Examining ‘edge effects’: Sensitivity of spatial network centrality analysis to boundary conditions

Jorge Gil
Delft University of Technology, Faculty of Architecture, Department of Urbanism
j.a.lopesgil@tudelft.nl

Abstract

With the growth of interest in the use of spatial network analysis to study the urban and regional environment, it is important to understand the sensitivity of the centrality analysis results to the so-called “edge effect”. Most spatial network models have artificial boundaries, and there are some principles that can be applied to minimise or eliminate this effect. However, the extent of its impact has not been systematically studied and remains little understood. In this article we present an empirical study on the impact of different network model boundaries on the results of closeness and betweenness centrality analysis of a road network. The results demonstrate that the centrality measures are affected differently by the “edge effect”, and that the same centrality measure is affected differently depending on the type of distance used. These results highlight the importance, in any study using spatial networks, of correctly defining the network’s boundary in a form that is relevant to the research question, and selecting appropriate analysis parameters and statistics.

Keywords

Spatial networks, network centrality, network boundary, edge effect, sensitivity analysis.

1. Introduction

Spatial network analysis has become an important method in the study of urban and regional configuration to address a wide range of phenomena, including human mobility, economic and energetic performance, social equity, individual health, and sustainable development in general. Empirical studies dealing with real world spatial networks use in most cases artificially bounded networks. In these studies, considerable attention is given to the type of network model used, the analytic algorithms applied, and their parameters, much less mentioned is the definition of the model’s boundary. The network model excludes network structures and events happening beyond the boundary of the model, and because the analytic algorithms are fundamentally relational this affects the results in the network model. This bias is called the “edge effect” (Okabe & Sugihara, 2012, p. 41) and affects all nodes of the model, not only those on or adjacent to its boundary. The “edge effect” problem is relevant to all fields dealing with spatial networks, hence obviously relevant to the field of space syntax (Hillier, Penn, Hanson, Grajewski, & Xu, 1993; Penn, Hillier, Banister, & Xu, 1998; Hillier & Iida, 2005; Peponis, Bafna, & Zhang, 2008; Chiaradia, Hillier, Schwander, & Wedderburn, 2012) and to other street network analysis methods, such as Multiple Centrality Analysis (Porta et al., 2009) or Urban Network Analysis (Sevtsuk & Mekonnen, 2012).

This is a matter of concern that raises questions regarding the reliability or significance of the network analysis results (Ratti, 2004; Joutsiniemi, 2010, pp. 186–189). In space syntax research several approaches have been proposed over the years to deal with the “edge effect”, namely extending the network model for analysis with a ‘catchment area of the catchment area’ around the
area of interest (Hillier et al., 1993), using a radius of analysis working as a moving boundary to calculate local measures (Penn et al., 1998; Hillier & Penn, 2004; Turner, 2007), or a specific ‘radius radius’ based on the mean depth of the most integrated line in the system (Hillier, 1996). These approaches are not always seen as effective, but no alternative methods are proposed other than not calculating global closeness in acknowledging the problem with metric distance (Porta, Crucitti, & Latora, 2006). Therefore, the “edge effect” on artificially bounded networks needs to be more thoroughly understood and tested, to improve the network analysis results: their reliability, their descriptive and predictive power, their consistency across locations. Figure 1 illustrates the “edge effect” on a street network where the study area is first analysed using the immediate boundary (left) and then using a large extended boundary (right), calculating closeness centrality (top) and betweenness centrality (bottom) using angular weights.

What is the “edge effect" of different network boundary definitions? To what extent are centrality measures affected by the “edge effect”? What parts of a model are affected, and how? What approaches can we take to address this problem? This work aims to start addressing these questions, presenting the results of experiments on the impact of different network model boundaries on closeness and betweenness centrality measures, using different types of distance
weights. In the next section we review previous work on the network “edge effect”, followed by the study’s methodology and the presentation of the results of a series of experiments. We conclude with a discussion of the results and point some directions of future research.

2. Background

The study of “edge effect” or “boundary effect” in spatial analysis mostly applies to point data in Euclidean space (Griffith & Amrhein, 1983). When it comes to quantitative studies on the “edge effect” of spatial networks there are few examples. A comprehensive study by Park (2009) compares the performance of network centrality and intelligibility in predicting pedestrian and vehicular movement for a systematically defined range of network boundaries. Park stresses the importance of stating the principles and decision behind the network model’s boundary definition as part of the research design. Krafta (1994) shares this concern and carries out tests for different study area boundaries correlating with pedestrian movement, and explicitly defines an approach to deal with edge effect. Sadler et al. (2011) demonstrate and take into account the impact of edge effect on the reach to destinations (shops) from the locations within an administrative boundary.

