Correlating Densities of Centrality and Activities in Cities: the Cases of Bologna (IT) and Barcelona (ES)

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Abstract:

This paper examines the relationship between street centrality and densities of commercial and service activities in cities. The aim is to verify whether a correlation exists and whether some categories of economic activities, namely those scarcely specialized activities oriented to the general public and ordinary daily life, are more linked to street centrality than others. The metropolitan area of Barcelona (Spain) is investigated, and results are compared with those found in a previous work on the city of Bologna (Italy). Street centrality is calibrated in a multiple centrality assessment (MCA) model composed of multiple measures such as closeness, betweenness and straightness. Kernel density estimation (KDE) is used to transform data sets of centrality and activities to one scale unit for correlation analysis between them. Results indicate that retail and service activities in both Bologna and Barcelona tend to concentrate in areas with better centralities: in fact the spatial distribution of these activities correlates highly with both simple and compound measures of centrality. This confirms the hypothesis that street centrality plays a crucial role in shaping the formation of urban structure and land uses. Moreover, results suggest that a locational rule seems to link to street centrality those economic activities oriented to the general public.

1. Location and Centrality in Cities

"No matter how good its offering, merchandising, or customer service, every retail company still has to contend with three critical elements of success: location, location, and location" (Taneja, 1999, p.136). What is *location*? Why does it matter? A simple and intuitive answer is: *centrality*.

A central place has one special feature to offer to those who live or work in a city: easy accessibility from immediate surroundings as well as from far away. Accessibility may be transformed to visibility and popularity. Therefore, a central place tends to attract more customers, has a greater potential to develop into an urban landmark and a social catalyst, and is more likely to offer a larger diversity of goods and services such as museums, theatres or office headquarters. A more central location commands a higher real estate value and is occupied by a more intensive land use. Central locations in an urban area have the potential to sustain higher densities of retails and services, and are a key factor for supporting the formation and vitality of urban "nodes" (Newman and Kenworthy, 1999). Centrality emerges as one of the most powerful determinants for urban planners and designers to understand how a city works and to decide where renovation and redevelopment need to be placed.

Centrality does not only affect how a city works today, but also plays an important role in shaping its growth. If one looks at where a city centre is located, it is most likely to sprout from the intersection of main routes, where some special configuration of the terrain or some particular layout of the river system (or water bodies in general) makes the place compulsory to pass through. That is one of the dominant theories that explain where a city begins. Then, departing from such central locations, the city grows up over time with gradual additions of dwellings, residents and activities: first along the main routes, then filling the in-between areas, and then developing streets that realize loops and points of return. As the structure becomes more complex, new central streets and places are formed and stimulate growth of residents and activities around them. This evolutionary process has been driving the formation of urban fabrics and the advancement of human civilization throughout most of the seven millenniums of city history.

Centrality appears to be somehow at the heart of that marvellous hidden order that supports the formation of “spontaneous” and organic cities (Jacobs, 1961). It is also a crucial issue in the contemporary debate on searching for more bottom-up and “natural” strategies of urban planning beyond the modernistic heritage. Centrality has been studied in many branches of urban research, especially in economic geography and regional analysis (Wilson, 2000) and transportation planning (Meyer and Miller, 2000; Goulias, 2002). In most cases, centrality has been dealt with as a means to measure the relationship between activities among places, and the focus is on those relationships rather than on centrality itself. In essence, this has led to an interpretation of centrality in an intuitive notion that a more central location is a place “closer” to all others.

In urban planning and design, centrality is the core issue addressed by *space syntax*, a methodology of spatial analysis, even though under notions of “visibility” and “integration” (Hillier and Hanson, 1984; Hillier, 1996). Space syntax has opened a whole new range of opportunities for urban designers to develop a deeper understanding of several structural properties of city spaces. The model has achieved significant successes in the practice of countless urban regeneration programmes in the UK and elsewhere, and helped urban planners and designers in making good decisions and reframing the debate on pivotal issues such as crime, self-surveillance, community building and renovation of large housing estates in the last two decades or so. Despite of these successes, urban designers often perceive space syntax as a quantitative threat to the creativity embedded in the art of city design, while on the other side researchers in spatial analysis and geo-computation often find it lacks rigorous expression and clear disciplinary references.

The *Multiple Centrality Assessment* (MCA) model (Porta et al, 2006a, 2006b; Cardillo et al, 2006; Crucitti et al, 2006a, 2006b; Scellato et al, 2006; Scheurer and Porta, 2006; Scheurer et al, 2007) follows a broader tradition in centrality assessment which draws back to structural sociology since the early 1950s (Bavelas, 1948, 1950; Freeman, 1977, 1979; also see an overview by Wasserman and Faust, 1994), and more recently in the "new" physics of complex networks (Boccaletti et al, 2006). By experimenting this stream of studies and the network analysis in a spatial environment, MCA works on the forefront of a growing wave of interest for Geographic Information research (Batty, 2005). Therefore, the MCA model shares with space syntax the fundamental *values* that refer to the structural interpretation of urban spaces for urban planning and design, while offering a new and deeply alternative *technical* perspective.

The first hypothesis for this study is that *centrality captures the essence of location advantage in an urban area, and its value should be reflected in the intensity of land uses, in this case, densities of economic activities*. The second hypothesis is that *certain categories of activities correlate better than others with street centrality, and more specifically that "secondary" activities (Jacobs, 1961), i.e. those retail commerce, low-skilled service and professional activities related to ordinary daily needs and the contact with the general public, are more correlated with street centrality than highly skilled, larger or more specialized activities*: this would provide a bridge between the structural properties of urban layouts and the functional, economic and social basis for the evolution of compact, liveable urban communities at the scale of the neighbourhood, a major issue in the current debate of sustainable urban planning and design.

After a previous investigation of the first more general hypothesis recently worked out for Bologna, the capital city of the Emilia-Romagna region in northern Italy, (Porta et al, 2007) we are hereby deepening a similar approach for the case of Barcelona, the capital city of the Catalunya region, Spain: in the present study, however, the availability of a massive database of the location of all economic activities in year 2002 allows a much more detailed analysis of activities and makes it possible to pose and verify the second hypothesis.

