

SPATIAL SEGREGATION MEASURES: A METHODOLOGICAL REVIEW

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ABSTRACT

Quantitative indices of segregation are powerful tools for summarising the spatial relationships between population groups and thereby providing the basis for analysis and public policy intervention. While the broad concept of segregation may be intuitive, measurement is challenging because of the complexity of varied dimensions and spatial arrangements. Many traditional measures can be criticised for over-simplification or over-reduction, not least in their treatment of geographical space. Over the last several decades, however, a series of measures has been developed to explicitly incorporate the spatial arrangement of population groups as well as their interactions. This paper reviews the development of spatial segregation measures, particularly focusing on the mathematical formulation of spatial arrangement/relations. In addition, several related issues are discussed, including representation of spatial interaction, spatial scale and statistical inferences. Also, this paper presents an overview of existing software tools that are readily available for calculating some of the reviewed measures. Finally, discussions on challenges and future research are provided.

Key words: Segregation, spatial, geographical information system (GIS), quantitative indices

INTRODUCTION

Segregation can be broadly defined as the degree of spatial separation between two or more population groups in a region (e.g. Newby 1982). The uneven distribution of groups across urban space has long been a fundamental characteristic of modern cities (Lloyd *et al.* 2015; Wong 2016). On the one hand, segregation reflects social inequalities, and tells us something about how these inequalities are changing, as current debates on the suburbanisation of poverty show. They also reflect wider factors, notably historic inequalities or patterns of land use, as well as past efforts in planning intervention. On the

other hand, segregation is important for its influence on society and social relations. Many argue that it acts as a positive feedback mechanism, exacerbating inequalities not just reflecting them; this is the thrust of the neighbourhood effects literature (e.g. van Ham *et al.* 2012). Others see current levels of segregation as benign or even advantageous for society. No matter how segregation affects social welfare, better understating the degree and nature of segregation in a region is critical to effective policy making in relation to social equity (Johnston *et al.* 2014).

There has been a long history of efforts to derive measures which summarise segregation, reducing the complexity of spatial

relations to a single indicator. Debate occurred around the different dimensions along which segregation could be conceptualised (Massey & Denton 1988) and around the principles on which measures should be selected (James & Taeuber 1985). For example, Massey and Denton (1988) proposed five dimensions of segregation: **evenness, exposure-isolation, concentration, centralisation and clustering**. It has also been argued, however, that they can be reduced to **evenness-clustering** and **exposure-isolation** (Reardon & O'Sullivan 2004), **evenness-concentration** and **clustering-exposure** (Brown & Chung 2006), or the super-dimensions of **separateness (summarising (un)evenness, isolation, and clustering) and location (summarising concentration and centralisation)** (Johnston *et al.* 2007). Apparently, the five dimensions overlap. Therefore, using them to classify or evaluate segregation measures may be confusing.

Further, the development of segregation measures has gone through several phases with different emphases. Sociologists and demographers led efforts initially. These measures evaluate the population distribution across areal units, population mix and potential interaction within areal units. The one most well-known might be the **dissimilarity index D** (Duncan & Duncan 1955a), which can be formulated as in (1):

$$D = \frac{1}{2} \sum_i \left| \frac{p_{i,g}}{p_g} - \frac{p_{i,\bar{g}}}{p_{\bar{g}}} \right|, \quad (1)$$

where i is the index of spatial unit; g, \bar{g} represent two population groups; $p_g, p_{\bar{g}}$ are total population of the two groups in the entire study region; $p_{i,g}, p_{i,\bar{g}}$ are population of groups g, \bar{g} in spatial unit i , respectively.

Most of these measures like D share a number of significant limitations. **First**, they throw away a great deal of spatial information, **treating the urban system as being composed of discrete units**, each divorced from surrounding areas as if it was an island. **Second**, they **focus on a global summary for a city or region**, assuming spatial relations are consistent across that place. **Third**, they **look at residential space without paying attention to the varied**

locations in which people spend time across the course of a day.

A typical example is the 'checkerboard problem' (White 1983) that is often used to investigate the properties of segregation measures (Wong 1999, 2002a; Dawkins 2004; Harris 2016), as shown in Figure 1. **The four arrangements reflect different levels of segregation in most people's perceptions**. However, the values of D are the same, namely, it fails to distinguish between different spatial arrangements. In fact, the value of D will always be 1 as long as each spatial unit is occupied exclusively by one population group (White 1983; Morrill 1991; Wong 1993).

Recently, there have been varied attempts to overcome these limitations. Some researchers incorporated spatial elements into non-spatial indices to create the spatial versions of these measures (e.g. White 1983; Morrill 1991; Wong 1993, 2002a, 2005; Reardon & O'Sullivan 2004). Others used inherently spatial measures, such as the centrophraphic measures, to summarise point locations (e.g. Wong 1999; O'Sullivan & Wong 2007). From a spatial perspective, segregated situations are often expected to have certain population groups highly clustered around certain areas. Spatial autocorrelation statistics have been used to evaluate the degree of similarity between neighbouring values and researchers have suggested using different spatial autocorrelation statistics to measure segregation (e.g. O'Sullivan & Wong 2007).

