Beyond boundaries

Geographical aspects of urban health

Veldhuizen, E.M.

Beyond Boundaries

Geographical Aspects of Urban Health

Els Veldhuizen

*B*eyond *B*oundaries

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Beyond Boundaries
Geographical Aspects of Urban Health

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CHAPTER 1

General introduction

Spatial variations in health exist at multiple geographical scales. The list of common diseases in the Global North is different from the list of diseases in the Global South. Health conditions differ between continents and countries and within countries as well (e.g. WHO & WMO, 2012; Groenewegen et al., 2003). E.g. urban dwellers are confronted with other health problems than rural dwellers (e.g. Verheij, 1996; Mainous & Kohrs, 1995; Eberhardt & Pamuk, 2004). Even at the city scale differences in health can be observed: e.g. obesity is not equally distributed across cities (Smith et al., 2010; Lakes & Burkart, 2016).

These spatial variations in health suggest that the area where people live has an impact on their health. A lot of epidemiologic and geographical research is dedicated to studying geographies of health and the ways in which the environment influences health conditions. Researchers are trying to find out how strong area effects on health are and how they emerge. Answers to these questions can be used to reduce health disparities and improve public health. Although the research field has a long history, the answers to these questions are not yet clear.

1.1 Explanations for spatial variation in health outcomes

Generally, three types of explanations are used to explain differences in health between places (Macintyre & Ellaway, 2000). The first type comprises *compositional explanations*. Obviously, health differences can be related to the type of people living in different areas. If older people are more often ill compared to young people, more unhealthy people will be observed in areas with a relatively large number of older people. This type of explanations explains health differences by differences between the individual characteristics of people living in various areas; differences are the result of *individual effects*.

In most cases compositional explanations cannot completely explain health differences between areas. In some areas relatively more (un)healthy people might be observed than would be expected based on individual characteristics. How can this be explained? Two possible explanations might be relevant for the remaining area differences: the influence of the environment (e.g. Diez Roux & Mair, 2010; Mair et al., 2008; Paczkowski & Galea, 2010; Pickett & Pearl, 2001) or selective migration (e.g. Verheij et al., 1998; Norman et al., 2005; Van Lenthe et al., 2007).

In the case of influence of the environment, the literature refers to *area effects, neighbourhood effects* or *contextual effects*. There are many potential pathways, mechanisms and linkages connecting the neighbourhood context and various individual outcomes (see for example, Galster, 2012). Area effects on health can be the result of characteristics of the physical and functional environment such as the presence of polluting industries (e.g. Green, 1995), high traffic densities (e.g. Chakraborty, 2009), quality of the dwellings (e.g. Krieger & Higgins, 2002), availability of health services (e.g. Gulliford et al., 2002) or green space (e.g. Van den Berg et al., 2010). In addition, effects can be the result of characteristics of the social environment such as the type of people living in the neighbourhood; these effects are sometimes referred to as structural effects. Neighbours can cause stress, offer support and influence health-related behaviour. Youth hanging out in the streets, noisy neighbours and people from other ethnic groups can cause stress and stress, in turn, can cause health problems. Maintaining good relationships with neighbours may result in support in times of need which might have a positive impact on health. The presence of relatively many people with a (un)healthy lifestyle (e.g. smoking, cycling) in the neighbourhood may stimulate others to adopt a similar lifestyle which in turn might have an impact on health as well (e.g. Yen & Syme, 1999).

A third explanation for differences in health between places is *selective migration* based on health or health risk factors. Migration based on health is referred to as direct selection and migration based on health risk factors (such as smoking or drinking) is referred to as indirect selection. Health determines migration if residents migrating to less deprived neighbourhoods are healthier than those who stayed behind or if residents migrating to more deprived neighbourhoods have more health problems than those who stayed behind (Boyle, 2004; Boyle et al., 2009).

1.2 Environmental influences on health

The idea that place matters to health is not new. Epidemiologists and geographers have had a long tradition of interest in the influence of the environment on health. In the 19^{th} century, Medical Geography, which focuses on the spatial relation between human health and environmental factors, was flourishing. Since the spatial distribution of disease is an important research topic, mapping plays an important role in Medical Geography (Kistemann et al, 2002). A classic example of research in this field dates back to 1854. In that year, John Snow worked as a physician in the district Soho in London. Many of the inhabitants of Soho died of cholera and Snow suspected local drinking water as the main cause of infection. At that time, people had to fetch water from pumps. By plotting the location of victims and water pumps on a map (figure 1), the emergent spatial patterns revealed that the pump situated in Broad Street, which was clearly surrounded by most victims, was probably the main cause of the epidemic. Snow advised the city council to remove the pump from public use, which stopped the epidemic (Gilbert, 1958; McLeod, 1998).

Figure 1. Cholera outbreak in the district Soho in London in 1854

Left: original map of John Snow drawn by cartographer Charles Cheffins (source: Published by C.F. Cheffins, Lith, Southhampton Buildings, London, England, 1854 in Snow, John. On the Mode of Communication of Cholera, 2nd Ed, John Churchill, New Burlington Street, London, England, 1855). Right: a modern reproduction of the map using Geographical Information Systems (GIS).

During the 20th century, most epidemiologic research focused on individual-level risk factors to explain spatial variations in health. There was relatively little interest in the role of the environment (Diez Roux, 2001). This might be partly the result of a lack of large datasets with individual information and appropriate methodologies to distinguish the effects of context and composition.

In the 1990s, interest increased in the possible role of the environment in influencing health outcomes (Macintyre et al., 1993; Curtis & Jones, 1998). On the one hand, it was the result of growing social concern about the consequences of neighbourhood effects for people's health and well-being. It was recognised that research into whether and how neighbourhood characteristics affect health was needed in order to formulate more effective public health strategies (Owen et al., 2016). On the other hand, the emergence of new methodological approaches, such as multilevel analysis, has stimulated research into area effects on health. Before the introduction of multilevel analysis, individual-level health outcomes were commonly explained using regression models which included both individual-level and area-level independent variables as individual-level attributes. This violated the assumption of independence of observations as people living in the same area (ward or census tract) will have the same score on the area-level variables. This resulted in an underestimation of the standard errors of the area effects, which could result in too optimistic conclusions about the significance of these effects. Multilevel models made a great contribution to studies of area effects on health by creating the possibility to include individual and area-level variables in a statistically correct way (Owen et al., 2016).

1.3 Defining the spatial concept neighbourhood

In most research on area effects on health, the area of interest is the residential neighbourhood. But what is a neighbourhood? The answer seems obvious, but it is certainly not. The term neighbourhood can be defined in multiple ways: officials define the neighbourhood administratively, but different groups (e.g. different age groups) and individuals have their own perception of a neighbourhood which may be quite different (Kearnes & Parkinson., 2001; Sykes, 2011). For example, Vallée et al. (2014) found that perceived neighbourhoods were four times larger in rich than in poor areas.

Defining neighbourhood as a 'person's immediate residential environment, which is hypothesized to have both material and social characteristics potentially related to health' (Diez Roux, 2001, p.1784) does not provide useful information on what its geographical boundaries should be (Owen et al., 2016).

A major point of criticism regarding research on neighbourhood effects and health, and neighbourhood effects research in general, is that it remains limited by the way 'the neighbourhood' is defined and operationalised. A common practice in the past has been to define residential neighbourhoods as administrative areas such as census tracts and wards. Generally, these units are designed to cover the country or city with units of roughly similar size, a reasonably compact shape, and a degree of social homogeneity. As such they may not be appropriate for health research because the boundaries will probably not correspond to the relevant geographic neighbourhood for health outcomes (e.g. Flowerdew et al., 2008; Root, 2012; Siordia & Matthews, 2016; Owen et al., 2016).

Using administratively defined areas poses three problems which may result in real area effects being hidden while spurious effects are displayed (Owen et al., 2016). Two of these problems are related to the geographic theory of the modifiable areal unit problem (MAUP). The MAUP is a classic problem in statistical analysis of geographical data. Its essence is that neighbourhood effects are partly determined by the way the neighbourhoods are defined (Openshaw, 1984; Haynes et al., 2007; Spielman & Yoo, 2009). The first problem is referred to as the *scale effect*. According to the scale effect, there may be major differences in results regarding neighbourhood effects depending on the size of the units used. The second problem concerns the *zonation effect*. The zonation effect, sometimes called the aggregation effect, shows that there may be major differences in results depending on how the study area is divided up, even at the same scale (Flowerdew et al., 2008).

The third problem of using administratively defined areas is that *boundary effects* may occur. Boundary effects occur especially when administrative boundaries are not relevant in the daily lives of residents. Residents living near the border of administrative areas may relate more to neighbouring administrative zones (Flowerdew et al., 2008).

The evidence suggests that a neighbourhood definition is required that is consistent with how context has an effect on specific health outcomes and at what spatial scale these mechanisms work (e.g. Diez Roux, 2001; Owen et al., 2016). Therefore, the neighbourhood of interest to researchers should vary depending on the research question and research topic. This implies that the definition should not be restricted to administratively defined areas but needs to be much more flexible to be relevant, meaningful and useful.

1.4 Mechanisms linking neighbourhood characteristics and health

The research field has two important objectives. The first one is to determine the nature and the relative importance of neighbourhood effects (what characteristics are important for health and how much influence do these characteristics have?). The second objective is to explain how these characteristics influence health (what are the mechanisms driving these effects?). Understanding at what spatial scale these mechanisms work is essential for a relevant neighbourhood definition which is needed to find the correct answers to these questions.

Previous research suggests that physical and social characteristics of a neighbourhood, such as neighbourhood SES (socio-economic status), ethnic density, the presence of a hazardous waste facility, green space, social cohesion or collective efficacy, may influence health. The influence can be direct or indirect (Blakely & Woodward, 2000). An example of a direct pathway is air pollution affecting a person's respiratory system. Indirect pathways are often more complex. Green space can stimulate people to be physically active which in turn might prevent overweight and related health problems. In general, characteristics of the social environment are linked to health via two types of indirect pathways: the link can be established via the *experience of stress or support* or via the *adoption of good or bad health-related behaviour*. A low density of the own ethnic group in the neighbourhood can cause feelings of stress which have a negative influence on health, while a high density of the own group may result in support with positive influences on health (e.g. Das-Munshi et al., 2010). Prevailing norms in a neigbhourhood regarding smoking and alcohol use can stimulate or retain others from smoking or drinking and many cycling people in the neighbourhood might stimulate others to go for cycling as well (Ball et al., 2010).

The mechanisms through which area characteristics influence health operate at different spatial scales. Some mechanisms might operate in the block in which a person resides, some might operate in a larger area around the block, some might operate at the level of administratively defined areas when for instance the hypothesised processes involve district-specific policies (Kwan, 2012; Root, 2012). If the hypothesised processes involve stress or social support, influenced by for instance ethnic composition, a micro-spatial scale may be more appropriate for identifying effects because people might be most confronted with people living nearby.

1.5 Beyond administrative boundaries

Despite the problems mentioned in section 1.3, most studies have used relatively large scale administratively defined areas because these areas are easily identified, replicable and secondary source data were for a long time only available for these units (Weiss et al., 2007).

Recently, opportunities for a more flexible definition of neighbourhoods have increased as a result of the growing availability of data and extended possibilities for spatial analysis. Big data, the increasing willingness to make administrative micro-scale data available for research and widespread diffusion of geospatial data acquisition make new relevant highly accurate spatial data sources available to health research (Owen et al., 2016). Furthermore, the increasing use of Geographical Information Systems (GIS) offers opportunities to create data at a relevant spatial scale and to employ methodologies that were previously impossible. GIS have proved valuable in different ways. First of all, it enables the integration of multiple layers of interdisciplinary spatial data such as health, environmental, social and demographic data for spatial analysis (Richardson et al., 2013). While the original map of John Snow allowed for visual analysis only, the same information entered into a GIS allows for additional advanced spatial analyses. Secondly, it allows the measurement of area characteristics and the analysis of effects of these characteristics on health at different, flexible spatial scales (National Research Council, 2010; Weiss et al., 2007; Flowerdew et al., 2008). Finally, GIS are extensively used to identify clusters or hotspots of diseases or other health-related problems (Kistemann et al., 2002).

To avoid the problems associated with administratively defined areas, several alternative neighbourhoods have been defined. Generally, there are two approaches to constructing alternative, more effective neighbourhoods. One approach is based on *exposure* with regard to a particular environmental determinant of health. Several studies use so-called *bespoke environments* to define the neighbourhood (Schuurman et al., 2007; Frank et al., 2004; Propper et al., 2005; Propper et al., 2007). In this methodology, each individual has been designated an area of a certain distance or with a certain number of people around the home location. For these individual neighbourhoods exposure is measured to a specific environmental risk factor for health. This methodology avoids scale and boundary problems by putting the individual in the centre of his or her residential neighbourhood and by allowing easy construction of bespoke environments (buffers) of different sizes. Other studies experimented with automated zone design software which groups a set of basic areal units into a smaller number of zones in order to create the most effective neighbourhoods. The criteria used in the grouping process might include combinations of the number of zones required, constraints on the population size of each zone, the compactness of zone shape and a requirement to maximise the homogeneity of specified variables within each zone (e.g. Flowerdew et al., 2008). Kwan (2012) pleads the use of GPS to define relevant neighbourhoods by tracking the activity space of residents. GPS data provide information on where and how much time people spend around their home with very high spatial and temporal resolutions allowing to assess people's environmental exposures within their residential neighbourhood much more accurately. Moreover, more qualitative methods have been adopted to define the relevant neighbourhood based on the perceptions of residents. These neighbourhoods are often referred to as perceived neighbourhoods (Weiss et al., 2007). A variety of map drawing activities can be used to explore how people perceive their residential environment (Fraser et al., 2013).

Another approach to constructing relevant areas for research on environmental influences on health is to focus on the spatial distribution of health and potential determinants of health. In this approach the focus is on ‘unhealthy’ hotspots. In these areas the rate of occurrence of a particular phenomenon (for example alcohol-related ambulance attendances, a particular disease or a vulnerable population group) is far above its average occurrence (e.g. Stopka et al., 2014). To explain the higher incidence of health-related problems in hotspots, environmental characteristics of the hotspots and their surroundings are being studied (e.g. Schuurman et al., 2009).

1.6 This thesis

In this thesis we employ the hotspot approach and the bespoke environment approach. In none of our studies the neighbourhood boundaries are determined beforehand. We test these methodologies using different data sources and different health-related themes within the context of the Dutch capital Amsterdam, the city in which the two involved research institutes are situated and for which very small-scale data are available. The availability of small-scale data and GIS enables us to pay specific attention to the relation between area and health at very local spatial scales, something which only a few studies did before. Familiarity with the city may help us to interpret the results.