The remainder of this paper is organized as follows. Section 2 describes the methodological foundations of the case studies with reference to centrality measuring and mapping and to the problem of correlating centrality with the location of activities. Section 3 presents the case studies: the Bologna case, already presented in a previous work, is briefly summarized, while on the other hand the Barcelona case is illustrated in detail. Section 4 presents the results of the study with reference to the two hypothesises mentioned above and a conclusion on the reliability of the methodology adopted for centrality assessment in spatial environments. The paper is concluded in section 5 with a brief summary.

2. Multiple Centrality Assessment (MCA) and Kernel Density Correlation (KDC): a methodological outline

The scope of this study is to shed some light on the possible correlation between the centrality of streets and the location of economic activities in an urban environment. In both the Bologna and Barcelona cases, economic activities were provided in geo-referenced and qualified ArcGIS layers. As for the quantification of street centrality we take advantage of the MCA model, while in order to spatially correlate street centrality with activities' location we firstly calculate the density of both street centrality and activities and then correlate such densities: basic information on these two procedures are therefore illustrated in the following in this section.

2.1 Multiple Centrality Assessment (MCA)

Multiple Centrality Assessment is a complex of GIS-based computer-operated procedures aimed at quantifying and mapping, both locally and globally, the centrality of urban streets according to a set of different centrality indices. As quoted above in section 1, MCA has already been presented in a number of recent studies to which we forward the reader for any further inquiry. In this section, however, we shortly illustrate the basic notions in order to easy the understanding of the present research report.

In an urban fabric, streets (links or edges) are represented in a GIS system as linear features with two end nodes and, possibly, one or more intermediate vertices. The MCA model assigns a set of centrality values to each street segment (Porta et al, 2006a,b; Crucitti et al, 2006a,b). Here we briefly present the three of them applied in this research: *closeness* (C^C), *betweenness* (C^B) and *straightness* (C^S).

Closeness centrality C^C measures to what extent a node is close to all the other nodes along the shortest paths of the network. C^C for a node *i* is defined as:

$$C_i^C = \frac{N-1}{\sum_{j=1;j\neq i}^{N} d_{ij}} \tag{1}$$

where N is the total number of nodes in the network, and d_{ij} is the shortest distance between nodes *i* and *j*. In other words, the closeness centrality for a node is the inverse of average distance from this node to all other nodes.

After calibrating the shortest path between any two nodes, it is straightforward to compute C^C for all the nodes in the network. C^C may be interpreted as proximity, and also captures the notion of *accessibility* of a place. The closer a place is to other places, the more accessible it is. The family of closeness measures has been widely used in urban and regional analysis. In essence, it reflects the *cost* of overcoming spatial separations between places with population and activities.

Betweenness centrality C^B is based on the idea that a node is more central when it is traversed by a larger number of the shortest paths connecting all couples of nodes in the network. C^B is defined as:

$$C_i^B = \frac{1}{(N-1)(N-2)} \sum_{j=1;k=1;j\neq k\neq i}^{N} \frac{n_{jk}(i)}{n_{jk}} \qquad (2)$$

where n_{jk} is the number of shortest paths between nodes *j* and *k*, and $n_{jk}(i)$ is the number of these shortest paths that contain node *i*.

Using an analogue in a social network, C^B is like the kind of prominence of a person who acts as intermediary among a large number of other persons. In MCA, C^B captures a special property for a place in a city: it does not act as an origin or a destination for trips, but as a pass-through point. C^B represents a node's volume of through traffic. A place with better betweenness may benefit from this important property.

Straightness centrality C^S originates from the idea that efficiency of communication between two nodes increases when there is less deviation of their shortest path from the virtual straight line connecting them, i.e., more "straightness" of the shortest path. C^S is defined as:

$$C_i^S = \frac{1}{N-1} \sum_{j=1;j\neq i}^{N} \frac{d_{ij}^{Eucl}}{d_{ij}} \qquad (3)$$

where d_{ij}^{Eucl} is the Euclidean distance between nodes *i* and *j*, or the distance with the virtual straight connection. C^S was originally proposed in non-spatial networks as a normalization procedure (Vragovìc et al, 2005). In spatial networks, C^S reveals a totally different meaning related to human cognitive processes in navigating complex spatial structures. C^S measures the extent to which a place can be reached directly, like on a straight line, from all other places in a city. It is a quality that makes it prominent in terms of “legibility” and “presence” (Conroy-Dalton, 2003).

In this study, first, all three *global* centrality indices were calculated as all nodes and edges in the network participated in the computation: namely global closeness C^{C}_{glob}, global betweenness C^{B}_{glob}, and global straightness C^{S}_{glob}. As an example, Figure 1c shows the variation of global betweenness C^{B}_{glob} across the street network in Barcelona. In addition, one *local* closeness centrality index was calculated for the nodes located within a distance d=1.600mt from each node I, denoted with C^{C}_{1600}. As shown in a previous study (Porta et al, 2006b), local measures are useful to overcome the *edge effect*, i.e., the distortion that lowers the centrality values near the edge of a network. Such a distortion turned out to be very significant for the closeness index when calculated on highly fragmented networks. Moreover, global centrality measures do not reveal network properties on a local scale whereas local measures portray relationships determined by spatially limited “catchment” areas like the neighbourhood or the district. In Bologna, two different centrality indices, closeness and straightness, were calculated locally: differently than in Barcelona, the search range was set as d=800mt, therefore local closeness and local straightness were denoted as C^{C}_{800} and C^{S}_{800} respectively.

We have developed an ArcGIS extension to prepare the street network data for MCA computation. The module first cleans up the street network in an ArcGIS shapefile format for most common errors, then generates nodes at intersections and links the nodes’ IDs to the polyline attribute table, and finally generates a “connectivity table” that stores for each street its length, the IDs of the two end nodes and their *x,y* coordinates. The connectivity table is then processed by a *C++* script that computes the centralities of all nodes: the centrality of each street is equalled to the average centrality of the street's two nodes. The results from the *C++* program are fed back to ArcGIS for mapping and other spatial analysis such as, in the next phase, the Kernel Density Correlation (KDE).

