Formulating a General Spatial Segregation Measure*

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Most traditional segregation measures, such as the index of dissimilarity *D*, fail to distinguish spatial patterns effectively. Previously proposed spatial measures modifying *D* suffer from several shortcomings. This article describes a general spatial segregation index based upon the concept of composite population counts, which are derived from grouping people in neighboring areas together to account implicitly for spatial interaction of groups across unit boundaries. The suggested spatial index can overcome the disadvantages of previous indices and can assess the spatial extent of the segregated clusters. The results offer a more comprehensive depiction of spatial segregation of a region. **Key Words: composite population counts, interaction, neighborhood definition, spatial extent, spatial segregation.**

Introduction

Researchers from various disciplines have proposed many measures to reflect the level of segregation (Kaplan and Holloway 1998). After an extensive evaluation of numerous segregation measures, Massey and Denton (1988) concluded that segregation has five dimensions: evenness, exposure, concentration, centralization, and clustering. They also suggested that the evenness dimension is the most important among the five dimensions, and the dissimilarity index *D* proposed by Duncan and Duncan (1955) is the most effective measure to capture the evenness dimension. Even though these five dimensions have very strong spatial connotations, and together they provide a rather comprehensive description of segregation, no single measure can capture multiple dimensions effectively to provide a coherent evaluation of segregation level. The classical checkerboard pattern suggested by White (1983) can serve as an example to illustrate that the *D* index is very effective in reflecting the evenness dimension but weak in capturing other dimensions.

A related issue with some existing segregation measures is to treat boundaries of enumeration units as impermeable boarders separating people. Morrill (1991) proposed *D(adj)*, an adjustment of *D*, to account for the spatial interaction between population groups across enumeration units. Later, Wong (1993) suggested several variations of *D(adj)* by incorporating more geographical factors likely affecting segregation among population groups across areal units.

The *D(adj)* index and its variations are relatively effective in capturing the distribution of population groups among neighboring units, but they suffer from two major shortcomings. Under very unusual spatial distribution patterns, the values of this set of spatial measures may not be bounded between 0 and 1. Even though this type of situation is remotely possible in reality, nonetheless, the 0–1 is a desirable mathematical property. Another limitation of the set of spatial indices is related to their effectiveness in reflecting the geographical scope of segregated neighborhoods. The geographical scope can be perceived as the spatial extent of the neighborhood, and it is related to the size and level facets of the scale issue (Marston 2000). To a large degree, they correspond to the concentration and clustering dimensions of segregation as identified by Massey and Denton (1988). The current specifications of *D(adj)* and its variations are only effective in capturing spatial segregation at the local scale (immediate neighbors), and thus they are limited to shedding light on the concentration and clustering dimensions, or the geographical scale of segregation.

The major objective of this article is to formulate a general spatial segregation measure that possesses the strengths of existing spatial segregation indices in distinguishing different population patterns but does not suffer severely from the two drawbacks discussed above. To

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address the problem related to the mathematical property of *D(adj)* and its variations, the concept of composite population count will be used (Wong 1998). To better identify the spatial extent of segregation, a flexible neighborhood definition is adopted and a multiscale approach to evaluate segregation is suggested. The next section will provide a brief review of relevant spatial segregation measures and demonstrate their two major limitations. The third section will present the formulation of the proposed general spatial measure. The fourth section will illustrate how the general measure can be used in a multiscale context to provide a more comprehensive documentation on the spatial extent of segregation. A conclusion will follow.

Review of Selected Spatial Segregation Measures

A Family of Spatial Segregation Measures

No doubt the most popular measure of segregation found in the literature is the dissimilarity index *D*. Formally, it is defined as

$$D = \frac{1}{2}\sum_i \left| \frac{w_i}{W} - \frac{b_i}{B} \right| \tag{1}$$

where b_i and w_i are black and white population counts in areal unit *i*, and *B* and *W* are the total black and white population counts of the entire study region, respectively, using the traditional two-group, black–white setting. Similar to many popular indices and measures, a very important and desirable property of *D* is that it ranges from 0 to 1, indicating no segregation to perfect segregation, respectively.