All the above methods are bounded by the ecological approach and concerned about the residential pattern. **Analysis is based on census or administrative units** and data are aggregated population counts by groups. **But the segregation notion refers to one's experience with other population groups, and the experience extends from residential space to other socio-economic spaces**. Thus, a new set of measures considering the activity patterns of individuals, and their interaction with other groups has been proposed (e.g. Wong & Shaw 2011; Farber *et al.* 2015).

The aim of this paper is to review the development of spatial segregation measures following the four approaches described above. In addition, several related concepts relevant to implementing those indices,

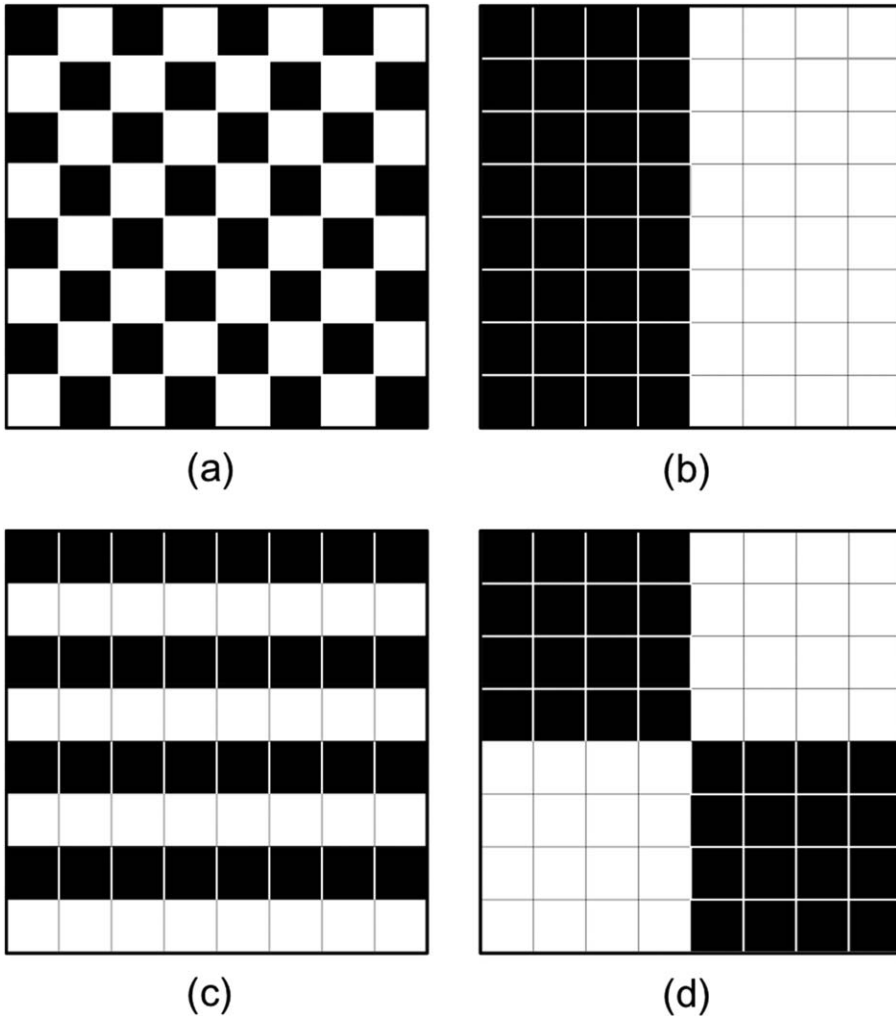


Figure 1. Examples of the ‘checkerboard’ problem (four different spatial layouts of two population groups represented by black and white grid cells).

including representation of spatial interaction, spatial scales and statistical inference, are discussed. The motivation is both to enable researchers to **make more informed choices between them** but also to encourage their use in both academic and **policy-related applications**, so that we can achieve more sophisticated discussions about the meaning and importance of segregation.

This paper has two distinct contributions to existing literature. One is we discuss the significance testing of spatial segregation indices and present off-the-shelf software

tools that can implement various spatial segregation measures, which has been ignored in previous reviews. The other is we discuss the challenges posed by two conceptual and methodological issues in the studies of segregation measures.

SPATIAL INDICES FOR URBAN SEGREGATION

This section reviews spatial indices following the four approaches that characterise the

development of spatial segregation measures, but is divided into five subsections. Efforts in spatialising traditional measures can be divided into two groups. We review the first group focusing on the family of **dissimilarity indices** often used in **racial-ethnic segregation** where the population is divided into discrete classes. Then we review the second group which belongs to the family of ordered indices focusing on **income segregation or inequality**. Following on we review the second approach using spatial distribution indices to summarise population distributions. Then we discuss how spatial **clustering statistics are used to reflect segregation**. Spatial indices exploiting the activity space concept are then reviewed. Table 1 summarises all the measures included in this review.

Spatial dissimilarity indices for discrete population groups – Several extensions of D explicitly incorporate spatial relationships between population groups in evaluating segregation levels. Examples include the work by White (1983), Morrill (1991), Wong (1993, 1998, 2005) and Reardon and O'Sullivan (2004).

