Cities' Fingerprints: A Complex Network Approach

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Abstract

This paper presents a set of tools that can be used to measure and understand cities' morphology. The first method is a urban block based algorithm, following the methodology presented by Louf and Barthelemy (2014) in where every block in a city is measured according to a definition of anisotropy[2] in order to have a distribution of geometric forms describing the city; the second set of tools is exclusive of this document and it consists in a street network approach, in where a matrix of distances within the street network is estimated, in order to have a measure of how *far* is every point from one another in a particular urban landscape. Both methods were applied to a universe of 116 cities in Mexico, all of which have at least 100 thousand inhabitants.

I. Introduction

Urban Morphology is the study of how the physical landscape of human settlements evolve over time. It has been used as an application in the field of network analysis, it is important in anthropology to understand how ancient civilizations evolved, is gaining relevance in urban studies to design transportation systems, in hydrology to plan resource management and even in economics, to understand how urban shape and morphology relate with social variables such as employment and business concentration.

Under the notion of urban morphology, cities can be interpreted either as a set of blocks or as a set of nodes and edges as represented in **Figure 0.** Each one of those potential interpretations can lead to a wide range of different methodologies.

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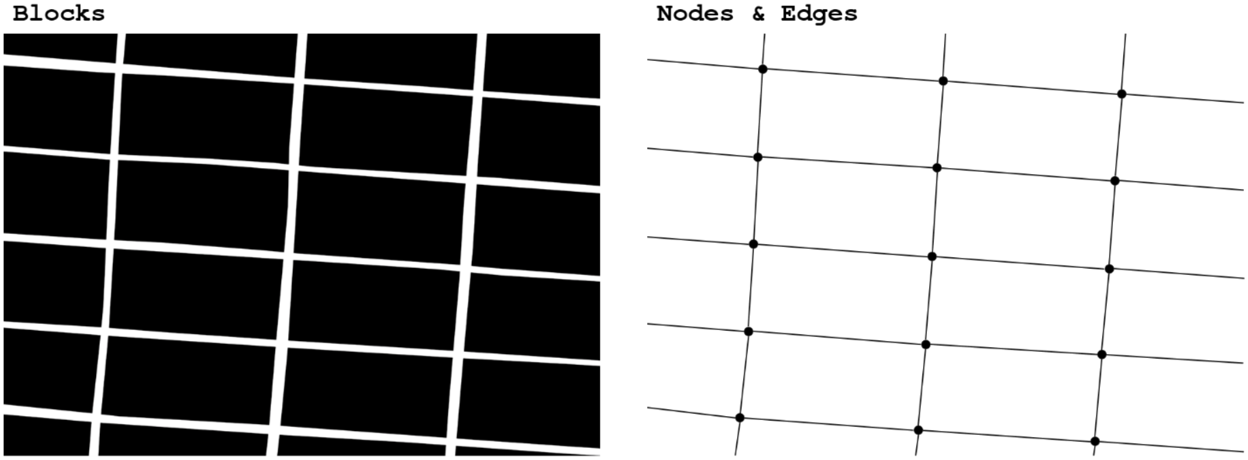
[2] From Wikipedia, "Anisotropy is the property of being directionally dependent, as opposed to isotropy, which implies identical properties in all directions."

This paper explores and compares two methods, a first one in where cities are viewed as a collection of geometrical shapes given by their blocks and a second one in where cities are described by the lines and intersections of their street patterns.

The first method was developed by Louf and Barthelemy (2014) and it attempts to measure all blocks within a city, given a particular definition of anisotropy. The second method is an alternative approach presented in here, in where a grid of equidistant points is draw in a city, a square matrix of distances between all those points is calculated in order to have a clue of how well every point in a city is connected to each other.

Figure 0. Two Ways to Interpret Cities' Morphology

Blocks **Nodes & Edges**



The purpose of this paper is threefold, first to apply Louf and Barthelemy's block-based method to a universe of 116 cities in Mexico; second, to define a new algorithm relying on an alternative approach in where urban morphology is approximated by their street patterns and apply this second street-based method to the same universe of 116 Mexican cities; finally, the third purpose is to assess how both methods speak to each other, by checking if there is a pattern of correlation across cities classified by each method.

By doing this, the contribution of this paper is to develop a measure that can be used for instance to rank cities according to the ability they have to mobilize their inhabitants across space; to evaluate transport policies and the development of new physical infrastructure; or even to calculate the size of costs that a particular physical infrastructure on street have in human mobility.[3]

To accomplish those purposes the present document is organized as follows. The next section is a review of the recent work in the field of urban morphology. Sections III and IV present each one of the algorithms in detail. Section V presents the results of applying the different algorithms to the universe of 116 Mexican cities.

II. Motivation

As the urban population grows all over the world, cities are becoming the landscape in where most of the social phenomena occur. It is then a natural response from social sciences and policy analysis to extend the reach of new research to its implications for urban life.

In one of the seminal works in this matter, Sargent (1972) addressed this need of science for *nomothetic studies* addressing the forces, physical and economical, behind the form in constant evolution of cities. Or as Bin and Claramunt (2004) put it, the need for urban studies allowing to address the relative importance of streets according to their connectivity, the level of integration of a particular street network and in general, how the streets are interlinked to each other.

Strictly speaking, urban shape or morphology isn't just a matter of physical form, but a *complex* of spatial, economic and temporal forces that conduct cities to their particular shape at any moment in time. Following the same principles described in Sargent (1972), Spatial forces in a city deal with direction and dispersion of the physical deployment of cities; economic factors include employment sources, standards of living and residential variables like public services and

[3] Bin and Claramunt (2004) present a wider discussion on the importance and applications of urban morphology.

schooling; finally Sargent talks about Temporal factors affecting the functioning of the economic and spatial variables, such as new technologies in transportation, demographic changes, real business cycles and their effects on demand, credit and investment that end moving people across space within a city. Considering this, as pointed in Claes *et al* (2006), urban economics is now considered to be the study of geography as *the space of flows* meaning that *places derive their success from their position in networks*.[4]

Considering this extended definition of urban morphology, there are at least two directions in where the literature of this field have evolved. First a set of developments, both mathematical and computational, with the aim to develop instruments to measure the morphogenesis[5] of cities in their spatial dimension, we could say that following Sargent's definition of spatial factors. Examples of this literature are Porta *et al* (2006), who measured centralities[6] in urban street systems; Bin and Claramunt (2004) who measured interconnectedness in street networks, they find among other things that in general *the number of steps required to connect two points within a city is in general very small.*[7] Other example in the mathematical approach of urban morphology is Xie and Levinson (2007), they complemented the traditional measures of network theory in street networks like connectivity and accessibility with new measures, in particular their study proposes heterogeneity, connection pattern and continuity as new measures to extract from street networks. All these methods rely heavily in the interpretation of streets geography as planar graphs in where every street is an edge that connects every node that comes from the intersection of streets.

A second body of literature in urban morphology are more concerned with the economic and temporal forces described above using again

[4] Claes et al (2006)
[5] According to Wikipedia, *Morphogenesis is the biological process that causes an organism to develop its shape*.
[6] A concept in network theory and graph theory referring to the relative importance, by the number of connections, of every node within a network.
[7] Bin and Claramunt (2004)

Sargent’s categories. Examples of this are can be found in the work of Alain Bertaud or Walter Isard.

Both algorithms in this paper should be understood in the first category described above, as methods dealing with the spatial factors in urban morphology. The work of Louf and Barthelemy (2014) introduced a particular new approach in where cities are viewed as a collection of polygons characterized by their blocks, as opposed to the traditional literature in where cities are interpreted as a collection of nodes and edges.