2.2 Kernel Density Correlation (KDC)

As illustrated above in section 2.1, by means of the MCA model three centralities (C^B, C^C *and* C^S) for each of the nodes of the cases' street networks are computed, based on which centralities for each edge are calculated as the average of its two end nodes; on the other side, we have a certain number of activities in the cases' study areas. All nodes, edges and economic activities are consistently geo-referenced but of course the street network and points of economic activities remain distinct spatial features. In order to analyze the relationship between them, our first task was to transform the two data sets to one scale (analysis unit) so that such a comparison may be made. The methodology that we used, presented in Porta et al. (2007), is named Kernel Density Correlation (KDC) and is summarized in this section.

We transform both the data sets in a new framework (e.g., a raster system), and examine the relationship between the *density of street centralities* and the *density of activities* at the same scale. We therefore may realize a data transformation from one scale or analysis unit to another by means of *spatial smoothing* and/or *spatial interpolation* techniques; among the many possible choices of spatial smoothing (e.g., floating catchment area, Kernel density estimates, and empirical

Bayes estimation) and spatial interpolation methods (e.g., trend surface analysis, inverse distance weighted, thin-plate splines, and kriging) (Wang, 2006, pp.35-53), in the present research the *Kernel Density Estimation* (KDE) method is applied. Basically, the KDE uses the density within a range (window) of each observation to represent the value at the centre of the window. Within the window, the KDE weighs nearby objects more than far ones based on a *kernel function* (Silverman, 1986; Bailey and Gatrell, 1995; Fotheringham et al, 2000, pp.146-149). By doing so, the KDE generates a density of the events (discrete points) as a continuous field (e.g., raster), and therefore converts the two data sets to the same raster framework and permits the analysis of relationship between them.

Our choice of KDE was made for at least three reasons.

- First and most importantly, by using the density (or average attributes) of nearby objects to represent the property at the middle location, the KDE captures an essential property of spatial phenomena, that it is not the place itself but rather its surroundings that make it special and explains its setting. Therefore using the KDE here – as opposed to more traditional arc-by-arc “direct” correlation approaches like those between street “integration” and socioeconomic and environmental indicators addressed by Penn and Turner (2003) – is not only a need for converting the data scale but also a necessity of accurately capturing the true experiential notion of the degrading and overlapping effects of different events differently located in space.

- Secondly, the KDE uses a kernel function to value the contribution of a nearby object to the density estimate more than a remote one, as stated in Tobler's (1970) first law of geography, i.e., "everything is related to everything else, but near things are more related than distant things." This property of distance decay for spatial interaction is widely recognized by urban researchers. The family of gravity models follow the same notion with strong theoretical foundations and have many successful applications in urban and regional studies (Fotheringham et al, 2000, pp.213-235).
- Finally, the KDE is a standard tool in ArcGIS spatial analyst module, and the results can be easily integrated in ArcGIS for mapping.

A kernel function looks like a bump centred at each point x_i and tapering off to 0 over a bandwidth or window. The kernel density at point x at the centre of a grid cell is estimated to be the sum of bumps within the bandwidth:

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{x - x_i}{h}) \tag{4}$$

where *K( )* is the kernel function, *h* is the bandwidth, *n* is the number of points within the bandwidth, and *n* is the total number of events. All events x_i within the bandwidth of *x* generate some bumps reaching the point *x*, and contribute to the estimated kernel density there.

The kernel function *K(y)* is a function satisfying the normalization for a two-dimensional vector *y* such as:

$$\int_{R^2} K(y)dy = 1 .$$

A regularly adopted kernel is the standard normal curve:

$$K(y) = (2\pi)^{-1/2} \exp(-\frac{1}{2} y^2).$$

For convenience, our computation in ArcGIS used the following kernel function, as described in Silverman (1986, p.76):

$$K(y) = (3\pi)^{-1}(1 - y^2)^2 \quad \text{if} \quad y^2 < 1$$

$$K(y) = 0 \quad \text{otherwise} \tag{5}$$

One advantage of equation (5) is its faster calculation than the regular kernel. As the formula indicates, any activity beyond the bandwidth *h* from the centroid of the considered cell does not contribute to the summation.

As discussed above, activities are represented as points in a GIS system. ArcGIS has a built-in tool for kernel estimation. To access the tool in ArcGIS, click the *Spatial Analyst* dropdown arrow > *Density* > choose Kernel for Density Type in the dialog. Applying the tool to the data set of economic activities yielded the kernel densities. For computing the kernel densities of street network, we used centrality values for each street segment (edge) to weigh the contribution of each edge on the kernel "bump" at a grid cell. In other words, a kernel function is applied to each street so that its value is greatest on the line, diminishes with distance from the line, and reaches 0 at the distance *h* from the line. Differently from the densities of activities that are not weighted, the kernel density of street centrality at each grid cell in region *R* is the sum of all the kernel surfaces within the bandwidth *times the value of centrality in each surface*. In ArcGIS, this is implemented by selecting one of the centrality indices as the "population" (weight) field. By doing so, we are not computing just the density of streets, but the *density of street centrality*: in other words, we are weighting streets by their centrality.

One problem in using the KDE is the choices of particular kernel function and bandwidth *h*. Several methods have been proposed to pick up the best kernel function (Fotheringham et al, 2000: 155-157) or optimize *h* (Cao et al, 1994) according to the global structure of the dataset. However, while Epanechnikov (1969) finds that the choice among the various kernel functions does not affect significantly the outcomes of the process, Williamson et al (1998) and Levine (2004) point out that the choice of bandwidth is an important issue in any KDE applications. Recent advancements in Geographically Weighed Regression (GWR) research suggested using an *adaptive*, rather than *fixed*, bandwidth *h*: that is to say, *h* is larger in areas where events are sparser and smaller where they are denser (Fotheringham et al, 2002).