On the other hand, *D* has severe limitations in reflecting spatial segregation. *D* is partly a function of the level of internal homogeneity of each areal unit. If each unit is exclusively dominated by one population group, regardless of how the population is arranged among areal units spatially, the *D* value will be one, indicating a perfectly segregated situation. A major problem with the formulation of *D* is that it treats enumeration unit boundaries as actual boundaries separating people across units, and thus boundaries inhibit interaction or mixing among groups. This is a problem also shared by other aspatial segregation measures. A checkerboard configuration was adopted by Morrill (1991) and Wong (1993) to demonstrate how ineffective *D* is in capturing spatial segregation.

To formulate a spatial measure of segregation such that different population groups in neighboring units are not treated as spatially separated (Newby 1982), Morrill suggested that *D* be adjusted by incorporating a spatial adjacency term that will capture interaction of population groups across unit boundaries. Formally, the proposed index *D(adj)* is defined as

$$D(adj) = D - \frac{\sum_i \sum_j \left| c_{ij}{}^*(z_i - z_j) \right|}{\sum_i \sum_j c_{ij}} \tag{2}$$

where *D* is defined as before, z_i and z_j are the proportions of minority (or majority) of areal units *i* and *j*, respectively. While c_{ij} will be zero if *i* and *j* are not neighbors, it will be 1 if *i* and *j* are adjacent to each other. What the second term in *D(adj)* attempted to capture is the potential interaction of the two population groups in neighboring units if there is a differential in racial or ethnic mix. Then, the level of segregation evaluated by *D*, without considering the interaction of neighboring groups, is diminished or moderated by the potential interaction captured in the second term of the *D(adj)* index. Subsequently, *D(adj)* was modified further to become (1) *D(w)* to account for the varying intensity of interaction between neighboring units due to the variable lengths of shared boundaries and (2) *D(s)* to account for the compactness of neighboring units (Wong 1993). Recent studies indicate that, in most cases, the largest differences are found between *D* and *D(adj)*, but not between *D* and other spatial modifications of *D* (Wong 2004). Therefore, this article will focus mainly on *D(adj)*.

Limitations of Existing Spatial Segregation Measures

Even though the spatial measure *D(adj)* can account for the interaction among population groups across enumeration units, it is still limited in addressing the concentration and clustering dimensions of segregation. In Figure 1, three hypothetical population distribution patterns (b, c, and d) were generated based upon the original pattern of Washington, DC (a) according to the 2000 Census at the census tract level. The three hypothetical patterns were generated by swapping the white and black population in a certain tract with another tract. This swapping process was performed in multiple tracts to generate new patterns of population distribution. The three generated patterns (b, c, and d) are different from the original one in terms of the regional or macro distribution pattern. The original Washington, DC pattern (a) is characterized by the dominance of whites in the north and northwest, a few tracts around the center, and a small cluster on the east. Pattern (b) has more, but smaller clusters of whites with many mixed neighborhoods. Patterns (c) and (d) also have several white clusters, but each cluster has a higher concentration of whites or is more distinct from the surrounding areas, especially for pattern (d).

Even though the three generated patterns exhibit regional patterns different from the original distribution, they are not distinguishable by most existing measures of segregation, both aspatial and spatial. The first five columns in Table 1 report values based upon several segregation measures, both traditional (*D*) and spatial (*D(adj)*, *D(w)*, and *D(s)*), for the four population patterns described in Figure 1. As expected, because the population relocation process preserved the population mix in the swapping units, the *D* values for all these patterns are the same: 0.7738. Even though all spatial measures vary slightly among the four spatial patterns, they fail to distinguish these patterns effectively. One may find it difficult to judge which of the three generated patterns has the lowest level of segregation, but it should be quite obvious that all three generated patterns should have a lower level of segregation than the actual one (a). Unfortunately, even spatial measures fail to support this conclusion derived from visual inspection because these spatial measures are limited to comparing population mix in the immediate neighborhood or at a local scale without referring to the regional spatial patterns.

