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Analytically Derived Neighborhoods in a Rapidly Growing West African City: The Case of Accra, Ghana

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Abstract

Go to:

Large numbers of people are currently migrating from the poor, inland areas of West Coast Africa to the major cities of Lagos, Accra, Abidjan, and other budding metropolises (Figures 1 and 2). The infrastructure of the Sub-Saharan African cities is inadequate to service their burgeoning populations. An argument is presented for using scientifically derived neighborhoods as the building blocks for current African urban understanding and planning. In this paper, I will explore the neighborhood concept and use available data and new heterogeneity statistics to derive homogeneous neighborhoods. The statistics are explained and maps of Accra neighborhoods are given.

Figure 1
Migration from the rural areas.

Figure 2
Africa's West Coast Region

Keywords: Spatial Clusters, Neighborhoods, Heterogeneity, Accra

1. African Population Growth

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The chart that follows (Figure 3) indicates that Africa is the fastest growing continent in the world (United Nations, 2006). How the continent handles the rapid growth is of critical importance to international political and economic stability. It is expected that the population of Africa will increase from about 1 billion today to 2 billion in 2050, or Africa's population will constitute 22% of the world's people in 2050 while as a proportion of the world's population today it is 15% (US Census Bureau). Continued poverty and the unrest that comes from urban in-migration are issues that must be considered for the well-being of the entire continent. Greater Accra had a population of 1.4 million in 1984 and by 2000 the population increased to 2.9 million, doubling in size. The vast majority of migrants originated in the rural areas and smaller cities of the central part of Ghana and from nearby countries. What we have here is a clearing out of the rural areas (Weeks *et al*., 2010). The infrastructural system of the city is unable to completely service such a rapid inflow.

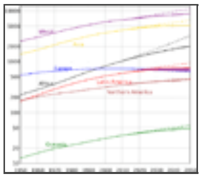

Figure 3
World population trends to 2050. Note that the slope of curve for Africa is greatest. Source: United Nations

In order to study the changes that are occurring one must look to modern social science techniques of analysis. This paper is designed to show some modern statistical procedures which aid us in the study of the nature of the West African city. The case study is that of Accra, Ghana, a city in which I have been doing analytical research for several years. We focus on the creation of a unit of analysis -- the neighborhood -- which seems well suited for the study of complex urban African environments.

2. The Role of Neighborhoods in Urban Planning

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The units of data collection by the Ghana government for Accra are enumeration areas (EAs). A decadal census has been taken most recently in 2010. EAs are generally aggregated, by officials, into urban sub-areas for city and metropolitan service organization. As in all cities, there have evolved over time unofficial neighborhoods that are well known sub-areas. We call these "traditional" urban sub-areas *vernacular* neighborhoods. Again, for many cities, Accra included, these vernacular neighborhoods have evolved into planning districts for housing, transportation and many social services such as health clinics. Under the influence of rapid in-migration, however, the tendency is for new neighborhoods to emerge and older neighborhoods to become more structurally heterogenous. In our study we show that vernacular neighborhoods, except for a few, are highly heterogeneous in terms of the usual measures of housing quality, health, and infrastructural elements like the availability of good quality water and electricity and in social/ethnic characteristics. As planning districts, the boundaries of vernacular neighborhoods cut across the homogeneity that might be found in scientifically constructed sets of EAs, making public policy based on vernacular neighborhoods difficult and inefficient.

In the social sciences, research is conducted at many geographic scales of inquiry: individuals, clusters of individuals, neighborhoods, census divisions -- from tracts to large regions. Vernacular neighborhoods, usually because they are well known, are the unit of choice in trying to come to grips with the social structure of cities. Increasingly, attention is being paid to the concept of neighborhood mainly because of its relevance to social processes such as immigration, life style, crime, unemployment, and housing quality (Kawachi & Subramanian, 2007). At one time clusters of census divisions approximated these types of homogeneous neighborhoods, but census divisions change much less often (or not at all) than the social processes that are contained within and beyond them (Subramanian *et al*., 2003). Thus, modern dynamic social science research suffers from the ever changing locations and geographic shapes of these types of social spatial clusters. In this paper, we discuss the nature of new neighborhood boundaries that are designed to aid in the planning process recognizing that vernacular neighborhoods will continue to be helpful for those that require well known place names. These new neighborhoods are quantitatively derived from algorithms designed to seek spatial homogeneity within important urban social and environmental variables. The algorithms are based on statistical procedures known in the spatial statistics literature as AMOEBA, *A Multidirectional Optimal Ecotope-Based Algorithm* (Aldstadt & Getis, 2006), and *Local Spatial Heteroscedasticity -- LOSH* (Ord & Getis, 2012).

