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DOES URBAN DENSITY FOLLOW CENTRALITY?

Empirical study on the influence of street network centrality on urban density and its implications for the prediction of pedestrian flows

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ABSTRACT

The aim of this paper is to explore the relationship between space syntax measures of network centrality and measures of urban density. To what extent do they correspond? How can space syntax parameters be optimized to account for urban density? We present findings from an empirical study where a range of urban density parameters are tested against space syntax measures of network centrality.

Space Syntax as an analytical framework has gained much attention due to its ability to predict complex behavioural phenomena such as movement flows or land use distribution using only little information about the environment. The movement network is modelled as a collection of visual axes and their relations, with no additional information about the environment included. This is rooted in the assumption that additional environmental variables, such as building density or land use, are either equally distributed or follow the centrality properties of the network (Hillier, 1999; Hillier 1996). Thus, all other environmental properties are treated as inherently embedded in the network configuration and therefore redundant. Indeed, empirical evidence shows that in many cases "over 60% of human movement can be predicted or explained purely from a topological point of view" (Lerman Rofe & Omer 2014).

Arguably, it is the extreme reduction of environmental complexity which has been the main innovation, but also the source of critical discourse about the Space Syntax method (Montello, 2007). Indeed, building densities and land use might sharply contrast with properties of network configuration, suggesting unresolved implications for the applicability of Space Syntax method as a movement predictor (Ratti, 2004).

Space Syntax analysis has been highly successful at interpreting aggregate movement flows in a network. However, this paper reflects the clear need to define under which conditions

Space Syntax analysis might be treated not only as measure of potential, but also as reliable predictor of human behaviour. For this purpose, we conducted a series of empirical studies testing the core assumption of the Space Syntax model about the multi-collinearity between configurational properties and a set of established urban density

KEYWORDS

Density, Network centrality, Pedestrian flow

1. INTRODUCTION

An ever-growing percentage of the world's population lives in cities. This brings with it great challenges. As cities are forecast to continue to grow, the issue of how we plan urban densification in the future is a key issue (Borukhov 1978). This paper looks at the relationship between street network centrality, urban density and movement. Urban density refers to the amount of built matter in a unit of space (Rapoport 1975), and there are different ways of calculating it. A common measurement that is standard practice in the planning disciplines is the FAR (floor area ratio). However, the concept of urban density is multidimensional and the measure varies according to the parameters used in calculating it, i.e. by varying the unit of built form used "floor", and/or by varying the unit of space used "area".

Space syntax methods allow for movement flows to be modelled using only the properties of the network (Hillier & Hanson 1984, Hillier 1996). The street network is modelled as a dual graph, where the street segments are the nodes in the graph. The social use of space is explored by analysing the network as a graph, using graph theory-based measures of centrality. Two such measures are often used and will also be applied in this paper: integration (the mathematical measure of closeness centrality) and choice (also known as betweenness centrality). Aggregate pedestrian flow (Hillier et al. 1993), route selection of individuals (Emo 2014) as well as more complex social phenomena such as the distribution of land uses and the distribution of urban forms (Hillier 1996) have been shown to be related to network topology. Additional measures such as metric reach and directional reach have also been shown to relate to the distribution of land use and pedestrian flows (Ozbil, Peponis & Stone, 2011). Research has also examined how the distribution of building typologies, land use and network centrality is related to the liveability of cities (Ye & van Nes, 2013). The temporal interrelation between street network centrality and other measures of urban form such as block density, block area, building height and street width has been studied by Al_Sayed and Penn (2016). Whilst the distribution of urban density is held to be related to network topology, to date no research has systematically tested this by considering all its dimensions. This is the aim of our paper.

Our main research question examines what effect spatial configuration has on urban density. We examine this by comparing measures of network centrality against five dimensions of density as defined by Pont and Haupt (2010). A second research question explores what effect spatial configuration has on the distribution of movement attractors. This is assessed by comparing network centrality with building intensity.

We address a gap in knowledge linking the effects of network centrality and urban density (or the density of urban form). The currently untested assumption is that built form is either i) distributed equally or ii) follows network centrality. The relationship between density-centrality in planned and unplanned cities needs to be tested in order to: 1) support the theoretical foundations of space syntax; 2) identify the limits of the applicability of network centrality as a predictor of movement; and 3) identify methods that extend the applicability of the space syntax method.

2. METHODS

2.1 NETWORK CENTRALITY

Measuring the centrality of spatial networks has been widely recognized in built environment research as valuable approach for understanding how urban systems are structured and used by their inhabitants. It has been shown that not only streets themselves are long lasting components of the urban realm (Marshall 2006), but also that their configurational properties remain stable over time (Strano et al. 2012). This approach is at the core of Space Syntax methods, which focus on how pedestrian flows are influenced by the structure of the environment, measured as a spatial graph (Hillier & Hanson 1984). The spatial configuration of the network is analysed using graph theory-based measures of centrality, where the streets are nodes in the graph. A particularly successful model of the street network for predicting pedestrian movement in the urban context is the "angular segment map" (Turner 2001, Hillier & Iida 2005, Turner & Dalton 2005, Varoudis et al. 2013). The spatial graph can be understood as a movement network consisting of vertices as visual axes[1] divided at their intersections (segments) and their connections as edges weighted by the angular deviation between the adjacent segments (see Figure 1b, 1c). It assumes that people move in straight lines and tend to choose the cognitively shortest path between the origin and destination (Hillier & Iida 2005).