As explained earlier, the KDE is not the methodological focus of this research, and is used here to transform the two data features to the same analysis unit. In the Bologna study we did experiment with different fixed *h* values to show the robustness of the results while in the Barcelona study we just used a fixed *h*=300mt. The choice of a fixed rather than adaptive bandwidth pertains to the purpose of the study: we are interested in understanding the relationship between the street network and basic services in an ordinary city. In Bologna, where we just had two distinct categories of activity, we chose *h*=300, 200 and 100 meters, which are widely used in urban planning and design to model the pedestrian catchment area at the scale of *neighbourhood*, *block* and *street*, respectively (Frey, 1999; Urban Task Force, 1999; Calthorpe and Fulton, 2001; Cervero, 1998, 2004); in Barcelona, where we dealt with 24 different categories of activity, we took into consideration just one bandwidth *h*=300 mt (the neighbourhood scale). A more detailed information on the cases of Bologna and Barcelona is provided in the next section.

Once the kernel densities of all street centrality indices and all activity categories are calculated for each cell in the study region, a “correlation table” is created by listing in record for every cell all density values taken from the correspondent cells of the density raster layers (Figure 2). The linear correlation is then calculated in every cell between each of the street centrality densities and each of the economic activity densities in terms of the Pearson index: the Pearson index *R*, ranging from -1 to 1, determines the extent to which values of the two correlated variables are "proportional" to each other. In general, the value of Pearson *R* decreases as the sample size increases due to statistical fluctuations (Taylor, 1982).

3. Study Areas and Data Preparations: a cases’ outline

The study of the Bologna case was presented in Porta et al. (2007), while the work on Barcelona is an entirely new study presented here for the first time. In Bologna, a some 400.000 inhabitants urban centre in northern Italy, we were given an information on economic activities limited to ground floor locations qualified as either shops or services (summing up to 9.676 points); that was enough, since the focus of our study was mostly on methodological issues. In Barcelona, the 1,7 millions inhabitants major urban centre in northern Spain, thanks to the Agencia de Ecologia Urbana we could access a massive database of 166.311 activities that included all economic activities of all kinds located at all floors and qualified in hundreds of hierarchical categories and sub categories. This data set was re-organized in a simpler set of 7 general categories and another set of 17 sub-categories selected for their prominent significance in the context of our study (Tab.1), which sums up to 24 categories of activity: for example we split the general category of retail commerce in the two subcategories of those retail activities that are – or are not – related with motor vehicles, because one hypothesis is that street centrality is more correlated with pedestrian than with motorized movement.

The street network in Barcelona (6.453 nodes and 11.222 edges) was significantly larger than that of Bologna (5.448 nodes and 7.191 edges). As for the Kernel density parameters, we set up the two cases differently: in Bologna we defined a rectangular the study region, with a cell size of 10mt of edge, while in Barcelona we tailored a polygonal boundary following the outer metropolitan ring roads, with a cell size of 10 mt of edge. This resulted in a raster database much larger in Bologna (2.771.956 cells) than in Barcelona (1.571.093). However, the rectangular shape of the Bologna study region left a larger amount of N*00* cells (i.e. cells with both densities of activities and density of street centrality equal to 0), which included up to the 66% of the data set, while the same share in Barcelona remained around the 54%. The number of raster cells that take values of density >0 for the two variables (street centrality and activities) obviously depends on the number, location and shape of streets and on the number and location of economic activities: because in Bologna we dealt with just two categories of activities (shops and shops+services), and both of them presented a similar spatial distribution and territorial coverage, in that case we included in the calculation of correlations all the N*XX* (both densities of activities and centrality >0), N*X0* (density of activities>0 and density of centrality=0) and N*0X* (density of activities=0 and density of centrality>0) cells. In Barcelona, however, we investigated in much deeper detail the correlation of many categories and sub-categories of activities: as expected, that led to a larger variation of the overall number of N*XX* cells, that spans from 688.482 cells (in the correlation between density of street centrality and density of *"IT, services to business and people, research & development activities"* – activity code #3, with 44.253 such activities present in the data set) to 219.970 cells (in the correlation between density of street centrality and density of *"Public Administration activities"* – activity code #73, with just 202 such activities present in the data set), while the sum of all N*XX*+N*0X*+N*X0* cells does not vary a lot around the 717.000-719.000 cells in all correlations. Thus in Barcelona, differently than in Bologna, we chose to run the correlation analysis just on N*XX* cells, i.e. cells where both densities of activities and centrality resulted >0: naturally, because of the exclusion of all N*0X* and N*X0* cells, which are cells located on the axis of the linear correlation chart, this more realistic procedure results in Pearson values significantly lower. Notwithstanding this "N*XX* effect", however, street centrality and economic activities in Barcelona, like we found in Bologna, consistently exhibit a very significant positive correlation, as we will see in the next section.

Finally, while in Bologna we calculated just four "simple" indices of street centrality, namely Global Betweenness (C^B_{glob}), Global Closeness (C^C_{glob}), Global

Straightness (C^S_{glob}) and Local Closeness (C^C_{800}, with d=800mt), in Barcelona we calculated more centrality indices (Tab.2): in fact, we added to the same set of "simple" indices used in Bologna (with the difference that Local Closeness in Barcelona is calculated with distance d=1.600mt rather than 800mt) the computation of four "composite" indices: Global Betweenness + Global Closeness + Global Straightness ($C^B_{glob}{}^{+C}_{glob}{}^{+S}_{glob}$); Global Betweenness + Global Straightness ($C^B_{glob}{}^{+S}_{glob}$); Global Betweenness + Global Closeness ($C^B_{glob}{}^{+C}_{glob}$); Global Betweenness + Local Closeness ($C^B_{glob}{}^{+C}_{1600}$).

The procedure for the creation of such composite centrality indices was drawn from that proposed in Thurstain-Goodwin and Unwin (2000) for the calculation of "town centredness": firstly each data set was normalized so that values in every cell were included in the range 0-1, then a new data set was generated where each cell was attributed the sum of the values of the corresponding cells in the normalized data sets.