III. Algorithm I[8]

Method

The first method of city classification reviewed in this paper is due to Rémi Louf and Marc Barthelemy. According to them, their intention is to present *a method to classify cities according to their street patters*,[9] by measuring every city’s block and associate them to an anisotropy measure. For this, they define a set of three measures for every block within a city as presented in Figure 1 (modules 1 to 3):

- Its area (A),
- the area of the hypothetical circumscribed circle (AC) and
- the ratio of both ($\Phi = \frac{A}{AC}$)

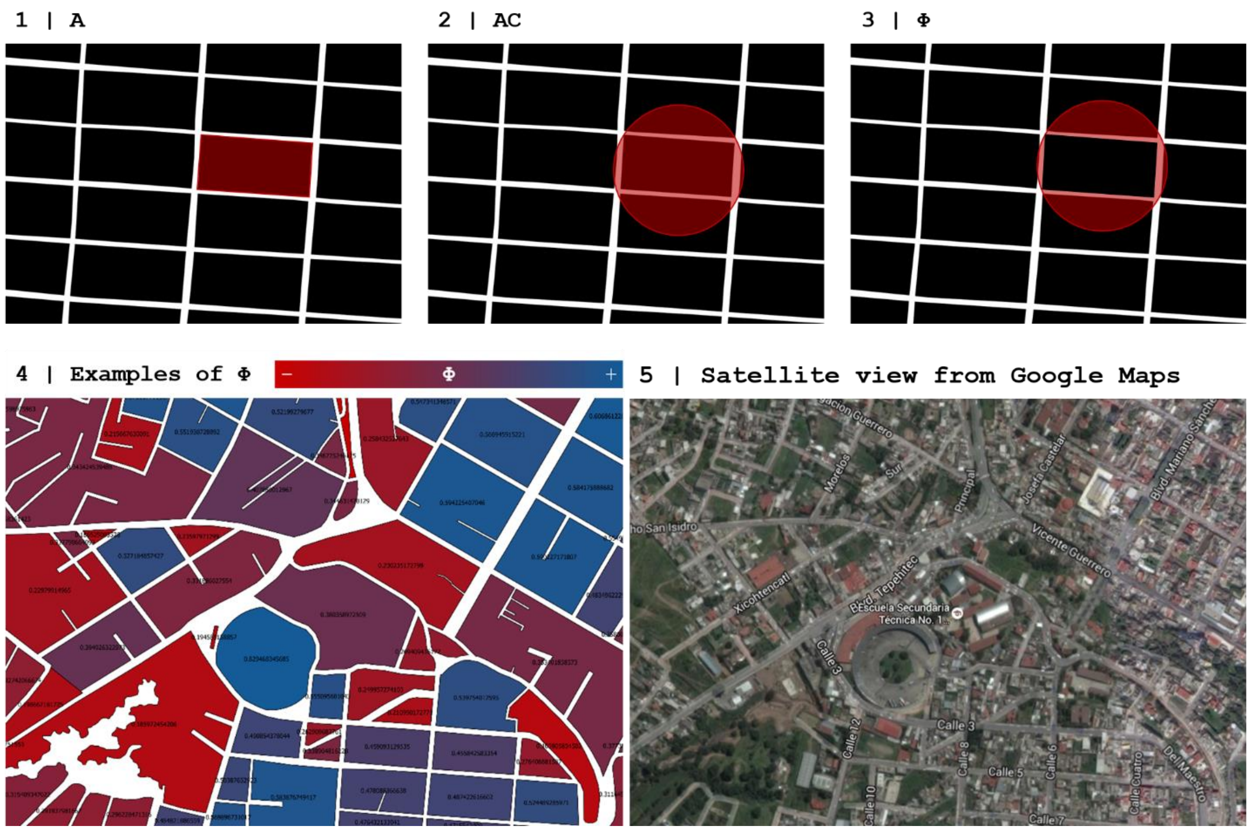
In the same Figure 1 are presented some examples on the value of Φ and a satellite view for a selection of blocks centered in the coordinates 19.3149952 latitude and -98.2472441 longitude of the Mexican geography.

The use of these measures serve to their purpose which in their own words, is to use the *conditional probability distribution of shape factor of blocks with a given area and define what could constitute the fingerprint of a city.*[10]

[8] As presented in Louf and Barthelemy (2014).
[9] Louf and Marc Barthelemy (2014)
[10] *Ibíd.*

Under this approach, *regularity* of the blocks is given by the value of Φ associated to it. The higher this value it means that it is close to be a circular block, the lower the value it means that is less regular in terms of its geometrical shape. Different examples of blocks and their values are presented in Figure 1.

Figure 1. Measures from Algorithm I



Note: The satellite view can be accessed in here: http://bit.ly/1r7t4a8

Once Φ is calculated for every block in the urban region of study, Louf and Barthelemy focus in its distribution, to later perform a hierarchical method of clustering and find the typology of cities they are looking for. According to their method, there seem to be only 4 types of cities into which every city should be categorized in.

Discussion over Algorithm I

One of the key elements of this algorithm is that it is based in the physical form of the blocks, as opposed to the traditional literature of urban morphology, where the usual object is the street network.

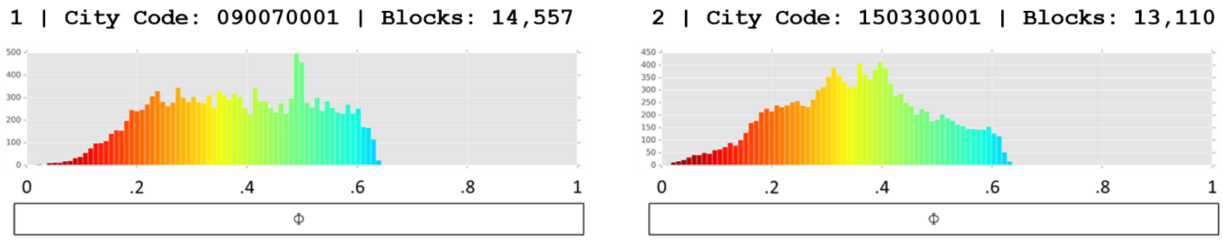
The key measure in their method is given by the value of Φ associated to every block. It can be seen that this value lives in between [0, 1] and that the bigger this number is, the more *regular* the block will be. However, data from the study case on the 116 cities in Mexico has shown that there is empirical evidence of a natural frontier around .64 in the value of Φ.

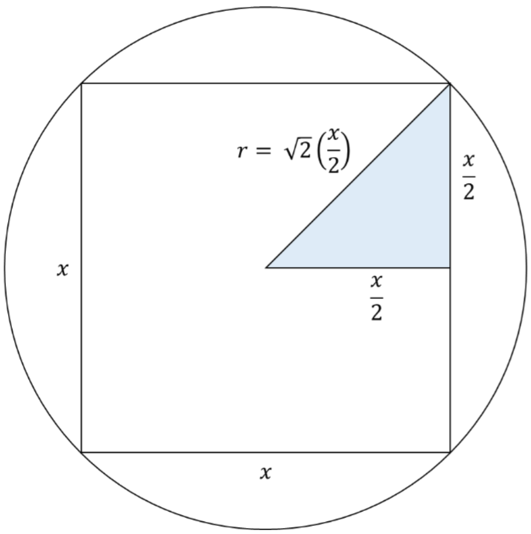
As example of this behavior in Φ, in Figure 1.5 are presented the correspondent histograms for the two largest cities in Mexico. Cities 090070001 and 150330001 have 14557 and 13110 blocks respectively and it can be seen from the figure that the majority of blocks have values of Φ smaller than .64. This natural threshold around .64 was found in all 116 cities in the sample and prove the fact that cities are usually built over a grid of square-based blocks. Actually, the number .64 is approximately equal to $\frac{2}{\pi}$ or the Φ value associated to a perfect square block. In figure 1.5 is also presented a formal proof for this proposition.

