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Multiscale Measures of Population: Within- and between-City Variation in Exposure to the Sociospatial Context

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Appreciating spatial scale is crucial for our understanding of the sociospatial context. Multiscale measures of population have been developed in the segregation and neighborhood effects literatures, which have acknowledged the role of a variety of spatial contexts for individual outcomes and intergroup contacts. Although existing studies dealing with sociospatial inequalities increasingly explore the effects of spatial scale, there has been little systematic evidence on how exposure to sociospatial contexts changes across urban space, both within and between cities. This article presents a multiscale approach to measuring potential exposure to others. Using individual-level register data for the full population of The Netherlands and an exceptionally detailed multiscalar framework of bespoke neighborhoods at 101 spatial scales, we measured the share of non-Western ethnic minorities for three Dutch cities with different urban forms. We created individual and cumulative distance profiles of ethnic exposure, mapped ethnic exposure surfaces, and applied entropy as a measure of scalar variation to compare potential exposure to others in different locations both within and between cities. The multiscale approach can be implemented for examining a variety of social processes, notably segregation and neighborhood effects. *Key Words: distance profile, entropy, ethnic exposure, spatial scale, urban form.*

鉴别空间尺度, 对于我们理解社会空间脉络而言至关重要。隔离与邻里效应的文献, 已发展出人口的多重尺度方法, 并以认识到各种空间脉络之于个人结果与群体互动之角色。尽管应对社会空间不均的既有研究正逐渐探讨空间尺度的效应, 然而对于暴露社会空间脉络, 如何在城市空间之中和之间改变, 却鲜少有系统性的证据。本文呈现评估对他者的可能暴露之多重尺度方法。我们运用荷兰总人口中个人层级的登录数据, 以及在一百零一个空间尺度中格外细緻的预定邻里的多重尺度架构, 评估在具有不同城市形态的三大荷兰城市中, 非西方少数族裔的比率。我们创造族裔暴露的个人与累积的距离概况, 绘製族裔暴露表面, 并将熵应用作为尺度变异的测量方法, 以比较城市间和城市中不同地点对于他者的潜在暴露。多重尺度方法能够用来检视各种社会过程, 特别是隔离与邻里效应。 关键词: 距离概况, 熵, 族裔暴露, 空间尺度, 城市形态。

Apreciar la escala espacial es crucial para nuestra comprensión del contexto socioespacial. Las medidas de multiescala de la población han sido desarrolladas en las literaturas sobre segregación y efectos vecinales, que han reconocido el papel de una variedad de contextos espaciales para los resultados individuales y contactos intergrupales. Aunque los estudios existentes que se refieren a las desigualdades socioespaciales exploran cada vez más los efectos de la escala espacial, escasa ha sido la evidencia sistemática recogida sobre el cambio a través del espacio urbano de la exposición a contextos socioespaciales, tanto dentro de las ciudades como a través de ellas. Este artículo presenta un enfoque a escala múltiple para medir la exposición potencial a otros. Usando datos de registro a nivel individual para el total de la población de los Países Bajos, y un marco multiescalar excepcionalmente detallado de vecindarios diseñados especialmente a 101 escalas espaciales, medimos la parte de las minorías étnicas no occidentales para tres ciudades holandesas dotadas de formas urbanas diferentes. Creamos perfiles de distancia individuales y acumulativos de exposición étnica, mapeamos superficies de exposición étnica y aplicamos entropía como una medida de variación escalar para comparar el potencial de exposición a otros en localizaciones diferentes, tanto dentro de las ciudades como entre ellas. El enfoque multiescalar puede implementarse para examinar una variedad de procesos sociales, notablemente segregación y efectos de vecindario. *Palabras clave: perfil de distancia, entropía, exposición étnica, escala espacial, forma urbana.*

Spatial scale is a critical dimension of social and physical attributes of an environment (Smith 2000; Reardon et al. 2008). The relevance of scale has been well established for the segregation literature (see, e.g., White 1983; Wong 2004; W. A. V. Clark et al. 2015; Jones et al. 2015), the neighborhood effects literature (Galster 2001; R. Andersson and Musterd 2010; Van Ham and Manley 2012; Vallée et al. 2015), and, more broadly, research on sociospatial inequalities (Suttles 1972; Manley, Flowerdew, and Steel 2006; Prouse et al. 2014), where scale is often addressed as one aspect of the modifiable areal unit problem (MAUP; see Openshaw and Taylor 1979; Manley 2014). Sociospatial inequalities can be more fully understood by exploring variation in geographic contexts across multiple scales, within the so-called spatial opportunity structure, rather than by confining to a single geographic context (Galster and Sharkey 2017). Crucial for understanding spatial foundations of social inequality is the measurement of population characteristics, whose multiscalar representations have evolved with the increasing availability of detailed spatial data.

One common way to explore scale is to compare measures of population at two or more spatial scales of neighborhood (see, e.g., the studies by Overman 2000; Johnston et al. 2004; Bolster et al. 2007; Vallée and Chauvin 2012; Duncan et al. 2014). Most studies use standard administrative units but acknowledge that these spatial units are often too large and do not represent the structure of the population in which they are interested. The neighborhood effects literature, therefore, increasingly uses bespoke neighborhoods, areas centered on an individual, to measure exposure to the sociospatial context (introduced by Johnston et al. 2000; Buck 2001; MacAllister et al. 2001). Using finer grained geocoded data has intensified the shift in the neighborhood effects literature from the neighborhood to a sociospatial context composed of scalable bespoke neighborhoods (E. K. Andersson and Malmberg 2014). Although the bespoke neighborhood approach is not indisputable (Vallée and Shareck 2014), it does provide a lens through which attention can be given to the effects of location when measuring population. Hipp and Boessen (2013, 293), who used "egohoods" (their term for bespoke neighborhoods) of different radii to explore variation in crime, argued that this "individual social environment perspective" captures heterogeneity across the city and represents the social landscape more accurately than fixed, nonoverlapping spatial units.

The individual social landscape can be conceptualized as a multiscale measure of population and represented as the spatial profile of a (residential) location. The idea builds on the segregation profiles introduced by Reardon and colleagues (Reardon et al. 2008; Reardon et al. 2009), which have developed into spatial profiles (see Spielman and Logan 2013; W. A. V. Clark et al. 2015; Fowler 2016; Hennerdal and Nielsen 2017). These spatial profiles depict for a focal location the potential exposure to others as scale changes and characterize places as complex sociospatial contexts. Although Fowler (2016) suggested how to describe segregation profiles using a range of indicators, expressing scalar variations in population measures, particularly for a larger number of scales, remains a big challenge.

The spatial profiles of potential exposure to others spread over the urban mosaic of neighborhoods. Contemporary cities are often ethnically and socioeconomically fragmented (Jenks, Kozak, and Takkanon 2008; Marcińczak et al. 2015; Tammaru et al. 2016), and some of them have evolved into polycentric urban regions (Danielzyk, Münter, and Wiechmann 2016). Very little attention has been given, though, to the issue of how exposure to others changes across scale throughout urban space, when moving through a single city or between multiple urban regions. Some studies used multiscale methods to compare specific scales in different metropolitan areas, without considering different urban forms (Lee et al. 2008; Reardon et al. 2008; Östh, Clark, and Malmberg 2014). Others demonstrated the need to define context for particular population groups located in specific parts of a single city rather than for the city as a whole (Manley et al. 2015; Johnston et al. 2016).