Distance is a fundamental metric to reflect the spatial relationship between geographical features and people. The index of spatial proximity (SP) by White (1983) utilises a distance function to represent how the potential for social interactions changes with distance. SP can be viewed as an average of intragroup proximities, weighted by the proportions of each population group. It has a value of 1 if there is no difference in the distribution of population groups, while **$SP > 1$ indicates clustering of people of the same group** whereas **$SP < 1$ implies members of one group live closer to another group**. Grannis (2002) extended SP for the case of multiple population groups.

The distance metric can be reduced to adjacency, a topological concept that indicates spatial relationship. **Adjacency has been used extensively to capture relationships between areal units in modelling spatial autocorrelation.** Morrill (1991) incorporates a spatial adjacency term w_{ij} in D to represent the potential spatial interaction among

population groups. The adjusted index $D(adj)$ is defined as:

$$D(adj) = D - \frac{\sum_i \sum_j |w_{ij}(z_{i,g} - z_{j,g})|}{\sum_i \sum_j w_{ij}}, \quad (2)$$

where $z_{i,g}$ and $z_{j,g}$ are the proportions of group g in spatial units i and j , respectively; w_{ij} has a value of 1 if units i and j are adjacent or 0 otherwise. **The formulation of D implies that populations in neighbouring units do not interact, as the boundary is treated as an absolute barrier of interaction.** Given that most boundaries are not hard barriers to interaction, the second term in (2) was introduced to reflect the spatial interaction between adjacent units. If population shares between neighbouring units are different, interaction between these populations will lower segregation level. Subsequently, Wong (1993) proposed two modified versions of $D(adj)$: $D(w)$, which assumes longer shared boundaries between units enable more spatial interaction, and $D(s)$, which assumes the compactness of neighbouring units affects interaction between units.

The dissimilarity index D and its spatial versions have a practical limitation: **they compare only two groups while many societies have multiple racial-ethnic and socio-economic groups.** Morgan (1975) and Sakoda (1981) proposed a version for multiple groups, $D(m)$. Similar to D , $D(m)$ assumes no interaction among populations in neighbouring units and is therefore aspatial. Wong (1998) proposed the spatial version, $SD(m)$, which has a structure identical to $D(m)$. What makes $SD(m)$ spatial is the use of the composite population counts instead of the original population counts. The composite population count of a unit includes the population in the reference unit and populations in neighbouring units, removing the unit boundaries as the barriers to interaction. In other words, the concept of composite population counts assumes populations in neighbouring units are mixed and should be counted toward the reference unit.

Wong (2005) argued that the composite population counts can replace the original population counts in D , and proposed a

Table 1. *Summary of segregation measures.*

| Category | Description | Author | Software | | | |
|--|--|-----------------------------------|----------------------|----------------------|---------------------------------|-------|
| | | | ArcView extension | 'seg' (R package) | Geo- Segregation Analyser | Oasis |
| Non-spatial | Dissimilarity index | Duncan and Duncan (1955a) | ✓ | ✓ | ✓ | ✓ |
| | Gini index | Duncan and Duncan (1955a) | | | ✓ | |
| | Centralisation index | Duncan and Duncan (1955b) | | | ✓ | |
| | Multi-group dissimilarity index | Morgan (1975), Sakoda (1981) | ✓ | | ✓ | ✓ |
| | Exposure index | Liebertson (1981) | | | | |
| | Neighbourhood sorting index (NSI) | Jargowsky (1996) | | | | |
| | Typology for classifying ethnic residential areas | Poulsen <i>et al.</i> (2001 2002) | | | ✓ | |
| Spatial Spatial Dissimilarity Indices for Dis- crete Population Groups | Location Quotient (LQ) | Brown and Chung (2006) | | | ✓ | ✓ |
| | Spatial proximity (SP) index | White (1983) | | ✓ | ✓ | |
| | Multi-group SP | Grannis (2002) | | | | |
| | Dissimilarity index incorporating spatial adjacency | Morrill (1991) | ✓ | ✓ | ✓ | ✓ |
| | Dssimilarity index incorporating common boundary lengths | Wong (1993) | ✓ | ✓ | ✓ | ✓ |
| | Dssimilarity index incorporating common boundary lengths and perimeter/area ratio | Wong (1993) | ✓ | ✓ | ✓ | ✓ |
| | Spatial version of multigroup dissimilarity index | Wong (1998) | ✓ | | ✓ | ✓ |
| | General index of spatial segregation | Wong (2005) | | | | |
| | Spatial dissimilarity index | Reardon and O'Sullivan (2004) | | ✓ | | |
| | Spatial information theory index | Reardon and O'Sullivan (2004) | | ✓ | | |
| | Generalised spatial dissimilarity (GSD) index | Feitosa <i>et al.</i> (2007) | | | | |
| | Local GSD | Feitosa <i>et al.</i> (2007) | | | | |