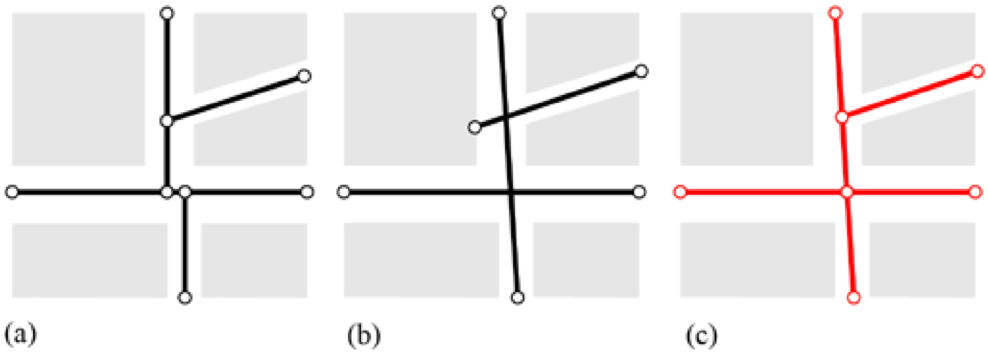

Figure 1 - Three different spatial network representations (a) Street centre line (b) Axial map (c) Segment map

Since there are several ways of assessing the relative importance of each segment, the concept of centrality is multidimensional. In our research, we apply measures of closeness and betweenness centrality because of their theoretical and empirical relationship to how people behave and use the urban space (Hillier & Iida 2005). The former represents how close, or integrated, any two nodes are in the network. The formal definition of angular closeness centrality comes from Sabidussi (1966):

$$C_c(p_i) = \frac{1}{\sum_k d_{ik}}$$

where d_{ik} is the length of a geodesic (least angle change shortest path) between node p_i and p_k (Hillier & Iida 2005). Betweenness centrality measures how likely a path is to be chosen as a segment on a random journey through the network, and is a measure of flow. Betweenness is defined according to Freeman (1977) as:

1 The axial map, which is the basis for the segment map adopted in this study, is constructed by drawing the minimal set of lines intersecting through all the convex spaces of the urban grid. For detailed instructions on how to draw the axial map see Hillier & Hanson (1984) and, on the algorithmic definition of the axial map see Turner, Penn & Hillier (2005).

$$C_B(p_i) = \sum_{j} \sum_{k,(j<k)} \frac{g_{jk}(p_i)}{g_{jk}}$$

where $g_{jk}(p_i)$ is the number of geodesics between node p_j and p_k which contain node p_i, and g_{jk} the number of all geodesics between p_j and p^k.

In addition to the two types of centrality measured, the measurement radius must be defined. It restricts the maximum distance between two segments considered in the analysis. As result, it is possible to adjust the network centrality measure based on the travel mode and physical ability of interest. Given the focus of this research on pedestrian movement, we adopt "the quarter-mile (400 m) as a rule of thumb for the walkable catchment area of an opportunity" (Vale & Pereira 2016). At the same time, various studies show a high variance in maximal walkable distance up to 1800 m (Larsen & El-Geneidy 2010) and there is a clear need for empirical calibration of this parameter. The calibration process and the choice of radius parameter for the case study presented in this paper will be discussed further in the results section.

2.2 DENSITY OF URBAN FORM

In general, the concept of urban density is restricted to a given boundary. Since any single density measure is "not nuanced enough to convey urban form" (Berghauser-Pont & Haupt 2010, p.79) we employ the following five dimensions of density, differentiating by the features of urban form being measured (Figure 2):

(a) Building intensity[2] is a measure of density capturing the total gross floor area (F) per area of a plan (A). Similarly, it is the established approach among urban network research to treat the buildings or their floor area as a movement attractor (Hillier 1999, Stahle et al. 2005). Consequently, the building intensity can be utilized to answer the second research question about relation between network centrality and density of movement attractors.

$$D_{BI} = \frac{F}{A}$$

(b) Building coverage is a measure of the relationship between built area (B) and area of the plan (A). It identifies how developed an area is along a scale of zero (no development) to one (the whole area is occupied by buildings).

$$D_C = \frac{B}{A}$$

(c) Building height is the ratio between total gross floor area (F) and built area (B). It reflects the average number of storeys of a plan.

$$D_{BH} = \frac{F}{B}$$

(d) Spaciousness[3] expresses the ratio between open space and total floor area (F). It reflects the pressure on the development of open space. The measure can be interpreted as the amount of open space on the ground per unit of built floor area.

$$D_S = \frac{A - B}{F}$$

2 Building intensity can also be found in literature under the alternative terms "Land use intensity", "Floor space index" or "Floor area ratio".