Considering this, one potential extension to their work could consist into check whether if their results are robust or not to the particular way they measure the anisotropy of the blocks. The idea behind their selection to measure anisotropy is that the most compact shape is the circle,[11] however other methods like the Polsby-Popper that is measure as the ratio of the area of a polygon and the area of a circle with the same perimeter, could lead to a different results.

[11] A further discussion can be found in here: http://bit.ly/1TVAURK

Figure 1.5 Empirical Evidence of Φ Frontier





Proposition. For any square block with area x^2, the associated value Φ will be equal to $\frac{2}{\pi}$

Proof

$$A = x^2$$

$$AC = \pi r^2 = \pi\left(2\left(\frac{x}{2}\right)^2\right)$$

$$\frac{A}{Ac} = \mathbf{\Phi} = \frac{\mathbf{x^2}}{\pi\left(2\left(\frac{x}{2}\right)^2\right)} = \frac{\mathbf{2}}{\pi} \approx 0.637$$

Q.E.D ■

It is interesting though that their method using small city cells, in this case their urban blocks, can be used to compute not only city level analysis but sub-city spatial measurements, allowing to compare neighborhoods and small communities within cities.

Regardless these considerations, their approach is innovative enough to be applied at a subnational level. They perform their analysis over 131 cities in the world and this paper below does the same in 116 cities in Mexico. These cities were selected considering a population threshold of 100 thousand inhabitants.

As it was stablished before, the purpose of this paper is not only to apply Louf and Barthelemy’s method but to present an alternative computational instrument to classify cities, according in this case to their street network.

This second algorithm is exclusive of this paper and uses rudiments of network theory to transform cities' street webs into proper networks or planar graphs, in where every intersection is a node and every street is an edge.

IV. Algorithm II

Method

A second algorithm was developed trying to extend the efforts in urban morphology related with understanding cities as networks. This second algorithm is feed with some rudiments of network theory to reduce urban complexity in street patterns to a single number. This new measure can be used to rank cities according to the ability they have to mobilize their inhabitants across space; to evaluate transport policies and the development of new physical infrastructure; or even to calculate the size of costs that a particular physical infrastructure on street have in human mobility.

When dealing with complexity, the question is always how to reduce a complex system into a manageable number of interactions, representative values or functions. Cities can be considered complex systems, for the amount of human interactions they hold; the way they are deployed in space or the way they evolve in time. Therefore, complex theory and network mechanics should be instruments that combined with economics or sociology, will yield better ways to understand cities and urban landscapes.

Following Xie and Levinson (2007), cities can be described as directed planar graphs, composed of a collection of nodes and edges that interconnect them. Formally:

$$city = \{\boldsymbol{N}, \boldsymbol{R} \mid there\ is\ a\ rout\ \boldsymbol{r}\ connecting\ all\ \boldsymbol{n}\ and\ \boldsymbol{n}'\ in\ \boldsymbol{N}\}$$

If we have two points in a street network, it is possible to calculate the Euclidean Distance ($e\_distance$) between them and the length of the shortest path across the network connecting both points, as presented in Figure 2. This paper relies on Dijkstra method to calculate the second distance presented here as Dijkstra Distance (*d_distance*).[12]

The purpose of the algorithm consists into grid a set of equidistant points given a street network, measure both d_distance and e_distance between all of them, in order to have a collection of pairs from which it will be possible to estimate a model of the form:

$$\boldsymbol{d\_distance} = \beta * \boldsymbol{e\_distance} + u$$

Figure 2. Measures from Algorithm II

Given this definition, the interpretation of β in such a model could be of a factor measuring how well points are interconnected within a city.

The formal steps of this second algorithm are as follows:

1. Define a city
2. Draw a regular grid over it
3. Extract the centroids of the grid. This gives a network of points regularly deployed, equidistant in space to be connected through the street network.

[12] A discussion on this method is presented in here: http://bit.ly/1MURZs9. The way this paper use it is described in the documentation of the code http://bit.ly/1VPp6AA.

4. Use Dijkstra's algorithm to find the shortest path through the streets between all points.
    - Here is important to notice that there are P points in a city to be connected by this algorithm, the number of connections or routes to be find will be given by:

$$\frac{P!}{2! * (P-2)!}$$

5. Every pair of points have now two distances, a Euclidean distance <**e_distance**> and a distance from Dijkstra's method <**d_distance**>.
6. These two distances define a model that can be estimated through an OLS method of the form:

$$\boldsymbol{d\_distance} = \beta * \boldsymbol{e\_distance} + u$$

7. By applying this method to a set of cities we have an estimate β for each city, allowing to compare them according to it, rank them or indexing.

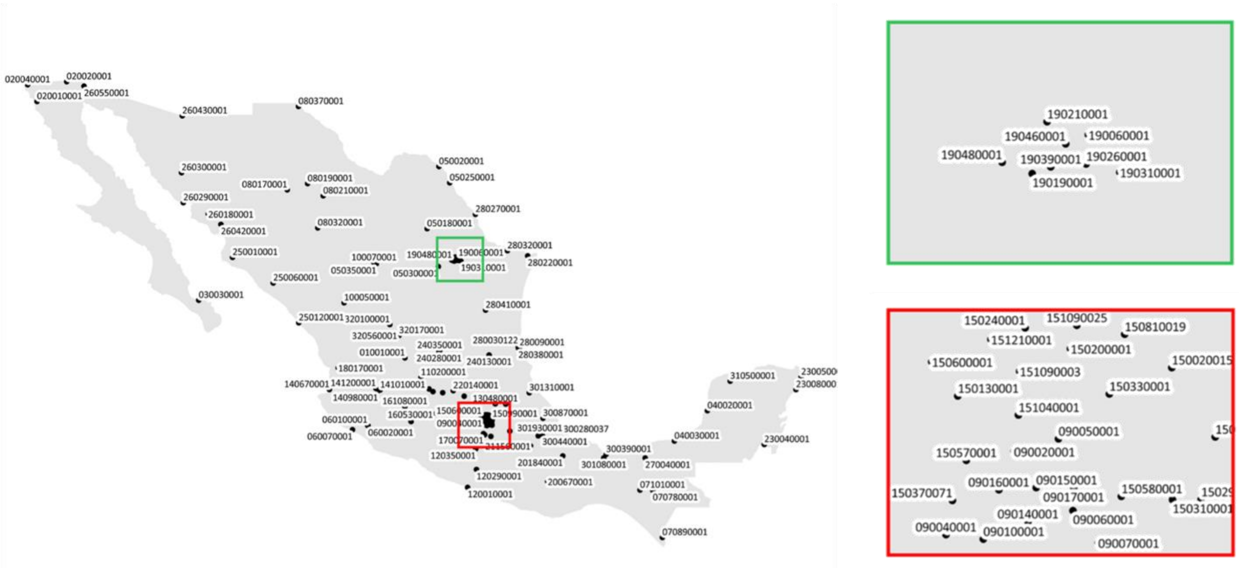
V. A Study Case

One of the goals of this paper was to apply both methods, the one following Louf and Barthelemy's methodology and the proper introduced in this document, to a particular reality of a universe of comparable cities.