Amsterdam is the capital of the Netherlands with a population of more than 820,000. The city is intensely urbanised with 4,457 inhabitants per km^2. The city is growing and has become increasingly diverse. It is now the city with the largest number of different nationalities in the world and has frequently been described as super-diverse with people from more than 170 countries (Crul & Schneider, 2010). Half of the inhabitants of Amsterdam are native Dutch, but it is expected that this figure will have fallen to around 40 percent in 2030. Approximately 35 percent of the population belong to an ethnic minority – people from Surinam, the Netherlands Antilles, Turkey, Morocco, and non-industrialised nations (OIS, 2015).

The city has a long tradition of social democracy which may have resulted in relatively low levels of segregation. Social housing policies and urban renewal schemes limited sharp differences in living conditions amongst its population. However, since the economic crisis in 2008 trends in the opposite direction can be observed. The A10 ring road, which separates the pre-war and post-war parts of the city, is frequently seen as a barrier, both physically and mentally, dividing the rapidly gentrifying inner city neighbourhoods from the periphery of the city where most of the low-income households live (Savini et al., 2016).

The health conditions of the inhabitants of Amsterdam are not evenly distributed across the city. The Amsterdam Health Monitor provides information about the health, risk factors, and wellbeing of the inhabitants of Amsterdam. Results from the 2012 Monitor show clear spatial variations in health outcomes. For instance, it seems that residents in the districts North, South East and New West report more often psychological problems, chronic diseases and overweight. Compared to other districts, relatively many older people in the districts West and East appear to have problems with daily activities. In contrast, in the districts Centrum and South much more, and often too much, alcohol is being consumed (GGD Amsterdam, 2012). Possibly these differences can be explained by individual characteristics but differences might also be the result of area effects.

Objectives of this thesis

The main objective of this thesis is to employ spatial methodologies with the aim to provide a more accurate identification of environmental determinants of health in Amsterdam.

The following research questions are examined:

- Can the clustering of health problems into hotspots be understood by environmental characteristics of these areas?
- Are individual health outcomes associated with specific area characteristics, after controlling for known individual-level determinants of such outcomes?
- At what spatial scale do these area characteristics influence health outcomes?

Data used for this thesis

The studies in this thesis use primarily quantitative research methods and data. Individual health measurements were provided by three datasets. The first dataset, The State of the City 2009 (in Dutch, "De Staat van de Stad"), included information on health and individual characteristics of 4351 inhabitants of Amsterdam.

The survey was conducted by the Department of Research and Statistics of the municipality of Amsterdam (OIS).

The second dataset, the 2012 Amsterdam Health Monitor, surveyed 7218 adult inhabitants and includes information on a wide range of health-related and individual characteristics. This monitor is updated every four years and is conducted by the Amsterdam Public Health Service.

The third dataset we used is the HELIUS (Healthy Life in an Urban Setting) study. HELIUS is a large-scale cohort study on health and healthcare among different ethnic groups living in Amsterdam. For our studies, baseline data collected from 2011 until 2014 were used (N=14092, including 2962 Turkish and 3000 Moroccan participants).

The final dataset we used contains alcohol-related ambulance attendances counts between 2006 and 2011 and was provided by the Regional Ambulance Services Agglomerate Amsterdam (RAVAA).

For our area measurements, we used integral demographic and socio-economic registries at the level of six-digit postcodes maintained by the Department of Research and Statistics of the Municipality of Amsterdam (OIS). Additional area-specific information was derived from the city's Department of Planning and the Department of Transport and Infrastructure. Furthermore, we used Google Street View to describe the built environment.

Qualitative methods and data were used in one of our studies to provide additional information on the local context of hotspots of alcohol-related ambulance attendances. This information could not be captured by quantitative measures or by using Google Street View. The information was gathered during field visits and by holding face-to-face interviews with key informants.

Outline of this thesis

Part I (chapters 2 – 4): studies employing the hotspots approach

Chapter 2 presents an online tool for mapping spatial concentrations in demographic and socio-economic data for the region of Amsterdam. The mapping methodology goes beyond administrative areas with fixed boundaries by introducing 'data-driven dynamic geographies'. The tool might be helpful in the identification of small-scale hotspots of risk populations for specific health outcomes. Such information can be used in local urban health policy to direct interventions to the places where these interventions will be most effective.

Chapter 3 is an exploratory study using mixed methods aimed to characterise the environment of hotspots of alcohol-related health incidents outside the entertainment areas of Amsterdam. We used both quantitative and qualitative methods in order to explore the full range of possible (combinations of) environmental determinants responsible for the increased occurrence of alcohol-related health incidents.

Chapter 4 identifies hotspots of alcohol-related health incidents in the entertainment areas of Amsterdam. It presents a controlled before-and-after evaluation that investigates how levels and trends of alcohol-related health incidents changed after implementation of a new alcohol policy in 2009 in some of the entertainment areas which allowed alcohol outlets in two of the five hotspot areas to extend opening hours. The presence of intervention and control areas and the availability of data before and after the policy implementation (2006-2011) created a unique experimental setting.

Part II (chapters 5 – 7): studies employing the bespoke environment approach

Chapter 5 presents a cross-sectional study assessing associations between socio-economic environment and self-rated health. The study defines the neighbourhood as a so-called bespoke environment and assessed the association at different spatial scales. We controlled for individual-level demographic and socio-economic characteristics that could be considered to be potential confounders to the association between health and the environment.

Chapters 6 and 7 have a similar approach. Apart from controlling for the essential individual characteristics, we controlled for the socio-economic environment as well. **Chapters 6** and 7 both focus on the association between ethnic composition and health. In **Chapter 6** the association between ethnic composition and self-rated health is assessed for 8 different ethnic groups. **Chapter** 7 focuses on Turks and Moroccans and the influence of ethnic composition on self-rated health and a physical and mental component score (PCS and MCS). Additionally, the study explores whether associations vary within Amsterdam.

Finally, **Chapter 8** summarises the main findings of the studies, discusses some methodological considerations and reflects on the main findings. Furthermore, it presents implications and recommendations for future policy and research.

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CHAPTER 2

Crossing boundaries: mapping spatial dynamics of urban phenomena at micro scale to support urban management in the Amsterdam urban region

Abstract

Maps are widely used to provide urban managers with information on critical urban issues such as deprivation, unemployment, and segregation. Although administrative boundaries have always played an important role in map making, they are not meaningful for revealing the spatial dynamics of urban phenomena that vary within wards, cross ward boundaries and do not necessarily stop at the city boundary. Recently, very detailed (spatial) data have become available providing opportunities for new types of urban mapping. To process these data into meaningful maps, three aspects are important. First, information on maps should be produced at a spatial scale that is relevant for a particular urban phenomenon. Second, to reveal and monitor urban dynamics, maps of a phenomenon at different moments in time are needed. Finally, to accommodate access to these maps for potential users without (much) expertise in mapping, they should be provided through an easy to use tool.The Regional Monitor Amsterdam (RMA), an online GIS application, deals with these aspects. The purposes of this paper are to explain the mapping methodology adopted in the RMA and to illustrate the usefulness of the tool in urban management. This methodology goes beyond administrative mapping areas with fixed boundaries by introducing 'data-driven dynamic geographies'. We argue that this methodology produces relevant information by recognizing the scale at which urban phenomena occur. The monitoring tool assists in answering policy questions by easy access to relevant maps for different moments in time.

2.1 Introduction

Urban societies are changing at unprecedented rates and are becoming more diverse (Tasan-Kok *et al.*, 2013). Urban populations are growing and the ethnic composition of the population has become more heterogeneous as a result of large-scale migration. Socio-economic processes and advances in transportation and communication technology turned monocentric cities into polycentric metropolitan regions (Burger, 2011). These trends create new opportunities such as stronger regional economies due to agglomeration benefits (Faludi, 2004) and innovation due to ethnic diversity (Lee, 2014). However, these trends may increase problems and create new challenges as well such as competitiveness between urban centres, increased traffic congestion, increasing inequalities, deprivation, unemployment and segregation.

In the Amsterdam region, the increasing polycentricity is reflected in the demographic and economic sphere and in intraregional residential mobility. As a consequence, traditional monocentric views on the city need to be revised: social deprivation, ethnic minorities and employment are no longer phenomena typical for the city of Amsterdam only. The share of inhabitants of non-western origin is growing rapidly in the surrounding municipalities. Both the labour market and housing market function at the regional level. Different concentrations of employment have developed in the urban region and different urban centres become attractive during different phases in people's lives. Households without children are over-represented in Amsterdam and in smaller older cities such as Haarlem while family households appear particularly in new towns such as Almere and Haarlemmermeer. Although Amsterdam remains the major centre of activities and employment the newer and older urban subcentres in the region (such as Amstelveen, Almere, Haarlem, Haarlemmermeer, Purmerend and Zaanstad) have become increasingly important. Rather than competing with Amsterdam, they develop in a complementary way (Musterd *et al.*, 2006).

In such polycentric, diverse and dynamic urban environments space-time information is indispensable to formulate adequate policies containing both local and regional components (Musterd *et al.*, 2006). Recently, the increasing ability to collect data from multiple sources with higher spatial and temporal resolutions, also referred to as 'big data', offers opportunities to enhance our understanding of urban dynamics and the functioning of cities and urban regions. However, these 'big data' poses a number of epistemological, methodological and ethical challenges (Kitchin, 2013). In order to be useful for urban managers and policy makers new methodologies and tools are needed to turn the huge amount of available data into meaningful and accessible information.

Maps as information mediators

Maps have always been important in communicating spatial information. They reveal spatial patterns not easily identified by tables or graphs. With the increased availability of micro-scale data and the evolution of advanced information and communication technologies, the application of Geographical Information Systems (GIS) within the urban policy practice has increased rapidly. To date, several easy-to-use online GIS applications have been developed to inform urban policy and to make urban management more efficient and effective. In this context, we can distinguish four types of tools. The first type are interactive thematic online applications. Such applications offer thematic maps on a wide-range of urban indicators or composite indices at different geographical scales and for different moments in time, with varying functionalities regarding interactivity, map representation and analysis (Smith, 2016). Second, GIS-based e-governance tools have been developed, to both inform citizens on the state of urban neighbourhoods and to provide a means to citizens to inform the government on the malfunctioning of particular municipal services. (Gullino, 2009; Pfeffer *et al.*, 2015). A third type concerns tools that support participatory planning and policy making, where citizens can provide their inputs through a GIS-based online application (Kyttä *et al.* 2013). Finally, with the wider availability of all sorts of data - increasingly real-time or near real-time - the most recent tools are city dashboards, where different kinds of data visualizations are combined, including interactive thematic maps on different urban phenomena (Kitchin *et al.*, 2014).

The Regional Monitor Amsterdam discussed in this article relates to the first type of tools. Many of the interactive thematic online applications represent population and housing registries and statistics in graphs and thematic maps. The majority of these tools spatially represent individual indicators such as the percentage of 1-person households, with DataShine (http://datashine.org.uk) or the online neighbourhood monitors of several Dutch municipalities (www.buurtmonitor.nl) being illustrative cases. There are also tools that focus on a particular theme and visualize its spatial pattern through a composite index. Examples are the Dutch Leefbaarometer to monitor the perception of quality of life (www.leefbaarometer.nl), the Demowijzer to monitor demographic change (www.demowijzer.nl), the British Luminocity tool (http://luminocity3d.org) to map multiple themes, the London Profiler (Gibin et al. 2008) to monitor, among other things, multiple deprivations, or the Peruvian socio-economic index application Sisfoh (http://www.sisfoh.gob.pe).

Methodological considerations of mapping

In the Netherlands, public and private bodies collect a lot of data at six-digit postcodes level. In urban areas, these are rather small units sized approximately 50 x 50 meters and include 10 to 20 households. Mapping such small units results in maps which do not provide clear patterns and are difficult to read and to interpret. Hence, in order to produce meaningful spatial information, such data should be aggregated and grouped into larger mapping units. Aggregating spatial data can be done in different ways, is endowed with methodological challenges and produces different outcomes (e.g. Monmonier, 1991).

Interactive thematic online applications aggregate base data to standard administratively defined areas and provide thematic maps (so-called choropleth maps) to visualize geographical patterns and to compare districts or wards. However, maps displaying information at the scale of administratively defined spatial units do not sufficiently capture the current situation of increasingly diverse and dynamic urban environments. Especially maps based on larger administrative units, such as wards and districts, are prone to scale and boundary problems (Openshaw, 1984a; Rees, 1997). *Scale problems* refer to the underlying assumption of choropleth maps that the phenomenon to be mapped is homogeneous within a mapping unit and evenly distributed across the unit. As a result, the accuracy of these types of maps decreases as distribution variability increases (MacEachren, 1982). Considering today's diverse environments, administratively defined areas may be too large to explore micro scale spatial variability. For instance, pockets of urban poverty within an administrative ward may be hidden because very deprived areas may be compensated by less deprived areas within the same ward (Martinez *et al.*, 2016). Obviously, averaging low and high values within administrative areas results in a loss of information.

Boundary problems refer to the fact that choropleth maps suggest an abrupt change in a phenomenon at the administrative boundary whereas changes are typically more gradual (Harris *et al.*, 2004; Schuurman *et al.*, 2007; Martin, 2009; Poulsen *et al.*, 2011). While inner-city boundaries are not able to reveal urban dynamics operating on a micro-scale in *increasingly diverse urban settings*, outer city boundaries are losing relevance in *increasingly polycentric urban settings*. Several phenomena, such as the labour and the housing market, cross municipal boundaries and should be approached both locally and regionally (Musterd *et al.*, 2006). Examining maps of urban phenomena at both the local and the regional scale can reveal the position of municipalities within the region and can lead to new insights in developments in and between municipalities.

Both scale and boundary problems are related to the Modifiable Area Unit Problem (MAUP), which is a common and well-documented problem associated with data aggregation. The MAUP discusses the considerable effect of choice for a particular mapping unit on the representation of a phenomenon (Openshaw, 1984a). Another problem of aggregated data is ecological fallacy, which refers to the erroneous assumption that an individual being part of an area will have a characteristic which is predominant in the area as a whole (Openshaw, 1984b).

To some extent, scale and boundary problems can be overcome by raster approaches which aggregate data to a regular grid consisting of equally sized cells. The finer the grid the more detail can be mapped. The kernel density method is an illustrative example as it deviates from standard administratively defined areas and accounts for within area-variation (Ratcliffe and McCullagh, 1999). It turns base data (mostly point data) into density surfaces (rasters) which can be used to identify hotspots. This method is particularly useful to map event data and is therefore frequently applied in crime and disease mapping. The number of crimes or infections is aggregated within a specified search radius producing a continuous surface (raster) of event distribution. However, while this procedure addresses to some extent the MAUP, it requires considerable expert knowledge for implementation.