Another issue with the family of *D*-adjusted spatial indices is their mathematical properties. The theoretical maximum of *D(adj)* is 1, but the minimum is not 0. It is possible that the second term in Equation 2, which reflects the potential interaction between groups in neighboring units, can be slightly positive when a few neighboring units are very different in population mix, while the overall segregation level of the entire region is very low (*D* is very close to zero) because of a relatively even distribution of the two groups. Then *D(adj)* could be slightly negative in this unusual situation. Figure 2A indicates such a hypothetical situation with two population groups: A and B. Each unit in Figure 2A has one hundred people. The two groups have an equal share in 140 units out of a total of 144. This overall pattern should yield a very low level of segregation. But in the middle of the region (in fact, it can be anywhere in the region), four adjacent units are exclusively dominated by one or the other group. The potential interaction between the two groups among these units is very high and thus creates a positive value in the second term of Equation 2. As a result, the region gives a *D* value of 0.0278 and *D(adj)* value of −0.0008. The two other spatial measures, *D(w)* and *D(s)*, are virtually zeros.

In empirical studies, the odds that the above hypothetical or similar situations will arise are extremely low, and the values of these indices should not be interpreted in absolute, but in relative, terms. Nevertheless, it is desirable to have an index or any indicator with a more preferable theoretical range of 0–1.

A General Spatial Segregation Measure

In addition to the desirable 0–1-bounded property, a preferable spatial segregation measure should be able to capture the spatial dimension of segregation effectively. Instead of capturing the potential spatial interaction between population groups among areal units explicitly, as in

Table 1 *The Values of D, Its Spatial Versions D(adj), D(w), and D(s), and the Generalized Index (GD) for Washington, DC, 2000 Census Tract Data (a), and Its Three Generated Configurations (b, c, and d)*

	D	D(adj)	D(W)	D(s)	GD (neighbor)
a. DC.	0.7738	0.5087	0.5433	0.6482	0.4932
b. Generated	0.7738	0.5052	0.5269	0.6459	0.4711
c. Generated	0.7738	0.5092	0.5301	0.6476	0.4745
d. Generated	0.7738	0.5088	0.5221	0.6455	0.4455