A universe of 116 cities in Mexico where selected to apply both algorithms. One of the reasons to choose this particular case study is the availability of comparable GIS data for these cities. Figure 3 presents the geographical distribution of 116 cities that constitute the universe for both methods to be applied.

The National Institute of Statistics and Geography in Mexico (INEGI) provides data at block level for a universe of more than 4500 urban localities. There is a hierarchy of administrative geography in the way Mexico is subcategorized. Mexico is a federal republic with 32 states, including Mexico City, 2457 municipalities, 4501 urban localities and about 187,721 rural localities.

Figure 3. Cities



The selection of the 116 cities was made over the universe of 4501 urban localities, defining a threshold of localities with at least 100 thousand inhabitants. For each one of these cities both methods were applied, in the case of Louf and Barthelemy's method using every block within this set of 116 cities and in the case of the second algorithm, using the corresponding street layer. INEGI provide both types of information for every locality.[13]

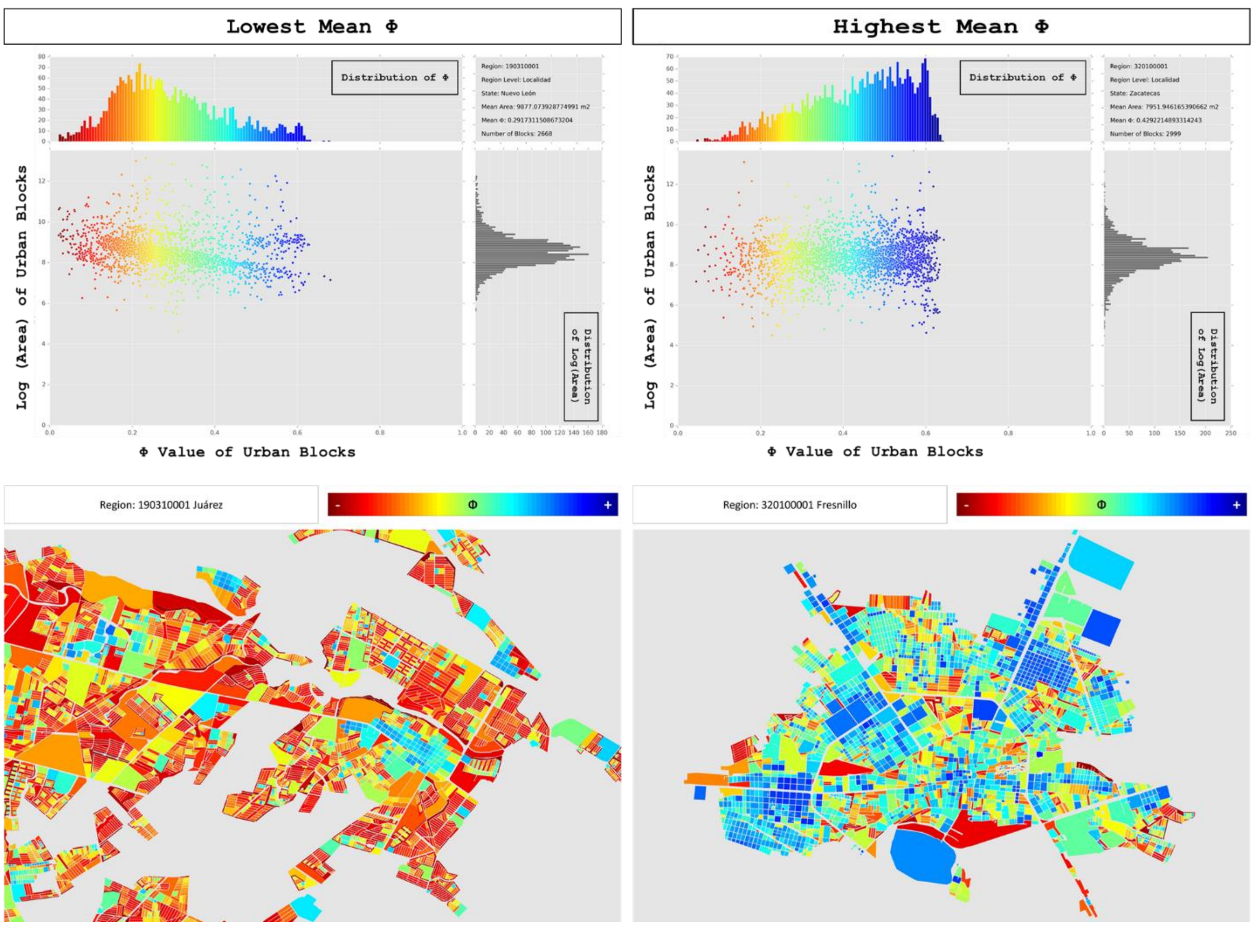
In the case of the application of Louf and Barthelemy's work one extension was explored, regarding potential evidence for spatial concentration on the values of Φ according to a Moran's Index.[14] This measure actually can be interpreted as an empirical evidence for how cities are built over time and how urban planning changes over time.

[13] The information is provided in GIS standard of shapefiles. INEGI provides block and street layer at state layer and a common clip method was performed to extract the blocks and streets corresponding to every locality of interest.

[14] Moran's Index measures spatial autocorrelation and categorizes the geographical entities, in this case blocks, in clusters depending if there is a spatial concentration of blocks with high values of Φ (labeled as HH) or a spatial concentration of blocks with low values of Φ (labeled as LL). A further discussion on how this method is performed it can be found in here: http://arcg.is/1O9l8jF.

Figure 4 presents examples of how Louf and Barthelemy's work has been applied to the case study of 116 largest cities in Mexico. In this figure are presented the distribution over the values of Φ and the *log* of the areas of every block in two instance cities, city 190310001 and city 320100001 as cities with the lowest and the highest mean Φ for their blocks.

Figure 4. Cities with Lowest and Highest Mean Φ



In Figure 5 is presented a geographic representation of Moran's I categories of HH and LL clusters, again for cities 190310001 and 320100001 as examples. This extension is interesting because offers evidence of how clustered are block shapes, measured by the definition of Φ. The study case found that for every city in the universe of 116 entities studied in here, there is evidence of clusters of high values of Φ (HH clusters) and low values of Φ (LL clusters). This result is highly intuitive, since there are neighborhoods and urban planning that produce clusters of highly similar blocks. However, this measure can later be correlated with age of the clusters to check changes of urban planning over time. In Figure 6 the density of the mean Φ for each city is presented, and it is centered on a value of .38 mean Φ.

In figure 7 is presented an example, using cities 150020015, with the lowest value of β and 140670001 with the highest value of β as examples of how the second algorithm was applied. The range of estimated β's across cities goes from 1.16 to 1.81. This means that in cities like city 150020015 every pair of point are connected through the street network by a 16 percent longer distances than the Euclidean distance between them. Similarly, any two points in cities like 140670001 in where the estimated beta was 1.8, are connected by a distance in the road network 80 percent higher than the distance between them.

These numbers can be interpreted as the cost society has to pay in terms of distances for having a world with physical infrastructure in the form of street networks, as opposed to a world in where every pair of points is simply connected by their Euclidean distance.

In Figure 8 are presented all estimated models in the left and the density of β's across cities in the right. The mean β is 1.32 and the standard deviation is .12. The range of the β's goes from the smallest 1.16 to the highest 1.81.