The aim of this article is to better understand the effects of scale and location on the measurement of potential exposure to others. The article presents a multiscale approach to measuring potential exposure to the sociospatial context by addressing the following objectives: to (1) explore how scale matters for measuring exposure to sociospatial context; (2) propose a novel method of measuring scalar complexity of exposure to sociospatial context in different locations; (3) show how scale affects exposure to sociospatial context in different ways in three different cities in The Netherlands; and (4) show how locational differences in exposure to sociospatial context fragment the city at multiple scales for different population groups.

This study used register data including the full population of the Netherlands, whose place of residence

was geocoded at the level of 100-m by 100-m grid cells. We studied three cities with different urban forms, namely, Amsterdam, Utrecht, and Groningen. Around each cell in these cities, we delineated bespoke areas at 101 spatial scales, capturing very diverse contexts from the immediate surroundings of a dwelling, to much larger areas. In these areas, we measured the share of non-Western ethnic minority people (contextual characteristic often used; see, e.g., K. Clark and Drinkwater 2002; Friedrichs, Galster, and Musterd 2003; Moore and Diez Roux 2006) and mapped the ethnic exposure surface of the cities. We then focused on individual locations and created their distance profiles, spatial profiles consisting of measures of population in 101 bespoke areas defined using Euclidean distance. Using Shannon's (1948) entropy index, a complexity measure originally derived in information theory, we quantified the variation in multiscale measures of non-Western population and compared different locations within and across cities. For the three cities, we created cumulative distance profiles, and on the example of Amsterdam, we compared the individual distance profiles for two population groups (Western and non-Western).

Ethnic Exposure in Urban Space: The Role of Spatial Scale

Distance and its meanings are at the core of research into sociospatial inequality. Distance relates to access to employment and public facilities; exposure to crime, violence, and site-specific pollution; as well as potential access and exposure to other people. Proximity to other people features social networks, contact, and interaction with others (Logan 2012). In socially and ethnically diverse cities, social distances and ethnic identities are often reflected in spatial distances (Häußermann and Siebel 2001; Berding 2008). Different ethnic or income groups are often segregated within and between cities (see, e.g., Friedrichs and Triemer 2009; Marcińczak et al. 2015; Tammaru et al. 2016). The fact that people tend to locate close to their coethnics (Schelling 1971) has many underlying causes but is also thought to have effects on the socioeconomic outcomes of individuals (Friedrichs, Galster, and Musterd 2003). The segregation literature generally assumes that sociospatial isolation of groups intensifies intergroup prejudice (Tredoux and Dixon 2009). In line with this, the *contact hypothesis* relies on the idea that interaction among members of different

groups reduces intergroup prejudice (Allport 1979; Pettigrew and Tropp 2006). Along with the positive aspects of proximity to other groups, the neighborhood effects literature generally hypothesizes that living in a spatial concentration of disadvantaged people negatively affects individual health, employment, or educational outcomes of people (see Van Ham et al. 2012, 2013; Manley et al. 2013).

Although exposure to other people is studied for various reasons, all studies related to sociospatial inequalities rely on some measure of population characteristics. The representation of these characteristics depends on scale as a spatial or temporal dimension used to measure and study phenomena (Gibson, Ostrom, and Ahn 2000; Montello 2001). Many social processes have quite complex spatial and temporal dimensions, with a high degree of uncertainty, as defined within the uncertain geographic context problem (UGCoP; Kwan 2012). Specifically, spatial scale is one aspect of the MAUP, concerned with the size of spatial units (Openshaw and Taylor 1979; Manley 2014). Population data available for social research have long been too limited to explore the scalar complexity, however.

Standard administrative areas are frequently deployed to represent individual sociospatial contexts. Despite being practical, conventional spatial units have a number of limitations. Administrative units are designed for specific purposes, such as jurisdiction or postdelivery, rather than for social research, and are unlikely to reflect the spatial processes contained within the data (see Jones et al. forthcoming). Further, administrative units do not always conform to temporal consistency through multiple redesigns and boundary changes over time. Biases arise as a consequence of the boundary effect, whereby people living close to the edge of an administrative unit might experience greater connection with people in an adjacent unit than to those in the unit in which they live. The limitations of administrative units might culminate in a mismatch between the analysis scale and the actual phenomenon scale (Montello 2001). For example, even when available at more than one scale, administrative units are never small enough to represent people's immediate environment. Lee et al. (2008) empirically demonstrated the limitations of administrative units (census tracts) in measuring residential segregation, supporting the use of multiple spatial scales.

With the increasing availability of geocoded microdata, researchers can more adequately represent people's sociospatial contexts at the scales relevant for the

social processes under study, such as segregation and neighborhood effects. On the one hand, microgeographic data present substantial methodological challenges, offering a potentially infinite number of possible scales and zonation schemes. On the other hand, such detailed data are also a resource of new information about the area under investigation (Manley, Flowerdew, and Steel 2006). The finer the spatial data, the greater the possibilities for analyzing various scales, starting with exploratory analysis. Mapping sociospatial inequality using microgeographic data makes it possible to reveal and investigate small-scale spatial patterns (vom Berge et al. 2014), whereas larger scales remain important for mapping spatial opportunity structure (Knaap 2017). More accurate geographic data provide information on both the microlocations where exposure to other people starts (around one's home) and how the population to which individuals are potentially exposed to changes in continuous space.

Scale from the Individual (Bespoke) Perspective

Bespoke neighborhoods are increasingly used as an alternative to administrative units to represent people's sociospatial contexts. A bespoke neighborhood is a neighborhood that has the residential location of an individual in the center and represents an exposure surface to sociospatial phenomena. As a consequence, the bespoke neighborhoods of two neighboring individuals overlap but are not the same. An ideal estimation of the environment that people are exposed to on a daily basis would require substantial information about their daily space–time paths (Hägerstraand 1970). The inquiry of individual daily activities, social networks, and perception of spaces (Mennis and Mason 2011; Kwan 2012) has provided important insights into people's actual activity spaces and "personal cities" (Weber and Kwan 2003). Because such information is often not available, especially not for large populations, bespoke neighborhoods can be created around people's residential locations but also around workplaces and other key locations on space–time paths.

An increasing number of studies have used bespoke neighborhoods around people's places of residence to assess neighborhood effects on personal health and health-related issues (Duncan et al. 2014), political attitudes and voting behavior (MacAllister et al.

2001; Johnston et al. 2004), or socioeconomic status (Bolster et al. 2007; R. Andersson and Musterd 2010; Hedman et al. 2015). These studies usually compare two or more spatial scales of bespoke neighborhoods in an attempt to relate different spatial scales to different contextual influences on individual outcomes. As Vallée and Shareck (2014) noted, bespoke neighborhoods are not considered "better" than administrative units. Certainly, people do not necessarily reach and experience their environment equally in all directions, just like their activities are not determined by arbitrary administrative boundaries. The idea of placing an individual in the center and measuring the socioeconomic composition of the surrounding area is largely supported by studies on residents' perceptions, where people are asked to delineate their neighborhood themselves. The main finding from these studies is that neighborhoods as defined by residents are different, notably smaller, than conventional spatial units such as census tracts (Omer and Benenson 2002; Lohmann and McMurran 2009; Coulton, Jennings, and Chan 2013). As noted by Hipp and Boessen (2013), respondents generally place themselves in the center of the neighborhood, although this is rarely highlighted in the findings of such studies (but see Coulton et al. 2001; Grannis 2009).