The previous studies acknowledge and test the impact of edge effect on the performance of spatial network models, but do not look at the general sensitivity of the network measures used. Such studies on the sensitivity or robustness of centrality measures of networks can be found in the field of Social Network Analysis (SNA) (Bolland, 1988; Borgatti, Carley, & Krackhardt, 2006; Costenbader & Valente, 2003; Villas Boas, Rodrigues, Travieso, & Costa, 2008; Zemljič & Hlebec, 2005). However, the nature of these networks is very different (i.e. small size, non spatial, not sparse, complete and finite) and the focus is on the robustness to errors stemming from incomplete or wrong data sources, and from difficulties to survey accurately and define the population. All centrality measures show a certain level of error depending on the type of problem with the network, but it is difficult to draw direct parallels to the case of spatial networks.

In SNA, the definition of the network boundary is another topic widely researched with explicit classification of approaches (Laumann, Marsden, & Prensky, 1983), as the boundary definition is an important outcome of a theoretically informed decision (Scott, 2000, p. 54). In SNA, defining the boundary means finding the entire population set and is a problem of determining links between known nodes (individuals) and defining a notion of membership and type of membership to a group. In spatial networks, linking the boundary definition of a study area to the notion of membership (e.g. to a neighbourhood) might be a relevant approach. In terms of analysis boundary, in SNA there are methods for random sampling of a population from the whole, when this is too big. According to Scott (2000, p. 59) there are good reasons to assume that this sampling results in unreliable data and does not give a reasonable sample of relations, suggesting that one should in those cases abandon global analysis and focus on egocentric analysis. In these cases, the network can be defined locally starting from an individual using the snowball sampling technique and selecting relevant links up to a certain depth (Diani, 2002; Scott, 2000, p. 61). This represents a sort of catchment area that is also applied in spatial networks when defining a buffer or radius for analysis, suggesting that this is a valid approach for avoiding the edge effect in centrality analysis of networks.

3. Methods

This study examines the “edge effect” in centrality measures of spatial networks through a series of experiments carried out on an empirical data set of a real-world road network of the Randstad region in the Netherlands. The road network model uses a road centre line representation prepared from OpenStreetMap data, following the procedures described by Gil to select the relevant segments from data attributes and correct the geometry (Gil, 2015). This geographic model is then translated into an undirected weighted graph, with a dual representation to allow for the calculation of a wider range of distance weights (i.e. metric, angular, axial, continuity and topologic), using the principles described in (Gil, 2014). The resulting graph is then analysed using R igraph version 0.7 (Csardi & Nepusz, 2006) to calculate closeness and betweenness centrality.
Examining 'edge effect': Sensitivity of spatial network centrality analysis to boundary conditions

The experiments measure the network centrality of a series of hypothetical study areas of the city of Amsterdam, under varying model boundaries. The study areas cover three scales – i.e. neighbourhood, district and city – and are delimited by what one can consider a "natural boundary" (Figure 2 a), namely the canals, the ring road, and the urbanised limit, respectively. The study areas are combined with different analysis limits to provide a range of model boundary scenarios to run the different experiments. The model boundary can be the study area boundaries themselves, larger natural boundaries (Figure 2b), automatic 6 km buffers of the study area boundaries (Figure 2d), and circular boundaries of increasing radius (6 km) and varying centre location (Figure 2c). The analysis results always report to the values within one of the study areas, providing a consistent sample of results for the different model boundaries. The analysis scenarios studied in this work are described in the following section, in light of the specific question they are testing.

In each experiment, the equivalent network centrality measures of the various scenarios (i.e. the algorithm, distance type and radius) are compared pairwise using Pearson and Spearman correlation to measure their difference, and a simple linear regression model is applied. If the results of two scenarios are identical, then the coefficient of determination (R2) value is 1, otherwise, a R2 value smaller than 1 indicates the error margin between the results of the two scenarios, and the smaller the R2 the greater sensitivity of the network measure to the boundary scenario. This simple linear
model is appropriate because we are comparing identical measures that under normal circumstances would be totally correlated.