For a more detailed discussion of methods to map micro-scale data we refer the reader to Pfeffer *et al.* (2012). In general, the choice for a specific aggregation method depends on the nature and spatial detail of the base data to be mapped and the purpose of the map.

The Regional Monitor Amsterdam

The Regional Monitor Amsterdam (RMA), an interactive thematic online application, monitors urban dynamics with respect to the demographic and socio-economic situation and the housing market in the Amsterdam urban region. It turns local statistics collected at the level of six-digit postcode into useful information for urban managers and researchers. It also addresses the scale and boundary problems addressed above. Unlike other online GIS applications which focus on general spatial distributions within administrative areas, this tool focuses on *spatial concentrations*. These spatial concentrations are polygon objects consisting of adjacent six-digit postcode areas that meet a set of rules for identifying spatial concentrations (further elaborated in Section 2). In these areas the rate of occurrence of a particular phenomenon (for example the share of people receiving unemployment benefit) is far above its average occurrence.

Using the concept of spatial concentrations has two advantages. First, relevant information is filtered from large data registries available at the six digit postcode level. The resulting maps of spatial concentrations direct the attention to areas that deviate from the average situation, which can be helpful in identifying potential problem areas and prioritizing areas for policy intervention. Second, spatial concentrations are *data-driven flexible* objects: not bound to administrative boundaries and determined by the data of the phenomenon under consideration. Accordingly, the size and shape of the resulting polygons differ between phenomena and years. As these objects are determined by the underlying data, concentration maps provide a more realistic representation of spatial patterns and dynamics compared to conventional choropleth maps based on fixed administratively defined areas.

The monitoring tool accommodates the monitoring of spatial dynamics of urban phenomena at the *local* and the *regional* scale to meet both local and regional policy information needs. For each phenomenon, both local and regional spatial concentration areas are constructed. Local concentration areas are based on the city average of a particular phenomenon in a particular city while regional concentration areas are based on the regional average (see further Section 2). To our knowledge this is the first interactive thematic online application using a data-driven approach that creates flexible spatial units and pays attention to the rate of occurrence and dynamics of urban phenomena both at the local and regional scale. In the next sections we will explain the procedure to create spatial concentration areas and show relevant application areas of the tool.

2.2 History and mapping methodology of the regional monitor Amsterdam

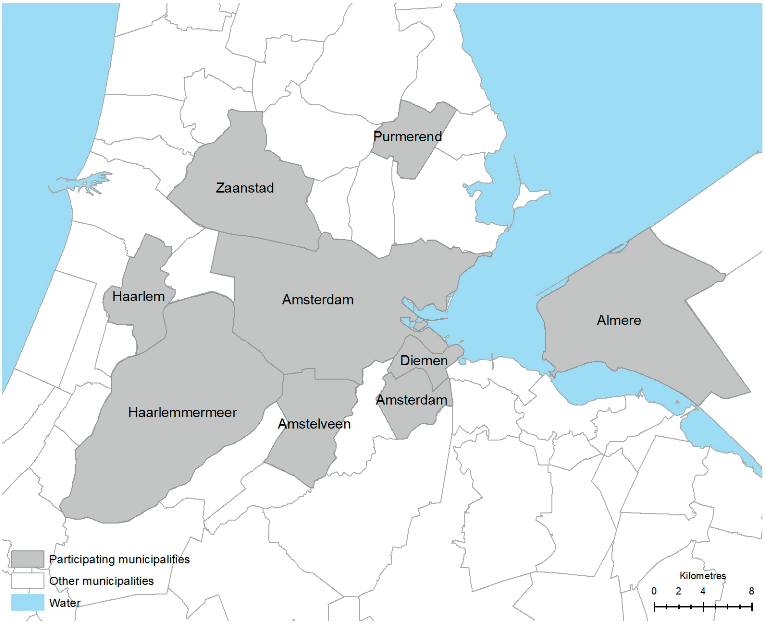
History

The development of the RMA is rooted in the Amsterdam City Monitor (ACM). The ACM was a joint initiative of the Urban Geography research group of the University of Amsterdam (UvA) and the department of Research and Statistics of the municipality of Amsterdam, which developed an interactive GIS application consisting of map layers of spatial concentrations in Amsterdam for a variety of themes from 1994 onwards.

With the increasing diversity and polycentricity of the Amsterdam region and a gradual policy shift towards area-based interventions (Andersson & Musterd, 2005), the ACM actors recognized the relevance of producing information on micro-scale urban dynamics within a regional perspective. Such information was considered to be useful for informing urban policy and research on developments in the region. It triggered the idea to develop a regional monitoring tool. In 2003, a small pilot, based on the design and mapping methodology of the ACM and data from just a few municipalities, served as an incentive to get other larger municipalities in the Amsterdam region involved. Within a year, the eight major municipalities, displayed in Figure 1, committed to the project.

Now the RMA provides public access to maps on several urban themes at both the local and the regional scale and from the year 2000 onwards. The mapped themes include ethnicity, age, household composition, social security benefits, home ownership, average property value, building periods of houses, and employment. The tool is intensively used to provide information for fact sheets and annual reports such as 'The State of the City' produced by the department of Research and Statistics (Gemeente Amsterdam, 2013).

Figure 1. Participating municipalities



Source of GIS data: CBS, 2014

The RMA is the product of a collaborative effort of a variety of actors. The larger municipalities in the region of Amsterdam contribute by delivering their data, local knowledge and knowledge about information needs. The University of Amsterdam coordinates the project and offers support in terms of scientific expertise in urban studies and geographic information analysis. I-mapping, a company experienced in web-cartography, takes care of the technological implementation. Representatives of all participating partners attend the bi-annual meetings of the working group RMA. In these meetings further development of the tool with respect to functionality, content, design and usage is being discussed.

Key aspects of monitoring are systematic data processing and representation in a standardized and regular manner (de Kool, 2008). The base data of the RMA consist of time series of local statistics for the six-digit postcode on demography, socio-economic issues, housing, employment and locational data (XY co-ordinates and postcodes of home addresses). Since municipalities collect and prepare these data according to collaboratively developed standards these local datasets can be combined into a regional dataset. To provide meaningful information for urban management, the RMA methodology aggregates postcode areas with over-representation of a phenomenon into new, larger spatial units: spatial concentration areas.

Mapping methodology

Spatial concentrations are clusters of adjacent postcode areas where the occurrence of an urban phenomenon is *far above* the average rate of occurrence of that phenomenon within the overall geographic area of interest, either an individual municipality (local/city scale) or the combination of the larger municipalities of the Amsterdam region (regional scale). *Far above* is defined as the mean plus two standard deviations of the respective characteristics. Furthermore, the idea of mapping concentrations is based on binominal variables (one category against all others). In Box 1 the steps to create the spatial concentrations are described in a nutshell. More details on the procedure including justification for the various choices are given in Pfeffer *et al.* (2012).

Box 1: Construction of spatial concentration areas

1 Spatial delineation of the six-digit postcodes obtained by applying the convex hull algorithm to the point locations of home addresses belonging to the same postcode. This results in polygons of different sizes, depending on the street layout.

2 Matching the thematic data to the postcode geography created in step 1.

3 Calculating descriptive statistics for each group (e.g. household categories) and the concentration threshold, determined by the mean plus 2 times the corresponding binomial standard deviation (stdev)*.

4 Marking a postcode area as a concentration area based on the statistically derived concentration threshold in step 3.

5 Removal of marked postcode areas with low densities to avoid statistical bias (less than 20 / hectare).

6 Spatially extending the remaining marked postcode areas (buffer of 25 metres width) to create adjacency or overlap with neighbouring postcode areas.

7 Aggregating extended marked postcode areas that are adjacent or overlap into postcode aggregates to create delineated spatial clusters representing concentration areas.

8 Recalculating the attribute data for each postcode aggregate (spatial concentration area).

*Note that in cases of very small reference groups a standard deviation of 1 is applied.

To keep close to recognizable geography on the ground, postcode areas are delineated as polygons around home addresses in a vector GIS. Users may feel more familiar with these kinds of objects which reflect the actual street layout compared to the geography of raster cells.

In the following, the clustering of 1-person households in 2011 is used as an example to illustrate the procedure applied to create spatial concentrations at the local and regional scale.

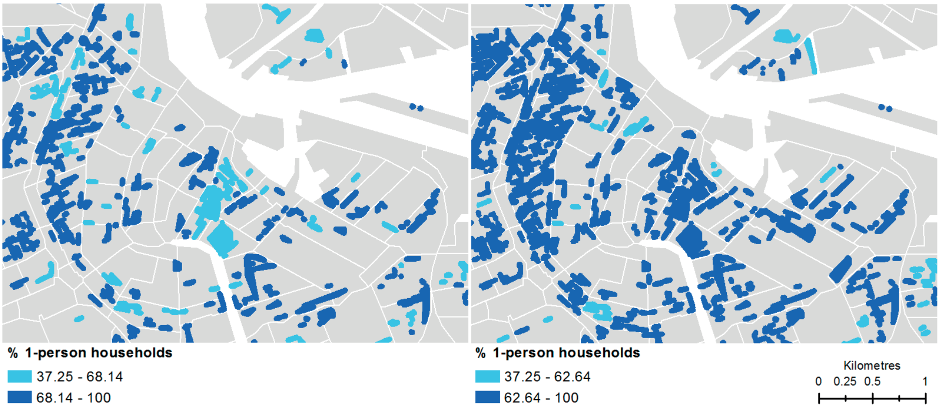
Local concentration areas

In 2011, 381,155 households lived in Amsterdam, of which 178,820 were 1-person households. The city mean of this household category is 46.92 %, with the associated binomial standard deviation of 10.61. Considering the definition of the concentration threshold in step 3 (Box 1), postcodes with a share of non-family households above 68.14 % are marked as concentration postcodes and are combined with adjacent or overlapping concentration postcodes into clusters of 1-person households according to steps 5-8. It results into maps of spatial concentrations of 1-person households for the year 2011 as visualized in Figure 2 on the left hand, zoomed to the centre of Amsterdam. By default, the monitor classifies all spatial concentrations into two categories. Objects coloured in darker blue indicate that in these clusters the share of 1-person households is above 68.14 %. The objects in light blue refer to clusters with a percentage of 1-person households below 68.14. The latter category represents clusters that, after buffering, also include postcode areas that do not meet the concentration criterion. As these postcode areas are included in the aggregation of 1-person households to the concentration cluster (step 8), the percentage of 1-person households drops below 68.14.

Regional concentration areas

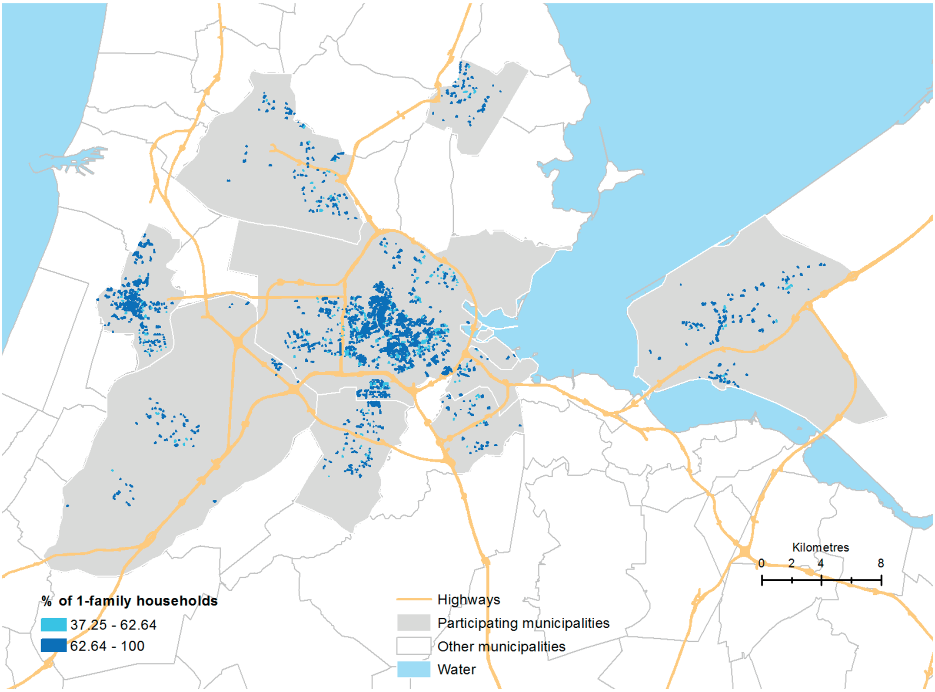
In 2011, 737,503 households lived in the seven larger municipalities of the Amsterdam region, of which 300,090 were 1-person households. The regional mean of 1-person households of 40.69 % together with a binomial standard deviation of 10.97 results in a regional spatial concentration threshold of 62.64 %. So postcode areas with a share of 1-person households above 62.64 % are marked as concentration areas to be aggregated into postcode aggregates according to step 5-8. This results in a regional map of spatial concentrations of 1-person households for the year 2011 as visualized in Figure 3. The importance of the regional perspective is illustrated by Figure 2. The map on the right side shows that if spatial concentration areas are examined at the regional scale, the center of Amsterdam has a considerably higher number of concentration areas. This is a result of the lower concentration threshold due to the lower regional mean.