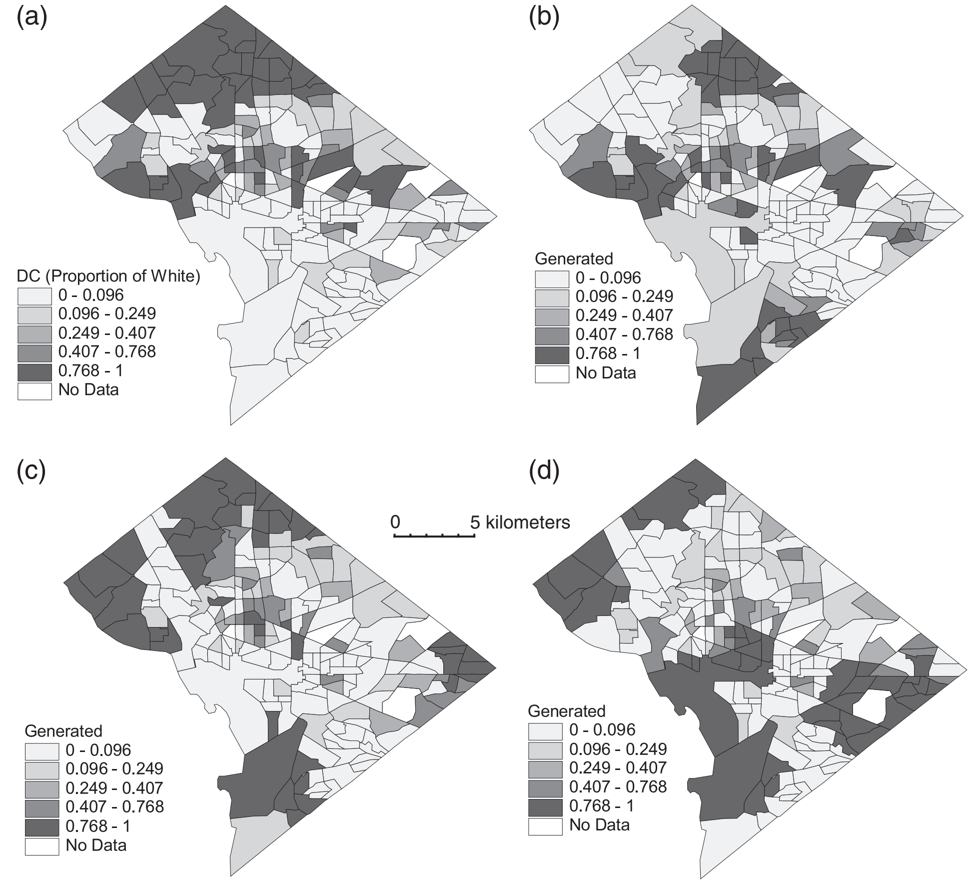

Figure 1 *Proportions of white for Washington, DC 2002 census tract data (a) and its three generated configurations (b, c, and d).*

the formulation of *D(adj)*, by adjusting the level of *D*, it is possible to capture the interaction information indirectly by using the concept of composite population counts (Wong 1998), which treat different population groups in neighboring units as if they are in the same unit. The composite population count, for instance, of whites in areal unit *i* is defined as

$$cw_i = \sum_r d(w_r) \tag{3}$$

where w_r is the white population count in areal unit *r*, d(.) is a function defining the neighborhood of *i*, *r* refers to an areal unit within the study region, and *r* can be *i*. Similarly, we can define cb_i, the composite population count of blacks in areal unit *i*, in the same manner as in Equation 3 by using b_r. Essentially, these composite counts include populations in the neighboring units of *i* such that people in different population groups within the neighborhood of *i* can interact as if they are in the same unit as in *i*. Based upon these composite population counts, a spatial segregation index, *GD*, computed in the same way as *D*, can be defined as

$$GD = \frac{1}{2}\sum_i \left| \frac{cw_i}{\sum_i cw_i} - \frac{cb_i}{\sum_i cb_i} \right| \tag{4}$$

where the denominators are the total composite population counts of whites and blacks for the entire study area. The *GD* index is bounded between 0 and 1, as its computation is essentially identical to *D*, but using composite population counts with a spatial connotation. On the other hand, this measure accounts for the potential