In addition to this statistical test, we produce maps of the residuals of the linear model that show the spatial distribution of the error. The residuals indicate how the results being compared are distanced from the linear regression line. If the result on a node is higher for the x-axis measure the point is below the regression line and the residual is negative. On the contrary, if the result on a node is higher for the y-axis measure the point is above the regression line and the residual is positive. We use a colour scale from blue (negative) to red (positive) to map the residuals, where a colour close to white indicates little to no change.

4. Experiments

In this section we run through a series of experiments that test the sensitivity of network centrality analysis to a range of spatial network model boundary conditions. These experiments demonstrate visually the “edge effect” and quantify the impact of the “edge effect” on closeness and betweenness centrality, for different network distance types and for different analysis radius distances.

Visualising the “edge effect”

As already demonstrated in Figure 1, the results of centrality analysis within an urban area of study are different depending on the extent of the network model’s boundary surrounding that area. In this particular example, since the area is small, one can see differences across the study area and not only at its borders. Does this also hold for larger study areas? And is the “edge effect” of closeness and betweenness identical? To answer this we calculate and map the three study area scales’ residuals of a linear model of centrality using angular distance and global radius without extended boundary (Figure 2a) against the same measure for the outer ‘natural’ perimeter (Figure 2b). These maps are presented in Figure 3 and the corresponding scatterplots of the linear model in Figure 4, with closeness in the left column and betweenness in the right column. The first rows of Figures 3 and 4, illustrating the neighbourhood scale, display the difference between the closeness maps in Figures 1a and b, and the difference between the betweenness maps in Figures 1c and d, respectively. The following rows show the same comparison for areas of different scales.

The first observation is that there are ‘winners’ (red) as well as ‘losers’ (blue) across the whole analysis areas, and across the scales. ‘Losers’ are not concentrated in a ring along the perimeter. Although Figures 3 c and d seem to show it, this can be explained by the ring road connected to the network of the region that in the local model loses in centrality value, and one can also find ‘losers’ encroaching close to the city centre. On the other hand, ‘winners’ can also be found near the study area perimeter, and even mixing and alternating with ‘losers’.

In closeness centrality, if an urban area close to the model boundary is indeed naturally bound without continuity, it appears in the residuals as a ‘winner’. If, on the other hand, it has some type of continuity just beyond the boundary, like the ring road, it becomes a ‘loser’. In betweenness centrality, the “edge effect” is related to the hierarchy of the segments in the road network. Segments of a higher hierarchy than that defined by the model boundary are ‘losers’ (e.g. a national road in an urban boundary), while those with an important role within that boundary are ‘winners’ (e.g. a primary urban road).

The “edge effect” is more marked in closeness centrality where the residuals concentrate in more or less homogeneous areas, and the areas with small residual values are fewer. Betweenness centrality seems to suffer less from “edge effect”, with most of the area showing very small residual values. However, there is a strong “edge effect” concentrated in the highest betweenness centrality street segments. This is clear from the plots of Figure 4 (b, d and f), where the distribution of points spreads away from the regression line as the betweenness values increase. It contrasts with the plots for closeness (Figure 4 a, c and e), where the maximum deviation from the regression line is similar for high, medium and low centrality values.
Figure 3: Maps of the residuals of the linear regression model between the local boundary and the outer perimeter boundary for global angular distance centrality analysis: a) neighbourhood closeness, b) neighbourhood betweenness, c) city closeness, d) city betweenness, e) metropolitan closeness, f) metropolitan betweenness. The maps use a natural breaks colour scale, where red represents positive residuals and blue negative.
In some cases (Figure 4 e), the extremes of the distribution it converges on the regression line, indicating stability for the highest and lowest closeness centrality values. While this set of maps and scatterplots help us visualise and locate the edge effect in spatial terms, the following experiments quantify the extent of the effect for different types of distance.

**Figure 4:** Scatterplots of the linear regression models between the local boundary and the outer perimeter boundary for global angular distance centrality analysis: a) neighbourhood closeness, b) neighbourhood betweenness, c) city closeness, d) city betweenness, e) metropolitan closeness, f) metropolitan betweenness.
Increasing the size of the model boundary

In the next experiment we take as a benchmark the model with the outer perimeter boundary (Fig. 2b) and run on this model closeness and betweenness centrality analysis for global radius (without cut-off) using the five different types of distance. We then compare these results with those of other models with constrained natural boundaries from the neighbourhood to the metropolitan scale (Fig. 2a and b), using the same analysis parameters.