Figure 2. Concentration areas of 1-person households in the center of Amsterdam based on the local (left) and regional (right) concentration threshold



Source of GIS data: RMA, 2015

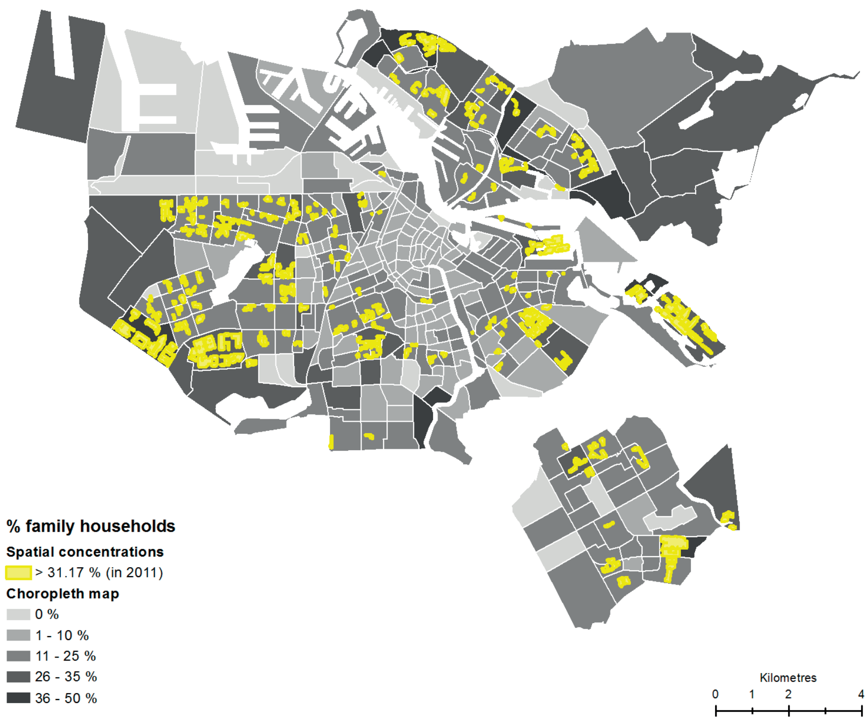
Figure 3. Regional concentration areas of 1-person households in the larger municipalities of the Amsterdam region in 2011



Source of GIS data: RMA, 2015; CBS, 2014; Rijkswaterstaat, 2014

Figure 4 compares the local concentration areas of family households in Amsterdam with the conventional choropleth map showing the same variable. The choropleth map provides a *general spatial distribution* of family households, but is not able to reveal the heterogeneity within or across neighbourhoods. Moreover, the choropleth map attracts the attention to the larger neighbourhoods. The map with spatial concentrations shows the *specific spatial* pattern of micro zones with an over-representation of family households. In the choropleth map an administrative unit can be part of the 36-50 % class, without having one or more postcode areas included in the unit that have a value greater than 31.17 % (the threshold value for concentration areas). This is the case in situations of values within postcodes just below the threshold (tested in rule 4) combined with filtering postcodes of low densities (rule 5).

Figure 4. Local concentration areas of family households in Amsterdam on top of a conventional choropleth map



Source: GIS data: RMA, 2015

Accessibility

The RMA is an open online GIS application (http://www.regiomonitor.nl). Through a graphical user interface users without GIS expertise can view and query the spatial concentration layers and create tailor-made maps that meet their information needs. They can select the desired spatial scale (local or region), phenomenon, year, the type of reference map for orientation and the zoom level. In addition, users can adapt the map by changing the default selection criteria, number of ranges and the symbology. In order to protect privacy of residents, the monitor does not display spatial concentrations which contain less than 15 cases. For people with GIS-expertise the tool offers the possibility to export map layers to a standard GIS file format (shapefile) in order to perform additional, more advanced spatial analyses in a GIS environment.

2.3 Application areas

The Regional Monitor Amsterdam can be applied for exploring and monitoring urban phenomena and formulating and testing of hypotheses about spatial concentrations and local and regional developments. We give some examples of application areas based on three types of questions which are considered relevant for urban policy and research.

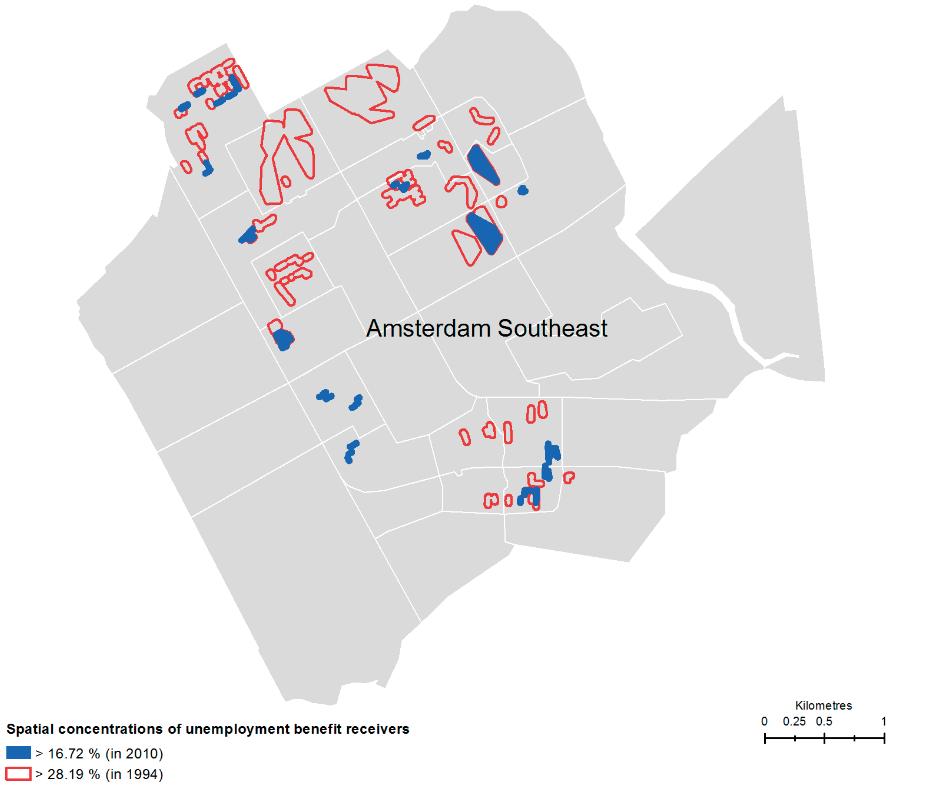
Which changes occur in a specific concentration area in a specified period?

For a long time, the district Zuidoost in Amsterdam has had a negative image because of a clustering of problems related to drugs, crime, early school leaving, and unemployment. To improve this neighbourhood, an elaborate physical and socio-economic renewal programme was implemented between 1992 and 2009. Socio-economic renewal was strongly focused on job creation. A key question for assessing the effectiveness of urban policy is whether the efforts led to improvements. Between 1994 and 2010 the concentration criterion changed significantly from 16.7 to 28.2 percent indicating that the overall situation in Amsterdam has improved. Examining spatial concentrations of unemployed inhabitants in the district Zuidoost between 1994 and 2010 (see 5) shows that although the situation has improved considerably some concentration areas are persistent, for example the two areas in the northern part. This might be an incentive for further research to find out what is going on in these specific areas.

Which changes occur in the spatial distribution of concentration areas of a phenomenon in the region?

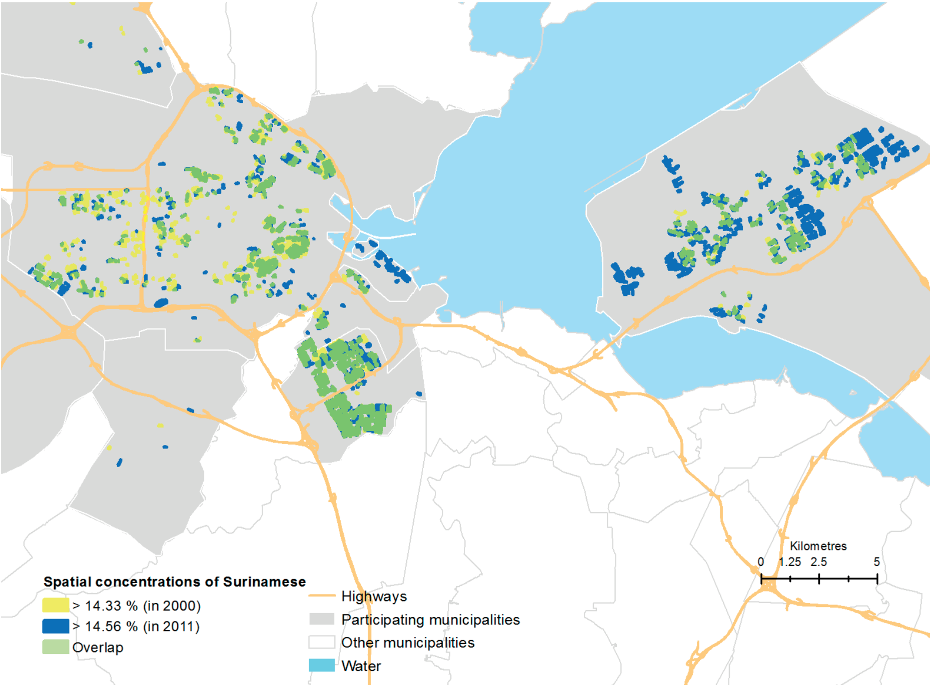
The presence of (clusters of) ethnic groups is often considered a typical characteristic of major cities like Amsterdam. Maps produced with the RMA show that this perception is out of date. Examining the maps of concentration areas of Surinamese (Figure 6) and Moroccans (Figure 7) shows that these groups are increasingly migrating and also tend to cluster in other municipalities in the region. Surinamese are increasingly migrating to Almere and concentration areas of Moroccans arise particularly in Almere and Haarlem.

Figure 5. Local concentration areas of people receiving unemployment benefit in 1994 and 2010



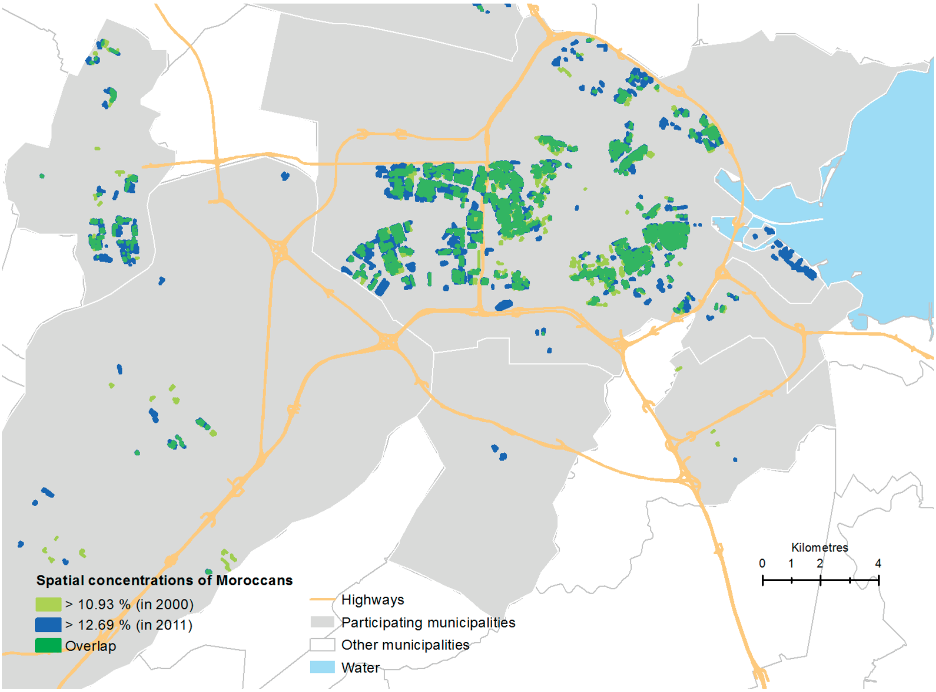
Source: GIS data: RMA, 2015

Figure 6. Regional concentration areas of Surinamese in 2000 and 2011, zoomed to Amsterdam and Almere



Source: GIS data: RMA, 2015; CBS, 2014; Rijkswaterstaat, 2015

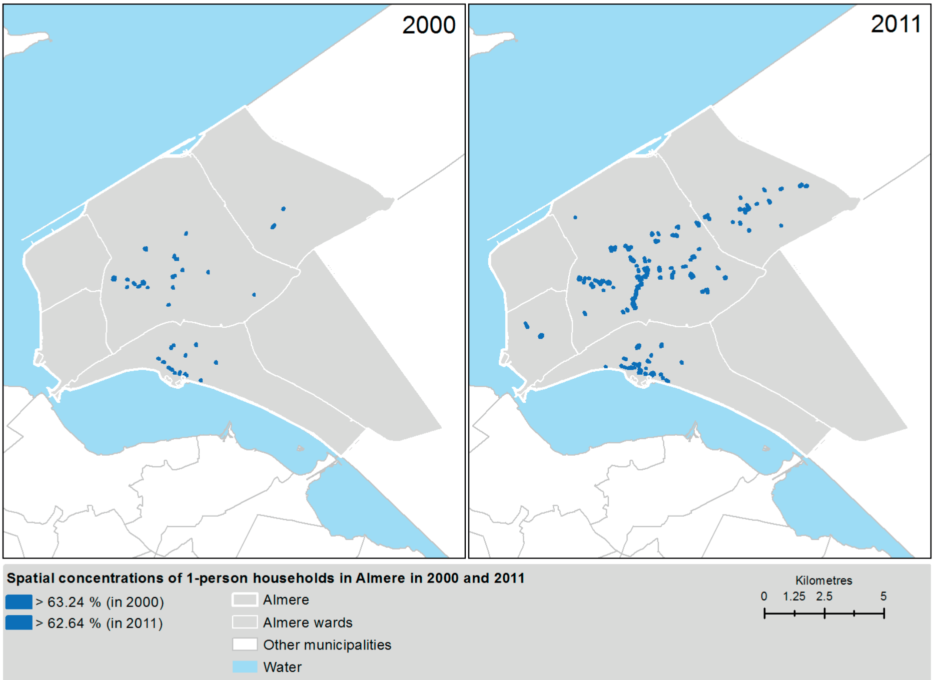
Figure 7. Regional concentration areas of Moroccans in 2000 and 2011, zoomed to Amsterdam and Haarlem



Source: GIS data: RMA, 2015; CBS, 2014; Rijkswaterstaat, 2015

Another persistent idea which is out dated concerns the assumption that 1-person households prefer to live in cities, while family-households choose for the sub-urban region. Figure 8 illustrates the increasing popularity of Almere for 1-person households. Changes in the distribution on 1-person households within the region may have consequences for planning appropriate housing for this group in some municipalities.

Figure 8. Local concentration areas of 1-person households in Almere in 2000 and 2011.