Table 1: *Continued*

| Category | Description | Author | Software | | | |
|---|---|------------------------------|-------------------|-------------------|--------------------------|-------|
| | | | ArcView extension | 'seg' (R package) | Geo-Segregation Analyser | Oasis |
| Income Segregation Indices for Ordered Groups | Generalised NSI | Jargowsky and Kim (2005) | | | | |
| | Spatial NSI | Feitosa <i>et al.</i> (2007) | | | | |
| | Spatial rank-order entropy index | Reardon <i>et al.</i> (2006) | | | | |
| | Standardised spatial Gini index (G_{ST}) | Dawkins (2004) | | | | |
| | Spatial ordering index as an extension of G_{ST} | Dawkins (2007) | | | | |
| | Localised version of centralisation index | Folch and Rey (2014) | | | | |
| Spatial Distribution Indices | Ellipse-based index | Wong (1999) | ✓ | | ✓ | |
| | Surface-based index | O'Sullivan and Wong (2007) | | | | |
| Spatial Clustering Indices | focal LQ | Cromley and Hanink (2012) | | | | |
| | Local Moran's I | Anselin (1995) | | | | ✓ |
| | Getis-Ord local G | Getis and Ord (1992) | | | | |
| | Local segregation index incorporating spatial interaction | Wong (2002a) | ✓ | | | |
| | Extension of Getis-Ord local G incorporating ordinal social classes | Meng <i>et al.</i> (2006) | | | | |
| Indices applied to Activity Space | Socio-spatial isolation indices | Schnell and Yoav (2001) | | | | |
| | Exposure index using individuals' activity spaces | Wong and Shaw (2011) | | | | |
| | Exposure index incorporating trip lengths | Farber <i>et al.</i> (2012) | | | | |
| | Index of social interaction potential | Farber <i>et al.</i> (2013) | | | | |
| | Exposure index using space-time prisms | Farber <i>et al.</i> (2015) | | | | |

general index of spatial segregation, GD , which is a function of neighbourhood size. Computing GD over a range of neighbourhood sizes can depict how segregation varies with geographical scale (Wong 2005).

The concept of composite population counts was adopted in several subsequent developments. Reardon and O'Sullivan (2004) developed a set of spatial segregation indices, including a spatial dissimilarity index \tilde{D} and a spatial information theory index \tilde{H} , using a modified version of the composite population counts. Instead of treating the entire unit as part of the neighbourhood of a reference unit and counting its total population toward the reference unit's composite population, they proposed applying a spatial kernel centring at the reference unit. The kernel centre has a larger weight and farther locations have smaller weights. Thus, the modified composite population count of the reference unit is the weighted population counts of neighbouring units.

Instead of using the population density as in Reardon and O'Sullivan (2004), Feitosa *et al.* (2007) proposed a local generalised spatial dissimilarity ($LGSD$) index based on local population intensity. The local population intensity is a weighted average estimated by spatial kernel functions and independent of the size of spatial units. Further, by summing all the $LGSD$ together, the generalised spatial dissimilarity index (GSD) can be obtained for the entire region.

Income segregation indices for ordered groups – A distinct feature of D and its spatial extensions is that their application is limited to populations in discrete categories. Such indices are not suitable for continuous variables. To address this issue, a family of spatial ordering indices have been developed, largely built on the neighbourhood sorting index (NSI) and the Gini index.

NSI is an index of income segregation and is defined as the ratio of two standard deviations: one is of neighbourhood mean personal income and the other is of individual personal income, with larger values implying higher degrees of income segregation (Jargowsky 1996). NSI is aspatial because it does not reflect how populations are

segregated spatially by income, that is, shifting the populations and their incomes among areal units will not change the NSI value.

Jargowsky and Kim (2005) proposed a generalised NSI that accounts for the incomes in neighbouring spatial units. Based on the same concept of local population intensity as in GSD , Feitosa *et al.* (2007) extended NSI to a spatial NSI , which can be expressed as the ratio of the between-locality variance to the variance of the entire study area. Both generalised NSI and spatial NSI are smoothing techniques in the sense that the mean income of each neighbourhood is recalculated by including its neighbours' average income, parallel to the concept of composite populations for count variables.

Reardon *et al.* (2006) argued that results of NSI -based measures are not often comparable as the incomes can change over time, but ranks of income are more robust. They proposed a spatial rank-order entropy index, \tilde{H}_r , which only involves the rank ordering of incomes. \tilde{H}_r is a rank-order index, but is spatialised using \tilde{H} , the spatial information index as mentioned above. \tilde{H}_r can also be calculated for each population group in order to compare the within-group income segregation (Reardon & Bischoff 2011).

The Gini index, is widely used to measure (income) inequality (Duncan & Duncan 1955a). Again, relocating people of different income levels will not change the index value because of its aspatial nature. Dawkins (2004) developed a standardised spatial Gini index G_{ST} to measure racial segregation, which is calculated as the ratio of the spatial and aspatial Gini indices. In this case for racial segregation, both Gini indices are derived from the proportions between the two population groups, but for the aspatial index, the proportions are in a descending order and for the spatial index, the proportions are in a chosen spatial order. The measure indicates if the spatial arrangement of the population intensifies or dilutes segregation. Dawkins (2007) extended G_{ST} to a spatial ordering index to measure spatial income segregation, where neighbourhoods are ranked spatially according to per capita income.