3 Equivalent to the Open Space Ratio.

(e) Network density is a measure of the concentration of the network (I) per area of the plan (A). The unit of the measure is expressed as metres of network (represented as street centre lines) per square metres of ground area. Due to the focus of the study on pedestrian movement, only the walkable part of network has been taken into account.

$$D_N = \frac{I}{A}$$

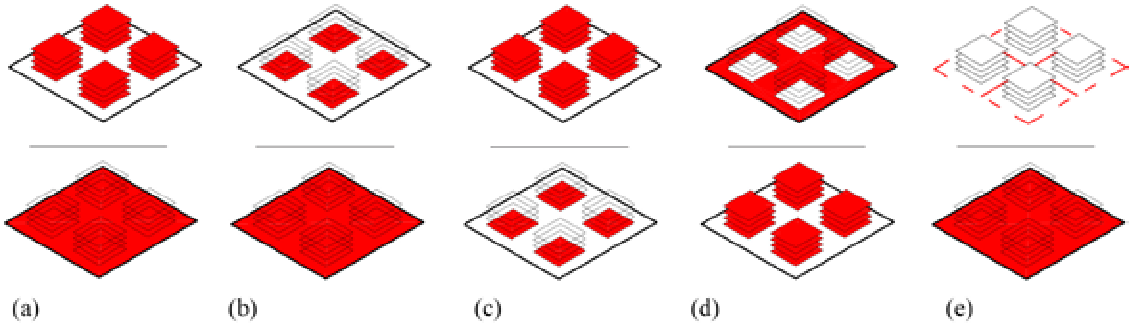

Figure 2 - Numerator and denominator of the five dimensions of density used in the paper: (a) Building intensity, (b) Building coverage, (c) Building height, (d) Spaciousness, (e) Network density (from Berghauser-Pont & Haupt 2010, p.94-96)

After specifying the numerator and denominator of each density measure, the boundary of analysis must be defined. This step is a critical part of any spatial analysis, since the definition of scale and shape of boundary has direct impact on the results of an analysis. In geography, it is known as the "Modifiable area unit problem (MAUP)" (Openshaw 1983) and has been approached by either avoiding arbitrary decisions in definition of boundary area, or at least systematically measuring its effects (Taylor, Gorard and Fitz 2003).

In our case, the boundary is supposed to capture the density of urban form around each network segment. For this purpose, the analysis boundary has been generated offset from the network segment with each point on the boundary equally far from the closest point on the segment. Regarding the size of the offset, it's radius, we argue that instead of arbitrarily defining a single boundary offset, we can avoid the effect of MAUP by systematically studying this parameter. For this reason, we evaluate the effect of network centrality on the density of urban form for 14 different offset radiuses ranging from 20 m to 800 m (Figure 3a).

Once the boundary has been generated, three variables (Network length, Gross floor area, Built up area) are needed to calculate the five density measures and are assessed by considering only the urban form inside the boundary (Figure 3b).

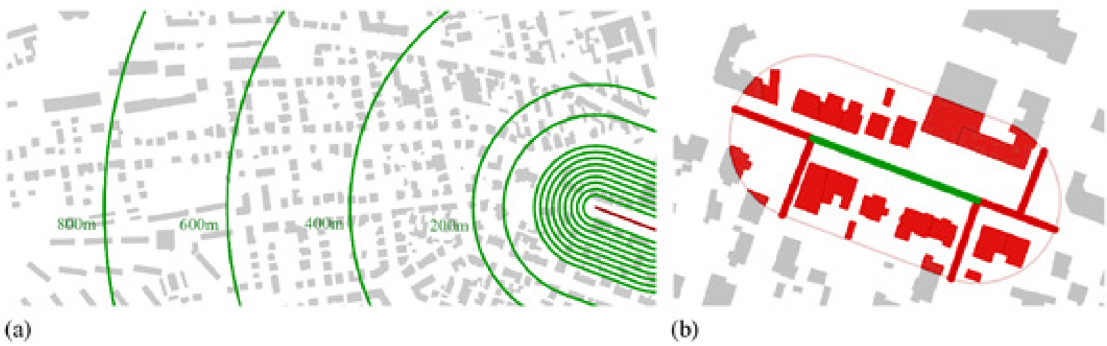

Figure 3 - (a) 14 offset radiuses defining the boundaries of urban density (ranging from 20 m to 800 m). (b) Urban form for a given radius at a given segment

2.3 CASE STUDY WEIMAR

In this section, we present an empirical study conducted in the town of Weimar (Germany), which aims to measure the effect of network centrality on urban density and movement attractors. Weimar has a range of morphological patterns, from the organically evolved medieval town centre, to the regular grids of 19th century urban expansion areas and large slab-housing estates built in the 1970s (Figure 4). Furthermore, its size (64,131 inhabitants, 84.420 km²) makes it possible to analyse the entire town, eliminating the bias known as the "edge effect" resulting from the partial analysis of larger urban systems (Gil, 2015)[4]. Weimar's size and compact shape also promotes walking as a main mode of travel, which fits with the focus and methods chosen in this study.