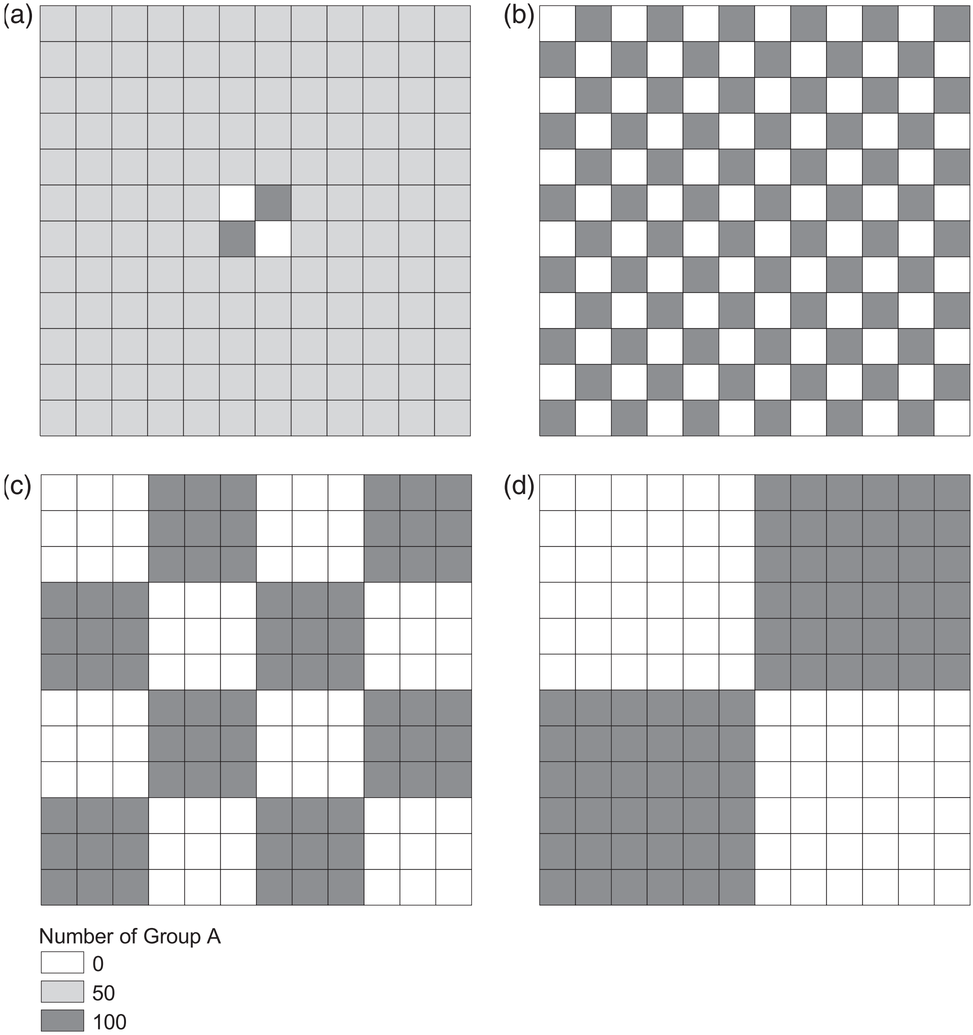

Figure 2 *The hypothetical configuration (a), which gives spatial indices a slight negative value, and three configurations (b, c, and d) with different degrees of spatial clustering.*

spatial interaction between groups among neighboring units. Procedurally, the composite population counts, cw_i and cb_i, are computed first for each areal unit in the study region to derive the total composite population counts of the two groups before executing Equation 4. The computation procedure for cw_i and cb_i is similar to the process of deriving spatial moving averages for each areal unit in the study region, but the moving window is not constant in size and shape, as the neighborhoods of different units of *i* will be not be the same in the irregular polygon structure.

Using *GD*, and the immediate neighboring units as defined by the rook's case, the configuration shown in Figure 2A will have a value of 0.0179, slightly lower than the aspatial *D* of 0.0278, because the potential interaction between the two groups in the center units is accounted for by *GD*. Using the Washington, DC example again, the last column in Table 1 is the *GD* index. Because there are many ways to define the neighborhood of a given areal unit *i*, all units adjacent to *i* will be counted as the neighborhood of *i*. The *GD* value for Washington, DC is slightly lowered than *D(adj)*. The *GD* values for the other generated configurations of Washington DC are lowered than the original configuration as expected. This trend is reasonable in the sense that the original clusters of whites in the north and northwest District of Columbia are dispersed to other parts of the region in the generated configurations, and thus the levels of segregation should be lowered in those hypothetical configurations. In other words, *GD* can discriminate the spatial distribution patterns of population more effectively than *D(adj)*. However, a stronger power of discrimination is warranted.

Spatial Extent of Segregation

In order to provide a stronger power to discriminate different spatial distribution patterns, ideas from ordered neighbor analysis may be useful in enhancing the power of *GD* to identify the spatial extent of segregation (Boots and Getis 1988). The four maps in Figure 1 exhibit different distribution patterns in terms of the size of clusters. In general, besides the population ethnic mix, the overall level of segregation is also determined by the size of the population clusters and the difference in population mix between the clusters and their neighbors. Large clusters preclude more people within the clusters interacting with other groups outside the clusters, while small clusters with relatively high concentration of one group may not create a highly segregated situation if neighbors of the clusters are heavily populated by the other group such that intergroup interaction across units is feasible.

The original Washington, DC configuration primarily has one big cluster of whites in the north and a stretch of clusters slightly north of the city center. Among all four maps, the original one has probably the largest patch of white population. Patches of whites in Figure 1B are probably the smallest in size among the four maps, but neighbors of those patches are usually not dominated by blacks. Therefore, its spatial segregation level (according to the *GD* values in Table 1) is lower than the original Washington, DC, configuration, but not as low as the configuration in Figure 1D, where many small patches of whites are adjacent to blacks-dominant units. Patches or clusters in Figure 1c are bigger than those in Figures 1B and 1D, but smaller than that in Figure 1A. Therefore, its *GD* level ranks the second among the four.