The concept of spatial order has also been employed in the centralisation index (Duncan & Duncan 1955b), which orders neighbourhoods using their distance to the city centre and thus represents the relative segregation to the centre of an urban area. Considering the polycentric nature of modern cities, Folch and Rey (2014) proposed a localised version of centralisation index and argued that it could be an effective indicator of population segregation.

Spatial distribution indices – Another type of index focuses on the spatial distribution of the population. Since segregation implies spatial separation, segregation levels can be reflected by spatial correlation among population groups. Conceptually, if two population groups have similar spatial distributions, they are less separated and have low segregation. This type of measure only compares the spatial distributions among population groups and assumes that the locations of individuals are known or can be reasonably represented by certain point locations.

Wong (1999) suggested using centographic measures such as the standard deviational ellipse to capture the spatial distribution of population groups. Comparing the standard deviational ellipses of different population groups can reflect their segregation level. Ebdon (1988) and Wong (1999) described how a standard deviational ellipse is fitted to a set of points, indicating the distribution of a population group. Thus, the segregation measure based on the ellipses can be expressed as follows (Wong 1999):

$$S = 1 - \frac{E_1 \cap E_2 \cap \dots \cap E_m \cap \dots \cap E_M}{E_1 \cup E_2 \cup \dots \cup E_m \cup \dots \cup E_M}, \quad (3)$$

where E_m represents the ellipse of population group m and M is the total number of population groups. Conceptually, the index compares the spatial interaction and the union of the ellipses. The value of S ranges from 0 (all groups have identical spatial distribution with ellipses overlapping each other perfectly) to 1 (groups have very different spatial distribution with no overlapping ellipses). Other measures capturing the spatial

distributions of different populations can be compared to formulate other indices reflecting the segregation levels among population groups.

O'Sullivan and Wong (2007) considered not just where people are located, but also the intensity of their distributions. They overlaid the spatial kernel into every raster cell to estimate the population density. Population density levels of each population group over the region can be represented by a surface. Using these surfaces, they proposed a surface-based measure, which is defined in the same manner as S in (3) but using volumes of the intersection and the union of probability density functions rather than ellipses.

Spatial clustering indices – As evenness-clustering is an important dimension of segregation, spatial clustering indices have been widely employed as an indicator of spatial segregation. Common examples include location quotient (LQ) (Isard 1960), rule-based typology (Poulsen *et al.* 2001, 2002), local Moran's I (Anselin 1995), Getis-Ord local G (Getis & Ord 1992) and density-based measures (O'Sullivan & Wong 2007).

LQ was initially proposed to evaluate the concentration of an industry in a region in comparison to the national average. In terms of segregation, it is the ratio of a population group's share in a spatial unit to its share in the entire region (Brown & Chung 2006). Poulsen *et al.* (2001, 2002) proposed a rule-based typology for classifying ethnic residential areas, accounting for both concentration and isolation. However, both of those approaches are virtually aspatial in the sense that they do not consider the spatial relationships among neighbouring units. Given that, Cromley and Hanink (2012) extended LQ to the focal LQ by incorporating the spatial structure of the reference population group using geographic weights.

According to Massey and Denton (1988) and others, concentration is a separate dimension in most conclusions. However, when an area has a concentration level higher than the others, how is that different from characterising a clustering in that area? Conceptually, the

five segregation dimensions may not be differentiable in certain situations.

In spatial analysis, local indicator of spatial association (LISA) statistics, including local Moran's I (Anselin 1995) and the G statistics (Getis & Ord 1992) are usually employed to identify local clusters in spatial data. For example, in measuring racial segregation, the value of local Moran's I at spatial unit i reflects how the proportion of a group in i is similar to the proportions in neighbouring units. A high value of local Moran's I indicates a clustering of similar proportions (either high proportions reflecting a hot spot or low proportions reflecting a cold spot) and a low value indicates a clustering of dissimilar proportions. However, this application of spatial autocorrelation measure considers the degree of clustering of only one population group. Spatial relationships between groups are ignored.

Borrowing the approach of modelling spatial associations in G statistics, Wong (2002a) developed a local index using the product of population counts between reference and neighbouring units, reflecting one group's exposure in the reference unit to another group in the neighbourhood. Meng *et al.* (2006) further extended Getis-Ord local G by incorporating a social difference coefficient to handle ordinal social classes such as poor, middle and rich. These approaches are based upon spatial clustering indices, but are modified to measure exposure between population groups.

Indices applied to activity space – Most of the segregation measures in existing literature are intended for use with aggregated data to describe segregation patterns in residential space. Increasingly, the exclusive focus on the residential space has been challenged, as individual experiences in other socio-economic spaces are also important to determine if one is segregated from other groups. Thus, locations in which people spend their daily lives, i.e. their activity spaces, may need to be considered. To reflect an individual's experience of segregation, the exposure dimension is considered the most effective (e.g. Schnell & Yoav; 2001; Wong & Shaw 2011; Farber *et al.* 2012, 2015).

Activity space can be considered as 'the subset of all locations within which an individual has direct contact as a result of his or her day-to-day activities' (Golledge & Stimson 1997, p. 279). By measuring activity space from two dimensions (territorial and interactive), Schnell and Yoav (2001) developed socio-spatial isolation indices to represent an individual's isolation from others. Lower values of these indices represent higher levels of exposure to another group and larger values indicate higher tendencies of isolation from people of another group.