Figure 5. Moran's Spatial Autocorrelation

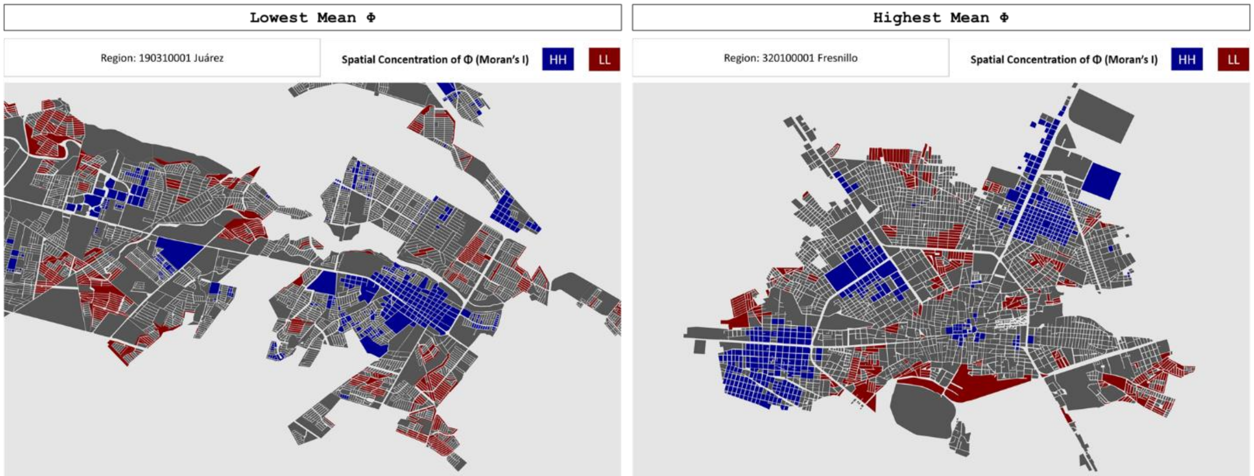


Figure 6. Mean Φ Density in 116 Cities

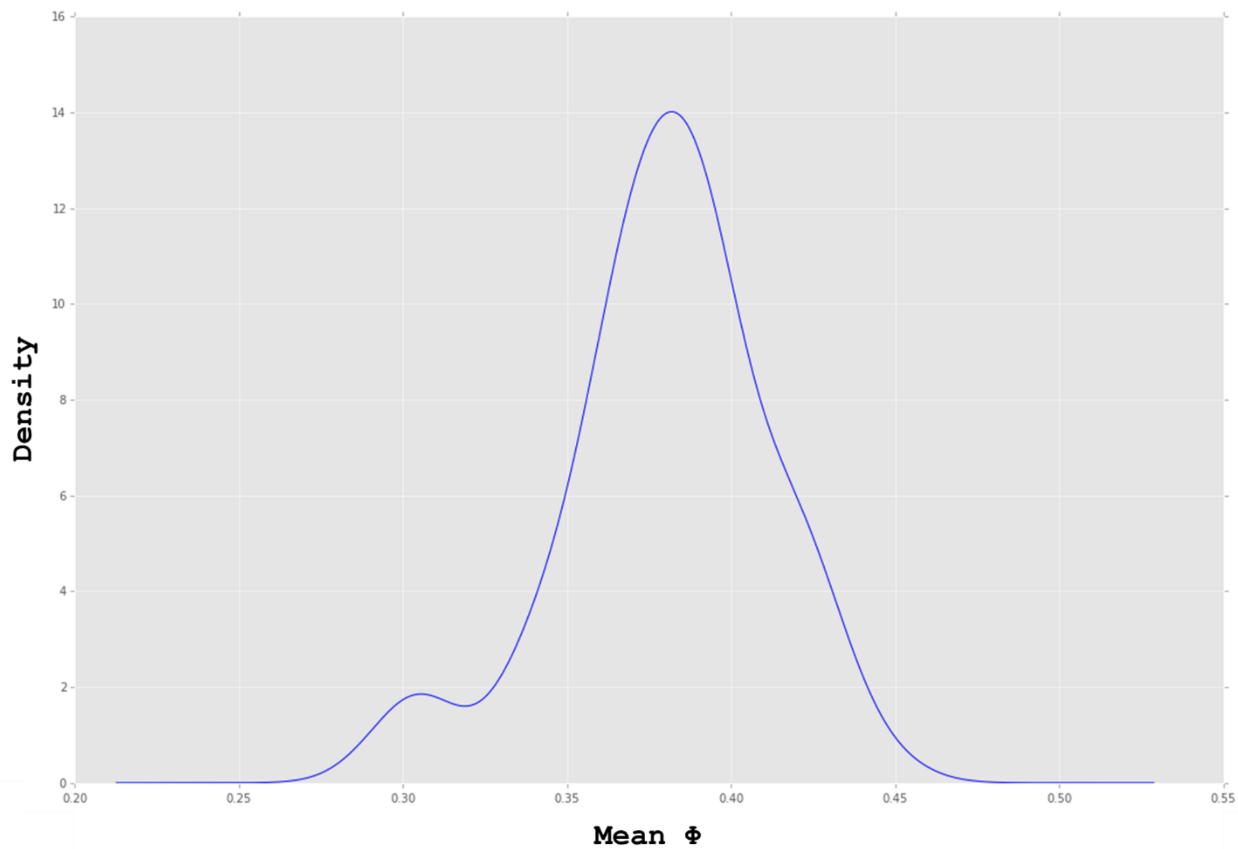


Figure 7. Cities with Lowest and Highest β

Lowest β	Highest β

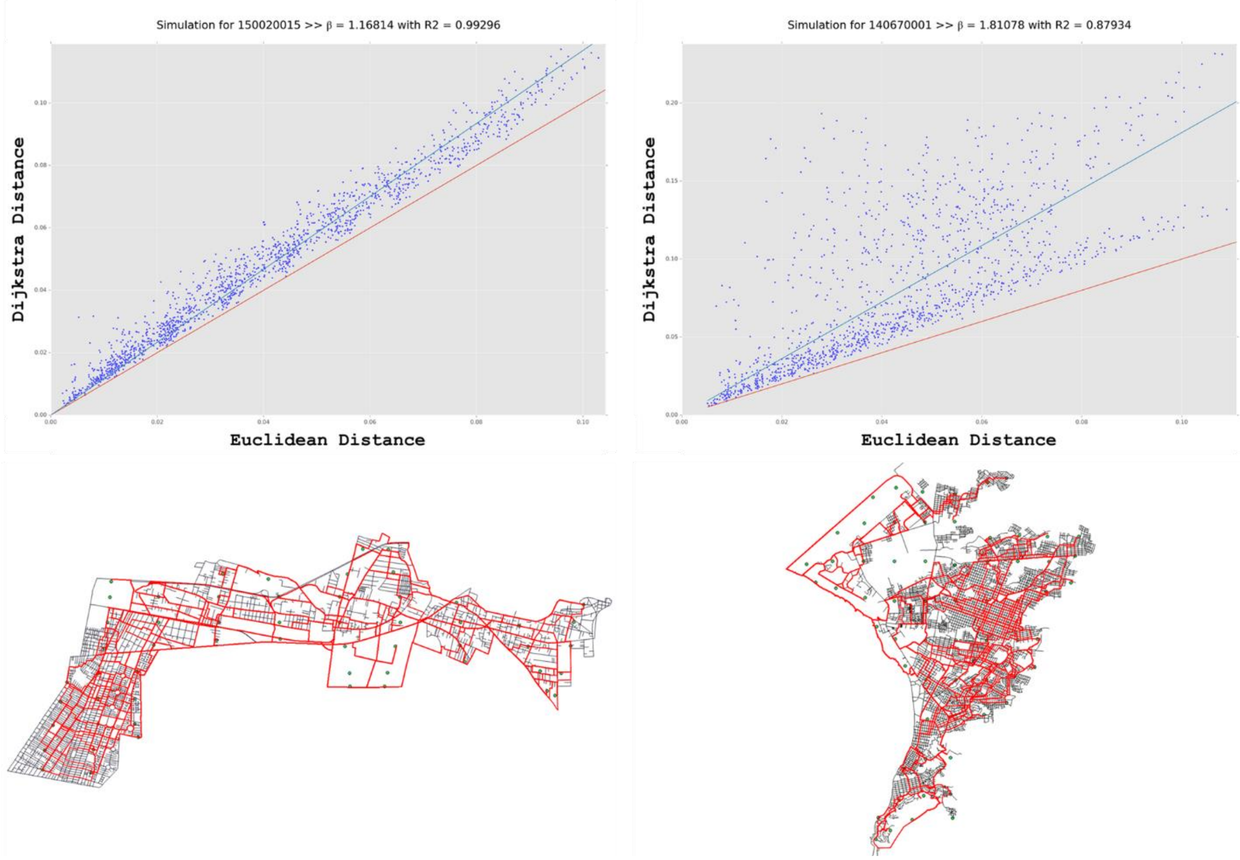
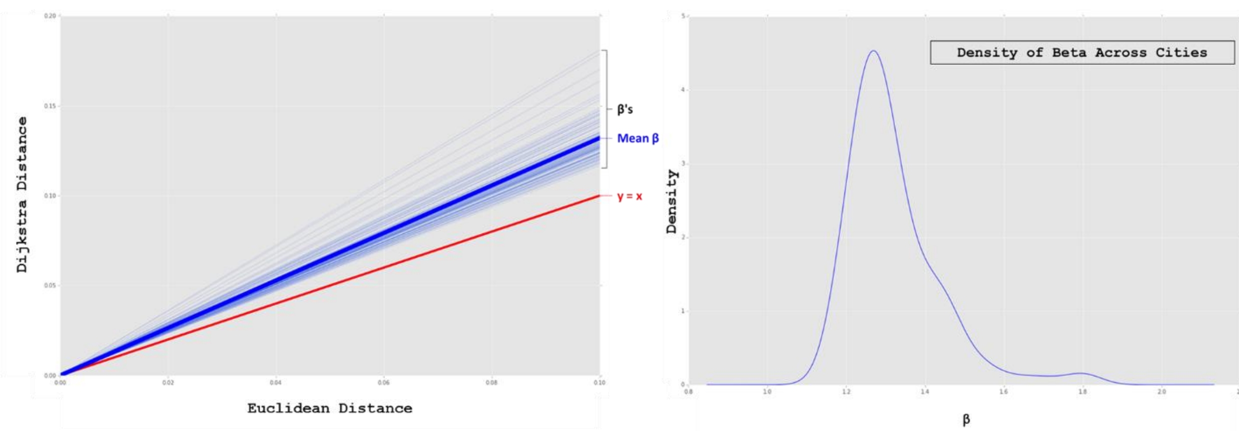


Figure 8. β Density in 116 Cities



ID	City CODE	City Name	City State	Population	Algorithm I		Algorithm II	
					Mean Area	Mean Φ	Beta	Dijsktra Distance SD
1	050180001	Monclova	Coahuila	215,271	14845.48565	0.398821634	1.399327306	0.040210364
2	070780001	San Cristóbal de las Casas	Chiapas	158,027	15068.73608	0.387289851	1.289187828	0.019205077
3	070890001	Tapachula	Chiapas	202,672	9873.426232	0.391677874	1.337712134	0.022855881
4	080170001	Cuauhtémoc	Chihuahua	114,007	14896.77964	0.427453025	1.236540025	0.025844516
5	080190001	Chihuahua	Chihuahua	809,232	11214.89303	0.396473037	1.218678819	0.061588427
6	080210001	Delicias	Chihuahua	118,071	10269.38514	0.361583553	1.178966999	0.017227457
7	080320001	Hidalgo del Parral	Chihuahua	104,836	10131.17334	0.369007107	1.237742643	0.021229891
8	080370001	Juárez	Chihuahua	1,321,004	13335.26366	0.389466612	1.198220742	0.07266907
9	090020001	Azcapotzalco	Distrito Federal	414,711	9325.304994	0.395363721	1.300033865	0.018666379
10	090030001	Coyoacán	Distrito Federal	620,416	9144.059733	0.387068531	1.235109337	0.023982421
11	090040001	Cuajimalpa de Morelos	Distrito Federal	160,491	27295.93878	0.376659232	1.474568759	0.02345428
12	090050001	Gustavo A. Madero	Distrito Federal	1,185,772	7099.36916	0.365577541	1.26870061	0.038004088
13	090060001	Iztacalco	Distrito Federal	384,326	6800.489684	0.412523366	1.241121068	0.021293927
14	090070001	Iztapalapa	Distrito Federal	1,815,786	6322.997377	0.381481997	1.224558398	0.034798825
15	090080001	La Magdalena Contreras	Distrito Federal	238,431	11620.30824	0.364117977	1.346301577	0.016890968
16	090100001	Álvaro Obregón	Distrito Federal	726,664	10990.63236	0.368056536	1.406745271	0.033576391
17	090110001	Tláhuac	Distrito Federal	305,076	9914.461863	0.421579873	1.486451454	0.030570206
18	090120001	Tlalpan	Distrito Federal	574,577	15028.53625	0.389124254	1.287113824	0.03098493
19	090130001	Xochimilco	Distrito Federal	407,885	20853.55692	0.37109726	1.352355407	0.040406396
20	090140001	Benito Juárez	Distrito Federal	385,439	9092.272765	0.416145379	1.45011575	0.017217731
21	090150001	Cuauhtémoc	Distrito Federal	531,831	9078.504263	0.433305138	1.635470029	0.025020377
22	090160001	Miguel Hidalgo	Distrito Federal	372,889	15909.27662	0.394122962	1.335663241	0.026735559
23	090170001	Venustiano Carranza	Distrito Federal	430,978	8163.707313	0.387355971	1.352689412	0.023601935
24	100050001	Durango	Durango	518,709	7089.446794	0.39378523	1.198417338	0.033943518
25	100070001	Gómez Palacio	Durango	257,352	8351.581249	0.381059559	1.233281336	0.025126341
26	110070001	Celaya	Guanajuato	340,387	10675.4505	0.369775301	1.34282945	0.02661146