3. Neighborhoods as Building Blocks for Social Research

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In recent years, definitions of what constitutes a neighborhood have received attention because of their centrality to the work of social scientists. The chief assumption for any definition is that a neighborhood is homogeneous in some well-defined regard (see Weeks *et al*., 2010 for a review). Neighborhoods' importance becomes evident when the context of human behavior and actions are taken into account. It is now assumed that an individual's actions and reactions are not fully understood unless the context of an immediate activity space, or neighborhood, is taken into account (Subramanian, Jones and Craig, 2003).

Many statistical procedures require spatially sampled data where a given observation is to some degree independent of others nearby. Thus, there is a need to group observations into neighborhoods so as to avoid, as much as possible, the phenomenon of spatial autocorrelation in the sample. Neighborhood, when rigorously defined, helps create unbiased samplings of spatial units. A neighborhood evokes a high degree of spatial autocorrelation from place to place within itself and low levels of spatial autocorrelation between places within itself and places beyond its borders.

The difficulty of finding relevant data using neighborhood definitions remains problematic, however. A neighborhood characteristic of interest, say, a particular age cohort, may cut across a census division, resulting in some degree of error when attempting to define a neighborhood when the only data available are based on census divisions (Weeks *et al*., 2007).

Unfortunately, *neighborhood* as a concept is taken lightly by most researchers who deal with them. Often there is a weak definition or no definition at all. In fact neighborhoods are often spoken of as though there is a tacit agreement with readers as to what constitutes a neighborhood. Relatively few studies in which neighborhoods constitute the basic sampled unit rigorously define the term or call into question the use of neighborhood boundaries. Thus, qualitatively delimited neighborhoods suffer from the biases incurred by the researcher. Sometimes neighborhood units are used as if some sort of governmental authority has sanctioned their use. No explanation is given on how those neighborhoods were delineated. Commonly used neighborhood units are often vernacular in nature, that is, based on popularly based parts of a city that many people intuitively think that they know. The boundaries of these neighborhoods are often fuzzy at best.

Institutional biases may appear when it is convenient for planners to divide up a region in a way in which resources can be allocated (Figure 4). This is a problem simply because the neighborhood boundaries may not correspond to the perceived demand for the resources. In any case, it is important to divide an urban area into something that can be used for planning purposes. Sometimes these governance or planning areas become the official neighborhoods of the region. Too often, however, these unit boundaries fail to change as the urban area undergoes marked changes both physically and socially. Thus, in many instances, commonly named neighborhoods are of only historical interest or evoke some sort of mental image that may be out of date or erroneous.

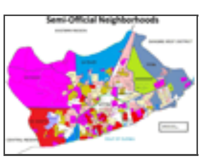

Figure 4

Perhaps the most damaging aspect of qualitatively demarcated neighborhoods is the geographical scale at which neighborhoods are drawn. In social science research, it is not immediately clear if neighborhoods are one-block units, a few contiguous blocks, or an entire sub-region in area or some other arbitrarily constituted area.

4. Urban Neighborhood Defined for this Study

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The word neighborhood in an urban setting conjures two mental constructs: contiguity and homogeneity. Thus, a basic definition of an urban neighborhood is of a contiguous and reasonably homogeneous aggregation of smaller spatial units (usually city blocks, census tracts or other enumeration areas of varying spatial extent). The homogeneity is derived from any one or more variables that constitute a collection of people having certain characteristics, institutions that spatially cluster, or a landscape quality for which people identify (a waterfront, a valley, etc.). The variable can be linked to a common history, some aspect of the area's past, an ethnic group, a socio-economic area of some character, or an age cohort. In social science research, it is often the case that a neighborhood is represented by a disproportionate number of members of a particular socio-economic, ethnic, or age cohort group within some local area. It would be helpful if those who use the term clearly state just what kind of definition they are using and to what extent there is homogeneity in the variables used for the definition.