An individual is not located in the center of a single bespoke neighborhood but in the center of a range of nested and interconnected areas. This is important because the share of ethnic minorities, for instance, in a larger area surrounding an individual dwelling can be an indicator of the neighborhood population trajectory, which might influence people's decisions to move in or out (Crowder and South 2008). Thus, whereas too coarse aggregations mask relevant spatial patterns, an exclusive focus on smaller areas removes neighborhoods from their broader context. Within the social sciences, the continuous approach to spatial scale has been most prominent in segregation research. Although scale was long ago recognized as crucial for developing more advanced segregation measures (see, e.g., White 1983; Wong 2004), the continuous perspective on scale arose with the "segregation profiles" presented by Reardon and colleagues (Reardon et al. 2008; Reardon et al. 2009).

The idea of segregation profiles motivated several researchers to explore how local conditions of segregation blend with broader spatial contexts (Spielman and Logan 2013; W. A. V. Clark et al. 2015; Fowler 2016; Hennerdal and Nielsen 2017). These studies focused on understanding spatial patterns of

segregation by grouping locations to form homogenous clusters, whereas defining context and measuring individual exposures in particular locations has received less attention. Spielman and Logan (2013) created individual profiles (which they termed *egocentric signatures*), although they aggregated the profiles into clusters. Therefore, their method mainly aims at improving our understanding of the social structure of cities and not at assessing individual exposures. Fowler (2016) went perhaps the furthest in exploring the multiscale segregation profiles by describing the functional form of a profile. In line with other U.S. studies employing segregation profiles, the author used block-level population counts converted to a population density surface and interpolated to raster cells (see Reardon and O'Sullivan 2004) to create microgeographies.

Neighborhood effects research is by definition interested in individual exposures to sociospatial context and benefits from multiscalar population measures. Scalable bespoke neighborhoods motivated by segregation profiles but using population counts (the *k* nearest neighbors) have been implemented in modeling neighborhood effects in Sweden (E. K. Andersson and Malmberg 2014), as well as for measuring segregation (Östh, Clark, and Malmberg 2014; Östh, Malmberg, and Andersson 2014). Thus, both segregation and neighborhood effects research have been shifting from measuring characteristics of a fixed neighborhood to the analysis of individual exposures in a multiscalar geographical context, with the aim to better understand residential context.

Although different methods can be used for creating bespoke neighborhoods, they are all scale-dependent and need not solely rely on Euclidean distance or population counts. For example, road network (Van Ham, Hooimeijer, and Mulder 2001; Frank et al. 2005; Oliver, Schuurman, and Hall 2007) and travel time buffers (McGuirk and Porell 1984; Wang 2000; Reardon et al. 2008) more accurately measure access to jobs, services, or resources but can only be feasibly performed in small-sample studies, because of the data requirements and computational complexities. Critically, regardless of the method chosen to derive bespoke neighborhoods (different types of distance or population thresholds), researchers still need to make decisions regarding the scales at which area characteristics are measured and to be aware of the way in which altering scale changes the results. This study contributes to the literature by proposing a method of measuring scalar complexity of exposure to sociospatial context in different locations.

Distance Profiles of Sociospatial Context and Urban Form

Ideally, the scale of bespoke neighborhoods should be theoretically specified; for example, by associating different mechanisms of neighborhood effects with different spatial scales (Galster 2012). For many social processes related to segregation and neighborhood effects, however, a clear theory of scale is lacking, or they might be operating at multiple scales simultaneously. Arguably the main reason is that the scale of many social phenomena largely depends on the particular geographic setting, so that processes might operate differently in different locations within one city and between cities. In this article, we conceptualize sociospatial contexts as distance profiles of potential exposure to others. We argue that the complexity of these distance profiles strongly depends on the urban mosaic of neighborhoods and, therefore, on urban form.

Urban form is essentially multiscalar, as it is used to describe both intra- and interurban patterns and connections at multiple spatial scales (Kloosterman and Musterd 2001a; Davoudi 2003). A simple way to categorize urban forms is by distinguishing monocentric and polycentric cities. This distinction appeared as cities with multiple centers (polycentric cities) emerged, as opposed to the monocentric cities with one central business district (Anas, Arnott, and Small 1998; van Houtum and Lagendijk 2001). Contemporary cities are rarely monocentric, though, but rather polycentric to different extents. Polycentricity within cities is characterized by multiple clusters of population and economic activities, which merge into one larger interdependent system (Anas, Arnott, and Small 1998).

At the same time, urban regions with cities as centers have developed. These urban systems involve two or more formerly independent and distinct cities that are located relatively close to each other and have started to integrate more, such as the Dutch Randstad, the Flemish Diamond, and the German Ruhr regions (Dieleman and Faludi 1998; Kloosterman and Musterd 2001b; Meijers 2007; Danielzyk, Münter, and Wiechmann 2016). So, two scales of polycentricity are the most obvious (the city and the regional scale), although at a more elaborate level, both intra- and interurban polycentricity can have various scales.

Although the concept of polycentricity predominantly relates to economic and institutional structures, the spatial distribution of different population groups is also one aspect of polycentricity, which goes hand in hand with urban fragmentation in a wider social, cultural, and economic context (Jenks, Kozak, and Takkanon 2008). The urban mosaics of larger cities show a variety of neighborhoods with different types of housing and with concentrations of ethnic and socioeconomic groups (Tammaru et al. 2016). The concentration of disadvantaged groups often leads to territorial stigmatization of certain parts of the city, which might extend to much larger scales than what is usually characterized as the neighborhood. As a result, parts of some metropolitan cities, such as New York's Bronx, Berlin's Neukölln, and Amsterdam's Bijlmer, have a "blemish of place" at the national or even the international level (Wacquant 2007). With increasing social polarization and the growing size and diversity of racial and ethnic "minorities," economic status and ethnicity have become some of the most important factors of spatial fragmentation in urban space (Champion 2001; Jenks, Kozak, and Takkanon 2008).

Fragmentation in the urban discourse is usually interpreted as a generating process or a way of operating the city or as a spatial phenomenon or state but also as an urban experience or a way of perceiving the city (Kozak 2008). We apply multiscale measures of population as a means to assess sociospatial fragmentation in urban space as potential exposure to "others" in urban space. The distance profiles we use to measure the potential exposure to others will be affected by intra- and interurban polycentricity. Population measures at different spatial scales will be affected by urban form and, as a result, altering scale will reveal different profiles of potential exposure depending on the location within a city but also between cities. As different ethnic groups occupy different spaces in cities, multiscale measures of population reveal important ethnic differences in the exposure to others at various scales (Manley et al. 2015; Johnston et al. 2016). Besides the within-city variations, cross-metropolitan comparisons of segregation have shown different impacts of spatial scale in different metropolitan regions, without addressing the issue of urban form (Lee et al. 2008; Reardon et al. 2008; Östh, Clark, and Malmberg 2014). The aim of this article is to better understand the effects of scale and location on the measurement of potential exposure to others, by profiling the scalar complexity in different places both within one city and across cities with different urban forms.

Data and Methods

We used individual-level register data covering the full population of The Netherlands, geocoded on 100 m × 100 m grid cells, for the year 2013 (Sociaal Statistisch Bestand [SSB]; see Bakker 2002; Houbiers 2004). For our analysis, we chose three distinct cities with different population sizes and inter- and intraurban forms. The first two are Amsterdam, the most populated city in the country (810,000 people living within 165 km^2), and Utrecht, ranking fourth (330,000 people, 95 km^2). Both Amsterdam and Utrecht are part of the Randstad, the largest conurbation in The Netherlands. The third city, Groningen, has the seventh largest population in the country (200,000) in an area of 80 km^2 and is spatially isolated in comparison with the other two cities. In terms of intraurban polycentricity, Amsterdam and Utrecht have more diverse urban structures than Groningen.