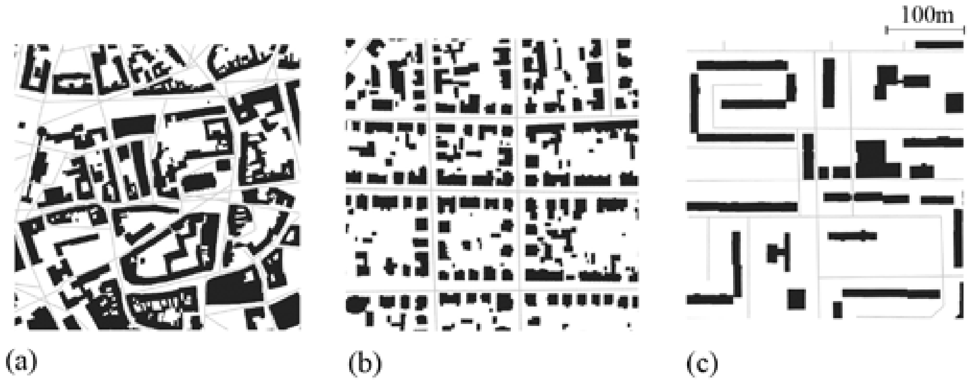

Figure 4 - Example street network patterns and building densities found in Weimar. (a) Historical centre (b) Regular grid (c) Large housing estates

2.4 DATA COLLECTION AND PROCESSING

The segment map used for calculating network centrality was drawn manually according to principles described in the method section, resulting in 3272 segments for the town of Weimar. To calculate the betweenness and closeness centrality for the network, the walking distance radius of the analysis had to be determined. For this purpose, we collected data on pedestrian flow at 120 locations throughout the whole of Weimar on three different days and three different times each day. Finally, the centrality measures were calculated using DepthmapX (Varoudis, 2012).

To calculate the density of urban form and network centrality, various data sources and software tools were used to collect, process and analyse the data. For the purpose of density calculation, the open source mapping platform OpenStreetMap.org was used to collect the data on building footprints, number of floors and street network. The density calculation was implemented and executed in the visual programming software Grasshopper for Rhino3d. The density was calculated for the same set of 120 locations as used to calibrate the pedestrian radius of centrality measures. To examine the effect of network centrality on urban density, we assess all five density measure for each location in 14 different offset radiuses resulting in 8400 measurements[5]. Finally, the statistical analysis and data visualisation was carried out in DecodingSpaces Rtools for Grasshopper (Abdulmalik & Schneider, 2017).

4 In the analysis of spatial networks, the 'edge effect' describes a bias in the analysis results as a product of the portion of the network included in the analysis (Okabe & Sugihara, 2012). Different measures have different degrees of sensitivity towards the 'edge effect', mostly depending on the radius of the analysis (Gil, 2015). In this case study, we avoid the 'edge effect' by analysing the entire town. As no additional settlements exist within the boundary of the maximum analysis radius (2000m) from the edge of the town, extending the edge does not change the analysis results.

5 The current limitation of the study to 120 locations out of 3272 possible is restricted by the amount of computation time needed for the density calculations. The current implementation of density measures requires on average 50 seconds of computation time for one location and offset radius (depending mainly on the offset radius). The overall computation time for all locations and radiuses is approximately 23 hours.

3. RESULTS

To evaluate the main research questions concerning the effect of network centrality on urban density and movement attractors, we adopted (a) Space Syntax methods to measure network centrality and (b) five density measures as descriptors of the distribution of urban form. In this section, we introduce the results of the Weimar case study targeting the research questions and steps required prior to answering them. First, to calculate network centrality, we will identify the analysis radius corresponding to pedestrian travel. Second, we evaluate the impact of boundary offset radius on the five density measures. Third, we identify how many variables are required to describe the urban form. In other words, we ask if the original set of five density measures can be reduced. Knowing the dimensionality of urban form is of great importance since it determines the minimum number of dependent variables we are going to predict with network centrality as an independent variable. In general, the more variables required to describe the density of urban form, the lower its predictability by a single centrality measure. Finally, we model the relationship between network centrality as an independent variable and density of urban form as a dependent variable in order to answer the two main research questions.

3.1 NETWORK CENTRALITY

To determine the pedestrian radius of the network centrality analysis, we systematically investigated the relationship between radius definition (from 100 to 2000 m) and the ability of betweenness centrality to predict pedestrian movement (Figure 5). We assess the R-square as a measure of fit calculated in the linear regression model with betweenness angular centrality as an independent variable and average pedestrian flow as a dependent variable. To comply with the normal distribution criteria of linear regression, we logarithmically (LN) transformed both variables (Figure 5). The highest R2 = 0.491 (p value ≤ 0.001) was found for a radius of 600 m (or a seven-minute walk). Furthermore, we conclude that the radius is more sensitive at a lower distance range, peaking at 600 m and then slowly falling towards a distance of 2 km with R2 = 0.058 (p value ≤ 0.05).