The city of Accra, Ghana, like most large cities of the world can be divided into neighborhoods depending on who, when, and for what purpose the delineation took place (Weeks *et al*., 2006). Government maps are of water districts, educational districts, electoral districts, and so on.

Sometimes these are brought together for data collection purposes or for comparisons to be made between districts (Songsore & McGranahan, 1993). Sometimes these districts are called neighborhoods, especially, if they are generally known and used for identifying location by the populace. In Accra, over many years, popularly known vernacular neighborhoods have been established by urban residents (Figure 5). A taxi-driver is well aware of say the whereabouts of the Nima neighborhood. This common knowledge affects data collection units used by both municipal authorities and the national government. Many kinds of districts such as school, water, and power, are bounded by the limits of these vernacular neighborhoods. Although the neighborhoods, so named, usually have a strong bonding factor, such as ethnicity, or historical development, they are clearly not rigorously defined. In fact, many of the vernacular neighborhoods that display, say, a heightened level of some generally useful variable, such as persons per room, are indeed rather heterogeneous. Still it is useful to employ the popular names of these vernacular neighborhoods so that locations can be identified in well known terms.

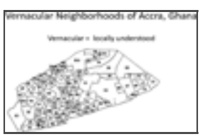

Figure 5

The view we take is that the creation of neighborhoods follows some scientifically defined purpose. That is, neighborhoods are defined in terms of explicitly stated variables. Examples of such neighborhoods are: a defined degree of socio-economic status, a defined level of ethnic residency, a certain proportion of age-based residents, a certain proportion of residents living in dwelling units in explicitly defined family structures, the proportion of residents living in a certain quality of dwelling unit, and so on. When the purpose is made clear, relevant variables (if they exist) are extracted from the census for the period in question.

The goal of quantitatively delimiting urban neighborhoods is to identify statistically significant, spatially homogeneous aggregations of spatial units. Not more than a dozen years ago, this goal could not have been achieved easily, but with the advent of spatial statistical methods, such neighborhoods can be identified, its boundaries drawn, and the neighborhood units used for analysis. The type of statistics needed for such work is called local statistics. An explanation and results are given in the next sections.

5. Techniques of Analysis

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When we speak of spatial in dealing with data, the implication is that observations are taken from a geo-referenced population. Results often are presented on maps where the nature of the pattern is of foremost concern. Spatial autocorrelation is the concept that helps to understand the nature of the mapped patterns (Getis, 2010). What has become evident over the last 30 or 40 years is that spatial statistics requires assumptions not included in other more common types of statistical study. In particular, the application of standard statistical procedures (e.g. tests and confidence intervals based upon the *t*-distribution) require independence of the observations. The presence of spatial autocorrelation can lead to inferences based upon standard non-spatial statistics that are misleading or incorrect (Getis & Griffith, 2002).

The spatial statistics literature is particularly noteworthy for its development of statistics of spatial autocorrelation. These are based on assumptions of spatial covariance (Moran's *I*), spatial difference (Geary's *c*), spatial addition and multiplication (Getis & Ord's *G*), among others. Each of these is used in particular circumstances where the goal is to identify one or more georeferenced observations that could not have occurred by chance taking into account the distance relationship embedded in the statistic's assumptions.