Source: GIS data: RMA, 2015; CBS, 2014; Rijkswaterstaat, 2015

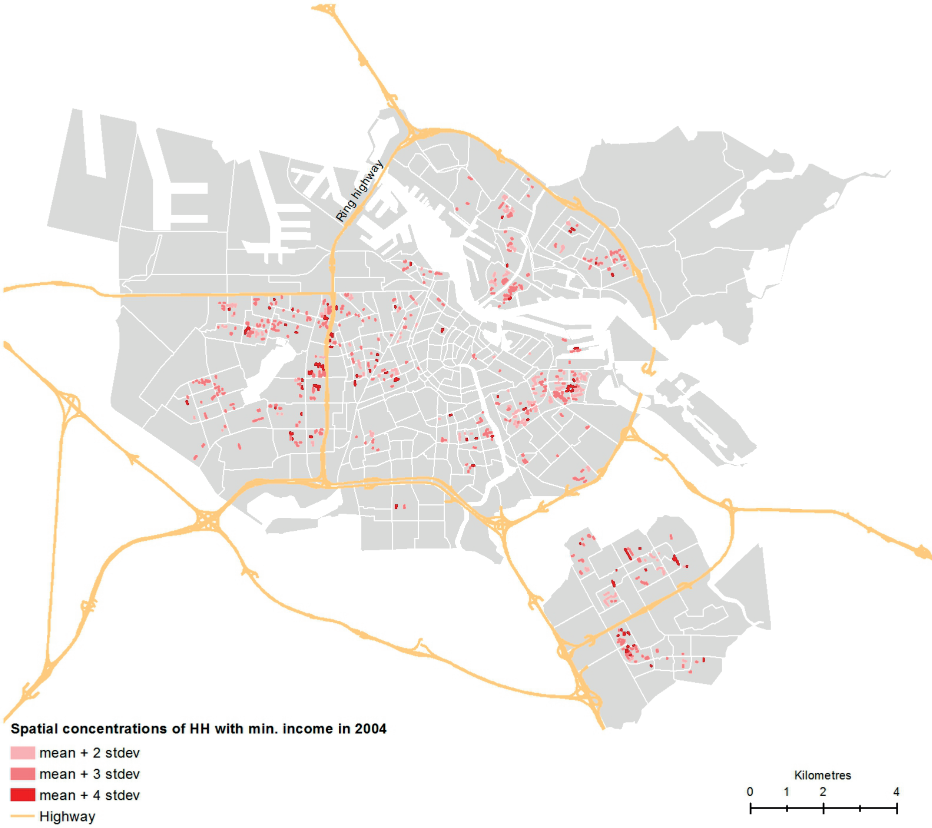
What is the spatial relation between different phenomena in the municipality (or region, ward, district)?

One of the ambitions of local governments is to reduce concentrations of deprivation and to prevent the emergence of new ones. To achieve this, a policy of neighbourhood mixing has been promoted in most European countries. The monitor can be used to evaluate the effectiveness of this policy.

Figures 9 and 10 show local concentration maps of minimum income households in 2004 and 2012. The maps classify the concentration areas in 3 types: standard concentrations (based on the average percentage of households with minimum income plus 2 stdev), strong concentrations (3 stdev) and very strong concentrations (4 stdev). The maps show that concentration areas increased in size and number. New concentration areas have emerged in several parts of the city: in the Western and Eastern district and in some parts of the Northern and Southeastern districts. Nowadays, more deprived people are living in areas with a large share of other deprived people. This is not in line with a policy of reducing socio-economic segregation.

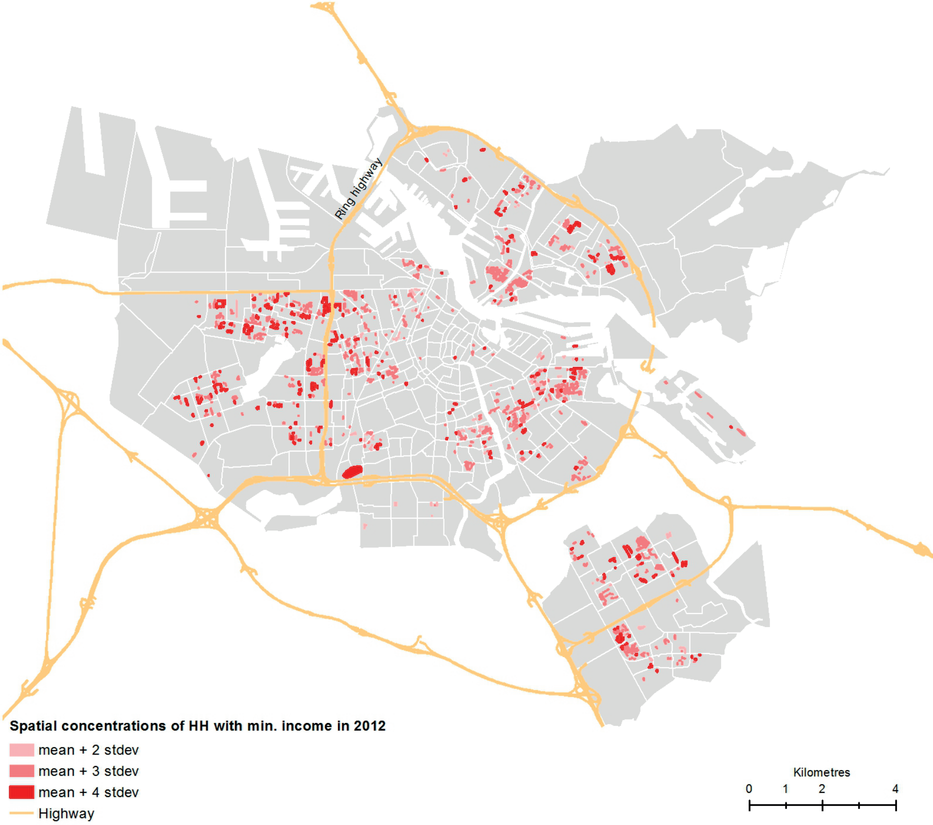
These spatial concentration maps of minimum income households fed a recent public discussion in Amsterdam on whether poverty increased beyond the typical ring highway of Amsterdam, being regarded by some as a distinct border dividing Amsterdam in two very different parts: a poor one and a rich one. Partly based on these maps, van Gent et al. (2014) state that demographical developments and housing policies undermine the Amsterdam ambition to be an 'undivided city'. They relate the shift of concentrations to the outer parts of the city to the decrease of social housing which mainly takes place within the ring highway. As a consequence low income inhabitants have to rely on housing in the outskirts and pockets of not yet restructured housing stock. Maps showing concentrations of characteristics of the housing stock and composition of the population can be very helpful when studying issues like this.

Figure 9. Local concentration areas of households with a minimum income in 2004



Source: Gemeente Amsterdam / O&S, 2004; CBS, 2014; Rijkswaterstaat 2015

Figure 10. Local concentration areas of households with a minimum income in 2012



Note that although the RMA mapping methodology has been adopted to create the maps this phenomenon is not (yet) included in the RMA monitoring tool.

2.4 Discussion

This article has highlighted the importance of mapping beyond standard administrative boundaries in the current situation of extremely diverse urban settings and increasingly polycentric regions. Unlike other interactive thematic online applications, the RMA differs in the following aspects. First, it focuses on concentration areas, and not on the average spatial pattern commonly displayed in standard thematic maps. It shows micro-scale spatial information in the form of deviating and striking urban phenomena. Second, the concentration areas are data-driven aggregates that are flexible, independent of administrative boundaries. Third, the RMA recognizes the importance of both the local and the regional scale and therefore applies local and regional concentration thresholds. Finally, the RMA tool offers high flexibility in terms of thematic queries or adjusting the presentation and design of maps; in other tools interactivity is often limited to indicator and theme selection and zoom options.

In order to demonstrate the usefulness of this tool in assisting urban policy and research, we have presented three illustrative examples.

Opportunities and limitations

The RMA provides spatial information about the dynamics of a variety of urban phenomena at a relevant scale. The graphical user interface of the RMA tool assists in exploring maps and adapting a map to specific information needs making information accessible for people without much time and/or experience in mapping. The maps can be used for monitoring urban phenomena and formulation and testing of hypotheses about developments at a local and a regional scale. Although the methodology uses the typical Dutch six digit postcode areas as base data, a similar procedure can be applied to other types of base data such as enumeration blocks of a population census like the one in Argentina (Martinez et al., 2016). We warn that many data, for instance survey data or geo-located social media data, are not suitable for mapping spatial concentrations because these are not complete enumerations.

The RMA is not only the product of a collaborative effort to produce information but it also accommodates increasing information needs about urban dynamics. It is an excellent way to mediate spatial thinking at multiple scales and to create awareness of the sensitivity of data aggregation to the choice of boundaries. It brings together researchers, policy makers and other professionals interested in urban dynamics both at the local and the regional scale. The regular meetings of the working group and public events accommodate discussions of both local and regional issues and further development of the tool. The long-term commitment of actors and the investments in maintenance and improvement of the tool illustrate the importance attached to the information provided by the RMA. The monitor is regularly used in publications (e.g. Ostendorf et al. 2008; Gemeente Amsterdam, 2013) and in various teaching modules at the University of Amsterdam.

Nevertheless, there are also some limitations. First, because each municipality is responsible for the provision and quality of the input data for the maps, mistakes are likely to occur. The input data would be less error-prone if centrally collected databases could be used. However, this requires either institutional commitment from Statistics Netherlands who collects, standardizes and validates the required data from multiple data agencies or a considerable budget to purchase the necessary data.

Second, in order to be used as a monitor maps need to be up-to-date (de Kool, 2008). Therefore, input data should be provided in time. A regional mean can only be calculated if all municipalities deliver their data in time. This is sometimes hard to realize and could be overcome by acquiring data centrally from Statistics Netherlands.

Third, concentration areas are quite complicated spatial objects and are different from choropleth maps normally used in urban practice. This makes interpretation of the maps difficult incurring for example ecological fallacies. Although the tool can be accessed by everyone with internet access, it is questionable whether many people will interpret the maps correctly. An extreme example of misinterpretation would be if overlapping concentration areas of unemployed and concentrations of Antilleans lead to the conclusion that all Antilleans are unemployed.

We further regret the absence of the smaller municipalities in the region. The main reason for their absence is lack of the necessary capacity and resources for processing the base data. Acquiring postcode data centrally from Statistics Netherlands could overcome this problem as well.

Finally, although many urban planners and decision makers recognize the need to cross boundaries, they are used to work with choropleth maps and do not want to lose 'their' boundaries at once. For this reason choropleth maps based on administratively defined areas have been included in the RMA recently. Now maps of spatial concentration areas can complement choropleth maps to enhance the understanding of the spatial nature of a phenomenon.

Future development of the RMA includes expanding the thematic content to meet new information needs such as adding health-related maps and some interface improvements. A useful functional extension would be the implementation of a toolbox that facilitates exploring spatial associations between multiple variables. While most monitoring tools focus on querying a single variable, targeting complex urban problems requires the combination of multiple dimensions. Analysing residential segregation or urban poverty in relation to other urban variables such as the composition of the housing market will help in understanding the resulting patterns of residential 'choices'. Another urban issue to be addressed would be the changing dynamics of crime hotspots, for instance in combination with changes in socio-economic area characteristics. Obviously it will be a challenge to implement such functionality without making the tool too complicated reducing accessibility.

Conclusion

The purposes of this article were to explain the mapping methodology adopted in the RMA and to illustrate the usefulness of the tool in urban management.

We have shown that by introducing 'data-driven dynamic geographies' instead of using fixed administrative boundaries we can filter relevant information from large data sets at the scale at which urban phenomena occur. Furthermore, the tool improves our understanding of the dynamics of urban phenomena at both the local and regional scale.

Offering this type of information through an interactive thematic online application facilitates the construction of tailor made maps for different years that can address information needs of urban policy makers and researchers. Hence, the monitoring tool assists in answering policy questions such as the existence of the persistence of concentrations of unemployment, the need to adapt housing policies to regional demographic dynamics, or whether social mix policies should be promoted due to the spatial clustering of social housing and low-income households.

The RMA has been collaboratively developed with policy professionals, urban managers and urban researchers. This ensures that the thematic content offered by the RMA matches their information needs. A collaborative effort is required to embed such a tool in institutions and processes to ensure long-term existence and use.

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CHAPTER 3

Environmental characteristics of hotspots of alcohol-related health incidents outside of the entertainment districts of Amsterdam

Abstract

While hotspots of alcohol-related incidents have been associated with alcohol outlet density, few studies have considered other environmental factors. We aimed to characterise the environment of hotspots outside of outlet density areas in Amsterdam. Using Geographical Information Systems (GIS), we identified hotspots of alcohol-related health incidents outside of outlet density areas based on the registry of alcohol related ambulance attendances. While quantitative data and methods were used to analyse victim profiles (including age, sex and home address) and temporal profiles (time of incident), we combined quantitative and qualitative information to develop environmental profiles of these hotspots. We identified 11 hotspots with 242 incidents outside outlet density areas. Results indicate substantial differences between incidents in these hotspots and incidents in high outlet density areas. Victims in these hotspots are older, more often male and live closer to the incident location compared to victims in high outlet density hotspots. Incidents are less likely to take place during the night and at weekends. In-depth analysis of four hotspots showed different combinations of contributing environmental factors, including (a) public parks bordering deprived neighbourhoods, (b) dance event facilities close to a traffic black spot, and (c) residential services for disadvantaged groups near 'hang-outs'. The study shows that hotspots of alcohol-related incidents can arise outside outlet density areas at locations where several other environmental factors cluster, particularly in more deprived areas. Such hotspots can be addressed in urban planning and urban design.

3.1. Introduction

Alcohol-related harm is a public health issue of critical importance. In 2011, 2732 alcohol-related incidents were registered by the ambulance service in Amsterdam, The Netherlands. The number of incidents involving people under the age of 25 almost tripled between 2001 and 2011, going from 216 to 609 incidents (Ujcic-Voortman et al. 2013). Because the prevention of alcohol-related harm would have great public health and societal benefits, a large body of research has attempted to reveal determinants of hazardous alcohol use and alcohol-related harm such as injuries and poisoning.

Researchers have increasingly turned their attention towards the environmental determinants of hazardous alcohol use (see, for example Bernstein et al. 2007; Karriker-Jaffe 2011; Robert 1999; Romley 2007). The focus of most of these studies has been on the social and socio-economic characteristics of the residential environment, or on the functional characteristics of locations where hazardous use of alcohol is common.

With regard to the residential environment, associations between neighbourhood socio-economic status and alcohol use were found, though the direction thereof varied between studies. Some studies have suggested that heavy drinking is more prevalent in deprived areas, possibly because of lower levels of social control over deviant behaviours and drinking being used by residents there as a coping mechanism to feel less miserable and stressed (Elliott 2000; Galea et al. 2007; Halonen et al. 2012; Stimpson et al. 2007; Cerda et al. 2010). Other studies have observed high levels of alcohol consumption in affluent neighbourhoods where drinking may be part of a privileged lifestyle focused on pleasure and comfort (Polak et al. 2005). Other studies have not found any significant association (Cornaz et al. 2009; Ecob and Macintyre 2000). For the Netherlands, Kuipers et al. (2012) found a lower prevalence of heavy alcohol consumption in deprived areas. This was partially explained by the presence of a large immigrant population with an Islamic background, which is traditionally associated with little or no alcohol consumption.

Other studies have adopted a micro spatial approach and have turned their attention towards the identification of spatial patterns of alcohol-related problems at lower spatial scales than administratively defined areas such as wards or census tracts (Parker et al. 2004). Many studies in this field draw on spatial modelling approaches and ecologic theories derived from the field of environmental criminology. Spatial modelling approaches are mostly used to identify areas at a micro-spatial scale with a higher level of specific problems (often referred to as 'hotspots'). To explain the higher incidence of problems in these hotspots, spatial relationships with functional characteristics of the hotspot and their surroundings are being studied (see for example Schuurman et al. 2009; Walker et al. 2014). Ecologic theories, such as routine activity theories and disorganization theories, are frequently used to understand the processes and mechanisms linking environmental characteristics to the clustering of problems in these specific places (Gorman et al. 2013).