27	110170001	Irapuato	Guanajuato	380,941	12216.61464	0.348786611	1.352709908	0.027292474
28	110200001	León	Guanajuato	1,238,962	11193.91664	0.359021468	1.280019737	0.050040581
29	110270001	Salamanca	Guanajuato	160,169	11863.55034	0.376868808	1.383334255	0.020720959
30	120010001	Acapulco de Juárez	Guerrero	673,479	7607.573957	0.372597968	1.457017929	0.087452824
31	120290001	Chilpancingo de los Bravo	Guerrero	187,251	7303.751929	0.358625812	1.283854061	0.021400425
32	120350001	Iguala de la Independencia	Guerrero	118,468	8237.983911	0.385562906	1.352006903	0.022496857
33	130480001	Pachuca de Soto	Hidalgo	256,584	10123.15388	0.374453578	1.388167972	0.035114158
34	130770001	Tulancingo de Bravo	Hidalgo	102,406	10579.80754	0.381469314	1.272023154	0.017197205
35	140390001	Guadalajara	Jalisco	1,495,182	8702.789097	0.417493844	1.263856992	0.03776857
36	140670001	Puerto Vallarta	Jalisco	203,342	10545.76797	0.426463555	1.810780405	0.048025109
37	140980001	Tlaquepaque	Jalisco	575,942	11209.534	0.389425598	1.325780108	0.052311971
38	141010001	Tonalá	Jalisco	408,759	10230.87011	0.402880289	1.562783982	0.039351746
39	141200001	Zapopan	Jalisco	1,142,483	13061.66349	0.374916068	1.296332794	0.05880155
40	150020015	Acolman	México	102,667	15003.92346	0.392340933	1.168140456	0.026798703
41	150130001	Atizapán de Zaragoza	México	489,160	15287.7395	0.361673367	1.701750801	0.046434783
42	150200001	Coacalco de Berriozábal	México	277,959	7955.871486	0.379529127	1.283728134	0.014116493
43	150240001	Cuautitlán	México	108,449	15060.05078	0.391514684	1.278637071	0.013845002
44	150250001	Chalco	México	168,720	9159.018513	0.302527177	1.214721914	0.013019763
45	150290001	Chicoloapan	México	172,919	11309.48259	0.369491376	1.204485495	0.015606654
46	150310001	Chimalhuacán	México	612,383	9154.567795	0.308654631	1.412031152	0.02931499
47	150330001	Ecatepec de Morelos	México	1,655,015	7994.054465	0.354061722	1.221583452	0.042531185
48	150370071	Huixquilucan	México	121,470	21816.99602	0.340431272	1.548749974	0.019248595
49	150390001	Ixtapaluca	México	322,271	9917.225101	0.344311221	1.301085482	0.021774763
50	150570001	Naucalpan de Juárez	México	792,211	9854.513808	0.342663221	1.273466098	0.028085697
51	150580001	Nezahualcóyotl	México	1,104,585	7269.948925	0.305724095	1.258623084	0.039687751
52	150600001	Nicolás Romero	México	281,799	13017.79755	0.359058951	1.263434925	0.019467515
53	150810019	Tecámac	México	242,272	17105.40969	0.356657791	1.26486926	0.02485378
54	150990001	Texcoco	México	105,165	14552.30796	0.392400426	1.275752876	0.007051877
55	151040001	Tlalnepantla de Baz	México	653,410	9904.732369	0.373628321	1.220898356	0.023386716
56	151060001	Toluca	México	489,333	15607.45857	0.420088197	1.290728429	0.032221124
57	151090003	Tultitlán	México	206,081	7844.404391	0.373817154	1.23960738	0.014060721
58	151090025	Tultitlán	México	156,191	5094.39074	0.399442267	1.280408168	0.010417116