For these cities, we studied the proportion of people belonging to non-Western ethnic minority groups within a highly detailed multiscalar framework. We simplified ethnicity into two categories, the first including native Dutch and other people with a Western background and the second representing people with a non-Western background.[1] Although we chose to focus on ethnicity for the purposes of the discussion that follows, the approach we exemplify is suitable for studying other population characteristics at multiple scales.

The core of our method consists of creating bespoke areas of 101 different spatial scales. The base scale is represented by the 100 m × 100 m cell itself, and the starting point for the measures is the share of non-Western people for each 100 m × 100 m cell in the three cities (each city map in the Results section displays approximately 68,000 cells). From the base cell as a center, other bespoke areas spread in 100 concentric circles, radii of which range from 100 m up to 10 km, with 100-m increments. Each of these bespoke areas is composed of all cells whose centroid is located within the specific bandwidth.[2]

To represent the ethnic exposure surface of the cities approached from different spatial scales, we created a series of uniform maps. In each map, the measured values at a specific scale are assigned to the base cell, although the values are based on measures for a single cell (0.01 km^2) up to its wider surroundings (314 km^2 for the largest circle). Increasing the scale might exceed the boundaries of a city and include parts of the surrounding area and even parts of other adjacent cities.

We then focused on specific locations and created individual distance profiles of ethnic exposure for each 100 m × 100 m cell, containing percentages of non-Western people measured at all 101 scales. For each individual distance profile (so for each cell), we expressed the scalar complexity using the entropy index. The concept of entropy has been used in many different scientific disciplines with different purposes and different formulas. Unlike the common use of entropy in the research of sociospatial inequalities—for assessing segregation between different population groups (see, e.g., Reardon and O'Sullivan 2004)—we use entropy to capture in one index the complexity of exposure to one population group at a range of spatial scales.

Our index is based on Shannon's (1948) entropy index, which was originally derived for measuring uncertainty of a message content in the information theory. We measured to what extent individual distance profiles vary within a range of values (0–100 percent of people with a non-Western background) in bespoke areas at 101 scales. So, the distance profile line can have one of 101 values[3] at each of the 101 scales. If the percentage is the same at all scales, the distance profile has low entropy. If the distance profile is spread over more categories (different percentages of non-Western people at different scales), the profile has high entropy. This is calculated as follows:

$$H\,(X) = \; -\sum_{i\,=\,1}^{n} p(x_i)\log_2 p(x_i),$$

where x_i is a value (percentage of non-Western people), and $p(x_i)$ is the proportion of scales with the same value. The minimum entropy would reach zero for a completely flat distance profile, whereas the maximum possible entropy for this number of categories and scales is less than seven. The theoretical maximum for an entropy profile would contain 101 values (0–100 percent of non-Western people) across the 101 spatial scales; that is, each spatial scale would have a different percentage of non-Western people. Low-entropy profiles are in general very flat, although at certain scales there might be sudden shifts.

Besides comparing the individual locations within and between cities using the entropy index, we compared the cities as a whole based on their cumulative distance profiles. Cumulative profiles of potential ethnic exposure compile the results for individual profiles along all the scales and consist of 101 parallel boxplots, with a single boxplot for each scale. This provides two useful insights, namely, into the variability within each scale—how population characteristics vary when measured at different locations within one city using the same scale (the within-scale variability), as well as into the variability between scales—how the measures vary when using different scales (the between-scale variability).

In addition to creating the aggregate population measures for specific cities, we also assessed intraurban fragmentation for different population groups. Therefore, we compared the exposures to non-Western ethnic minorities at different scales for Western and non-Western ethnic groups in the same city (Amsterdam). For this, we multiplied each individual distance profile with its occurrence (the numbers of Western and non-Western people who live in that cell). We then plotted the exposures of these two groups to non-Western people at multiple scales jointly in one graph to explore to which extent the exposures overlap or diverge.

Results

The series of city maps for Amsterdam in Figure 1 demonstrates the instability of multiscale measures of non-Western population in a continuous way. Figures 1A through 1D show the share of people with a non-Western background, measured at four different spatial scales, ranging from 100 m × 100 m cells (Figure 1A) to areas with a radius of 10 km (Figure 1D). The color of each cell in Figure 1A denotes the percentage of minorities in that actual cell, which represents people's immediate residential environment. This is an urban mosaic of ethnicity in Amsterdam, in which people have very different potential exposures to others as they open the front door of their house in the immediate surroundings of their dwelling. There are clear concentrations of minorities in the western and southeastern parts of Amsterdam (Westelijke Tuinsteden and Bijlmer) as well as the east and the north.

Figure 1B shows the percentage of non-Western ethnic minorities in a way that each 100 m × 100 m cell is colored based on the percentage of minorities in an area with a 500-m radius from that cell; Figure 1C shows the same for a radius of 2 km. These maps show potential ethnic exposure of people living in a particular cell for larger areas around their residence. Consider a cell in Figure 1A with a relatively low
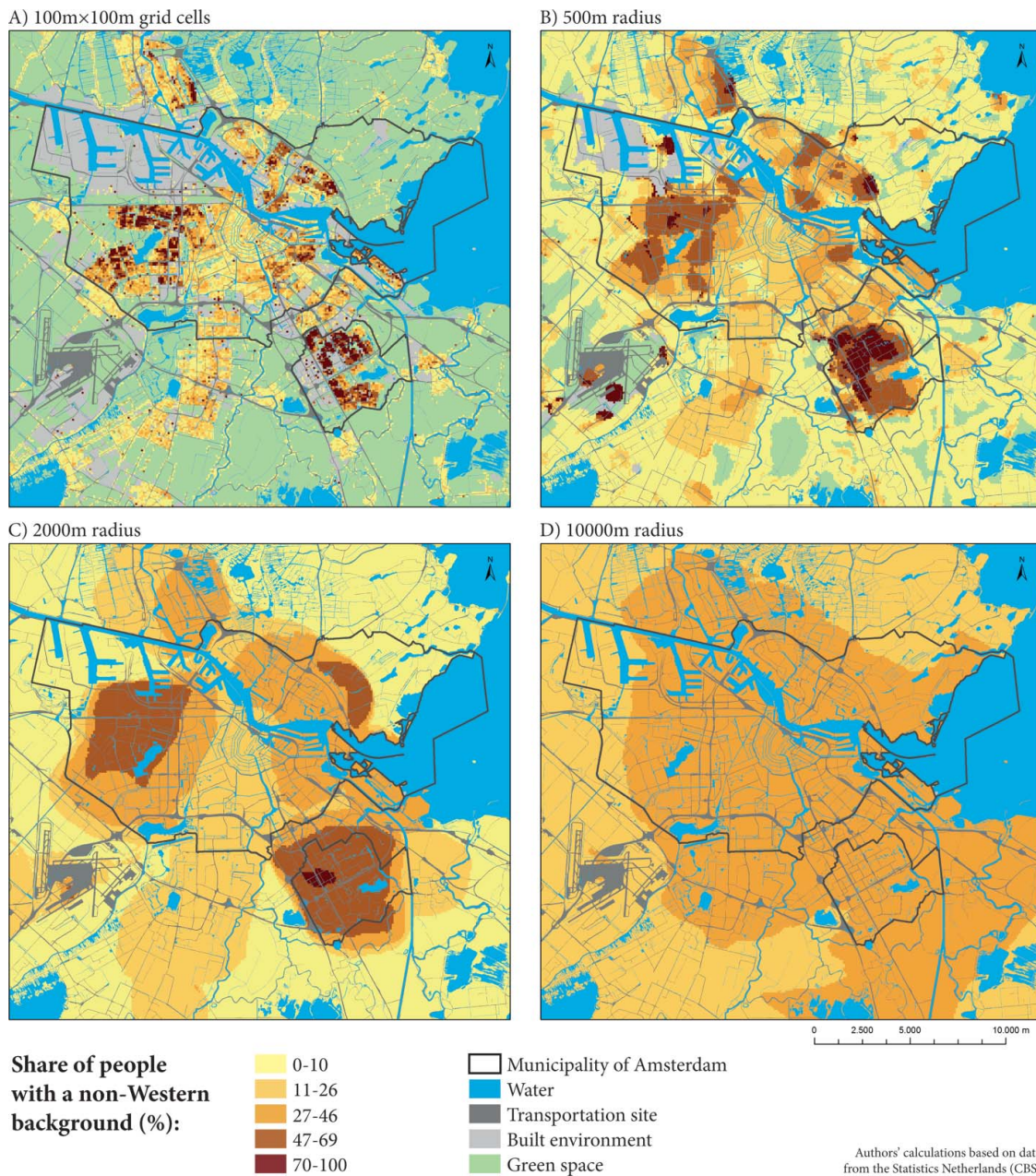
Figure 1. Maps of Amsterdam in 2013 for four sample scales: Share of people with a non-Western background in bespoke areas with various radii. (Color figure available online.)