Such studies are particularly useful to study associations between the functional environment and alcohol-related harm. One important theme in this literature is the density of alcohol outlets as a key determinant of hotspots of alcohol-related violence (Grubesic et al. 2011; Gruenewald and Remer 2006; Gruenewald et al. 2006), increased consumption (Van Oers and Garretsen 1993; Popova et al. 2009), alcohol-related incidents such as pedestrian injuries (LaScala et al. 2001; DiMaggio et al. 2016), vehicle crashes (Scribner et al. 1994; Treno et al. 2007), hospital admissions (Tatlow 2000), and other alcohol-related harm (Connor et al. 2011). Clusters of alcohol outlets in night-time leisure zones are known to be related to relatively high numbers of alcohol-related incidents (for a systematic review of studies, see Popova et al. (2009). Entertainment districts create the potential for alcohol-related problems, such as violence, by generating large numbers of people in various states of intoxication and who spill out onto the streets at closing time (Gorman et al. 2013). The routine-activity theory implies that clusters of alcohol outlets provide an opportunity for the intersection of offenders and targets which in the absence of guardianship may increase the risk of alcohol-related violence (Parker 2004).

The focus on outlet density may ignore the role of other environmental characteristics. Relatively few studies use a more comprehensive approach, i.e. one that considers the contribution of a wider array of environmental factors. In Worcester (United Kingdom) patterns of alcohol-related crime and disorder in the city centre were associated with various characteristics of the functional environment, with higher rates along the key route ways towards residential areas and retail zones, and close to functional sites such as the railway station and the shopping centre (Bromley and Nelson 2002). Similar studies on hotspots of violent injuries identified environmental features such as a high number of bars, recreation facilities, transit nodes, high density housing, public restrooms and homeless shelters (Braga et al. 1999; Cusimano et al. 2010; Walker and Schuurman 2012).

Until now, studies outside the scope of outlet density are relatively scarce as compared to the potentially large number of environmental factors that could play a role. Moreover, most studies have listed the role of isolated factors that are measurable in quantitative studies. Little attention has been given to the social-cultural or historical context of areas, and how these may interact with other environmental factors in generating or preventing alcohol-related incidents. To assess this complexity of factors, commonly used quantitative methods may need to be extended with qualitative approaches.

In this study, we focus on hotspots of alcohol-related incidents outside of areas with high outlet density in Amsterdam. Our aim is to characterise the local environments of these areas. We pay attention to a wide range of potential relevant aspects and use quantitative and qualitative techniques.

We had three specific aims. First, we aimed to identify hotspots of alcohol-related ambulance attendances in Amsterdam outside of the well-known outlet density areas. Next, we aimed to assess the victim and temporal characteristics of incidents in these hotspots, and to compare these with characteristics of incidents in hotspots with high outlet density. Particular victim or temporal patterns may guide further search for relevant environmental factors. Finally, for the four largest hotspots outside high outlet density areas, we created environmental profiles with the aim to identify combinations of environmental factors that could possibly contribute to the occurrence of alcohol-related incidents.

3.2. Materials and Methods

Study design

We used an exploratory, observational study design incorporating quantitative and qualitative methods.

Incidence data were acquired from the register of the Regional Ambulance Services Agglomerate Amsterdam (RAVAA). The register records the location and time of all ambulance attendances, characteristics of the persons involved, and the circumstances and nature of each incident. The information for each incident was derived from the incoming phone call, which is recorded by the operator in the emergency control room. Additional information came from attending paramedics, who gave feedback to the operator on details of the ambulance attendance, and from the emergency department in case of transportation of the victim to a hospital.

An alcohol-related incident was defined as an incident in which the person suffered from the direct or indirect consequences of alcohol consumption, predominately including poisoning, reduced consciousness, and wounds, but also other injuries. To classify injuries as alcohol-related we used the short descriptions of the incoming phone call, the situation encountered by the paramedics, and the feedback from the emergency department. Records were selected when at least one of the three short descriptions contained a keyword related to drinking, drunkenness, alcohol, or specific alcoholic beverages.

The dataset included 11,256 alcohol-related incidents from 2006 through 2011. We excluded incidents with no information on the precise spatial location. In the end, a total of 11,155 incidents were included in the study.

Identification of hotspots

We used Geographic Information Systems (GIS) to construct hotspots of alcohol-related incidents based on the incident's six-digit postal code. A six-digit postal code area is the smallest geographical area unit available. These units are sized approximately 50 x 50 metres. To construct hotspots, we applied the mapping approach described and employed by Pfeffer et al. (2012). In this approach, accurate boundaries are drawn based on six-digit postal code areas thus aiming at representing the actual distribution of observations.

We first identified postal areas with an increased number of incidents. For this, a postal code area was selected if the number of observed incidents was above a predefined threshold of at least two incidents involving an ambulance attendance. This threshold is equal to the Amsterdam average across all postal areas (being 0.6) plus two times the standard deviation. Next, adjacent selected postal areas were combined. The resulting spatial aggregates (clusters of selected postal areas) represented the hotspots.

To exclude outlet density as the main predictor of alcohol-related incidents, we excluded hotspots that contained two or more bars within a 100-metre buffer surrounding the hotspot. A 100 meter margin was included to take into account mobility of persons after visiting bars, which may lead to incidents occurring at some short distance from the bars of exposure. Moreover, we excluded all hotspots that were located within the city centre, because of the specific recreational and touristic functions of the city centre, and the deviant recreational behaviour of its highly transient population.

In order to have sufficient observations, we decided to restrict further analysis to the larger hotspots. The analysis of victim and temporal profiles (see below) was restricted to hotspots with at least 10 incidents. Further analyses, aimed to assess environmental profiles, was restricted to the four hotspots with the highest number of incidents.

A main issue in the construction of hotspots is whether basic areas should be weighted according to their population size, area of some other feature that is proportional to the expected number of alcohol-related incidents. The population size is a potentially relevant factor, but our basic areas hardly differ in these terms, because postal areas in The Netherlands are constructed such that each area serves about the same number of addresses. The area of the postal areas is not necessarily related to the expected number of incidents, as large areas may be relatively empty areas. Indeed, we found that among postal areas in Amsterdam almost no correlation between the number of incidents and area (.017) and population size (.019). Therefore, we decided to not weight areas because such a correction is not useful and would even be disturbing.

Victim and temporal profiles

For alcohol-related incidents that occurred within the selected hotspots (defined as group 1, N = 242), we compared victim characteristics (age, sex, place of residence) and temporal characteristics (day and time of incident) with that of two other groups of incidents: incidents in hotspots with high outlet density (group 2, N = 2210 and incidents within the city centre (group 3, N = 3205). Single incidents outside of any hotspot (N = 5498) were not included in the analysis.

Differences in victim and temporal profiles between the three groups of incidents were assessed by comparing means and using cross table analysis. In addition, we used logistic regression analysis to quantify the differences between the three groups in victim and temporal characteristics of the incidents. The incidents are the units of analysis. The dependent variables are the victim characteristics (such as age 18-24 or not) and the temporal characteristics (such as in the weekend or not). The independent variable is the group, where group 1, our group of interest, is the reference category. The results of the models are expressed in terms of odds ratios (OR) and the associated 95% confidence intervals (CI).

In many cases, it was not possible to classify incidents accurately according to the nature of the incident. The free-text descriptions of injuries are relatively short and during peak times the ambulance service had little time to report relevant information.

Environmental profiles

To create environmental profiles for the four largest hotspots with most incidents, we used both quantitative and qualitative data. To describe the social environment, we used integral social and socio-economic registries at the six-digit postal code level for the year 2009. These registries were maintained by the municipality of Amsterdam. For each hotspot, we aggregated the postal code data and we calculated the percentage of residents receiving social benefits (unemployment or welfare), the percentage of the population aged 18 through 24, the percentage of non-Western migrants, and the percentage of houses under social housing schemes. The functional environment was described using data from the city's Department of Planning, where the 'Map of Functions' described the function of each object on the map (for example, supermarket, discotheque, or hotel). Information on traffic infrastructure and traffic safety was obtained from the Department of Transport and Infrastructure. Furthermore, we used Google Street View to describe the built environment. We systematically observed the hotspots in terms of residential density, dwelling types, amount of green space, functions and road infrastructure.

Qualitative methods were used to provide additional information on the local context of the largest hotspots which cannot be captured by quantitative measures or by using Google Street View. More specifically, we sought to obtain information on the cultural and historical context of each area, on small-scale features not captured by area-wide data and on local activities. The information was gathered during field visits and face-to-face interviews with two persons for each hotspot: the district manager (responsible for the communication between inhabitants, municipality, schools and police within a specific area) and the police officer (responsible for safety and crime issues). We thus interviewed eight persons in total. These persons were chosen as they were familiar with the areas in which the four large hotspots were located, as each of them had worked for several years in their respective area. Because of the exploratory nature of our research, the interviews were unstructured and guided by the results of preceding quantitative analyses.

The resulting information consisted of eight sets of interview notes, each one to two pages long. We analysed the data systematically by preparing a matrix for each hotspot that lists the main topics that are relevant to alcohol-related problems (what, where, when, who, why) in the columns. Each matrix consisted of two rows representing the two key informants. The data in the matrix showed to what extent perceptions of the key informants were similar or different, and were used to construct the environmental profiles for each area.

3.3. Results

From 2006 through 2011, 11,155 incidents were recorded in 18,287 six-digit postal code areas. On the basis of our selection criteria, 11 hotspots with 242 incidents were identified for further analysis. Figure 1 shows the geographical distribution of these hotspots. By definition, they were located outside of areas with high outlet density and outside the city centre. Most hotspots were located within the "ring road", which is a circle of highways about 5 kilometre away from the city centre. The hotspots varied not only in number of incidents, but also in size and shape.

Table 1 compares the victim and temporal characteristics of the incidents in these hotspots with those of incidents in the other two groups of incidents. Compared with victims in high-outlet density hotspots and the city centre, victims in our hotspots of interest were on the average older and more often male. Also, these victims were more often residents of the surrounding neighbourhood (defined as the four-digit postal code area). Incidents in our hotspots of interest were less likely to occur during the night or during the weekend.

Figure 1. Hotspots outside of areas with high outlet density

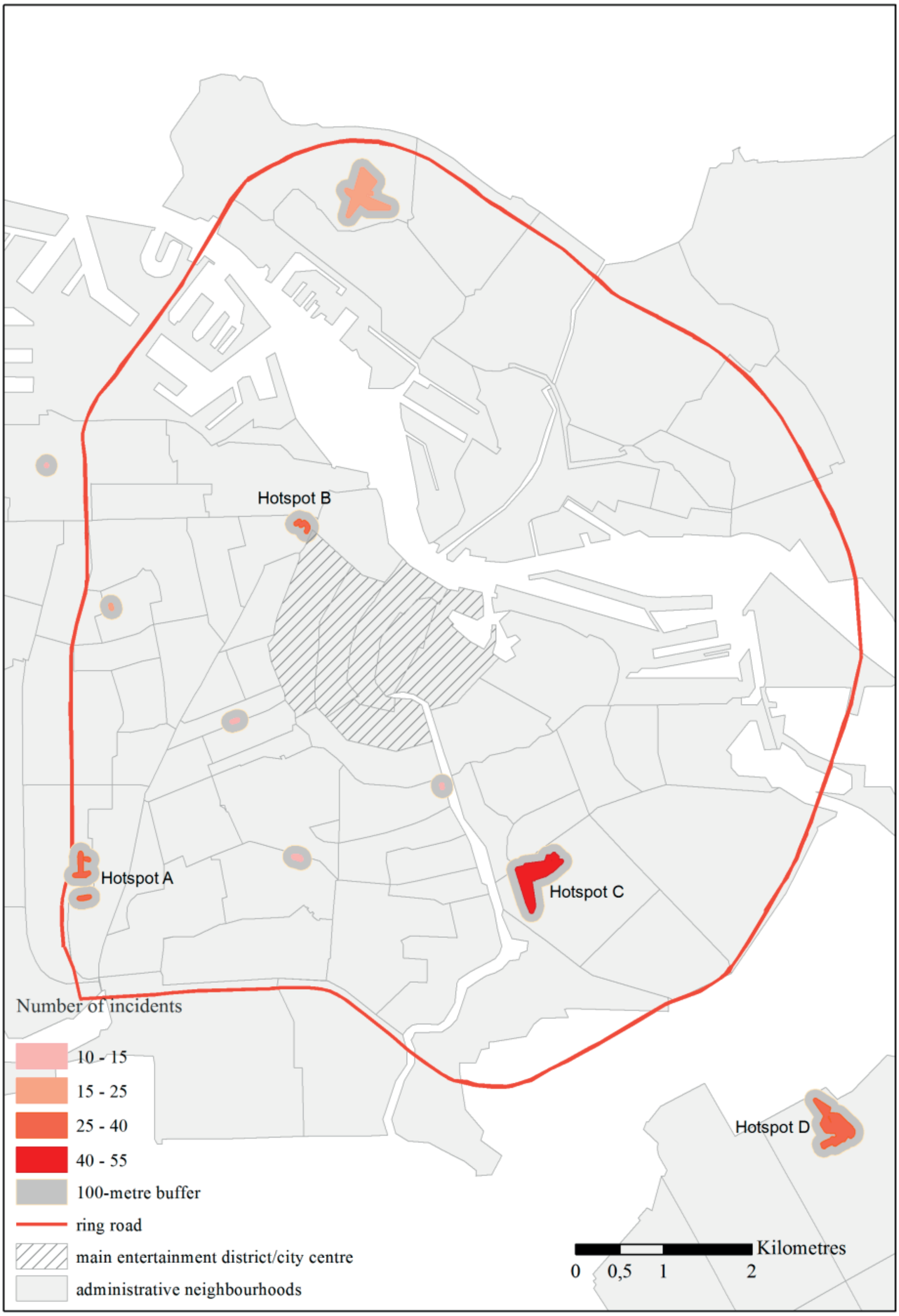

Table 1. Comparison of the victim and temporal characteristics of the incidents between the three groups

	Group 1: Incidents in hotspot, max. 1 café, outside centre	Group 2: Incidents in hotspot, more cafés, outside centre	Group 3: Incidents in entertainment district/ centre
N	242	2210	3205
Average age	42.1	39.0*	37.7**
% 18-24	11.7	21.2	23.0
OR (95% CI)	1.00 (ref)	2.02 (1.34; 3.06)**	2.24 (1.49; 3.38)**
% 50-65	26.5	18.6	17.3
OR (95% CI)	1.00 (ref)	.63 (.46;.86)**	.58 (.43;.79)**
% male	79.1	67.8	71.9
OR (95% CI)	1.00 (ref)	.56 (.40;.77)**	.67 (.49;.93)*
% living nearby	40.1	29.5	15.9
OR (95% CI)	1.00 (ref)	.62 (.44;.88)**	.28 (.20;.40)**
% weekend	31.8	44.0	46.2
OR (95% CI)	1.00 (ref)	1.68 (1.27; 2.23)**	1.84 (1.39; 2.43)**
% night	25.2	49.7	49.7
OR (95% CI)	1.00 (ref)	2.94 (2.17; 3.97)**	2.94 (2.18; 3.96)**

* Difference with victims in Group 1 is significant at the 0.05 level.
** Difference with victims in Group 1 is significant at the 0.01 level.