The above interpretations of the *GD* levels are feasible only with the assistance of maps. Without the maps, the four *GD* values in Table 1 may not help one understand the different sizes of clusters of whites depicted by the four spatial systems. The interpretations of the *GD* values are in the light of the size of the cluster. To detect different sizes of the clusters, the neighborhood function *d*(.) in Equation 3 can be modified. As suggested in the literature on ordered neighbor statistics, the nearest-neighbor statistic can capture local effect, while higher-order statistics (second or third nearest neighbors) can capture the regional effect. To provide a more comprehensive description of the segregation clustering pattern, the neighborhood function *d*(.) can take on a range of sizes to provide a better discrimination among distribution patterns. This idea is similar to the expanding circle framework used in the K-function analysis (Ripley 1976).

The hypothetical configurations in Figures 2B to 2D include clusters of various sizes. Figure 2B is a typical checkerboard pattern, while Figures 2C and 2D are configurations with increasing cluster sizes with total population counts of the two groups kept constant in these configurations. Given these configurations, the definition of neighborhood can take on various spatial extents. In this specific example, neighbors are defined according to the queen's criterion for illustration purpose. Therefore, the first-order neighbors will include the units directly to the east, west, north, and south, plus the four diagonal neighbors. The second-order neighbors will include those units one "ring" beyond the first-order neighbors, also using the queen's criterion.

Figure 3 shows the *GD* values of the hypothetical configurations in Figure 2 (b, c, and d only) according to various neighborhood definitions. The figure reveals several interesting aspects of using this approach to evaluate segregation. First, the *D* values of all three hypothetical configurations are 1, indicating perfect segregation because each areal unit is dominated by either group, regardless of how a pattern differs from others. Second, in general,

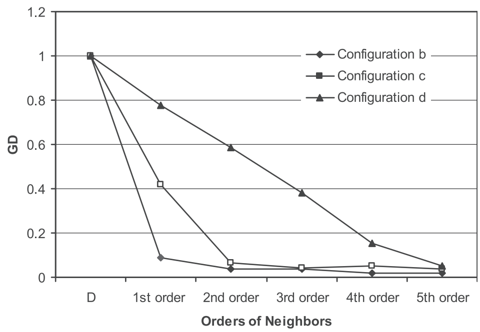

Figure 3 *Changes in the GD Index for the three hypothetical configurations with higher-order neighbors are used.*

as the neighborhood function extends to include higher order neighbors, the value of *GD* declines, indicating that additional units of more heterogeneous population mix are counted as neighbors to compute the composite population counts, and thus the level of segregation declines. Third, the pattern of decline in the *GD* values is related to the size of the segregated neighborhoods or clusters. The configuration in Figure 2B has the smallest clusters. When the neighborhood definition extends from no neighbors (i.e., *D*) to first-order neighbors, the level of segregation declines from 1 (when there is no interaction beyond one's areal unit) to almost zero (when interaction is limited to the immediate neighbors). In contrast, the configuration in Figure 2D has the largest clusters. As the neighborhood definition in computing the composite population counts expands, more heterogeneous areal units are included, but gradually, and thus the decline in *GD* value has not been as dramatic as in the configuration in Figure 2B. What is observed in Figure 2B also happens to the configuration in Figure 2C, which has intermediate-size clusters. *GD* values for Figure 2C do not decline as much as that for the configuration in Figure 2B, as reflected in Figure 3 when the first-order neighborhood definition is used. But when the neighborhood definition expands to include the second-order neighbors, the *GD* value declines to almost zero because the clusters in Figure 2C are bigger than those in Figure 2B, and the size of the clusters resembles the size of the neighborhood using the second-order neighbors.