4. Results

The results of the Bologna study (Porta et al, 2007) showed a strong positive correlation between the density of economic activities and that of street centrality, the meaning of "economic activity" being limited in that case to that of "ground-floor retail shops and services". More in detail, the study showed that at the scales of the neighbourhood and the block (bandwidth h=300 and h=200mt respectively) the location of shops alone and that of shops and services reached a strong correlation with C^B_{glob} (R values slightly higher and lower of 0,7 respectively); moreover, the same activity variables were found to correlate very well, especially at the scale of the neighbourhood, also with C^C_{glob} street centrality, though at a lower level (*R*=0,64 and 0,61). These results were interpreted as an initial support to the general idea that street centrality acts as a powerful determinant factor to the "intensity" (spatial density) of land uses in cities.

The first aim of the present study on Barcelona was to confirm the same idea, reformulated as the first hypothesis above in section 1. The second aim of this study was to make a step forward, trying to understand *which categories* of economic activities are more correlated to street centrality, with the underlining idea (the second hypothesis illustrated in section 1) that street centrality is especially important for the support of ordinary, everyday activities that are oriented to the general public and interact with the daily life of the neighbourhood.

As for the first hypothesis, results of the Barcelona study clearly confirm that economic activities and street centrality are highly and positively correlated in the urban space. In fact, the 192 *R* values resulting from the correlation of each of the 24 activity categories (Tab.1) with each of the 8 street centrality indices (Tab.2) give an average of 0,46 in a range that spans from 0,71 to -0,04. It should be noted that:

- 190 out of the 192 *R* values are >0;
- considering just the 7 general categories, the average of the 56 *R* values obtained by correlating them with the 8 centrality indices is =0,55 spanning from 0,71 (density of Global Closeness with density of *"Retail activities"* – activity code #1) to 0,32 (density of Local Closeness with density of *"Gross commerce"*, activity code #4);

- the *"Retail commerce"* general category alone (activity code #1) gives an average *R* value equal to 0,64 and the *"Hotel, b & b, hostel, restaurant, pub, café"* general category (activity code #2) one equal to 0,59 (Tab.3);
- 92 of the 192 *R* values (47,9%) are higher than 0,50;
- the first 19 positions in ranking give an average *R* value of 0,66 (Tab.4);
- the magnitude of the data sets used for correlations (the average number of cells included in the calculation in the 24 cases equals some 568.000 N*XX* cells), makes the results above statistically more significant .

As for the second hypothesis, results neatly support the idea that street centrality is especially a determinant for the location of those kinds of economic activities that are strictly related to the general public and the everyday life of urban communities. Considering just the 7 general categories, in fact, their average correlation with the 8 street centrality indices (Tab.3) gives a ranking where the higher two positions are held by *"Retail commerce"* and *"Hotel, café, bar, restaurants"*, while the lower two are held by *"Other activities not related to public"* and by *"Gross commerce"*. It should be noted that the third position in the same ranking is held by *"IT, services to business and people, research & development"*, but within this category there are large differences among sub-categories: *"Other services to people"* (activity code #93) and *"Other service activities"* (activity code #74) exhibit a high correlation with street centrality (*R* values respectively equal to 0,60 and 0,51) while on the other side *"Activities related to financial intermediation"* (activity code #67) and *"Insurance"* (activity code #66) take much lower *R* values (respectively equal to 0,34 and 0,31).

The locational rule that links this kind of “ordinary” (or “local”, “basic” or “community”) retail commerce and service activities with street centrality, therefore, emerges everywhere at the level of general categories as well as at that of sub-categories, while more skilled, specialized activities, or those more linked to motor vehicular traffic, appear to obey different locational rules.

5. Conclusions

In this research two hypothesises are investigated about the correlations that may occur in cities between the location of economic activities and the centrality of streets: firstly – and simply – that such a correlation does exist; secondly that some activities are more linked to street centrality than others, and more specifically that those activities or services oriented to the general public and everyday life are more correlated with street centrality than highly specialized ones. In order to verify those hypothesises we rely on a previously defined model of street centrality mapping named Multiple Centrality Assessment (MCA) and to a methodology of correlation with economic activities named Kernel Density Correlation (KDC) based on spatial kernel density. Findings of a previous study on the city of Bologna (Italy), which suggested that a strong correlation exists between street centrality and ground floor retail shops and services, is hereby confirmed for the city of Barcelona (Spain) after all economic activities at all floors have been included in the computation. The study of Barcelona also fully supports the idea that economic activities oriented to the general public like retail commerce, services to the person, or restaurants and cafes, are more linked to street centrality than highly specialized activities like financial intermediation, Public Administration, Health services or gross commerce.

These findings shed some light on a crucial issue in current international debate on sustainable urban design and “place-making”, like the need to approach (neo) traditional, compact urban developments by aggregating community retail and services along central “main” streets. Moreover, results support the predictive capacity of the MCA model: by virtue of this capacity, the MCA model can be an effective tool in the hands of urban designers and planners for the support of evidence-based, scientifically-grounded projects alternatives definition and cross-evaluations.

References

Bailey T, Gatrell T, 1995, *Interactive Spatial Data Analysis* (Addison-Wesley Publishers, Edimburgh)

Batty M, 2005, "Network geography: relations, interactions, scaling and spatial processes in GIS" in Fisher P, Unwin D, *Re-presenting GIS* (Wiley and sons, London, UK) 149 – 170

Bavelas A, 1948, "A mathematical model for group structures", *Human Organization* **7** 16 – 30

Bavelas A, 1950, "Communication patterns in task oriented groups", *Journal of the Acoustical Society of America* **22** 725 – 730

Boccaletti S, Latora V, Moreno Y, Chavez M, Hwang D-U, 2006, "Complex networks: structure and dynamics" *Physics Report* **424** 175 – 308

Calthorpe P, Fulton W, 2001, *The regional city: planning for the end of sprawl* (Island Press, Washington DC)

Cao R, Cuevas A, González-Manteiga W, 1994, "A comparative study of several smoothing methods in density estimation" *Computational Statistics and Data Analysis* **17** 153 – 176

Cardillo A, Scellato S, Latora V, Porta S, 2006, "Structural properties of planar graphs of urban street patterns" *Physical Review E, Journal of the American Physical Society* **73** 0661071-8