percentage of minorities but surrounded by other cells with the highest percentage of minorities. Then at the scale of the dwelling or street, the potential exposure to ethnic minorities is low, but as soon as the residents travel to the next street, their potential exposure to "others" increases.

The higher spatial scale of 10 km represents the ethnic makeup of the whole urban area (Figure 1D), which is very different from our starting point, namely, the lowest spatial scale of 100 m × 100 m, representing experiences of residents just around their home.

Different scales, therefore, reveal different lived contexts, as certain clusters of high concentrations of minorities are recognizable at specific scales but not distinctive at others. With these detailed geocoded data and the large number of scales, we can observe how measures of population gradually change with scale, as opposed to the cross-sectional view of specific scales.

Of particular interest in this study is the distance profile of potential exposure for all 101 scales, which depicts the path that specific location follows from the scale of context mapped in Figure 1A to the one in
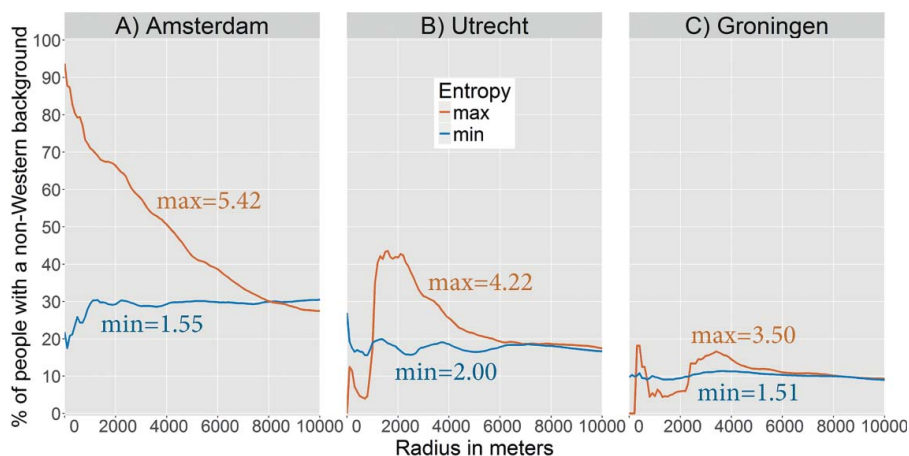
Figure 2. Individual distance profiles with minimum and maximum entropies in Amsterdam, Utrecht, and Groningen in 2013. (Color figure available online.)

Figure 1D. Each cell has its own distance profile showing how the share of non-Western people varies as we alter the scale in specific locations (with increasing distance from the starting cell representing a residential location). This profile represents the potential exposure to others as people move away from their location of residence. In this study, we propose to capture this variation in potential exposure in one entropy index, expressing the scalar complexity of exposure to ethnic minorities in each 100 m × 100 m cell in our study area. Figure 2 compares the distance profiles with the highest and the lowest entropies across the three cities (Amsterdam, Utrecht, and Groningen).

Distance profiles with low entropy are fairly flat; that is, the percentage of non-Western minorities is constant at most of the scales. The minimum entropy distance profiles from the three cities differ in the overall level of the share of non-Western minorities (around 30 percent in Amsterdam, 20 percent in Utrecht, and 10 percent in Groningen). The most constant multiscale measures of exposure to non-Western people are found in Groningen (Figure 2C). Amsterdam reaches almost the same minimum entropy in Groningen (Figure 2A), with more variant microscales. Unlike Amsterdam and Groningen, even the least variant distance profile in Utrecht slightly
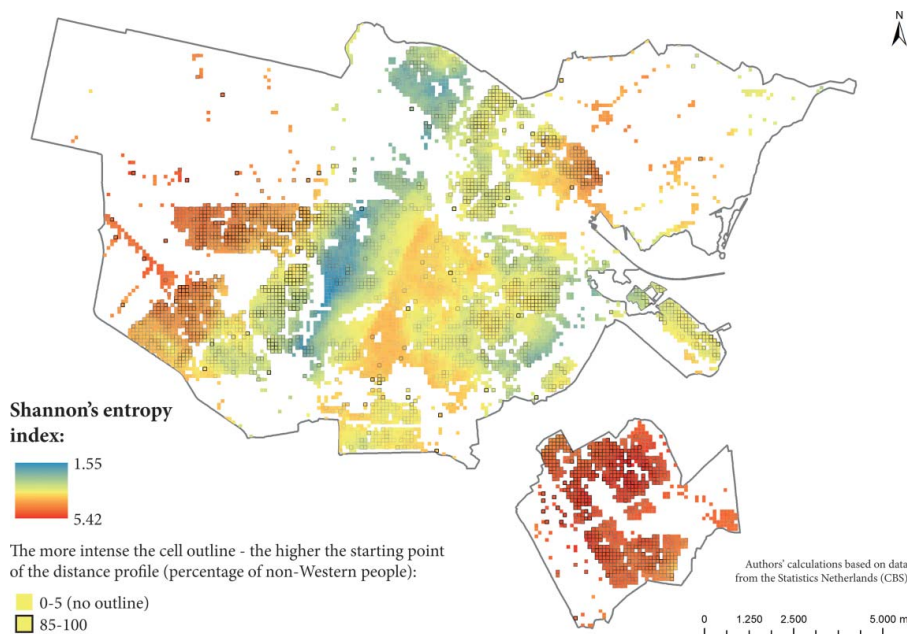

Figure 3. Entropy and starting point of distance profiles in Amsterdam in 2013. (Color figure available online.)

varies also at mesoscales, with an entropy of no less than 2 (Figure 2B).