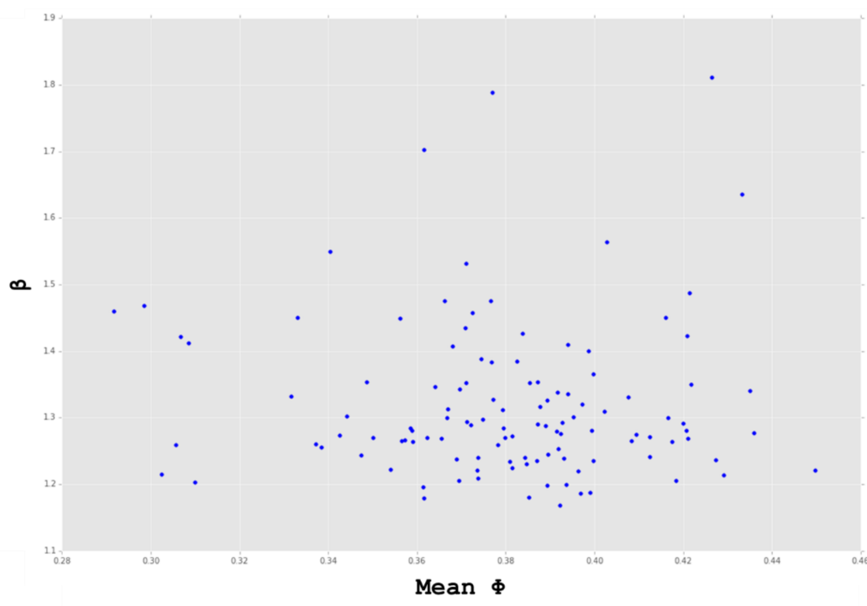
ID	City CODE	City Name	City State	Population	Algorithm I		Algorithm II	
					Mean Area	Mean Φ	Beta	Dijsktra Distance SD
59	151210001	Cuautitlán Izcalli	México	484,573	12442.2478	0.384424039	1.239146415	0.031744465
60	151220001	Valle de Chalco Solidaridad	México	356,352	5956.655798	0.418433741	1.205228808	0.020529054
61	160530001	Morelia	Michoacán	597,511	8310.879872	0.37995468	1.269702212	0.035306289
62	161020001	Uruapan	Michoacán	264,439	9138.496478	0.407674104	1.330043268	0.023662091
63	161080001	Zamora	Michoacán	141,627	8966.652401	0.387826271	1.31550325	0.018309975
64	170060001	Cuautla	Morelos	154,358	12970.33276	0.366220057	1.475048244	0.033331207
65	170070001	Cuernavaca	Morelos	338,650	17472.17573	0.382601313	1.384261925	0.03637959
66	170110001	Jiutepec	Morelos	162,427	13851.10081	0.383876564	1.426365317	0.020898468
67	180170001	Tepic	Nayarit	332,863	7713.262208	0.394143973	1.409516764	0.031524229
68	190060001	Apodaca	Nuevo León	467,157	12644.73866	0.298470744	1.468013223	0.045884993
69	190190001	San Pedro Garza García	Nuevo León	122,627	26973.76306	0.356294827	1.44883532	0.028773601
70	190210001	Gral. Escobedo	Nuevo León	352,444	12369.85883	0.306882924	1.421371646	0.042736976
71	190260001	Guadalupe	Nuevo León	673,616	10607.00601	0.331686077	1.331283619	0.035260185
72	190310001	Juárez	Nuevo León	151,893	9877.073929	0.291731151	1.458823589	0.029008589
73	190390001	Monterrey	Nuevo León	1,135,512	13042.06051	0.361473584	1.194776439	0.082892913
74	190460001	San Nicolás de los Garza	Nuevo León	443,273	11009.77621	0.309987608	1.203058655	0.027791717
75	190480001	Santa Catarina	Nuevo León	268,347	11578.28288	0.333059253	1.449331271	0.029794826
76	200670001	Oaxaca de Juárez	Oaxaca	255,029	8804.144517	0.371157547	1.531453505	0.008239568
77	201840001	San Juan Bautista Tuxtepec	Oaxaca	101,810	23309.95591	0.396866634	1.18545812	0.003145985
78	211140001	Puebla	Puebla	1,434,062	10708.67258	0.372129137	1.288224983	0.047938257
79	211560001	Tehuacán	Puebla	248,716	12849.35868	0.399158734	1.186656663	0.022322044
80	220140001	Querétaro	Querétaro	626,495	10168.83383	0.37376076	1.208812742	0.034218815
81	220160001	San Juan del Río	Querétaro	138,878	15784.68741	0.366959498	1.312614598	0.02497917
82	230040001	Othón P. Blanco	Quintana Roo	151,243	10859.78563	0.412570966	1.270310196	0.021739852
83	230050001	Benito Juárez	Quintana Roo	628,306	12234.03049	0.399834009	1.234797732	0.033393831
84	230080001	Solidaridad	Quintana Roo	149,923	13634.59395	0.409505837	1.273835668	0.026911675
85	240130001	Ciudad Valles	San Luis Potosí	124,644	9219.918547	0.421123721	1.267662331	0.022872668
86	240280001	San Luis Potosí	San Luis Potosí	722,772	12101.05418	0.378300695	1.258960644	0.062208476
87	240350001	Soledad de Graciano Sánchez	San Luis Potosí	255,015	7958.200829	0.371313366	1.293766449	0.022037413
88	250010001	Ahome	Sinaloa	256,613	8554.319411	0.397348622	1.31938956	0.028071615
89	250060001	Culiacán	Sinaloa	675,773	8319.101196	0.393223312	1.237964921	0.040195984
90	250120001	Mazatlán	Sinaloa	381,583	7751.751443	0.389625808	1.243896643	0.038301957
91	260180001	Cajeme	Sonora	298,625	9831.520782	0.362351987	1.268945749	0.028632658
92	260290001	Guaymas	Sonora	113,082	7887.601337	0.377273559	1.326925743	0.027334948
93	260300001	Hermosillo	Sonora	715,061	10547.02324	0.366879963	1.29878836	0.049325309
94	260420001	Navojoa	Sonora	113,836	10877.85895	0.449799988	1.220041223	0.021206745
95	260430001	Nogales	Sonora	212,533	14367.98612	0.33733148	1.259822146	0.026484251
96	260550001	San Luis Río Colorado	Sonora	158,089	8055.416623	0.38475548	1.229564866	0.030032605
97	270040001	Centro	Tabasco	353,577	16543.75706	0.37703491	1.788059452	0.032915893
98	280030122	Altamira	Tamaulipas	118,614	12207.02014	0.370981046	1.433837168	0.025351288
99	280090001	Ciudad Madero	Tamaulipas	197,216	14154.49935	0.421901314	1.349228142	0.023916411
100	280220001	Matamoros	Tamaulipas	449,815	11614.82491	0.347548286	1.243223285	0.039586476
101	280270001	Nuevo Laredo	Tamaulipas	373,725	15495.78982	0.420838493	1.280692001	0.044954214
102	280320001	Reynosa	Tamaulipas	589,466	13200.69127	0.3501995	1.269826488	0.05505379
103	280380001	Tampico	Tamaulipas	297,284	10472.26399	0.421037072	1.422253908	0.037286724
104	280410001	Victoria	Tamaulipas	305,155	9411.248167	0.392006942	1.253146732	0.024137283
105	300280037	Boca del Río	Veracruz	126,507	7972.991514	0.379319693	1.311212768	0.014425794
106	300390001	Coatzacoalcos	Veracruz	235,983	9467.779735	0.385340585	1.179779147	0.023744826
107	300440001	Córdoba	Veracruz	140,896	11415.84279	0.399898346	1.364895996	0.019681738
108	300870001	Xalapa	Veracruz	424,755	8856.886119	0.392791714	1.292197032	0.023565602
109	301080001	Minatitlán	Veracruz	112,046	16316.57046	0.416597717	1.299718925	0.019238628
110	301180001	Orizaba	Veracruz	120,844	13188.31984	0.435174205	1.339568491	0.014632007
111	301310001	Poza Rica de Hidalgo	Veracruz	185,242	11207.23676	0.408422683	1.264713375	0.019292302
112	301930001	Veracruz	Veracruz	428,323	5976.057253	0.402385671	1.3089597	0.024972637
113	310500001	Mérida	Yucatán	777,615	13754.90066	0.435952605	1.276762362	0.047866888
114	320100001	Fresnillo	Zacatecas	120,944	7951.946165	0.429221489	1.21320666	0.018811009
115	320170001	Guadalupe	Zacatecas	124,623	6396.935217	0.338564678	1.255453029	0.016337575
116	320560001	Zacatecas	Zacatecas	129,011	5587.515682	0.357309156	1.265844172	0.021800128