Cervero R, 1998, *The transit metropolis* (Island Press, Washington DC)

Cervero R, 2004, *Developing around transit: strategies and solutions that work* (Urban Land Institute, Washington DC)

Conroy Dalton R, 2003, "The secret is to follow your nose: route path selection and angularity'", *Environment and Behavior* **35** 107 – 131

Crucitti P, Latora V, Porta S, 2006a, "Centrality measures in spatial networks of urban streets" *Physical Review E, Journal of the American Physical Society* **73** 0361251-5

Crucitti P, Latora V, Porta S, 2006b, "Centrality in networks of urban streets", *Chaos, Quarterly of the American Institute of Physics* **16** 0151131-9

Epanechnikov V, 1969, "Nonparametric estimation of a multivariate probability density" *Theory of probability and its applications* **14** 153 – 158

Fotheringham AS, Brunsdon C, Charlton M, 2000, *Quantitative geography: perspectives on spatial data analysis* (Sage, London, UK)

Fotheringham AS, Brunsdon C, Charlton M, 2002, *Geographically Weighted Regression: the analysis of spatially varying relationships* (John Wiley and Sons, Chichester, UK)

Freeman L, 1977, “A set of measures of centrality based on betweenness”, *Sociometry* **40** 35 - 41

Freeman L, 1979, “Centrality in social networks: conceptual clarification”, *Social Networks* **1** 215 – 239

Frey H, 1999, *Designing the city: towards a more sustainable urban form* (Taylor and Francis London, UK)

Goulias K, 2002, *Transportation systems planning: methods and applications* (Boca Raton, FL)

Hillier B, Hanson J, 1984, *The social logic of space* (Cambridge University Press, Cambridge).

Hillier B, 1996, *Space is the machine: a configurational theory of architecture* (Cambridge University Press, Cambridge)

Jacobs J, 1961, *The death and life of great American cities* (Random House, New York)

Levine N, 2004, *CrimeStat III: a spatial statistics program for the analysis of crime incident locations (version 3.0)* (National Institute of Justice, Washington, DC)

Meyer M, Miller E, 2000, *Urban transportation planning* (McGraw-Hill, Columbus, OH)

Newman P, Kenworthy J, 1999, *Sustainability and cities: overcoming automobile dependence* (Island Press, Washington DC)

Penn A, Turner A, 2003, “Space layout affects search efficiency for agents with vision”, *Environment and Behaviour* **35** (1) 30 – 65

Porta S, Crucitti P, Latora V, 2006a, “The network analysis of urban streets: a dual approach” *Physica A, Statistical mechanics and its applications* **369** 853 – 866

Porta S, Crucitti P, Latora V, 2006b, “The network analysis of urban streets: a primal approach” *Environment and Planning B: planning and design* **33** 705 – 725

Porta S, Latora V, Wang F, Strano E, Cardillo A, Scellato S, Iacoviello V, Messora R, 2007, “Street centrality and densities of retails and services in Bologna, Italy”, arXiv:physics/0701111

Scheurer J, Porta S, 2006, “Centrality and connectivity in public transport networks and their significance for transport sustainability in cities”, paper presented at the World Planning Schools Congress, Mexico DF, 13-16 July 2006; copy available from S. Porta, Polytechnic of Milan, Milan.

Scheurer J, Curtis C, Porta S, 2007, “Spatial network analysis of public transport systems: developing a strategic planning tool to assess the congruence of movement and urban structure in australian cities”, paper presented at the Australasian Transport Research Forum, Melbourne, 25-27 September 2007; copy available from S. Porta, Polytechnic of Milan, Milan.

Scellato S, Cardillo A, Latora V, Porta S, 2006, “The backbone of a city” *The European Physical Journal B* **50** 221 – 225

Silverman BW, 1986, *Density estimation for statistics and data analysis* (Chapman and Hall, London)

Taneja S, 1999, “Technology moves in” *Chain Store Age*, May Issue, p.136.

Taylor J, 1982, *An introduction to error analysis: the study of uncertainties in physical measurements* (University Science Books, Mill Valley)

Thurstain-Goodwin M, Unwin D, 2000, “Defining and delimiting the central areas of towns for statistical modelling using continuous surface representations” *Transactions in GIS* **4** 305 – 317

Tobler WR, 1970, “A computer movie simulating urban growth in the Detroit region” *Economic Geography* **46** 234 – 240

Urban Task Force, 1999, *Towards an urban renaissance* (E&FN Spon, London, UK)

Wang F, 2006, *Quantitative methods and applications in GIS* (CRC Press, Boca Raton, FL)

Wasserman S, Faust K, 1994, *Social networks analysis* (Cambridge University Press, Cambridge, UK)

Wilson G, 2000, *Complex spatial systems: the modelling foundations of urban and regional analysis* (Prentice Hall, Upper Saddle River)

Williamson D, McLafferty S, Goldsmith V, Mollenkopf J, McGuire P, 1998, “Smoothing crime incident data: new methods for determining the bandwidth in Kernel estimation”, paper presented at the 18th ESRI International User Conference, San Diego, 27–31 July; copy available at: http://gis.esri.com/library/userconf/proc98/PROCEED.HTM

	Activity code			Number of points
	General Category	Sub Category	Description	
GENERAL CATEGORIES	0	--	Other activities (not related to public)	29.661
	1	--	Retail commerce	39.685
	2	--	Hotel, b & b, hostel, restaurant, pub, cafe	12.758
	3	--	IT, services to business and people, res. & dev.	44.253
	4	--	Gross commerce	12.723
	5	--	P.A., services of education, health and social assistance	12.348
	6	--	Associational, recreational and sport activities	14.883
	TOT			166.311
SUB CATEGORIES	1	50	Sell, fix and maintenance motor vehicles and fuel	3.375
	1	52	Retail exept motor vehicles, fix domestic and personal devices	36.310
	3	63	Activities related to transport and travel	2.961
	3	65	Financial intermediation, exept insurance	4.598
	3	66	Insurance	657
	3	67	Activities related to financial intermediation	563
	3	70	Real estate	10.343
	3	71	Rental of machines, domestic and personal devices	1.110
	3	72	IT activities	138
	3	73	Research & Development	202
	3	74	Other service activities	17.189
	5	75	Public Administration	2.966
	5	80	Education	4.655
	5	85	Health and social assistance	4.727
	6	91	Associational activities	5.721
	6	92	Recreational, cultural and sport activities	9.162
	3	93	Other services to people	6.492