The R² between the benchmark results and the other intermediate scale models are plotted in the line charts of Figure 5. The layout replicates that of Figures 3 and 4, with the study areas organised vertically and the centrality measures in the columns. Each chart reports on how the R² of centrality within a study area changes with increasing model boundary, with each line corresponding to a type of distance. The first point of the angular distance line (blue) corresponds to the residuals of Figure 3 and the scatterplots of Figure 4. The first expected result that can be observed in the plots is that as the model boundary increases, the results converge to those of the benchmark analysis, because the models become closer in shape and size. Nevertheless, the behaviour of the results with the different centrality measures and types of distance is not the same.

Figure 5: Charts of the R² of global closeness and betweenness centrality values for different types of distance, for varying smaller model boundaries against the outer limit model boundary. The R² is measured at a neighbourhood (a and b), city (c and d) and metropolitan (e and f) scales.
Looking first at closeness centrality (left hand column in Figure 5), the values converge with the benchmark results already at the metropolitan boundary despite the considerable difference in size to the outer perimeter. For most distance measures the $R^2$ is already close to or above 0.9 (Figures 5a, c and e). The values in the smaller neighbourhood sample are more variable for all measures when the network model is also smaller (neighbourhood and city), but stabilise from the metropolitan model onwards. Regarding the types of distance, angular, axial and continuity distances are similar and present a $R^2$ of 0.8 even in smaller network models. This indicates that they are less sensitive to the model boundary and model size. Segment topological distance starts with a lower correlation in smaller neighbourhood and city models, but from the metropolitan model is equivalent to the other topological and angular distances. Metric distance is very sensitive to the different model boundaries and shows consistently lower $R^2$ against the outer limit model, even on larger models with metropolitan and larger boundaries.

Looking now at betweenness centrality (right hand column in Figure 5), the $R^2$ values are generally lower than those of closeness centrality, also showing an increase as the size and shape of the model boundary approximates the benchmark model. Nevertheless, the different sample sizes show less tendency for stability as the sample size increases, with $R^2$ growing more linear and gradually as the model boundary size also increases. With betweenness there is no consistent pattern between the results of different types of distance.

Figure 6: Charts of the $R^2$ of betweenness centrality rank of varying smaller model boundaries against the outer limit model boundary (a, c and e). Scatter plot of the betweenness ranks of the neighbourhood (b), city (d) and metropolitan (f) study area boundaries against those of the outer limit boundaries.
The low $R^2$ of betweenness centrality results (0.6 to 0.7, in Figure 5f), even when we compare the metropolitan boundary model with the outer perimeter model, is rather surprising given the much smaller residuals variation shown in the maps (Figure 3) and the general impression from previous research that betweenness is less sensitive to “edge effect”. The scatter plots of Figure 4 provide a clue to the answer. The low $R^2$ is caused by the lack of fit by a small number of nodes that correspond to those with a higher hierarchy in the models. If instead of using Pearson correlation of absolute values we use Spearman’s correlation of ranks, the picture changes dramatically (Figure 6).

Now the $R^2$ of the betweenness results of different model boundaries is very high (0.9 or above) from the city size model upwards, for every type of distance, showing greater stability to “edge effect” than closeness. What this tells us is that the betweenness values are concentrated on the highest ranked nodes, and the absolute values are very dependent on the total number of nodes in the model. Once we consider only the rank of the nodes, we can see that the results are very similar and converge early on and achieve high $R^2$ even for smaller model boundaries. This rank effect is not observed with closeness centrality.

**Shifting the network boundary centre**

One of the recommendations in defining the model’s boundary is to centre it on the object of study. However, this also raises the question if this positioning artificially places centrality where it is expected or desired. In the previous experiment, could the stability of the city study area results stem from the fact that the boundaries are relatively centred? In this experiment we test the impact of shifting the model boundary centre while keeping its shape and size, using the circular boundaries (Figure 2c). The benchmark is the centre circle, calculating closeness and betweenness centrality for global radius using different types of distance. The $R^2$ is calculated for the same measures within the city study area, with the boundary shifted to the North and to the East, where their centre is just outside the study area. The results are presented in Table 1.

With closeness centrality, the experiment confirms that metric distance is much more sensitive to the position of the analysis boundary in relation to the object of study, when compared with geometric or topological distances, where the impact is minimal, with $R^2$ above 0.94 (Figure 7). With betweenness centrality, this does not occur, and metric distance has a slightly higher $R^2$ than angular and axial distances. If we consider the betweenness rank values, the $R^2$ values of all types of distance are very close to 1, indicating that the shift of the boundary has minimal impact on betweenness centrality analysis.