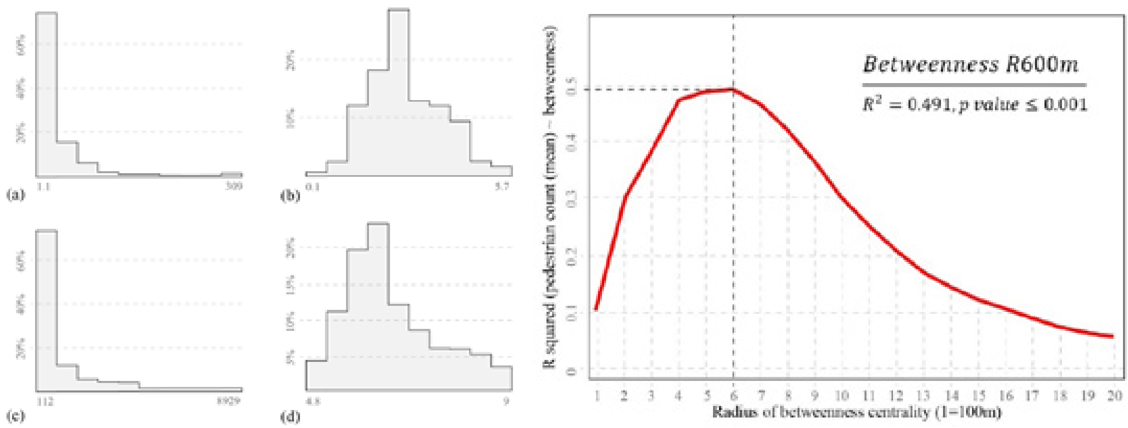

Figure 5 - Distribution of movement potential (betweenness centrality R600) and measured movement (mean of all 9 counting sessions) before and after LN transformation. (a) measured movement, (b) measured movement after LN transformation, (c) Betweenness centrality, (d) Betweenness centrality after LN transformation. (e) Graph showing the relationship between the radius of betweenness centrality (in 100 m steps) and its ability to predict pedestrian movement (in R2).

3.2 DENSITY OF URBAN FORM

We analysed the impact of boundary offset radius (ranging from 20 m to 800 m) on the five density measures. We examined how (a) variance and (b) the average value of each density measure change by increasing the offset radius. The change in variance across the offset radiuses while keeping the mean constant can be seen as a measure of the ability to pick up differences in the distribution of urban form over the 120 analysis locations. Based on the results presented in figure 6a, we can conclude that for all five variables with growing analysis boundary, the variance drops and became more homogenous. At an offset radius of 800 m, the variance of the density measures account for only 1 to 22 % of what was measured at an offset radius of 20 m.

Additionally, we observe that in four out of five cases (except the building height) not just the variance but also the average values are highly influenced by boundary radius. Here the most sensitive parameters are spaciousness and network density with 40 – 80 % drop in comparison to the average values between a radius of 20 m and 60 m (Figure 6b). We conclude that beyond the 60 m radius, the average values remain stable with a fall-off in the case of Network density, Building intensity and Coverage and a slight increase for Spaciousness.

We conclude that the boundary radius parameter has an impact on both the middle and spread of distribution of the density measures and therefore has to be taken into account.

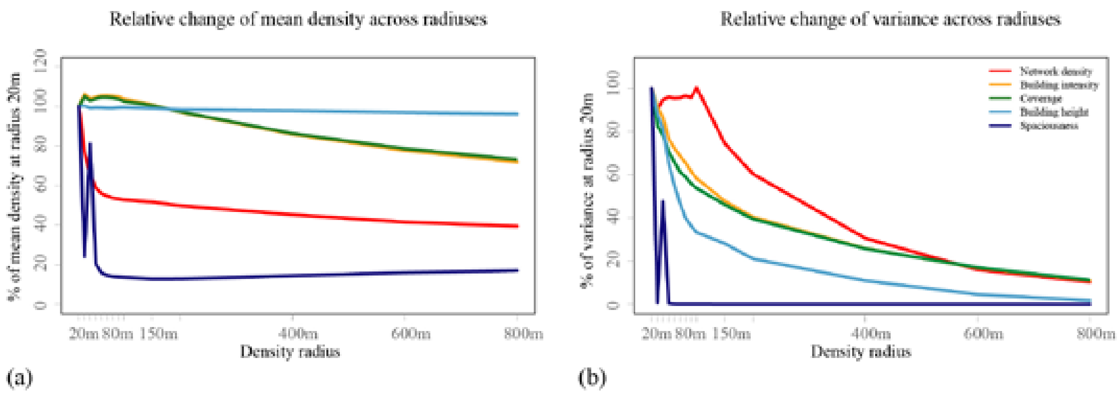

Figure 6 - (a) Change of variance across radiuses relative to variance at radius 20 m. Measure at all radiuses were centred to mean = 0. (b) Change of average density across radiuses relative to average density at radius 20 m.

Next, we evaluated the covariance between the five density measures to determine how many independent variables are required to describe the distribution of urban form. For this purpose, we examine the correlation matrix between the five density measures at all radiuses resulting in 140 unique correlations[6]. Irrespective of the boundary radius, we can observe the same pattern of highly significant correlations between three variables (Building intensity, Coverage and Spaciousness) with Pearson's correlation coefficient |R| ≥ 0.92. Similarly, the Building height is independent of the other density measures across all offset radiuses. Furthermore, as illustrated in Figure 7, the relationship of Network density to Building height, Coverage and Spaciousness increases from |R| ~ 0.26 at radius 20 m to |R| = 0.93 at radius 800 m.