Table 1. The 7 general categories and 17 sub-categories of economic activities in Barcelona

Notation	Index
$C^B{}_{glob}$	Global Betweenness
$C^C{}_{glob}$	Global Closeness
$C^S{}_{glob}$	Global Straightness
$C^C{}_{1600}$	Local Closeness (with d=1600mt)
$C^B{}_{glob}{}^{+C}{}_{glob}{}^{+S}{}_{glob}$	Global Betweenness + Global Closeness + Global Straightness
$C^B{}_{glob}{}^{+S}{}_{glob}$	Global Betweenness + Global Straightness
$C^B{}_{glob}{}^{+C}{}_{glob}$	Global Betweenness + Global Closeness
$C^B{}_{glob}{}^{+C}{}_{1600}$	Global Betweenness + Local Closeness (*d*=1600mt)

Table 2. The 8 (4 simple + 4 composite) street centrality indices applied in Barcelona

General category		R value
Activity Code	Description	
1	Retail commerce	0,64
2	Hotel, b & b, hostel, restaurant, pub, cafe	0,59
3	IT, services to business and people, res. & dev.	0,56
6	Associational, recreational and sport activities	0,54
5	P.A., services of education, health and social assistance	0,54
0	Other activities (not related to public)	0,49
4	Gross commerce	0,48
All general categories		0,55

Table 3. Ranking of the average linear correlation *R* values of the 7 general categories of activities with the 8 street centrality indices in Barcelona

#	Activity Code	Street Centrality	*R* values (N*XX*)
001	1	C^{C}_{glob}	0,708921880802
002	*52*	C^{C}_{glob}	0,691016758153
003	1	$C^{B}_{glob}{}^{+C}_{glob}$	0,690688659337
004	1	$C^{B}_{glob}{}^{+C}_{glob}{}^{+S}_{glob}$	0,686441720771
005	*93*	C^{C}_{glob}	0,681533526861
006	2	C^{C}_{glob}	0,679716274528
007	*52*	$C^{B}_{glob}{}^{+C}_{glob}$	0,669134066075
008	*52*	$C^{B}_{glob}{}^{+C}_{glob}{}^{+S}_{glob}$	0,666435030252
009	*93*	$C^{B}_{glob}{}^{+C}_{glob}$	0,662352555346
010	3	$C^{B}_{glob}{}^{+C}_{glob}$	0,653871937003
011	3	$C^{B}_{glob}{}^{+C}_{1600}$	0,653871937003
012	1	$C^{B}_{glob}{}^{+C}_{1600}$	0,653532387403
013	1	$C^{B}_{glob}{}^{+S}_{glob}$	0,652947810657
014	*93*	$C^{B}_{glob}{}^{+C}_{glob}{}^{+S}_{glob}$	0,651048641408
015	2	$C^{B}_{glob}{}^{+C}_{glob}$	0,641807348490
016	2	$C^{B}_{glob}{}^{+C}_{glob}{}^{+S}_{glob}$	0,636900541818
017	*52*	$C^{B}_{glob}{}^{+C}_{1600}$	0,634610400470
018	*52*	$C^{B}_{glob}{}^{+S}_{glob}$	0,631088449986
019	*74*	$C^{B}_{glob}{}^{+C}_{glob}$	0,622211307155