Back to the Washington, DC example, Figure 4 shows the *GD* values using different neighborhood definitions. After computing the centroid distances between all possible pairs of census tract in Washington, DC (a 188 × 188 distance matrix), the minimum, maximum, and average distances of each tract to all other tracts were derived. Subsequently, the averages of the minimum, mean, and maximum among all units were derived to provide regional summary statistics in terms of the distances between pairs of tracts. Approximately, the average minimum, mean, and maximum distances between tract centroids are 0.4 miles, 4 miles, and 8.67 miles, respectively. Using these distances, three neighborhood definitions are formed: the average minimum distance, *d*(min), the average mean distance, *d*(mean), and the average maximum distance, *d*(max). The *d*(neighbor) definition, which is also used in computing *GD* in the last column in Table 1, is also used here. It includes only the adjacent units (i.e., the queen's case) as neighbors. Implicitly, the computation adopts different distance limits at which people can interact. Using *d*(neighbor) assumes that people can interact with other groups among the adjacent units only, while using *d*(max) allows people to interact as far as 8.67 miles in this example. Theoretically, one could use many more distance values to define the neighborhood in an incremental manner and to derive sets of composite population counts with different spatial extents as in the K-function analysis (Ripley 1976). But for illustration purposes, this article explores only four neighborhood sizes.

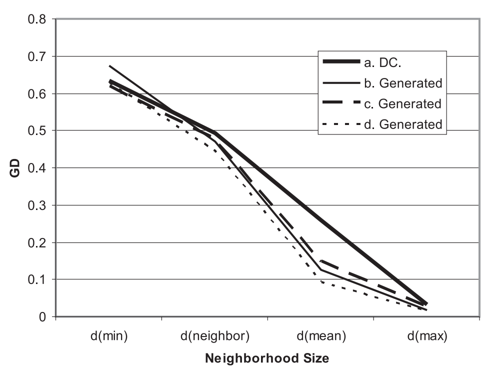

Figure 4 *Changes in the GD Index for Washington, DC (a) and three generated configurations (b, c, and d) when neighborhoods of different sizes are used.*

In general, the levels of spatial segregation reflected by *GD* decline as the size of the neighborhood definition increases in Figure 4, which can be interpreted in the same way as Figure 3. That is, if people are allowed to interact only locally, such as using *d*(min), the level of segregation will be relatively high, because population mix in the local area tends to be relatively homogeneous. If they are allowed to interact with people much farther away, using *d*(max) as the definition, the spatial segregation level will be much lower. However, an interesting observation in Figure 4 is that all generated configurations experience faster declines in spatial segregation levels than the original Washington, DC configuration. This situation is mainly attributable to the fact that clusters of whites and blacks in the original configuration are much larger than the clusters in the other generated configurations. As the neighborhood definition extends to *d*(mean), which is approximately 4 miles, a significant number of the population in the other groups is found within the neighborhoods in those generated configurations, but not in the original Washington, DC configuration. Therefore, the *GD* values of those generated configurations decline more rapidly than the original configuration. Using *d*(mean) as the neighborhood definition, configuration *d* has the lowest spatial segregation. It is partly because many units dominated by blacks are found within the neighborhoods (four miles) of those white clusters.

The definitions of neighborhood adopted so far implicitly assume that everyone within a given distance from a reference unit will interact with the people in the reference unit, regardless of how far they are from each other. However, the general "law" in geography, Tobler's First Law, and the literature in spatial interaction tell us that relationship diminishes over distance and people farther apart will have a lower intensity of interaction than people closer to each other. Using a binary "in-or-out" definition of neighborhood based purely upon distance is not too realistic. As spatial segregation has a spatial interaction connotation, the distance-decay parameter used in modeling spatial interaction can also be used to improve the neighborhood definition (Fotheringham and O'Kelly 1989).

In general, spatial interaction declines as distance increases. To model this inversed relationship between interaction intensity and distance, the weight in the model is usually the inversed distance weight, $1/d$. But many empirical studies reveal that a good specification of the weight is $1/d^{\alpha}$, where α, the distance decay parameter, is best to be 2. The value of the distance decay parameter may be derived or calibrated empirically, based upon data on commuting or travel. But without commuting data to determine a specific value for α, one may adopt a range of value to experiment how sensitive the result may be due to varying parameter values. In general, a larger α implies that the interaction is very sensitive to an increase in distance and that a slight increase in distance will dramatically reduce spatial interaction, and vice versa. In other words, using a large α forces the population to interact locally, and a smaller α facilitates longer distance interaction.