Wong and Shaw (2011) extended the original exposure index (Lieberman 1981) by replacing the areal units with individuals' activity spaces. Assume Ω_{il} is the activity space of an individual l of group g in spatial unit i , the exposure of l to group \bar{g} within Ω_{il} can be defined as:

$$E_{il,g \times \bar{g}} = \left(\frac{1}{p_{il,g}} \right) \left(\frac{p_{il,\bar{g}}}{t_{il}} \right), \quad (4)$$

where $p_{il,g}$ and $p_{il,\bar{g}}$ are the total population of groups g and \bar{g} within activity space Ω_{il} , respectively; t_{il} is the total population l is exposed to within Ω_{il} . $E_{il,g \times \bar{g}}$ in (4) can be extended to measure the exposure of all the people from group g in unit i to group \bar{g} by utilising the union of Ω_{il} for all l s (individuals) of group g (Wong & Shaw 2011). Thus, the spatial exposure measure constrained by the activity space concept for individuals can be expanded to deal with population groups.

The general notion of exposure through activity space has been extended further. Farber *et al.* (2012) proposed an exposure index with a similar form to Getis-Ord local G utilising trip lengths within activity spaces, intending to account for the general tendency that the intensity of interaction is inversely related to distance. The activity space of a person can be formally represented by a space-time prism, which defines the individual's spatiotemporal boundary given one's activity sites over time. Applying the exposure index concept in the space-time prism representation of activity space, Farber *et al.* (2013) proposed that the intersections of individuals' prisms indicate the area of social

interaction potential. The method can be extended to evaluate the spatiotemporal exposure between population groups (Farber *et al.* 2015).

Summary – We classified measures into categories partly according to their ability to capture different dimensions of segregation. If we try to match these indices to the five segregation dimensions, most indices for the first three types focus on the evenness dimension of segregation. Note that evenly distributed populations should not be misconstrued as the only condition for no segregation. In fact, these three types of index evaluate how (dis)similarly populations are distributed over space. The fourth type of measure focuses on the clustering dimension, but several scholars argue that clustering and evenness may be combined. The last type of index focuses on the exposure dimension, reflecting how different groups may interact over activity spaces.

These methods can also be classified as global, local and individual according to the units of observations. Global measures such as $D(adj)$, $D(w)$ and $D(s)$ are intended to summarise the overall segregation level across the entire study area, providing little information about the spatial variations in segregation across the study area, which might be of interest especially for large areas. Local indices such as $LGSD$, focal LQ and local Moran's I assess segregation for each spatial unit, reflecting the segregation levels at the neighbourhood or local scale. Finally, individuals' activity spaces can be used to generate the indices describing individuals' segregation experience, such as $E_{il,g \times \bar{g}}$ in (4).

DISCUSSION

As spatial segregation indices are geographic in nature, they are also subject to two fundamental problems facing any spatial analysis: representation of spatial interaction and spatial scales. The recent literature has been light in assessing the reliability (i.e. statistical significance) of those index values. It should be noted that there are numerous ways to represent spatial interaction, analyse spatial

scale and derive statistical significance. The review here focuses on the selected methods employed by the segregation measures discussed above. Finally, in order to successfully implement various measures, software tools are needed for both researchers and practitioners. These issues are discussed below.

Representation of spatial interaction – A key concern in measuring spatial segregation is how to represent spatial interaction among population groups. Distance has long been used as a simple indicator of spatial separation or connection moderated by a distance decay effect. Therefore, spatial segregation indices have employed distance-based functions (e.g. SP). Also, distance is used in delineating the local population intensity in $LGSD$. Another common way to quantify spatial interaction is by examining the common boundaries of neighbouring units. Populations in neighbouring spatial units are modelled to interact and lower segregation. Neighbouring relationship is often captured in spatial weights which are used in many spatial segregation indices (e.g. $D(adj)$). Obviously, the choice of spatial weights will affect the resultant values of segregation indices. Intersection between population groups is assumed if they share space. This is the essence of the set of spatial distribution and activity-space oriented indices (e.g. S in (3)).

While assuming that interaction reduces segregation is conceptually sound and including interaction in measuring segregation is logical, the current conceptualisation is crude and highly generalised. Thus implementing the concept involves a great deal of subjectivity. Specifically, no spatial segregation indices mentioned so far include actual interaction between population groups. The best we can say about these indices is that they capture the potential of interaction. All indices assume people interact over enumeration boundaries regardless of what the boundaries are. Some indices assume people interact if they are 'close by' or 'in the same location'. In reality, the degree and frequency of interaction between groups is driven by many factors, of which proximity is only one. The architecture and layout of buildings, street layout, traffic and pedestrian flow, how long people remain

stationary in a particular space, language and cultural barriers, communication technology and the nature of interaction – whether it business-related, social, planned, unplanned, whether people talk to each other in the same space or interact virtually via phone or social media – **all affect the intensity, degree and frequency of interaction between groups**. So we may want to be more modest about the claims that can be made about how well measures based largely on spatial properties can capture the true nature of interaction. In effect, these measures merely reflect how close or far people are apart spatially and to what extent they share similar locations. In a world where human interaction is increasingly done electronically and therefore aspatial, **to what extent does it matter if different population groups are spatially ‘separated’?** We are not saying that space doesn’t matter, but how do we gauge how much it matters and whether it’s importance changing?