Compared to minimum entropy profiles, the maximum entropies differ even more across the three cities. The closest profile to the theoretical maximum lies in Amsterdam (5.4). By contrast, the profiles associated with Utrecht do not reach this level, and the maximum in Groningen (3.5) corresponds to a medium entropy in Amsterdam. Therefore, maximum entropy demonstrates how relative the concept of scalar variability is in different settings; that is, what is considered big variability in one setting might be very different from what is considered big in another. On the other hand, minimum entropy underlines the difference in the broader, large-scale contexts of the cities, showing that scale-invariant measures of population might be constant across scale at very different levels in different settings.

As follows from Figure 2, Amsterdam has the biggest range of entropy, so the biggest variety of distance profiles. We have therefore mapped the distance profile entropy for all of the cells in Amsterdam to gain more insight into the within-city variability. Entropy was mapped together with the percentage of non-Western minorities at the lowest spatial scale, namely, the base cell or the starting point of the distance profile (see Figure 3). The ethnic composition at this lowest scale represents the potential exposure in the immediate surroundings of a dwelling, and what happens along the entire distance profile is represented by the entropy index. The combination of the values in the starting cell and the distance profile is important, as two distance profiles might have a similar entropy value but very different starting points.

Cells with the lowest entropy are predominantly located in a distinctive strip in the middle part of the city in the southwest–northeast direction (blue area, gradually changing to yellow). If we measure ethnic exposure in this part of the city, even big changes in scale of bespoke areas will not dramatically change the results, except for the smallest scales, where sudden shifts are possible. As can be seen by the cell outline, the base cells in the low entropy strip generally have a low percentage of non-Western ethnic minorities, which is around the city average or lower. Consequently, the inhabitants of these cells are not exposed to high percentages of minorities in their immediate locale, nor are they exposed to minorities as distance increases from their residence. There are also individual base cells, or small clusters of base cells, scoring low entropy with a very high percentage of ethnic minorities (dark outline), where the starting point of

the distance profile is very different from the rest of the profile. These small-scale concentrations of ethnic minorities are surrounded by larger areas with predominantly Western residents. In this case, small concentrations of ethnic minorities can be easily overlooked when bigger scales are used, although such small environments are relevant for studying social contacts in the neighborhood.

Cells with comparably high percentages of non-Western minorities in the southwestern part of Amsterdam in the Bijlmer have high entropy, often quite close to the theoretical maximum. This implies that the associated distance profiles have high starting values of ethnic exposure at a low scale and that the exposure drops considerably with increasing distance; for example, from 100 to 30 percent. Overall, the larger the scale, the lower the measured percentage of non-Western minorities as larger scales approximate city averages. Comparable patterns can be observed for profiles with high entropy but with a low starting point. Although starting low (so a very different potential exposure around the dwelling), these profiles reach high percentages of non-Western people at one of the lower spatial scales and then follow the gradual decline as described for the profiles with high entropy and a high starting point.

Although low entropy (flat profiles around the city average at multiple scales) and high entropy (gradual decrease of the share of minorities toward the city average) are fairly straightforward, medium entropy can be associated with different patterns of distance profiles. Medium-entropy profiles are sometimes "wavy," with different segments below or above the city average. In any case, the smaller the entropy, the closer the distance profile line is to the flat line of the city average. The most dramatic changes in potential exposure with increasing distance occur if the entropy is low and the percentage of ethnic minorities in the base cell is either very high or very low. Low entropy with a percentage of ethnic minorities considerably higher or lower than the city average means that the population measures at meso- and macroscales are consistent, whereas microscales are very distinct from their surroundings. The most gradual changes in potential exposure occur in profiles with high entropy, including very different percentages of non-Western people at various scales. These profiles can also start with both high and low percentages but, in any case, their high entropy indicates a downward slope of potential exposure toward larger scales.
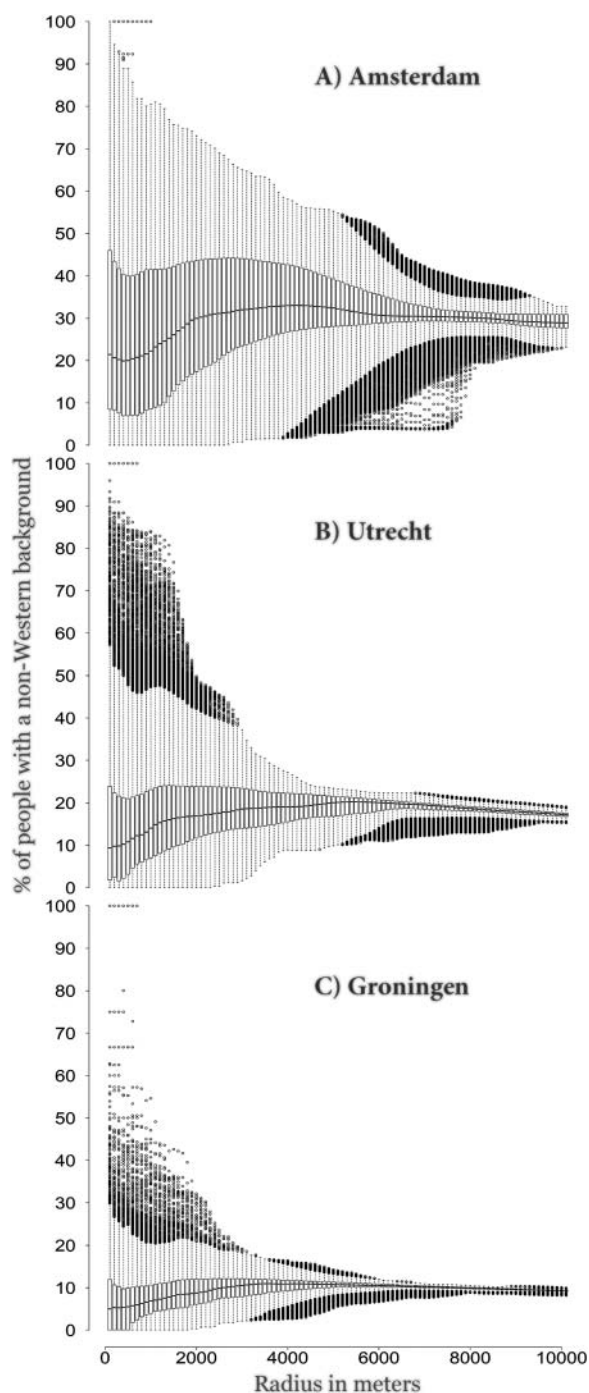
Figure 4. Cumulative distance profile of Amsterdam, Utrecht, and Groningen, in 2013: Boxplots for bespoke areas at 101 scales. *Note*: The dots represent outliers that lie outside 1.5 times the interquartile range above the upper quartile and below the lower quartile.

After focusing on individual distance profiles and comparing them both between cities and within the city of Amsterdam, we created cumulative distance profiles for Amsterdam (Figure 4A), Utrecht (Figure 4B), and Groningen (Figure 4C), to illustrate

the effects of different urban forms on measuring potential exposure to non-Western minorities. In each figure, an array of 101 boxplots jointly shows both the within-scale variability (information within each of the boxplots for each of the 101 scales) and the variability between scales (the changes in boxplots along the x-axis). In Amsterdam, the percentage of non-Western ethnic minorities at the smallest spatial scale (100 m × 100 m; the first boxplot at the left side of Figure 4) has the maximum variability (0–100 percent), with the interquartile range (covering the middle 50 percent of the data) between 8 and 46 percent and the median of 22 percent. On the contrary, at the 10-km scale (the last boxplot at the right), the median is 28 percent, with a much smaller range of values, because at higher spatial scales the percentage of minorities is averaged out over very large areas, approximating the city average.