Table 2 compares victim and temporal characteristics of incidents within the four largest hotspots (A to D), taking incidents in high outlet density hotspots as the reference group. Victim and temporal profiles differ between the four hotspots. Striking patterns include: a low percentage of incidents during the night in A; a high percentage of incidents during the night and during the weekend in B (comparable with the reference group); a high percentage of victims aged 18 through 24 and male victims in C (again, comparable with the reference group), and a high percentage of male victims, and of victims who reside in the surrounding neighbourhood in case of D.

Table 2. Victim and temporal characteristics of incidents in the four largest hotspots

	A	B	C	D	Ref. group (group 2)
Number of incidents	38	27	53	33	
Average age	43.2	44.4	39.8	47.4	39.0
% 18-24	10.5	16.7	19.2	0.0	21.2
% male	86.5	84.0	78.8	90.3	67.8
% living in neighbourhood	27.3	14.3	18.8	50.0	29.5
% weekend	23.7	51.9	25.9	33.3	44.0
% night	13.2	48.1	27.8	24.2	49.7

Figure 2 shows the built environment of the four large hotspots. The hotspots strongly differ in terms of residential density, dwelling types, amount of green space, and infrastructure. For example, hotspot A is a densely populated residential area bordering the ring highway. Hotspot B contains a recreational park and an important traffic junction. Hotspot C is a heterogeneous, relatively low populated area containing a diverse mix of functions such as family dwellings, apartments, schools, offices and a train station. Hotspot D is characterised by high blocks of flats surrounded by much public green space.

Figure 2. The built environment of the four large hotspots (source: Google Earth)

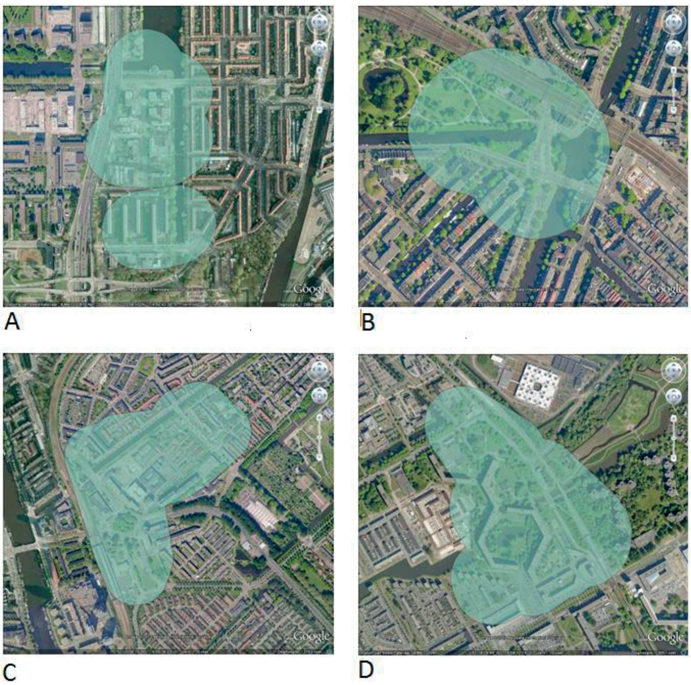

Table 3 lists characteristics of the social, functional and built environment of these four hotspots. All hotspots had populations with relatively low socio-economic status. A and C have facilities that may attract potential risk groups, such as a homeless shelter, a low-budget hotel, and student housing. In B and D alcohol is sold in local retail outlets such as supermarkets. Most hotspots have public locations that are attractive for drinking alcohol, such as benches in public green spaces.

Table 3. Presence of risk factors inside a 100-metre buffer surrounding the hotspots

Hotspot ID	**A**	**B**	**C**	**D**
Number of incidents	38	27	53	33
Functional environment				
Supermarket				X
Late-night shop				X
Snack bar		X	X	X
Café/bar		X	X	X
Restaurant	X	X		X
Discotheque/events		X		
Low-budget hotel	X		X	
Student housing	X		X	
Homeless/psychiatric/drug addiction services	X		X	X
Social environment*				
% non-employed >7		X		X
% social assistance >5.6	X	X		X
% age 18-24 >9.7	X	X	X	X
% non-Western migrants >30	X		X	X
% social housing >47.9	X	X	X	X
Built environment/public space				
Dangerous crossing/traffic black spot		X	X	
Main traffic route	X	X	X	X
Metro/train stop			X	X
Park/recreational green space	X	X		X

* Thresholds are set equal to the city average.

By combining this information with qualitative information that we obtained from interviews, we could construct environmental profiles for each of the four hotspots.

Hotspot A combines various environmental characteristics that all may be important. First of all, this area hosts a *homeless shelter* (HVO) whose residents often are *psychiatric patients*. Secondly, the surrounding streets are characterised by a high concentration of *social housing*. According to police officers, residents are less likely to call the authorities in the case of disturbances or nuisance. Along with the presence of *benches* surrounded by *public green space*, this contributes to an environment where alcohol consumers can spend time in relative anonymity. Thirdly, a shopping centre only a few hundred metres away creates opportunities for begging, getting alcohol, and socializing. The shopping centre is a *run-down area* and is generally avoided by older people and families with children. HVO users are perceived as having 'taken over' the square in the middle of the shopping centre. As long as they do not cause too much trouble, they are permitted to stay, or overlooked by law enforcement officers.

In hotspot B, two environmental constellations may explain the high number of alcohol-related incidents in this area. First, just outside of this hotspot, *big dance events and concerts* are organized at the Westergasfabriek Culture Park. Visitors of the events are channeled on a route way to the city centre which crosses the hotspot. Many road traffic accidents occur at a junction on this route way inside the hotspot (*traffic black spot*). Secondly, the area itself is characterised by high unemployment rates and a *high prevalence of socio-psychological problems*. There is a regular group of alcoholics, generally older men, who drink in the Westerpark, *an attractive public park with benches*. Aggressive situations have arisen there frequently.

Hotspot C has a high concentration of *student housing*. Notorious are student parties during which large quantities of alcohol are often consumed. In addition, this hotspot includes one of the key train stations in Amsterdam, which also serves as Amsterdam's principal *pick-up location for international low-budget hire cars*. The large numbers of young people waiting there in a holiday mood often generates a favourable context for alcohol and drugs consumption.

Hotspot D is located in a district with frequent problems related to drugs, crime, violence, early school leaving, and unemployment. An elaborate programme of physical and socio-economic renewal implemented between 1992 and 2009 improved the situation considerably. However, *drug-related problems* and other problems still occur. People with social problems are *concentrated* in two *big anonymous blocks of flats* in this hotspot. Moreover, this area attracts many visitors, including those from risk groups, because of the presence of shopping centre, metro station, youth centre, one local bar, and a centre for addicts. Aside from the bar, alcohol is also available in the supermarket, a late-night shop, and a number of 'tokos' (Asian food shops that also sell plastic bags of 'bitters' (drinks containing 42% alcohol). Additionally, the *green space (including comfortable benches)* that is abundant in this area, creates an attractive context for drinking.

A particular phenomenon in this area of Amsterdam are *flat parties*. Local residents, most of whom are from Africa, Suriname, or the Caribbean, organize parties for the 'extended family', including friends and neighbours. Much alcohol is consumed during some of these parties.

Further analyses of the short free-text descriptions in the incidence registry showed that incidents related to mental problems and alcoholism occurred relatively often in A, traffic incidents in B, hazardous alcohol use and drugs abuse in C and mental problems and violence in D. These type of incidents correspond with the environmental profiles of the different hotspots (as depicted above) For example, in B, the higher number of traffic-related incidents corresponds with the potential role of the traffic blackspot. Furthermore, the potential role of events at the nearby Westergasfabriek corresponds with the high percentage of incidents occurring during the night. Similarly, in D, the higher number of violence-related incidents corresponds with the unsafe character of this area and the high percentage of victims coming from surrounding neighbourhoods.

3.4. Discussion

This study has identified and described hotspots of alcohol-related ambulance attendances outside of the entertainment districts of Amsterdam. Compared with hotspots with high outlet density, victims are older, are more often male, and live closer to the location of the incident. Incidents in most hotspots are less likely to happen during the night or during the weekend. In-depth study of four hotspots revealed widely different ways in which specific local environments could possibly contribute to the occurrence of incidents in a neighbourhood.

Evaluation of data and methodology

Because the ambulance dataset provides information about the six digit postcode of the location of serious alcohol-related incidents we were able to accurately determine relevant hotspots, while the availability of micro-scale environmental data for the city of Amsterdam allowed us to characterise the hotspots that we identified.

A limitation of these data is that inaccurate registration could have led to greater underestimation of alcohol-related injuries. However, this underestimation could not have affected our results unless the degree of underestimation would systematically differ between the groups of incidents or between hotspots.

There are a variety of methods for determining hotspots. In general, the nature of the data and the purpose of study determine which method is most appropriate. We used the mapping approach described and employed by Pfeffer et al. (2012), because it produces hotspots with the geographical detail necessary for identifying small clusters of incidents and for describing their immediate surroundings. In this approach, accurate boundaries could be drawn based on micro areas comprising only a few addresses, thus neatly representing the actual distribution of observations. Hotspots represented by density surfaces based on grid cells –frequently used in crime hotspot analysis (Chainey and Ratcliffe 2005) – were not considered, because they assume a continuous distribution of observations over the study area. Such an assumption would greatly affect our ability to detect small-scale hotspots.

The number of alcohol-related incidents in hotspots outside of entertainment districts was relatively small, and our findings should be interpreted accordingly. However, on the scale of a few blocks, ten incidents involving ambulance attendances in just a few years is a phenomenon of significance to the local residents. Moreover, hotspots outside of entertainment districts may reflect the impact of environmental determinants that could create similar clusters of problems, though too diffuse to be noticed, in other parts of the city.

By preparing environmental profiles of hotspots, we aimed to identify environmental characteristics, or combinations of these, that may induce a concentration of alcohol-related incidents. We recognise that we should be careful to infer causality, because our analysis is cross-sectional and lacks a systematic comparison with characteristics of areas outside of hotspots. In our study, support for causal inference may come from two sources. First, to our knowledge of the geography of Amsterdam, many of the identified constellations of environmental factors are rare, and would very probably not be found in a random selection of control areas. Second, the victim and temporal profiles of the alcohol incidents often corresponded to the type of environmental factors that we identified in the qualitative analysis. Nonetheless, further mixed-methods are needed, preferably in other cities as well, to test for the plausibility and generalisability of relationships suggested by our analysis.

Interpretation and comparison with previous studies

Our study has shown that hotspots of alcohol-related incidents also occur outside of outlet dense areas. To date, no other study has explored the environmental characteristics of such hotspots by combining quantitative and qualitative methods.

We found that some hotspots emerged around social services such as a homeless shelter and a centre for addicts. However, many such services exist in Amsterdam without a corresponding hotspot in alcohol-related incidents, suggesting that the presence of such a service was in itself not sufficient to give rise to a hotspot. We found that the occurrence of hotspots depended upon the wider functional, physical, and social environment. More specifically, hotspots of alcohol-related incidents arose when combined with a favourable drinking context, including attractive locations where it is possible to sit and drink in relative anonymity.

A previous study (Schuurman et al. 2009) found hotspots of pedestrian injuries to occur where unsafe and complex traffic situations exist close to retail establishments that serve alcohol. We found a comparable pattern in one of our hotspots, where visitors of dance events have to cross a traffic black spot on their way home. These results imply that roadway design and traffic safety measures are particularly important at locations frequently visited by people under the influence of alcohol.

Our results fit with disorganization theory and more specifically the collective efficacy thesis as emphasised in research on neighbourhood crime (Shaw and McKay 1942; Sampson and Groves 1989). Collective efficacy refers to the ability of members of a community to control the behaviour of individuals or groups in the community (Sampson et al. 1997). We found that hotspots of alcohol-related incidents could occur in deprived neighbourhoods where social housing concurs with little social control and a high tolerance to deviant behaviour. In line with the collective efficacy perspective, social housing may hinder neighbourhood collective efficacy processes because of reduced social cohesion and fewer vested interests among community members Previous empirical studies found that more deprived areas show a higher level of acceptance of deviant behaviour (Friedrichs and Blasius 2003; Sampson and Raudenbusch 1999). Sampson and Raudenbush (1999) stressed the important role of home ownership. Financial investments provide homeowners with a vested interest in supporting the commonweal of neighbourhood life and in promoting collective efforts to maintain social control. In contrast, residents in more deprived areas dominated by social housing tend to be more indifferent to what goes on in their neighbourhoods and may be less likely to call the authorities in the case of disturbances like drinking in public.

3.5. Conclusions

This study has shown that hotspots of alcohol-related incidents may emerge outside of areas with high outlet density. Our results indicate that the local environment could give rise to hotspots of alcohol incidents in a great variety of ways which could not have been captured by statistical analyses of quantitative data. This underlines that place-specific context-sensitive research that include qualitative methods is needed to understand how local environments may induce or prevent the occurrence of alcohol-related problems.

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CHAPTER 4

The impact of extended closing times of alcohol outlets on alcohol-related injuries in the nightlife areas of Amsterdam: a controlled before-and-after evaluation

Abstract

Aims: The municipality of Amsterdam implemented a new alcohol policy allowing alcohol outlets in two of the five nightlife areas to extend their closing times from April 1st 2009 onwards. We investigated how levels and trends of alcohol-related injuries changed after implementation of this alcohol policy, by comparing areas with extended closing times to those without.

Design: A controlled before-and-after evaluation to compare changes in alcohol-related injuries between intervention and control areas.

Setting: Central district of Amsterdam, The Netherlands.

Participants: Alcohol-related ambulance attendances for control and intervention areas between April 1st 2006-2009 (respectively, n=544 and n=499) and April 1st 2009-2011 (respectively, n=357 and n=480).

Measurements: Alcohol-related injuries were defined as ambulance attendances for persons that suffered from direct or indirect consequences of alcohol intoxication. Injuries were counted per month in two intervention and three control nightlife areas. We used Poisson regression to assess changes in injuries.