Spatial scale – Like all spatial analysis techniques, spatial segregation indices are constrained by the geographical scale or level of spatial aggregation employed. That is, index values will differ when the same index is applied to data aggregated by different methods. This is known as the modifiable area unit problem (MAUP) (Openshaw 1984), which refers to the variability in analytical results due to changes in the spatial resolution and different zoning schemes for which spatial data are tabulated. The former refers to different granularities of spatial representation, while the latter means different ways to partition a region with the same spatial resolution.

Using smaller spatial units (i.e. finer spatial resolutions) will almost always lead to larger segregation index values, aspatial and spatial alike (White 1983; Wong *et al.* 1999; Krupka 2007). If population is more clustered, spatial measures would be less affected by varying spatial scale than aspatial measures (Wong 1997; Wong *et al.* 1999). Using simulated data, Rey and Folch (2011) examined the properties of four segregation indices – D , D_{adj} , NSI and the generalised NSI , and found D and NSI are more sensitive to the region size than their spatial counterparts.

The MAUP is inherent in the use of spatially aggregated data. As long as segregation measures rely on data tabulated by areal units, the scale and zonal dependencies of analysis results are not going to disappear. Segregation indices developed within the activity space framework mostly rely on individual level data. Using individual level data is a potential direction to avoid the MAUP effects on segregation measurements, but segregation based upon individual experience needs to be re-conceptualised as some notions such as evenness or clustering for areal unit data may not be applicable.

Statistical inferences – As discussed above, spatial segregation measures can be sensitive to the representation of spatial interaction and spatial scale. It is desirable to know the uncertainty associated with the derived indices. This issue was investigated to a certain degree soon after the dissimilarity index became popular (e.g. Cortese *et al.* 1976). Several studies have attempted to address this issue for non-spatial segregation indices using bootstrap tests (Brühlhart & Traeger 2005). However, Lee *et al.* (2015) found that standard bootstrapping approaches can perform very badly in the presence of spatial autocorrelation and the new method developed by Lee *et al.* (2015) performs much better, which has been applied to an centralisation index on the significance of the index difference across space or time (Kavanagh *et al.* 2016) and can in principle be applied to a wide range of spatial segregation measures.

For spatial segregation, a common concern is to test the obtained measures against randomness. Asymptotic theory and Monte Carlo simulation are two common methods employed for significance testing against randomness. The former has been widely applied particularly to spatial clustering indices. A similar method was used to test the significance of G -based exposure measures by Farber *et al.* (2012). In Monte Carlo simulation, population groups are randomly rearranged over space and segregation indices recalculated. If the randomisation process is repeated a larger number of times (e.g. 999), a pseudo p -value can be obtained,

representing the probability that the original spatial population distribution presents a higher level of segregation than other possible spatial arrangements of the same population composition (Anselin 1995). Feitosa *et al.* (2007) used Monte Carlo simulation to verify the significance of the identified segregation patterns.

However, the randomisation approach to test the significance of segregation indices has its limitations. For instance, when original population counts are randomly re-assigned to different areal units, the process implicitly assumes that an areal unit can accommodate any population size, disregarding the area of the unit or other physical constraints. This assumption is unrealistic, and therefore not all randomised distributions are feasible. Effective and conceptually sounded testing approaches are still warranted. In addition, randomness is often regarded as the underlying distribution for no segregation. But if two groups are distributed across areas in the same manner, the definition for no segregation according to D , then higher non-random distributions may still have no segregation. Therefore, the concept of no segregation is still fuzzy.

Software tools – Computing spatial segregation indices usually requires examining spatial relationships and implementing spatial analyses, which could be daunting tasks for researchers not familiar with GIS. As a result, applications of spatial segregation measures have been constrained by the availability of relevant software tools. Common software tools that provide functions for some of the aforementioned segregation measures are listed in Table 1.

Some tools developed in early eras were built upon popular commercial GIS software, utilising the spatial data manipulation and analysis functions in those packages (Wong & Chong 1998; Apparicio 2000; Wong 2002b, 2003). For example, the ArcView extension implemented several measures reviewed above like $D(s)$ and $D(w)$ (Wong 2002b). However, the fast-paced software environment quickly made these tools obsolete.