The interest in comparing the three city figures lies in the multiscale comparisons of potential ethnic exposures, which depend on different levels of polycentricity in population distributions. Where in Amsterdam the full range of values is covered (from 0–100 percent minorities in an area), this is less the case in Utrecht and much less the case in Groningen. Different population distributions are more clearly visible in the interquartile ranges. The quicker the interquartile range narrows, the more equally spread the population is within the urban area of the city. In other words, if the interquartile range is narrow at already a relatively local scale, as is the case in Groningen with its monocentric urban form, the percentage of ethnic minorities in local areas must be fairly representative of the city as a whole, whereas if the interquartile range is relatively wide even at higher scales, such as in the case of Amsterdam, it follows that there must be distinct clusters of ethnic minorities in specific parts of the urban environment.

The fluctuations of multiscale population measures are related to levels of polycentricity in both intra- and interurban forms of the cities. In Amsterdam, which is the largest of the three cities, the area encompassed by the city is much greater and more diverse than for Groningen (the smallest). Whereas Amsterdam is highly polycentric, Groningen has less conspicuous centers, even less than Utrecht, which covers only a slightly bigger area than Groningen. Therefore, the Groningen profile demonstrates that the whole city can be represented by a much smaller scale (around 4,000 m) than for Amsterdam, where there is
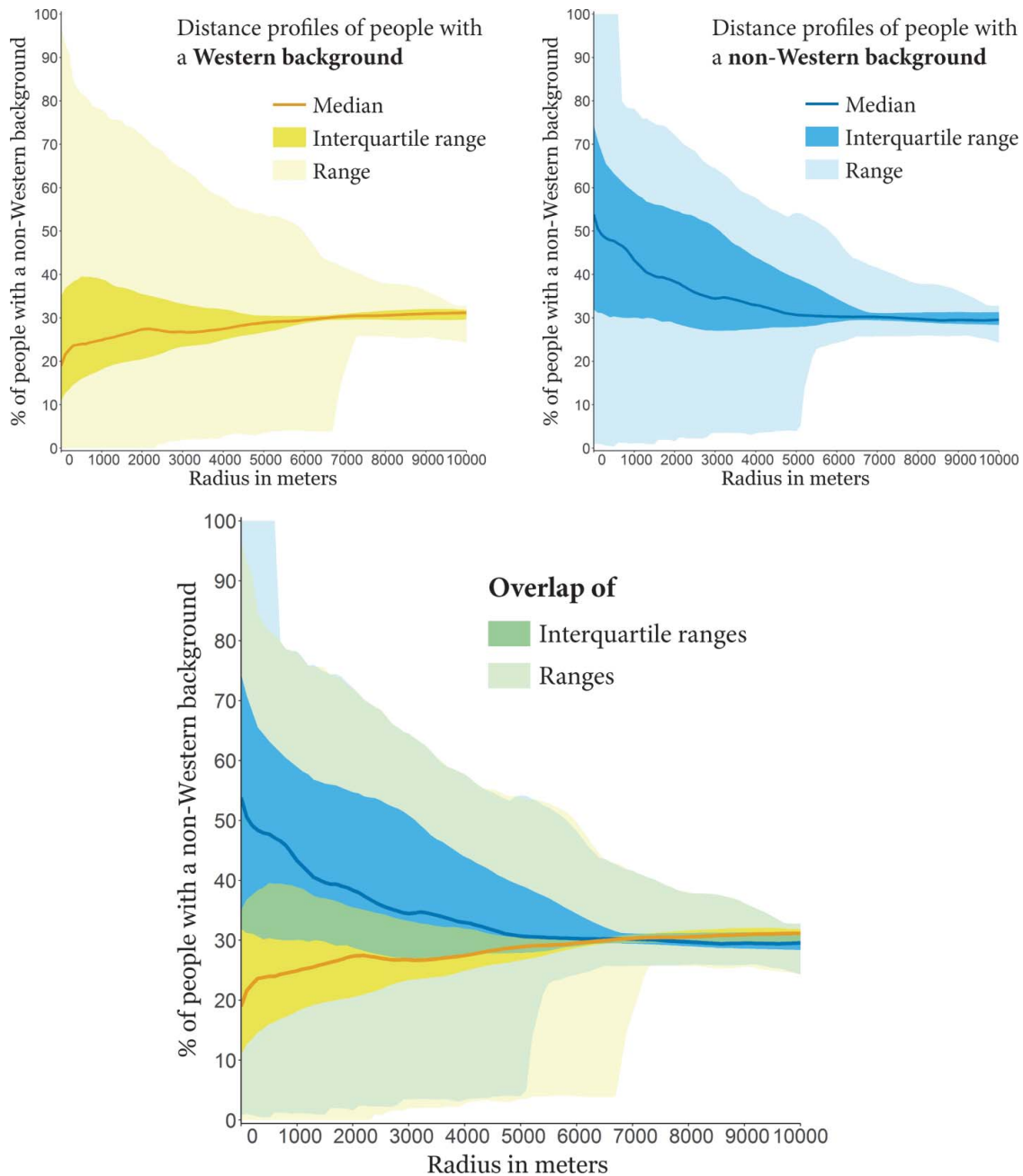
Figure 5. Fragmentation as potential exposure to others: Distance profiles of Western and non-Western people in Amsterdam in 2013. (Color figure available online.)

a far greater level of variation at much higher scales. In addition to intraurban form, the regional urban structure affects multiscale measures of population through exposure to the population of adjacent municipalities at higher scales and particularly at the edge of cities. In Amsterdam and Utrecht, the bespoke neighborhoods at larger scales (and those centered close to the city border also at smaller scales) include cells from the adjacent municipalities, whereas in Groningen, which is spatially relatively isolated from

other cities, spreading across the city border has minor effects on population measures, which is one of the reasons for only slight changes in the distance profile of Groningen at larger scales. Because of both intra- and interurban forms, the same scale captures different spatial contexts in different cities.

A crucial question at this point is why this all matters and what we can learn from comparing distance profiles for different residential locations and for different cities with different urban forms. Where the

literature is increasingly moving from using administrative areas to using bespoke individual neighborhoods, the question on what is the "right scale" is ever more pressing. Our approach is not to represent potential exposure to non-Western people at one particular scale of bespoke neighborhood but to use a (continuous) multiscale measure of population, represented as the spatial profile of a (residential) location. This profile includes a whole range of exposures and, crucially, we show that these profiles are very different for different locations in different cities. So, where two locations within the same city, or in two different cities, can have the same exposure value at one particular scale, it is likely that they will have very different profiles at a large range of scales. This is relevant when investigating neighborhood effects, because sociospatial interactions are likely to be multiscalar as well.

This is illustrated in the final step of the analyses. We have learned from the cumulative distance profiles that the potential exposure to non-Western ethnic minorities varies within and between scales in Amsterdam more than in Utrecht and Groningen. For research on segregation and neighborhood effects, it is important to investigate whether different population groups (in our case Western and non-Western ethnic groups) experience the ethnic exposure surface of their city in different ways. Figure 5 contains the share of non-Western ethnic minorities across the spatial scales for all individuals in Amsterdam and compares the two population groups. The range and interquartile range presented in Figure 4A are now split in two fragments, for each of the two groups, using color-coded areas (yellow for Western, blue for non-Western people).

