.201
Pittsburgh	0.3	0.48	0.56	0.11
Los Angeles	0.171	0.261	0.55	0.045

Final remarks

This article contributes to the literature on measuring the degree of centrality in urban agglomerations by proposing a very simple index that overcomes many of the limitations of established measures quantifying this phenomenon. Our UCI is closely related to the intuitive notion of monocentricity, and it measures change in urban spatial structure that other indices fail to capture, such as varying degrees of proximity among jobs, as shown with the experiments using hypothetical metropolitan forms. Furthermore, it is a normalized index that can be compared across different cities and through time, regardless of different urban shapes and sizes. The application of the index to hypothetical urban forms and to four case studies shows its ability to measure the centrality of extreme cases as well as empirical situations.

Our UCI clarifies the definition of the two extremes of the centrality scale: maximum monocentricity with all jobs concentrated in one single spatial unit and minimal monocentricity with either density of jobs distributed evenly throughout a territory or the largest number of dense centers that maximizes the distance between them.

Our UCI is not an end in itself. We hope that it will help in studies focusing on the relationship between urban spatial structure and commuting, and, additionally, on those examining the economic and environmental performance of cities.

Acknowledgements

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Notes

1 Clark (1951) was one of the first researchers to introduce density functions to urban populations, although without presenting a structured model as Alonso (1964) did. This functional form has been modified by many other studies trying to find a better match to actual spatial distributions of densities (Anderson 1982; Anselin and Can 1986; McMillen 2001; Griffith and Wong 2007).

2 As suggested by Crafts and Mulatu (2005), we decided to use the "self-distance," approximated by dii = (area/π) ^ 1/2, in the distance matrix, because this controls for variation in polygon size.

3 If employment activities are evenly distributed across space, the PI index is *not* equal to zero.

4 However, note 5 shows that the UCI is quite robust to changes in the resolution of a map. Changes of scope are inevitable because a researcher must define criteria for the boundaries of metropolitan areas. On the issue of relation with theory, Griffith and Wong (2007) stress the differences between empirically based approaches and urban economic theories based on deductive models, which go back to von Thünen.

5 We have calculated the same simulations using other hypothetical metropolitan forms of different grid resolutions (42×42 and 126×126). The differences in the UCI results are not greater than 2%.

6 The pictorial representations of these hypothetical urban structures are not presented in this article for the sake of brevity.

7 National Historical Geographic Information System (http://www.nhgis.org/.)

8 Area units for São Paulo are origin–destination zones, set by the survey taking into account the limits of Census tracts but bigger than them.

9 For Pittsburgh and Los Angeles, we have chosen to work with metropolitan statistical areas instead of other area designations, such as consolidated statistical metropolitan areas. However, for São Paulo and Paris, we were constrained by the data. If the official metropolitan area is much larger than the actual metropolis, then measures of monocentrality—including the UCI—will be biased upward.

10 We use a first-order queen's contiguity matrix and a 5% significance level in the GeoDa software.

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