**Table 1**: The coefficient of determination between the centrality results from the central model boundary and those from the East and North model boundaries. (in all cases $p < .001$)

<table>
<thead>
<tr>
<th>Distance type (R²)</th>
<th>Metric</th>
<th>Angular</th>
<th>Axial</th>
<th>Continuity</th>
<th>Segment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closeness shift East</td>
<td>0.4232</td>
<td>0.9602</td>
<td>0.952</td>
<td>0.9926</td>
<td>0.9448</td>
</tr>
<tr>
<td>Closeness shift North</td>
<td>0.7564</td>
<td>0.9972</td>
<td>0.995</td>
<td>0.9998</td>
<td>0.9928</td>
</tr>
<tr>
<td>Betweenness shift East</td>
<td>0.8398</td>
<td>0.827</td>
<td>0.8203</td>
<td>0.6325</td>
<td>0.8649</td>
</tr>
<tr>
<td>Betweenness shift North</td>
<td>0.9777</td>
<td>0.9614</td>
<td>0.9659</td>
<td>0.9831</td>
<td>0.9855</td>
</tr>
<tr>
<td>Betweenness shift East rank</td>
<td>0.9845</td>
<td>0.9968</td>
<td>0.9958</td>
<td>0.9898</td>
<td>0.9962</td>
</tr>
<tr>
<td>Betweenness shift North rank</td>
<td>0.9958</td>
<td>0.9994</td>
<td>0.9992</td>
<td>0.9998</td>
<td>0.9996</td>
</tr>
</tbody>
</table>
One should however note the difference between the East and North boundary shift results. The North shift $R^2$ is in all cases higher than that of the East shift, particularly in metric closeness and in all betweenness. Because the boundary shape, size and shift distance in relation to the study area centre are the same, this difference can only come from the network topology that gets included in the different models. The East boundary model covers partially the city of Almere, to the East of Amsterdam, causing a significant change to the representation of the metropolitan region. Nevertheless, the impact on both closeness and betweenness centrality is in most cases small. The results of closeness centrality analysis are shown in Figures 7 and 8, with a row for each distance type and a column for each model boundary, to offer a visualisation of the differentiated consequences of model boundary shift.

![Figure 7: Maps of closeness centrality of central Amsterdam calculated on the different circular model boundaries (columns), using different distance types (rows).](image-url)
Examining ‘edge effect’: Sensitivity of spatial network centrality analysis to boundary conditions

Using a local radius to eliminate “edge effect”

So far, in these experiments, we have only dealt with global radius network centrality measures, that consider the entire network when calculating each individual node. However, the use of a cut-off distance or local radius is common practice to eliminate the “edge effect”. This final experiment calculates closeness centrality of the outer perimeter model (Figure 2b) using angular and metric distances with different local radii (i.e. 400m, 800m, 1200m and 6000m). Then the results are compared with the same analyses of network models with different boundaries, namely the natural study areas (Figure 2a) and a buffer of 6000m around them (Figure 2b). The R² results are summarised in Table 2.

Table 2: The coefficient of determination (R²) for closeness centrality of local radii, between different network boundaries and the outer perimeter boundary.
The neighbourhood scale results are very sensitive to the small boundary, even with radius of 400m. Especially in metric distance, where the reported R2 values actually correspond to a negative correlation (the minus sign disappears when calculating the coefficient of determination). If we use the city model as a buffer of the neighbourhood, the edge effect is eliminated within the neighbourhood area for radius between 400m and 1200m. For a 6000m radius, there is edge effect in the neighbourhood study area because the city scale ‘natural’ boundary is closer than 6000m to the neighbourhood edge. This effect is more noticeable with metric distance.

At the city scale, while there is some edge effect from local radius, the R2 is very high and similar for angular and metric distances. As opposed to global radius centrality measures, the local radius edge effect should occur close to the boundaries, where the radius gets artificially shortened, as opposed to the centre of the study area, where the measurements are complete and the results identical between the city and outer perimeter models. If we use a metric buffer around the city the edge effect is completely eliminated for all radius distances up to 6000m. At the metropolitan scale the results are very similar, although the edge effect at 600m radius is very small. Although betweenness centrality was not calculated for different local radii, one should expect a similar outcome, where the presence of a buffer around the study areas with the size of the largest radius distance completely eliminates the “edge effect”.