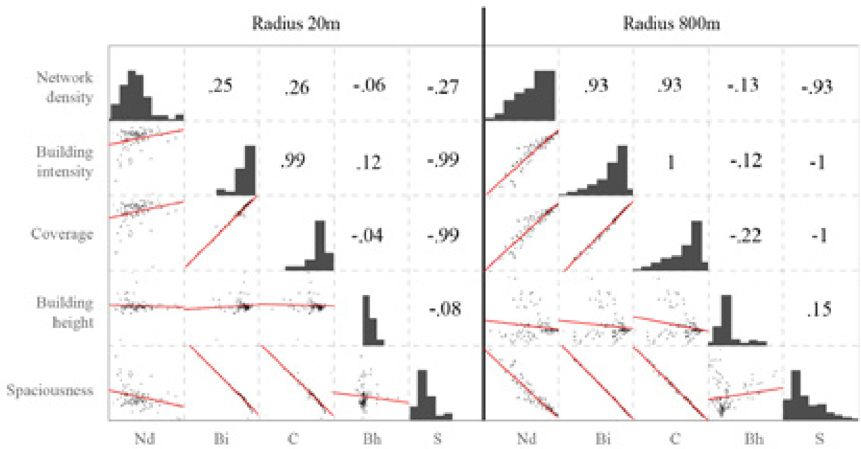

Figure 7 - Pearson's R correlation matrix between five density measures at offset radius 20 m and 800 m

6 The 140 combinations are a result of all possible combinations of five variables multiplied by the 14 radiuses.

Given the high correlation between the density measures, we expect the set of five variables could be reduced. With this in mind, we applied a factor analysis using generalized least square (GLS) estimation and an oblique rotation (Geomin Q) to reveal a smaller set of latent variables behind the five density measures. Our criterion for determining the number of factors is that it should explain at least 95% of the total variance. We confirm that the distribution of the urban form can be described by two, respectively three factors depending on the offset radius. For offset radiuses above 200 m, the two first principal factors account for 95% of the total variance (Figure 8).

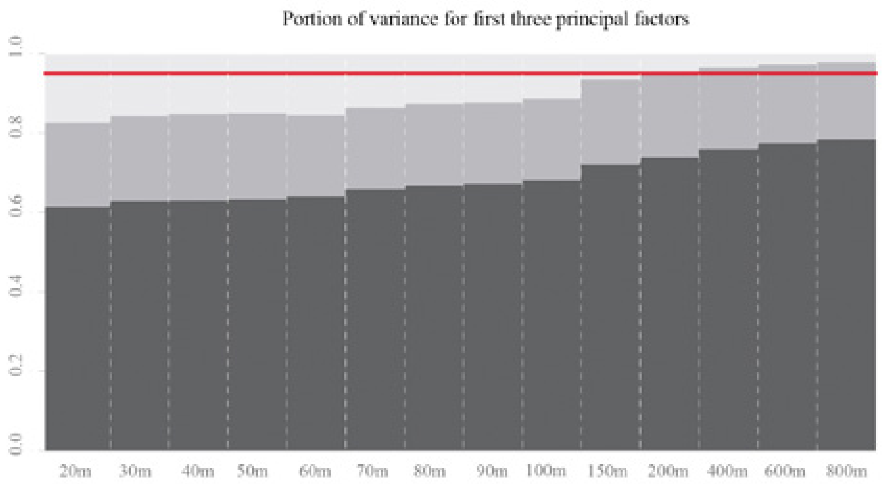

Figure 8 - Parallel factor analysis of five density measures across all 14 offset radiuses showing the portion of variance explained by the first three principal factors. The red line marks 95% of cumulative variance.

Furthermore, the factor analysis revealed that not only the number of factors but also the loading of the factors varies across the offset radiuses. The latent factors suggested by the exploratory analysis of the correlation matrix result in three latent variables at boundary offset radius (a) below 200 m labelled as Build-up density (Building intensity, Coverage, Spaciousness), Network density and Building height and (b) at 200 m and above labelled as Projected density (Building intensity, Coverage, Spaciousness, Network density) and Building height (Table 1).

	Offset radius 20 m			Offset radius 800 m	
	Factor 1 Build-up density	**Factor 2** Network density	**Factor 3** Building height	**Factor 1** Projected density	**Factor 2** Building height
Network density	0.1	**0.42**	-0.01	**0.94**	0.16
Building intensity	**1.00**	-0.01	0.07	**0.99**	0.02
Coverage	**1.00**	-0.01	-0.10	**0.96**	-0.16
Building height	0.00	0.00	**1.00**	0.00	0.99
Spaciousness	**-0.98**	-0.03	-0.03	**-0.99**	0.01

Table 1 - Factor loadings for extracted three respectively two factors as suggested by the parallel factor analysis.

To summarise, we confirmed that the definition of an offset radius has an impact on all five density measures on their own, as well as on the latent variables hidden in the data. Furthermore, we find that in the case of Weimar, the set of five density measures could be reduced to two, respectively three factors based on the offset radius. We argue that this can be attributed mainly to the uniform distribution of building heights throughout the town of Weimar (4 storeys on average). Consequently, by keeping the building height constant, we can reduce the Building intensity, Spaciousness and Coverage to a single measure (build-up area per area of plan).