In the table above are presented the results of both methods for the universe of 116 cities that constitute the study case of this paper.

A natural question is how both methods talk to each other. One way to relate them is by the mean Φ and the β describing each city. The question is if there is a correlation between cities with lower mean Φ meaning more anisotropy in their blocks and potential higher distances given by higher β. According to Figure 9 is interesting to notice no clear relationship between the two methods, meaning that the distribution of blocks shapes not necessarily explains how well connected are all points within a city.

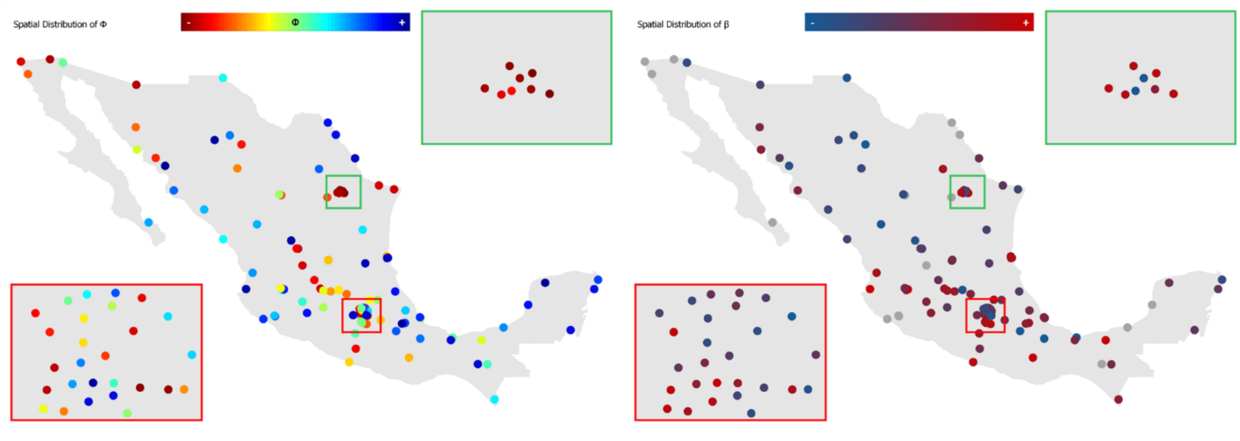
Another way to relate both methods is trying to find if there is a common geographic pattern between points. Figure 10 suggests that there is no evidence of spatial autocorrelation in the spatial distribution of either, mean Φ and the β of every city.

Figure 9. Cities' Mean Φ and β



Examples	Φ	β
5 Lowest	190310001	150020015
	190060001	080210001
	150250001	300390001
	150580001	201840001
	190210001	211560001
5 Highest	320100001	141010001
	090150001	090150001
	301180001	150130001
	310500001	270040001
	260420001	140670001

Figure 10. Cities' Mean Φ and β Geographical Distribution



Conclusions

This paper constitutes a modern approach in the sense that it relies on the use of computational tools to understand the urban morphology of cities. The intention was to apply an existing method to measure urban morphology, to develop a new one based on the street networks of cities and to identify potential relationships between both.

In the case of the second algorithm, the β on the estimated model it can be interpreted as the mean increase in the distance between two points introduce by physical infrastructure, from a world in where every point is connected through an Euclidean distance in space as opposed to a world in where every point is connected through a distance within a street network.

From a range of 1.16 to 1.81, the range of β's across cities it reveals important differences in the cost of mobility facing people in different arrangements of street networks.

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Data

Mexico Geo-Data: http://bit.ly/21dGDSl

All the procedures in this paper were conducted using Python and QGIS and for the case of Moran’s I it was used Arcpy. The code is available at: https://github.com/andrespdlr/cities_fingerprints