Table 4. The KDC results in Barcelona: first 19 positions in ranking

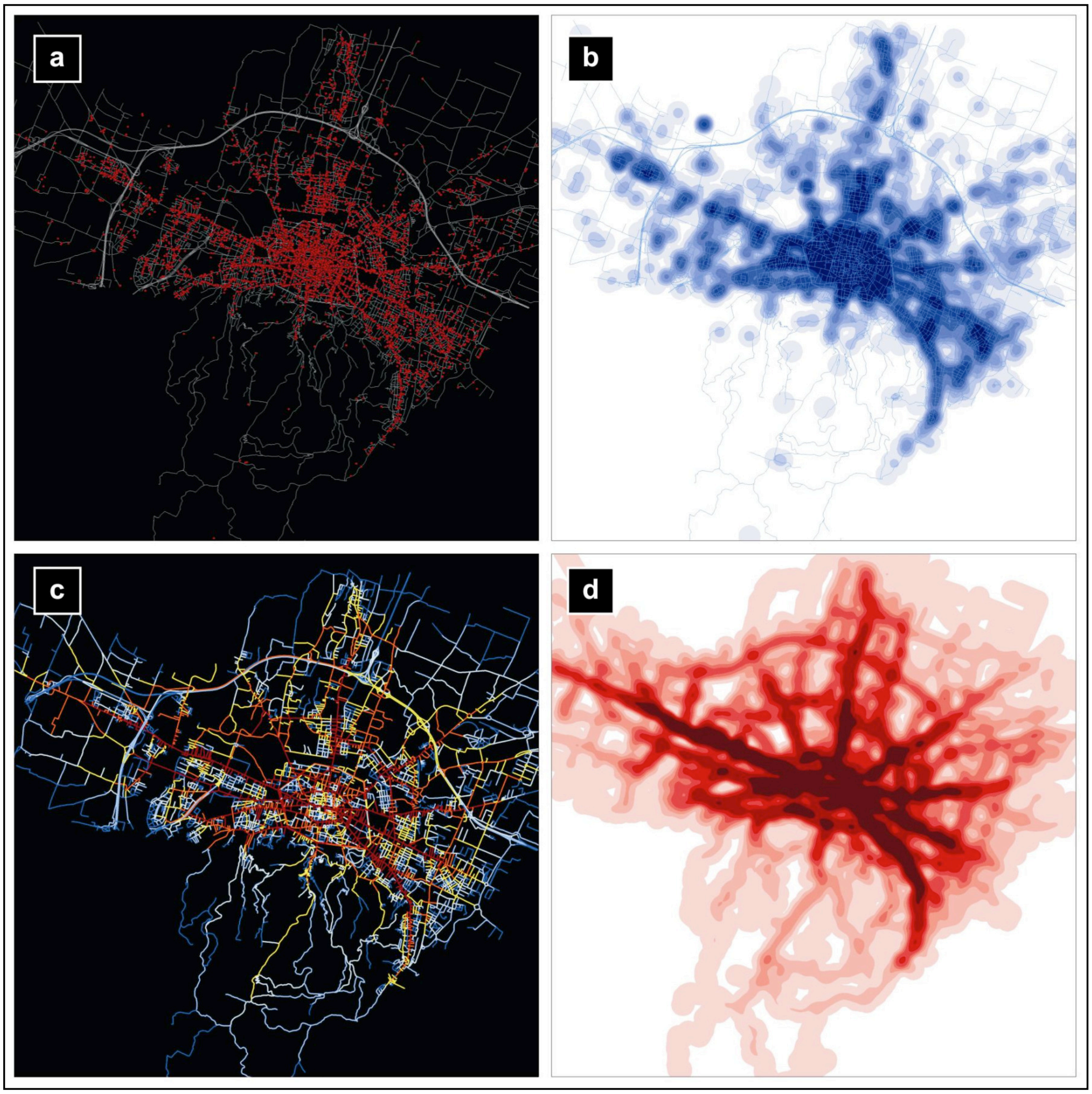

Figure 1. ***[to possibly be printed in colour]*** **Density of activity and street centrality: a) location of retail commerce activities (red dots); (b) Density (KDE, *h*=300m) of retail commerce activities; (c) Global Betweenness (C^{B}_{glob}) street centrality (blue for lower values and red for higher; (d) Density (KDE, *h*=300m) of C^{B}_{glob} street centrality.**

[TO BE SUBSTITUTED BY ONE ANALOGOUS IMAGE OF BARCELONA – THIS IS OF BOLOGNA]

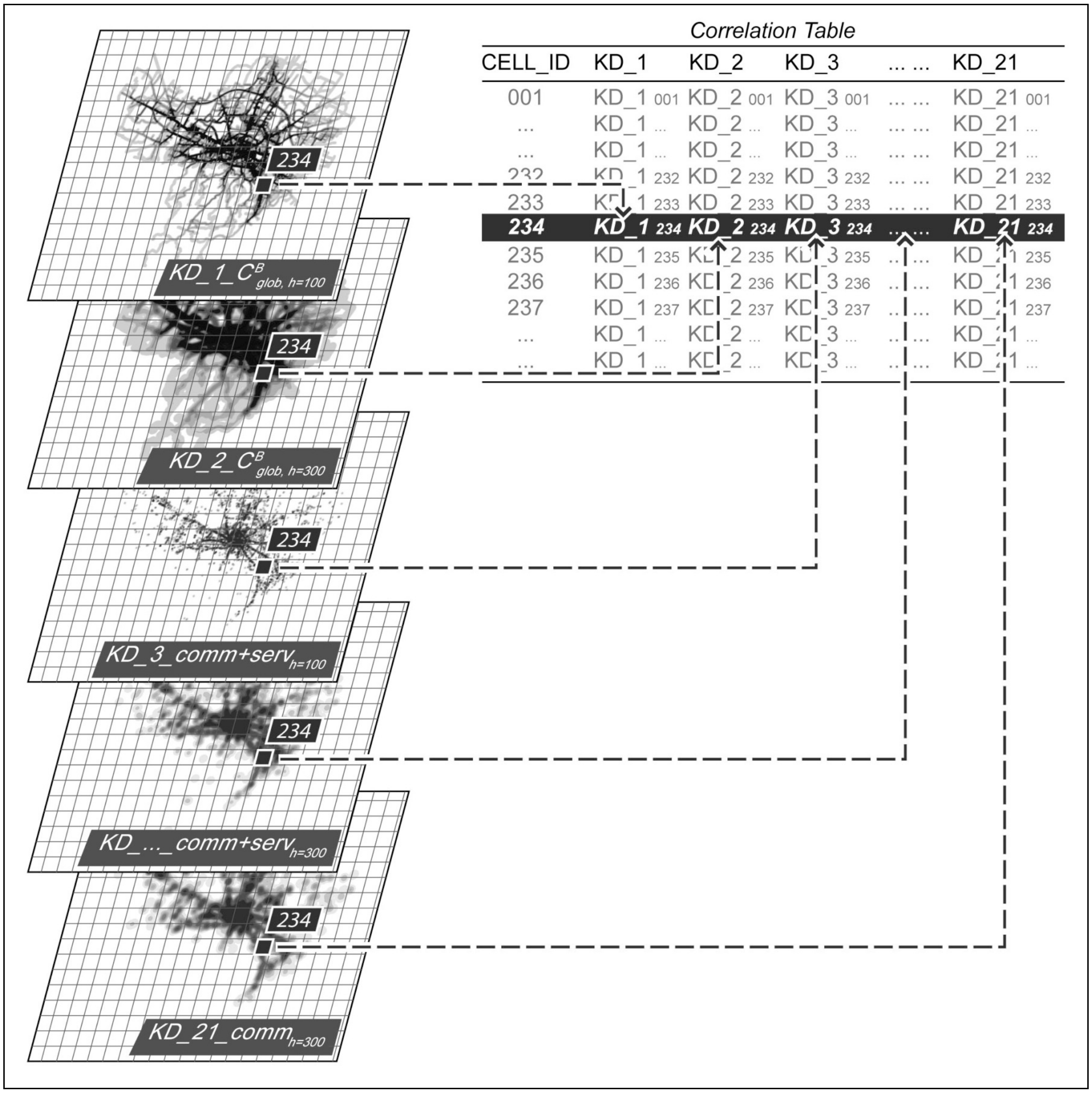

Figure 2. The construction of the "correlation table": illustration of a grid cell with attributes in various raster layers