The ranges of distance profiles of the two population groups are quite similar, with two exceptions (light blue and light yellow areas). Median and interquartile ranges, however, reveal considerable between-group differences. The bottom part of Figure 5 is constructed to show the overlapping distance profiles of the two smaller plots in the top half of Figure 5. The comparison of the profiles demonstrates that ethnic exposures of half of the non-Western minority people do not overlap with the ethnic exposure of half of the Western people at all spatial scales up to almost 7 km. Therefore, these groups have completely different ethnic exposures. Moreover, the overlap of the area above the first quartile of the non-Western profiles (covering 75 percent of profiles of non-Western people) and the area below the third quartile of the Western profiles (covering equal proportion of profiles of Western people) is as small as the

dark green area in the middle of the graph. In terms of the exposures gained by residents of Amsterdam, Figure 5 shows that the ethnic group to which an individual belongs clearly affects his or her sociospatial context in the same city at multiple spatial scales.

Discussion and Conclusions

This article started by acknowledging the importance of scale as a critical dimension of sociospatial context. Literatures on segregation and neighborhood effects have paid ample attention to the role of scale in understanding sociospatial inequalities and their effects on people. Increasingly, the literature uses bespoke neighborhoods besides conventional administrative units. Where most studies only consider one or two scales of neighborhoods, we have represented the sociospatial context as continuous, multiscalar, and complex, thus preventing the presentation of neighborhood (as a place of exposure) as a static single-scale entity (Manley, Flowerdew, and Steel 2006). This idea is related to the segregation profiles as introduced by Reardon and colleagues (Reardon et al. 2008; Reardon et al. 2009). Our contribution to the field is that we have conceptualized sociospatial contexts using complex distance profiles measuring potential exposure, in this case to ethnicity. We have captured this complexity by using entropy. Empirically, our distance profiles consist of bespoke areas over 101 scales. This exceptionally detailed approach confirms (and also intensifies) the relevance of spatial scale, long established in the segregation and neighborhood effects literature. Most important, the article offers ways to use scale to better understand exposure to the sociospatial context, by mapping various scales of context, quantifying the scalar variation, and comparing different places and different population groups across multiscalar urban space.

Underpinning the multiscalar framework is the idea that the spatial units representing people's immediate neighborhoods are the keystones that drive spatial patterns at both smaller and larger scales. This was illustrated in the maps of ethnic exposure surface of Amsterdam, starting from the microcontext of 100 m × 100 m grids to the ethnic makeup of a large urban area. The maps brought into focus the potential exposure to others when opening the front door of one's house (the microscale) but also the wider surroundings, what might be termed meso- and macroscales, which have also been shown to be important in

studies of urban phenomena such as segregation (see Manley et al. 2015). Together, the series of maps uncovered the social landscape of the city as multiscalar and continuous, consisting of various individual, overlapping sociospatial contexts.

A key contribution of this study is that we used Shannon's (1948) entropy to measure the variability of exposure to others across spatial scales for specific locations. The entropy index gives us insight into the scale aspect of the MAUP, by quantifying to what extent altering scale affects the measurement of contextual characteristics in different places. Entropy also expresses the uncertainty of a measurement at a given scale as representation for a wider range of scales. Further studies should test whether contextual effects on individual outcomes change in combination with scalar changes in contextual characteristics. This study has benefited from microgeographic grid data in The Netherlands, but the approach is still applicable in countries where such data are not available. For instance, the small census blocks in the United States, mesh blocks in New Zealand and Australia, and output areas in the United Kingdom all offer candidates for further exploration.

Besides quantifying the scalar variation as uncertainty of measuring contextual characteristics, the entropy index comprehensively describes a wide range of scales as a social environment beyond the immediate neighborhoods. The entropy index of a residential location combined with the actual exposure in this microarea showed that similar local contexts could have very different "context of context," including both abrupt and gradual changes toward the average share of ethnic minorities in the city. The meaning of this becomes more clear by using an example. When studying potential exposure to non-Western people, a distinction can be made between locations with very high microconcentrations of ethnic minorities immediately surrounded by a larger area with an average share of minorities and high microconcentrations that only gradually change toward the city average. The people living in these two hypothetical locations will have very different potential exposures to others when they move away from their dwelling, which is highly relevant for segregation and neighborhood effects studies.

The effect of scale becomes particularly apparent when comparing cities with different urban forms. This article systematically explored the variation in exposure to sociospatial context for a large number of scales in three different cities. Although urban form is rarely considered in research on sociospatial inequalities, we have argued and shown that urban form is related to how populations are arranged across space and how this affects multiscale measures of sociospatial context. At a given spatial scale, the context of context might be very different in different cities, notably with different size and urban form. Both interurban and intraurban polycentricity are reflected in ethnic concentrations at various scales. This is clearly seen when comparing the Amsterdam or Utrecht (different in size, but both parts of the Randstad conurbation) distance profiles of ethnic exposure with that of Groningen (almost the same area as Utrecht but spatially more isolated).

We illustrated the relevance of our multiscalar measures of population by comparing potential ethnic exposures for Western and non-Western people in Amsterdam. The two population groups are potentially exposed to very different shares of non-Western ethnic minorities even at larger scales, especially in a context of a polycentric urban form and strong urban fragmentation. Their ethnic exposure profiles, therefore, appear as different sociospatial fragments of the same city, persistent at a wide range of scales. Further studies should test in which ways and to what extents this multiscale fragmentation affects socioeconomic outcomes of individuals from the two population groups.

Finally, the multiscale measures of population revealed "social cliffs" (borrowing from the notion of social tectonics by Robson and Butler 2001) both in individual environments across urban space as well as between different population groups within one city. Exemplified with the share of non-Western minorities, our approach is applicable to other population characteristics, such as income, education, or age. The presented variation over scale urges caution in choosing singular spatial scales and suggests that attention must be given to multiple spatial contexts when exploring sociospatial inequalities. We find more variation and greater complexity in spatial patterns with more detailed spatial data and a wider range of scales, but this is a way to better understand exposure to others across urban space based on the location where one lives. Scalar variation is likely to be the result of systematic and predictable processes and, as such, warrants further intensive study in the research of sociospatial inequalities.

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Supplemental Material

Supplemental data for this article are available on the publisher's web site. The supplemental online video contains maps for all 101 scales in Amsterdam, Utrecht, and Groningen. The video gives an overview of all three study areas and demonstrates in detail the scalar changes in potential exposure to non-Western ethnic minorities.

Notes

1. Statistics Netherlands defines people to have a foreign background if they are first-generation immigrants (i.e., if they are born abroad) or if one of their parents belongs to the first generation. A distinction is made between Western and non-Western backgrounds, so that individuals from Europe (excluding Turkey), North America, and Oceania, as well as individuals from Indonesia and Japan, are defined as Western. The justification for the latter two ethnic groups being Western lies in their social and economic position in Dutch society. Conversely, people originating from Africa, South America, or Asia are categorized as people with a non-Western background, which is, according to most policymakers, comparable to "ethnic minorities" (Alders 2001).
2. We do not apply any distance decay function, as we want to robustly compare different scales, but our approach can be modified to investigate spatial scale in different ways.
3. We have rounded percentages to the closest integer. Coarser rounding has the effect of smoothing the profile

lines and leads to more similar entropies between different profiles.

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