In Figure 5, a range of α is used to compute the *GD* level of Washington, DC and its three derived configurations. The parameter α on the *x*-axis ranges from 4 to 1, implying from very localized interaction to regionwide interaction. As expected, spatial segregation level declines as the parameter relaxes (becomes smaller) to facilitate spatial interaction, but the impacts on segregation are not obvious until the parameter declines to 2. If the interaction is restricted to a very local scale, both the original Washington, DC configuration and configuration *b* have the highest level of segregation. The original Washington, DC configuration remains with the highest segregation level even when the

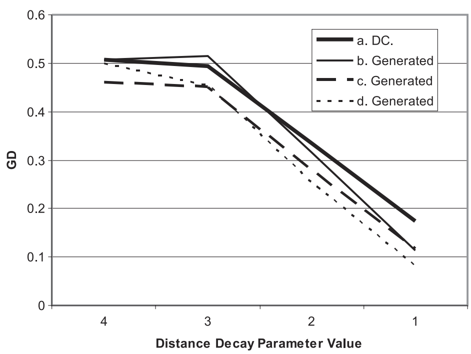

Figure 5 *Changes in the GD Index for Washington, DC (a) and three generated configurations (b, c, and d) when the distance decay parameter decreases from 4 to 1.*

parameter is relaxed to 1, while configuration *d* has the lowest level of segregation when the parameter is 2 or smaller as areal units dominated by the two population groups are close enough to allow interaction.

Summary and Discussion

The general spatial segregation measure proposed in this article is based upon the premise that interaction among population groups should not be constrained by the artificial boundaries of statistical enumeration units. People in different areal units can interact and are not perfectly segregated by enumeration boundaries if there are no effective physical or administrative barriers stopping people from interacting. The concept of composite population count, which treats people in the neighboring units as if in the reference unit, implicitly allows people in neighboring units to interact. The general spatial segregation measure is built upon this concept. The proposed index is spatial in nature, and its value is bounded between 0 and 1, a criterion that some previous spatial segregation measures fail to meet when very unusual spatial configurations are evaluated.

This article further elaborates the neighborhood concept adopted in computing composite population counts. Instead of using a fixed-size neighborhood, a flexible neighborhood definition framework was suggested in order to evaluate the spatial extent or the scale of segregated neighborhoods. In the implementation, the flexible neighborhood definition can accommodate different distances to define neighborhoods on one hand, and, on the other hand, different values for the distance decay parameter can be used in the inversed distance weight function to model interaction intensity. The flexible neighborhood framework enables the discrete delineation of neighborhood in different sizes (or areal extents). By using various sizes to define the neighborhood, the results may reveal the spatial extent of segregation or identify the size of the segregation clusters to reflect one of the clustering and concentration dimensions of segregation.

This approach is similar to the formulation of the G-statistic in studying spatial association (Getis and Ord 1992). The introduction of the distance decay parameter in the neighborhood definition avoids the discrete delineation of a neighborhood. Instead, interaction among population groups is now governed by distance decay behavior. This article relates the distance-weight function and the decay parameter in the power form, but other specifications, such as the exponential form, can also be used (Fotheringham and O'Kelly 1989). Though numerous measures of segregation have been introduced, no measure so far has been able to offer a discriminating power to distinguish different population patterns superior to *D(adj)* (Wong 1993). But the empirical study in this article indicates that *GD* out-performs *D(adj)*, which had been the most effective segregation measure.

The current approach in detecting the spatial extent or size of segregation has its limitations. Similar to the limitation of K-function analysis in detecting clusters of points with variable sizes, the current method in describing the spatial extent of spatial segregation will encounter the same problem. If the segregation clusters vary significantly in size, changing the neighborhood definition may not make it possible to detect the spatial extent of segregation effectively. This is because *GD*, similar to most segregation measures, is a summary or global measure. Global measures are not effective in handling spatial heterogeneity, and local approaches are warranted to evaluate local or subregional patterns of segregation (Wong 2002). ■

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