5. Discussion

From this series of experiments one can draw a couple of lessons that help understand and consequently deal with the “edge effect” of network centrality measurements on artificially bounded spatial networks. The first is that the “edge effect” is relational, affecting the entire area of study with some nodes gaining and some nodes losing in value and rank. The second is that as much as we would like to have one measure, one approach, or one solution to deal with the edge effect, there are many analysis parameters and boundary design options at stake.

In this respect, one should raise a few cautions. Firstly, while the previous experiments give general indications on the sensitivity of centrality measures to “edge effect”, they are not comparing the absolute values of the measurements, and these are expected to vary greatly across different network boundary setups. Secondly, the linear regression only reports the sensitivity or stability of the centrality measures and says nothing about their relevance for specific empirical studies. Just because a measure is less affected by edge effect, it doesn’t mean it should be used in detriment of others. Thirdly, while robustness to error is desirable, sensitivity to systematic or designed variation can also be desirable. One should select analysis parameters and methods that deal with the first while allowing for the second.

Ultimately, one has to make network modelling and analysis decisions that are adequate to the research problem and design, and then take measures to deal with the “edge effect” that are the
most adequate to that analytical set-up. Next is a summary of the experiment’s results that can influence the selection of analysis parameters and the definition of the model’s boundary.

**Analysis parameters**

Betweenness centrality values are sensitive to the size of the model and the edge effect affects in particular the nodes of higher rank. On the other hand, the rank of the results is very robust to network model boundary conditions, such as changes in size, shape or position, irrespective of the type of distance used. Closeness centrality can be sensitive to the size and position of the model boundary, depending on the type of distance used. Metric distance is generally sensitive to changes in the model boundary conditions, be it size or position. The topological and angular measures are in general more stable, especially when dealing with larger network models.

However, the different centrality measures and types of distance capture and describe different characteristics of the model. One should choose them based on relevance to the research problem, and use different ones to obtain a more complete description of the study area.

**Boundary definition**

The network centrality analysis results in small study areas (e.g. neighbourhood scale) are very unstable even when running local radius analysis. Unless the small boundary is real, one should embed the study area in a larger context. The size of this context remains open to further research. If the research design uses local radii, one should define a buffer measured from the boundary of the study area with the distance of the highest radius used. One should only use the centre of the area as a buffer origin if one is only interested in that central location, or to define a study area based on a buffer or catchment area. In this later case, one still needs to define an analysis buffer beyond the study area, or the ‘catchment of the catchment’ (Hillier et al., 1993). With such a distance based buffer as the model boundary, the “edge effect” disappears for local radii, and it is more accurate than defining manually an analysis boundary.

The concern with centring the study area in the network model is mostly related to the creation of an adequate buffer for local radius analysis. The experiment with shifting the boundary shows robust results for most analysis parameters (i.e. except metric closeness). Of greater impact however, is the spatial distribution of the nodes that get included (or not) in the boundary. The definition of the boundary, as an exercise of spatial sampling, should be a matter of careful design in setting up the research and the analytic model and should be meaningful in that context (Griffith & Amrhein, 1983; Miller, 1999; Park, 2009). One can eventually resort to survey based methods (Jenks & Dempsey, 2007) or automated methods (Dalton, 2007; Yang & Hillier, 2007; Arcaute et al., 2015) to help define a relevant spatial network model boundary.

6. **Conclusion**

This article offers a first empirical and quantitative approach to understanding the “edge effect” of the spatial network model boundary on the closeness and betweenness centrality analysis results of urban networks. Current methods based on local radii prove adequate to eliminate the “edge effect”, and the experiments seem to indicate that the impact on global radius can be controlled with adequately large network model boundaries and/or robust statistical methods. However, this study is limited to a single case in a specific geographic context and extending the experiments to other locations is required to confirm its findings.

For a better understanding and control of the “edge effect” problem, other studies need to be carried out in the future. The present approach should be supplemented with a systematic study that tests and explains the “edge effect” on the various analysis parameters and boundary conditions, applying sound theoretical and mathematical methods to a wide range of abstract graph models. The outcomes of such a study could be more easily translated into precise methods and tools, instead of empirical guidance. In addition, the study of the “edge effect” on spatial networks should be extended to other network metrics used in urban and street network analysis, such as...
straightness, reach, random walks or closeness and betweenness flow. Such studies should also consider the impact of employing different methods for defining the boundary’s buffer, e.g. using distances along the network instead of Euclidean distance and different distance weights.

References