In recent years, open GIS initiatives have promoted the development of many open

source and free software tools, which have greatly encouraged the adoption and use of spatial segregation measures. The *R* package ‘seg’ (<https://cran.r-project.org/web/packages/seg/index.html>) has implemented several spatial segregation indices such as SP and $D(adj)$. Another *R* package ‘spatialsegregation’ (<https://cran.r-project.org/web/packages/spatialsegregation/index.html>) provides a function for the spatial information theory index \bar{H} but primarily focuses on the segregation or mingling in multi-type spatial point patterns, and therefore is not included in Table 1. The ‘CARBayes’ (<https://cran.r-project.org/web/packages/CARBayes/index.html>) *R* package implemented the inference by Lee *et al.* (2015) for the index of dissimilarity and for the local and global relative centralisation index. The stand-alone software, Geo-Segregation Analyzer (Apparicio *et al.* 2014) is a multi-platform application that can calculate more than forty residential segregation indices. Particularly, the results of local measures can be mapped in the built-in viewer, enabling exploration of spatial variations in segregation. A limitation at present is that the outputs are text based and cannot be easily used as inputs for further analysis or visual summary.

The advancement in using the internet as the computational platform enables websites to provide computational and analytical services. Oasis, (<https://oasis.irstea.fr/>) an online system that computes many aspatial and spatial segregation and inequality measures, was developed by leveraging the internet as a platform to deliver analytical functions and services to the public. The backend of the system is supported by *R* procedures and functions. Using web-delivery approach broadens the access to these specialised tools.

CHALLENGES

Many issues discussed above have been addressed in the literature to some extent, but they have not been resolved ‘satisfactorily’. Some of these issues have been touched upon in a recent review (Wong 2016). Two additional challenges, one conceptual and one operational, are discussed further here.

Wong (2016) argues that despite decades of research on measuring segregation, a consistent and generally agreeable definition of segregation has not yet been formulated. Definitions of segregation may be determined operationally, depending upon the measures adopted. Then using different measures will change the definition (e.g. using the dissimilarity index D and isolation-exposure indices assume different definitions of segregation). The five dimensions of segregation (Massey & Denton 1988) have been used frequently as definitions conceptually, but recent debates show the five dimensions can be mingled together in different ways.

The bottom line is deciding which measure should be used as we are not short of measures of segregation but they capture different aspects of this complex, multi-faceted, and poorly-defined social construct. The issue is whether the measures really capture what we expect or intend them to explain. Measuring segregation is often the means, not the ends. The objective of measuring segregation is often to explore the relationships between some notion of segregation and certain outcomes or practices, for example, social actions such as discrimination or prejudice, which may lead to the creation of segregated neighbourhoods, or health outcomes such as a higher disease burdens for certain population sub-groups in a relatively segregated environment. Many studies have postulated possible relationships between segregation and various outcomes (e.g. Grady & McLafferty 2007), and the roles of segregation may be causal, moderating or confounding. The challenge, given a specific outcome or action, is which facet of segregation is the most relevant and which measure is the best to capture that facet. For example, one might be concerned that the population of a 'segregated' neighbourhood has not provided a reasonable level of access to health-care facilities. Measuring segregation in this case should capture the low level of accessibility to those facilities, but using the dissimilarity measure D will not be effective. Unfortunately, the complex and multifaceted relationships between segregation and various outcomes are still not well understood.

A trend in advancing segregation measurement is the move from ecological or place-based approaches using spatially aggregated data to individual or people-based approach using individual-level data to focus on individual's experience (e.g. Wong & Shaw 2011). The ecological approach has to deal with the (scale effect of the) MAUP, and to choose the appropriate areal unit or often the census enumeration unit as the proxy of neighbourhood for the analysis. The scale effect in choosing neighbourhoods of different sizes on segregation measurement is well documented (e.g. Wong *et al.* 1999; Reardon *et al.* 2009). Switching to a people-based approach and using individual-level data does not make the neighbourhood selection issue go away or simpler, but in fact makes the issue more complicated conceptually and operationally. Although the literature has logically suggested using activity pattern or activity space to define one's neighbourhood, such proposal is not without problems (e.g. Kwan 2012). Technically, a 'neighbourhood region' can be constructed based on one's activity locations. However, this neighbourhood region, regardless of which method is used to construct it, will include areas or places that the individual just passes through without stopping. Should those unvisited locations be included in the 'neighbourhood'? Another practical question is for how long the activity data should be collected in order to determine the 'representative' activity pattern. If only locations (points) of activities are considered, should the activity space just be a set of points with no areal dimension? While some of these issues seem to be trivial, they are nonetheless difficult practical but fuzzy conceptual issues in measuring segregation.

FINAL REMARKS

Quantitative indices of segregation are commonly employed in social sciences to represent the degrees of separation between social and population groups, particularly the isolation of more disadvantaged groups, and they can be powerful tools in assisting public policy formulation and decision-making. The

review conducted in this paper focuses only on spatial segregation measures, i.e. those which attempt to capture the spatial arrangement of population and the spatial interactions between groups in one way or another. Essential here is how to represent spatial interactions between population groups, spatial units, or individuals. Robust indices with values insensitive to changes in spatial scale are needed, but remain elusive. Further, determining the statistical significance is important to indicate the reliability of the obtained segregation values. The emerging open-source and online software tools have greatly facilitated the implementation of those spatial measures. Recent shifts from place-based to people-based measures of segregation were a significant conceptual advancement accompanied by the increasing availability of individual-level mobility data. However, the introduction of these new approaches also brought along the conceptual issues of defining ‘neighbourhood’ appropriately. We hope this review provides insights into future extensions or improvements on existing measures, and encourages wider use of these powerful techniques.

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