3.3 NETWORK CENTRALITY AS A PREDICTOR OF URBAN DENSITY

To quantify the effect of network centrality on the density of urban form and movement attractors, we conducted a series of linear regressions varying the three parameters that were previously identified as influential. First, the two different definitions of centrality (closeness and betweenness) were taken into account as predictors. By evaluating their individual and combined effects on urban density, we end up with three predictor parameters.

Next, we consider the boundary offset radiuses by conducting the regressions across the whole range of radiuses, resulting in 14 additional parameters.

Finally, at each offset radius, the urban form is described by five density measures. These could be reduced to a lower number of latent factors, however the composition of the factors and their number changes across the offset radiuses. On the one hand, the latent factors reduce the overall number of dependent variables and so the overall number of regressions. On the other hand, these variables are unique for each offset radius, which makes it difficult to interpret the results. In particular, we are not able to follow the influence of the offset radius in relationship to centrality and individual density measures. For this reason, we regress on the five original density measures as described in the Method section.

Combining the variation of all three parameters (three predictors, five dependent variables across 14 offset radiuses) we arrive at 210 unique regressions. To determine the effect of network centrality on urban density, we visualize the regression results by plotting the coefficient of determination (R squared) on the Y axis and the boundary offset radius on the X axis (Figure 9a). The results show that both centrality measures have a significant effect on four out of five density measures (except Building height). The strength of the effect varies based on the offset radius following the same pattern for all four significant regressions. This pattern can be described as an inverted U-curve starting with weak effects at small radiuses, then continuously rising to a peak which is followed by a fall-off toward large offset radiuses. The greatest deviation from this pattern can be observed at the smallest offset radiuses between 20 and 40 m. The fluctuations in the fit of the model measured by R squared can be accounted for by the high variance and change of average value at lower radiuses as discussed previously[7]. Therefore, we suggest considering the offset radius 40 m as the smallest radius suitable for describing the density of urban form in Weimar.

When comparing the effect of individual centrality measures, we conclude that closeness centrality is in general a strong predictor, with a peak at 400 m offset radius, accounting for approximately 70% of the total variance of all four significant density measures (*R^2 Building intensity = 0.685, R^2 Spaciousness = 0.705, R^2 Coverage = 0.685, R^2 Network density = 0.692* Network density). Betweenness centrality has its peak at 200 m offset radius, accounting for approximately 50% of total variance of all four significant density measures (*R^2 Building intensity = 0.422, R^2 Spaciousness = 0.458, R^2 Coverage = 0.387, R^2 Network density = 0.547* Network density).

To evaluate the combined effect of both centrality measures on urban density, we conduct multiple linear regressions with closeness and betweenness centrality as predictors and five density measures as dependent variables across all offset radiuses (Figure 9b). We realize that the effect of combined centrality follows the same pattern and reaches the same peak as in the case of closeness centrality as a single predictor (400 m, $R^2 \approx 0.7$).

7 From a morphological point of view, we find these high variations at locations where street width exceeds the offset radius defining the boundary of the density measurement area (Figure 6). In such cases, no urban form is detected resulting in extreme density values. We consider these measurements unreliable, since only a small increase in the offset radius can lead to an abrupt change in the description of the same urban form.

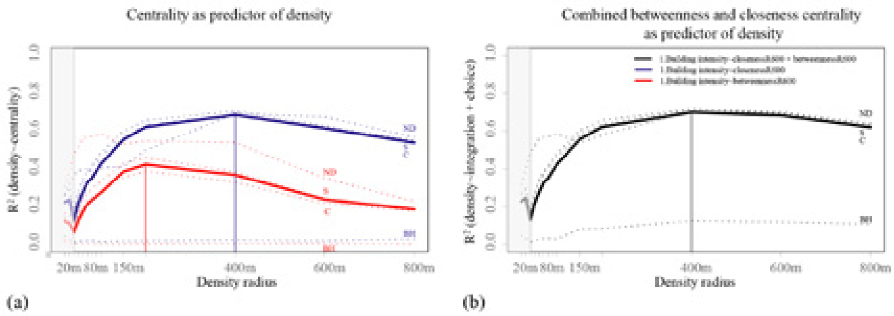

Figure 9 - (a) Betweenness (red) and closeness (blue) centrality as single predictors of five density measures across 14 offset radiuses. (b) Multiple linear regression with betweenness and closeness centrality as predictors of five density measures across 14 offset radiuses.

4. DISCUSSION AND CONCLUSIONS

The paper develops and implements a computational model for measuring the relationship between network centrality and urban density. We conducted an empirical study to test this for the case of Weimar. The empirical results show that network centrality is a strong and significant predictor of most aspects of the distribution of urban density, except the building height. Network centrality could also be related to distribution of movement attractors, however the strength of the relationship is highly dependent on the size of the boundary used to measure the density, the type of density measure and the definition of centrality.

Regarding the effect of different centrality measures on urban density, we found that closeness centrality is a better predictor) than betweenness centrality (accounting for 70% and 50% respectively of variance in the data). This might be explained by the difference in spatial distribution between the urban density and the two centrality measures. Neither closeness centrality nor the density measures change abruptly between two neighbouring locations, allowing these variables to evolve together. Betweenness centrality, on the other hand, can vary highly from one street to another, contradicting how density is distributed in space.