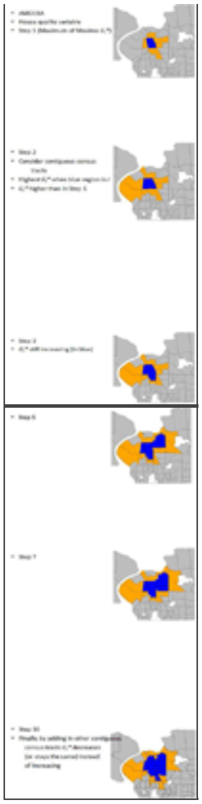
AMOEBA

AMOEBA is an algorithm for creating a cluster from univariate, georeferenced data (Aldstadt & Getis, 2006, Getis, 2004). In our explanation of AMOEBA we use the Getis-Ord local statistic G_i^* (Getis & Ord, 1992). At the outset, we compute the G_i^* value for a spatial unit *i* and its link (*k*) with one of its contiguous neighbors (*j*). The spatial link ($k = 1$) process is repeated for each *j*. If G_i^* increases absolutely for any of the *j* links over the G_i^* value for *i* alone, then those *j* units become a cluster together with the original i^{th} spatial unit. If, on the other hand, absolute G_i^* decreases then the *j* contiguous neighbor does not become a member of the cluster. This process continues for $k=2$, that is, the already existing members of the cluster are combined with their contiguous neighbors, one at a time. G_i^* is computed for the original i^{th} spatial unit one at a time with each new link added to the already existing members of the cluster. Again, if values absolutely increase, the new spatial unit is added to the cluster (Figure 6 provides a view of the sequence of steps). This process is repeated for $k = 3, 4, \ldots, max$ links. The maximum is the last link that increases the absolute value of G_i^* over the G_i^* value when the number of links was ($k_{max} - 1$). Representing spatial association between all *i* and *j*'s, the weight calculation for entry into W, the spatial weights matrix, within the maximum number of links (k_{max}) is given by (Getis & Aldstadt, 2010): When $k > 0$, $w_{ij} = \{P[z \le Z(k_{max})] - P[z \le Z(k_{ij})]\} / \{[P[z \le Z(k_{max})] - P[z \le Z(k_{ii})]\}$, for all *j* where $k_{ij} \le k_{max}$,,

$$w_{ij} = 0, \text{otherwise.} \tag{1}$$

Figure 6

Illustration of the sequence of steps leading to the final cluster shown in Step 10.



Read k_{ij} as the number of links connecting i and j in the cluster.

When $k_{max} = 0$, $w_{ij} = 0$, for all j.

The value z is the observed standard variate of the normal curve that represents a point in the probability distribution of the G_i^*. G_i^* is given in standard variates. Thus $P(z)$ is the cumulative probability associated with the G_i^*. The values of $Z(k_{max})$, $Z(k_{ij})$, and $Z(k_{ii})$ are, respectively, the standard normal variate for G_i^* at: the maximum number of links, the number of links separating i and j, and i itself ($k_{ii} = 0$). Thus, equation (1) represents that proportion of the normal curve between k_{ij} and k_{max}. Thus, w_{ij}, a cell value in the spatial weights matrix, varies between 0 and 1. Low values of w_{ij} imply that there is little or no spatial association and high values represent strong spatial association between i and j. When k_{ij} equals k_{max}, the weight is 0. Normally, the closer in links distance of j to i, the higher w_{ij}.

In sum, then, for each observation i, G_i^* values are obtained for all combinations of linked neighbors j and i within the maximum number of links. The set of j observations that maximizes the local statistic becomes a member of the cluster together with the i^{th} observation. The distinguishing feature of this approach is its flexibility in identifying spatial association of nearby units regardless of the configuration of those units.

AMOEBA Applied to Accra

The AMOEBA technique allows us to find statistically demarcated areas (clusters) based on the pattern of a single variable or a combination of two or more variables. The principle of finding clusters is straight-forward as explained above. but the actual algorithmic operation is a multistep procedure that starts with an EA that displays the highest score (*key EA*) on the variable(s) under study. This high score is derived from the position of the variable value on a distribution curve representing the variable in all EAs. The value in any EA is based on the variable value for the EA and for the EAs in the vicinity (neighbors) of the EA. The high score is expressed as a value of a spatial autocorrelation statistic, in this case G_i^* (Getis &

Ord, 1992), where i represents a particular EA. Having identified the key EA, then, in a series of steps additional EAs are added to the AMOEBA calculation only if the G_i^* of the group of EAs exceeds the value at the previous stage in the procedure (Figure 6). One of the properties of the G statistic is that if the key EA and the addition of further EAs increases the value of G_i^*, and the value exceeds the cutoff for statistical significance, a *cluster* (or neighborhood) of statistically significant EAs develops. The process of adding additional EAs comes to an end when there are no further increases in the value of G_i^*. The delimited cluster is then eliminated from further calculations and the process begins again. The procedure is complete when all statistically significant clusters are identified. These become the explicitly defined neighborhoods. If there is a need to have an exhaustive set of neighborhoods, the procedure can continue (without statistical significance) until all EAs become or are assigned to a neighborhood.