By looking at the impact of the boundary offset radius at which density is measured, we summarise that the centrality of the movement network has only a marginal effect on the immediate neighbourhood (40 m radius). The effect grows constantly with increased boundary radius peaking at 400 m for closeness and 200 m for betweenness centrality, falling again as the radius increases to larger distances.

The low effect of network centrality on its close surroundings suggests that there might be other factors driving the distribution of urban density at a local scale. We argue that this scale is of special importance for applications modelling pedestrian flow and movement attractors. Not all attractors contribute equally to the attractiveness of movement destination, giving more weight to closer and more accessible ones. For this reason, the empirical evidence collected in the Weimar case study suggests that the loading of the network with movement attractors only marginally follows the pattern of network centrality. As a result, we suggest that the explicit modelling of movement attractors might significantly improve the results of any analysis depicting human movement in urban environments.

As can be seen, the distribution of urban density and the distribution of movement attractors could not be explained as a product of any single variable – measures of network centrality and additional explanatory variables were required. This finding is based on (a) the linear regression revealing that more than 30% of variance in density is caused by other variables than network centrality (Figure 9), and (b) the factor analysis of density measures (Figure 8) showing that at least two orthogonal variables are needed to describe density of urban form and therefore it couldn't be fully predicted by a single centrality measure.

To identify those additional factors, we examined the spatial pattern of 120 residuals of the linear model predicting the density of urban form and movement attractors[8] based on closeness centrality (Figure 10). By looking at the direction and magnitude of the residuals we can recognize the factors influencing either an increase or decrease of building intensity which cannot be explained by network centrality alone. In general, we could identify three different types of additional factors, all related to the planning of: (a) building complexes, large housing estates (b) functional zoning or (c) infrastructure.

On the one hand, we found that the allocation of large housing estates doesn't follow the network centrality and in all cases the actual building density was higher than predicted. Together with building complexes, such as a university campus or a hospital, such large-scale developments are often planned at the edge of cities due to their space requirements. Consequently, the increased urban density doesn't match the low network centrality of these segregated areas. On the other hand, the functional zoning of cities together with their infrastructural elements, such as railway lines, prohibits specific areas from being developed, causing lower building densities than predicted by network centrality.

Given all these points, we conclude that our findings on the relationship between network centrality and urban density are a first step towards defining the applicability and extending the predictive power of the space syntax approach.

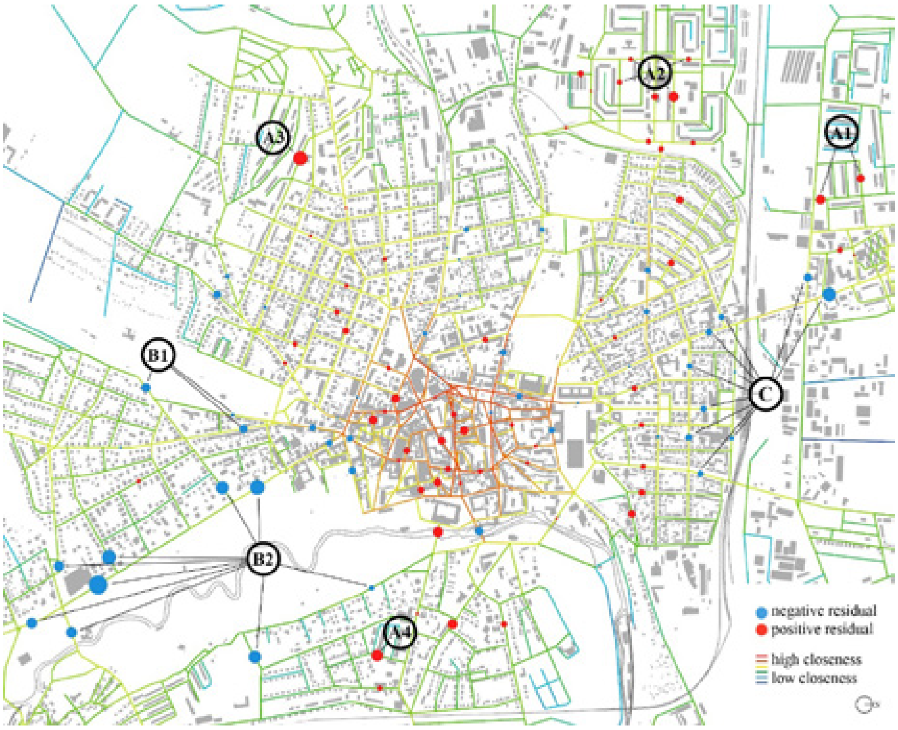

Figure 10. 120 residuals of linear regression of closeness centrality on building intensity (offset 400 m). The size of the circle identifies the magnitude and the colour the direction of the residual. A negative residual means that the predicted density was lower than the measured one. Additional factors influencing density are marked as large housing estates (A1) Weimar Nord, (A2) Weimar West, (A3) Weimar Süd; University campus (A4); Cemetery (B1); Park am Ilm (B2); Railway (C)

8 The spatial patterns of residuals are illustrated exemplarily and discussed through linear regression with closeness centrality as a predictor and building density at an offset radius of 400 m as the response variable. We have chosen this particular variation of centrality and density measures since it accounts for the strongest relationship between these two sets of variables.

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