In Accra, homogeneous neighborhoods can be delineated which conform to important environmental, social, and health related variables. These neighborhoods make sense from a planning perspective. The hetereogeneity in Accra induced by a large immigrant population can be broken down into meaningful homogeneous neighborhoods. For this study, we select three of what may be called structures of the urban environment. Each can be defined and data gathered by EAs. The structures are: a slum index (Figure 7), a quality of housing index (see Figure 8), and a remotely sensed vegetation index. The first two of these are made up of a number of variables parsed from a principal components analysis. The vegetation index was created by identifying the appropriate spectral bands from a remotely sensed image of Accra. We then use AMOEBA to find neighborhoods based on each of these structures. The variables are taken from the 2000 Ghana Census for 1,717 enumeration areas (EAs) in Accra, Ghana, and remotely sensed data taken from a satellite image of the city averaged for each EA.

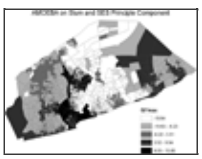


Figure 7

AMOEBA slum neighborhoods.

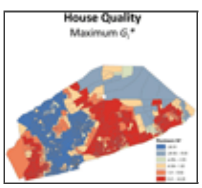


Figure 8

AMOEBA house quality neighborhoods. The blue values represent the lowest quality housing, while the red represents middle and upper income areas.

Techniques of Analysis: LOSH

The second procedure is a spatial variance analysis called *local spatial heteroscedasticity* (LOSH). For this we employ the H_i statistic to better understand the relationship between spatially overlapping variables (Ord & Getis, 2012). The statistic allows us to focus on the nature of the pattern of possibly spatially related variables. Values of the H_i statistic, in conjunction with the G_i^*, reveal the pattern of homogeneity or heterogeneity (Figure 9).

Figure 9

A hypothetical view of an urban region where the eastern area, outside of the urban region is non-urban with low G values, while the western area has low G values which excludes it from the cluster called Urban Region which has high G values. The H values **...**

As explained above, the local spatial statistic G_i^* identifies spatial association between a mapped point i

and the j points within distance d of i with respect to all j. It would be valuable to describe and assess the statistical distribution of the $\{x_j\}$ values that make up the cluster around i. This comment is consistent with the usual need to present summary statistics related to a data set. Examples of the usefulness of this assessment of LOSH are: a) exploring differential rates, such as disease rates, within a disease cluster, b) finding the degree of homogeneity or heterogeneity within an already delimited cluster, c) identifying trends in the homogeneity or heterogeneity surrounding a given ith observation, and d) identifying and testing for the existence of boundaries between districts. In addition, H_i can be used to study residuals of regression, including residuals from each equation created in a particular study in geographically weighted regression. Furthermore, the H-statistics may be used to define weights for generalized least squares.

To define a local mean about location i, we rescale G_i^* to the following form and use the x-bar notation:

$$\overline{\mathrm{x}}_i(d) = \frac{\sum_j w_{ij}(d)x_j}{\sum_j w_{ij}(d)} \tag{2}$$

Having defined the local mean for cell i, we may create "local residuals" of the form:

$$e_j(d) = x_j - \overline{\mathrm{x}}_j(d), j \in N(i,d) \tag{3}$$

These "residuals" have a zero weighted-mean over the local region of interest.

Using these local residuals we may explore local heterogeneity by using the local dispersion statistic:

$$H_i(d) = \frac{\sum_j w_{ij}(d)|e_j(d)|^a}{\sum_j w_{ij}(d)} \tag{4}$$

When $a = 1$ we have an absolute deviations measure, H_i1 and when $a = 2$ a variance measure, H_i2. Clearly other choices are possible, along with various robust forms to avoid outliers. In order to produce a standard measure, we should divide by the mean absolute deviation or variance for the whole data set. We may interpret the coefficients in the context of a search for "hot-spots"; that is areas with large Gi* values and considerable heterogeneity (e.g. city blocks with high crime interspersed with blocks of low crime) or homogeneity (uniformly high crime areas) (Figure 9):

There is no central limit effect and the distribution of variances is affected by non-normality. Fortunately it is possible to evaluate the mean and variance of the permutations distribution (i.e. considering the set of n! possible configurations as equally likely) and to approximate this distribution by a chi-square distribution. The expected value of the statistic, under random permutations, is

$$E_P(H_i) = 1 \tag{5}$$

The variance is:

$$Var_P(H_i) = \frac{1}{n-1}\left(\frac{1}{h_1 w_{i1}}\right)^2 (h_2 - h_1^2)[nW_{i2} - W_{i1}^2] \tag{6}$$

The chi-square distribution with *v* degrees of freedom has mean *v* and variance *2v*. If we match up the mean and variance with the values for the test statistic (with mean = *1* and variance = V_i say) we should use the statistic:

$$Z_i = 2H_i/V_i \text{with} 2/V_i \text{degrees of freedom.} \tag{7}$$

LOSH Applied to Accra

Figures 10, 11, and 12 show the three structures in our H_i framework. Note that in each of the maps, there is a high degree of heterogeneity in a north-south direction toward the middle of the urban area. This, in fact, is the area in which elevated numbers of migrants to Accra have settled. The already existing teeming slums in the eastern part of the city are not the destination of most migrants (based on data collected by Tuller, 2012). In fact, the correlation of slumness and number of migrants is −0.32, indicating that the migrants are not the very poor. Those who have come to Accra usually follow a two-step process, that is, they first settle on the cheap land outside of the city. When conditions are such that they can afford the city they move to the lower middle class areas, which are most prominent in the central portion of the Accra area. It is characteristic of Accra that some of the previously better-off neighborhoods are the destination of migrants who essentially service the well-to-do. Tuller (2012) has found that migrants are better educated than the non-mobile population. Literacy is at the 63% level for migrants and 54% for non-migrants.

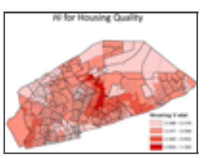


Figure 10

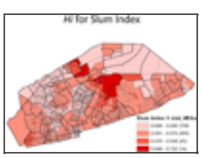


Figure 11

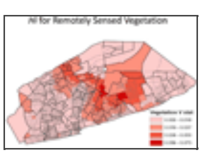


Figure 12

Using the huge traffic circle in the northeast quadrant of the city as a reference point, note that the most pronounced transition zones are just to the west on all three maps. House quality changes dramatically, “slumness” changes markedly and vegetation, which is a good indicator of wealth versus poverty in

Accra, also is discerned as heterogeneous between the high population density western areas and the much lighter density eastern areas.

A further map, Figure 13, shows, in more detail than can be identified on the scale of the other maps, the heterogenous-homogeneous nature of a prominent vernacular neighborhood called Nima. In Accra, mistakenly Nima is synonomous with slum. Figure 13 shows that there is a good deal of heterogeneity vis-a-vis slumness. It is only in the center of the district that there is a certain degree of slum homogeneity. Toward the north, the south, and the western edge slum heterogeneity is revealed by the H_i statistic.

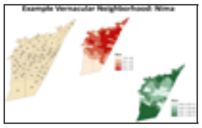


Figure 13
The middle map gives the degree of slumness in Nima; the worst areas are dark red. The map on the right shows the degree of heterogeneity in the EAs, the greatest in the very north and south and along the western edge.

6. Conclusion

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Using spatial statistics such as G_i^* and H_i reveal nuances and detail about the pattern of urban variables in any city. They are particularly well-suited for the study of rapidly growing third world urban environments. If traced over time, analytically derived neighborhoods can identify the evolution of new neighborhoods and alert planners to important changes in urban structure. In addition, by identifying heterogeneous areas, one can discern how migrations are affecting the development of neighborhoods. Anomalous conditions can be spotted quickly.

AMOEBA is an effective tool for identifying clusters. The LOSH statistics may be seen as a way to identify transitional regions within the study area. Studying urban structure using both AMOEBA and LOSH provides the opportunity to observe subtle characteristics of neighborhoods defined as either vernacular or analytical.

Acknowledgements

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Footnotes

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