Findings: After April 1st 2009, intervention areas showed a larger change in the level of alcohol-related injuries than control areas (Incidence Rate Ratio 1.34 [95% CI, 1.12;1.61]), but trends remained stable in both areas. This increase was only statistically significant for the following subgroups: 2.00-5.59 am, weekend days, males, individuals aged 25-34 years, and people transported to a hospital. However, the increase did not differ between subgroups with statistical significance.

Conclusions: A one hour extension of closing times in some of Amsterdam's nightlife areas was associated with 34% more alcohol-related injuries. This negative health impact should be considered when formulating policies on closing times.

4.1 Introduction

In the central district of Amsterdam, on April 1st 2009, in two out of five nightlife areas, alcohol outlets were permitted to extend their closing times by one hour. This policy change was part of a package that aimed to make the city more attractive for tourists and other visitors. However, extended closing times may also increase the prevalence of excessive alcohol use, which may not only affect health (e.g. alcohol poisoning) but also public order (e.g. crime and violence) (1).

Reviews by Stockwell *et al* (2) and Hahn *et al* (3) came to different conclusions on the health impact of extensions of two hours or less. The first review concluded that extending closing times lead to more consumption and harms, while the second concluded that evidence was scarce and inconclusive. However, most of the well-designed quasi-experimental studies published during the last decade (4-10) showed that a one to two hour change in closing times negatively affects alcohol consumption and alcohol-related harm, such as violence (4-6, 8, 9). Two of these studies included their control area from another city (9) or country (10), thereby limiting comparability between the intervention and control area. Besides this, earlier studies investigated the impact of extended closing times on either the outcome alcohol consumption (4-6), violence (4, 7-9), or alcohol-related traffic accidents (5, 10). To our knowledge none of the earlier studies with a controlled before-and-after evaluation investigated the impact of one to two hour extensions of closing times on more severe alcohol-related injuries, such as poisoning, reduced consciousness, fractures, wounds, and other injuries, for which an ambulance is needed.

The specific situation in the central district nightlife areas of Amsterdam made it possible to investigate with a controlled before-and-after evaluation whether extended closing times were associated with an increase in alcohol-related injuries during the night-time. The aim of our study is to assess both changes in levels – April compared to March 2009 – and changes in trends – injuries per month after compared to before April 1st 2009 – in nightlife areas with extended closing times compared to those without. We furthermore aimed to explore whether the impact of extended closing times varied according to day of the week (as closing times and the number of visitors and injuries differ during the working week and weekend), age and sex (as the level of alcohol consumption and vulnerability of intoxication differs between these groups), and type and severity of injury (to evaluate the importance of any impact observed).

4.2 Methods

Alcohol policy

Alcohol outlets in the central district of Amsterdam are either classified as day-time, evening, or night-time venues. Before April 1st 2009, day-time venues were allowed to be open until 3.00 am during Friday and Saturday nights (weekend nights) and until 1.00 am during weeknights. Closing times for evening and night-time venues were respectively 4.00 and 5.00 am during weekend nights and respectively 3.00 and 4.00 am during weeknights. None of the fast food venues were allowed to sell alcohol. Fast food venues could stay open until 6.00 am during weekend nights and 3.00 am during weeknights. It was assumed that extended opening hours for fast food venues compared to night-time venues during weekend nights lead to a more evenly distributed outflow of visitors and thereby less disturbance of public order.

The municipality of Amsterdam implemented a new alcohol policy (11), giving day-time and evening venues (excluding fast food venues) on the Leidseplein and Rembrandtplein the permission to extend their closing times by one hour, from April 1st 2009 onwards. Only the Leidseplein and Rembrandtplein were classified eligible because relatively few people live in these areas, streets are wide, and public transport is well organized. It was assumed that possible disturbances of public order and living environment due to extended closing times would be lower in these two areas compared to other nightlife areas. Alcohol outlets with a day-time or evening license could apply to extend their closing times. Applications could be submitted from January 2009, but closing times were only extended from April 1st 2009 onwards to allow time for review. To minimise the risk that extension of closing times caused problems of public disorder, alcohol outlets were also required to draw up a security plan. This plan and other safety issues (e.g., outlet history of safety and closing time offenses, and enforcement capacity of police) were reviewed by the police.

In addition to extending closing times, evening and night-time venues were permitted to stay open for an additional hour (cool-down hour). During this hour, outlets may not sell alcoholic or non-alcoholic beverages, the music volume is turned down, and lights are turned on after half an hour, but visitors are not obliged to leave. The municipal board assumed that extended closing times and a cool-down hour would result in an evenly distributed and controlled outflow of visitors (11).

Data

We used data from the ambulance service of the public health service of Amsterdam. These data contain information on time and day of the incident, location of the incident (six-digit zip code), characteristics of the victim (age, sex, residence), and the nature of the incident. This information was derived from the incoming call, which is recorded by the operator in the emergency control room. Information is supplemented with information from the paramedics, who gave feedback to the operator on details of the ambulance attendance, and with information from the emergency department in case of transportation to a hospital. For this study, registry data of the three years before until two years after the policy change were used (April 1st 2006 until April 1st 2011).

Outcome

An alcohol-related injury was defined as an incident in which the person suffered from the direct or indirect consequences of alcohol consumption, predominately including poisoning, reduced consciousness, fractures, and wounds, but also other injuries. To classify injuries as alcohol-related we used the short descriptions of the incoming call, the situation encountered by the paramedics, and the feedback from the hospital. Relevant records were electronically selected when at least one of the three short descriptions contained a predefined keyword related to drinking, drunkenness, alcohol, and specific alcoholic beverages. These selected records were manually checked and coded. This selection procedure was performed without knowledge of the location of the incident. Furthermore, we divided alcohol-related injuries into injuries in which violence was involved (mainly reduced consciousness/fractures/wounds caused by fights) and injuries in which no violence was involved (mainly poisoning and reduced consciousness/fractures/wounds caused by falling).

Geographical pattern

A Geographic Information System (GIS) was used to geocode – assigning a location on a map - alcohol-related injuries, based on their six-digit zip code (Figure 1). Each six-digit zip code is relatively small with a size of 25-100 by 25-100 metres. Our intervention areas (Leidseplein and Rembrandtplein) and control areas (Dam, Koningsplein, and Red-light district) consisted of all zip codes in and around these areas, and included zip codes which were located less than 105 metres (based on the distance between nightlife areas) from the core zip codes. Alcohol-related injuries within these areas were included in our analysis.

Figure 1. Alcohol-related injuries in the central district nightlife areas of Amsterdam

Variables

Intervention areas were those two areas with extended closing times, and control areas those three areas without. Time of incident was coded into 4-hour time spans starting at 6.00 am. At 6.00 am all restaurants, bars, and clubs are closed for at least one hour and most visitors have left the nightlife areas. Day of incident was classified into weekend day (from Friday 6.00 pm until Monday 6.00 am) and weekday (from Monday 6.00 am until Friday 6.00 pm). Age was coded into four categories: <25 years, 25-34 years, 35-44 years, and 45+ years. Other categorical variables used were the variables sex (man or woman), transportation to a hospital (yes or no), and violence (yes or no).

Statistical analysis

For our analysis, we excluded three days (i.e. New year's day, Queens-day, and Gay pride) which are all festive days with a much higher number of visitors throughout the entire central district, an increased availability of alcohol, and/or adjusted closing times. A total of 1880 alcohol-related injuries were included. Information from the incoming call or paramedics was missing for 81 out of 1880 injuries (4.3%) and information from emergency departments was missing for 413 out of the 1093 (37.8%) victims that were transported to a hospital. Only the latter and not the first percentage was different between the time period before and after the intervention (respectively, 29.1 versus 49.1%, $p<0.001$, and 4.1 versus 4.5%, $p=0.658$) and none of the percentages were different between intervention and control areas (respectively, 39.4 versus 36.1%, $p=0.261$, and 4.7 versus 3.9%, $p=0.385$).

A segmented time series design was used to compare changes in levels and trends of alcohol-related injuries between intervention and control areas (12). Direct changes (i.e., an immediate increase in levels) were investigated because outlets could increase their closing times on April 1st 2009 and gradual changes over time (i.e., a change in trends) were investigated because after April 1st 2009, the number of outlets with extended closing times may continue to increase. In our study two segments were present; the period before and after implementation of the new alcohol policy. We used a segmented Poisson regression to estimate separate baseline levels and separate slopes for these two periods.

Five nested Poisson regression models were built in order to estimate the changes in levels and trends after implementation of the new alcohol policy. Model 1 contained the variable 'area' (intervention versus control), time (in 'years'), and the interaction term 'area*years'. This interaction term estimates whether changes over time (=trend) differed between intervention and control areas. In Model 2, the variable ‘period’ was added, which estimates whether there was a change in the number of injuries after implementation of the new alcohol policy (=level). Model 3 additionally included the interaction term ‘period*area’, thereby estimating whether level changes differed between intervention and control areas. In Model 4, the additional interaction term ‘period*years’ was added. This term tests whether trends were different between the two periods studied (before and after April 1st 2009). Model 5 additionally included the 3-way interaction ‘period*area*years’, which estimates whether trend changes after implementation of the new alcohol policy differed between intervention and control areas. Multilevel Poisson regression models with nightlife area as cluster level showed very similar results as a single-level model, and therefore, we present the latter simpler model. The exponentiated betas of all models can be interpreted as an incidence rate ratio (IRR).

Models were fitted for all individuals (sex and age corrected), and for different strata defined in terms of time of incident, day of incident, sex, age, whether or not transported to a hospital, and whether or not violence was involved in alcohol-related injuries. For each stratum, we fitted a separate model that included the complete dataset. We introduced the 3-way interaction term ‘period*area (level change)*variable of interest (e.g. age)’ and we took as reference group the stratum of interest (e.g. 25-34 years). Analyses were performed in R version 3.0.2. with the ‘glm’ function including ‘poisson’ as family. P-values <0.05 were considered to indicate statistical significance.

4.3 Results

Table 1 presents the characteristics of the alcohol-related injuries. Between April 2006 and April 2011, 979 injuries occurred in the intervention areas and 901 injuries in the control areas. Most individuals were transported to a hospital and violence was not involved in the majority of alcohol-related injuries. Furthermore, the majority of injuries took place during the evening or night (10.00 pm-5.59 am) and during the weekend (especially in intervention areas). Most victims were men (especially in control areas) and younger than 35 years (especially in intervention areas).

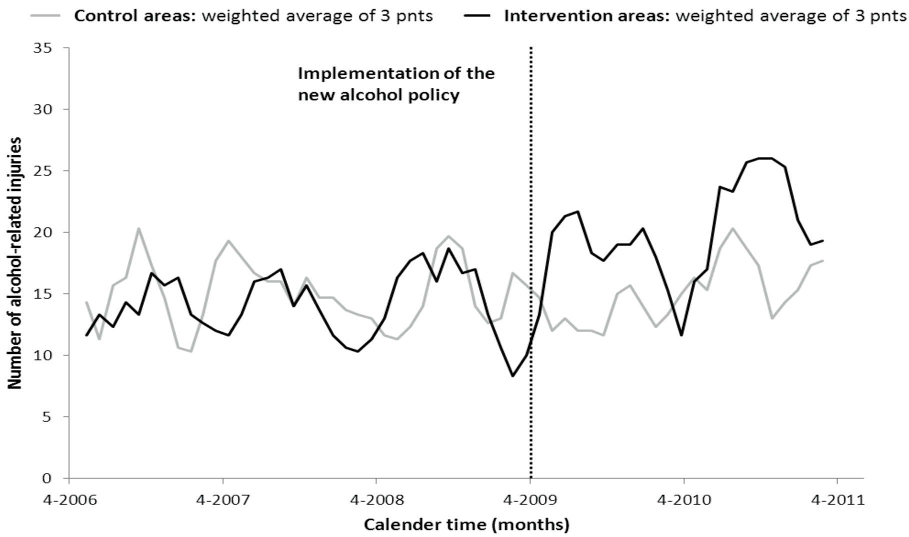
Table 1. Characteristics of alcohol-related injuries in intervention and control areas

	Intervention areas		Control areas	
	Period: April 2006-March 2009	Period: April 2009-March 2011	Period: April 2006-March 2009	Period: April 2009-March 2011
Injuries, total n	499	480	544	357
Injuries per month, mean n	13.9	20.0	15.1	14.9
Time, n (%)				
06.00 am-05.59 pm	39 (7.8)	32 (6.7)	107 (19.7)	46 (12.9)
06.00 pm-09.59 pm	50 (10.0)	32 (6.7)	118 (21.7)	70 (19.6)
10.00 pm-01.59 am	171 (34.3)	143 (29.8)	195 (35.8)	154 (43.1)
02.00 am-05.59 am	239 (47.9)	273 (56.8)	124 (22.8)	87 (24.4)
Day, n (%)				
Working week	179 (35.9)	174 (36.3)	224 (41.2)	131 (36.7)
Weekend	320 (64.1)	306 (63.7)	320 (58.8)	226 (63.3)
Sex, n (%)[§]				
Women	210 (44.6)	223 (46.9)	113 (21.9)	83 (23.9)
Men	261 (55.4)	252 (53.1)	404 (78.1)	264 (76.1)
Age, n (%)[§]				
<25	231 (51.0)	237 (53.7)	132 (26.1)	95 (29.1)
25-34	93 (20.5)	108 (24.5)	132 (26.1)	90 (27.5)
35-44	55 (12.2)	52 (11.8)	93 (18.4)	67 (20.5)
45+	74 (16.3)	44 (10.0)	149 (29.4)	75 (22.9)
Transportation to a hospital, n (%)				
No	203 (40.7)	207 (43.1)	224 (41.2)	153 (42.9)
Yes	296 (59.3)	273 (56.9)	320 (58.8)	204 (57.1)
Violence involved, n (%)				
No	474 (95.0)	434 (90.4)	513 (94.3)	341 (95.5)
Yes	25 (5.0)	46 (9.6)	31 (5.7)	16 (4.5)

[§] Sex is missing for 70 out of 1880 individuals and age for 153 out of 1880 individuals.

Figure 2 presents the crude number of alcohol-related injuries over time (weighted average of 3 time points = months) for both intervention and control areas. Before implementation of the new alcohol policy, injuries were comparable between all areas, with a small seasonal variation present. After the policy implementation, the number of injuries per month was higher in intervention areas.

Figure 2. Crude number of alcohol-related injuries over time



Models 1 and 2 presented in Table 2 show that in April 2006, the number of alcohol-related injuries was slightly lower in intervention compared to control areas, as indicated by IRRs <1 for the variable 'area' (Models 1 and 2: sex and age corrected IRR 0.84 [95% CI, 0.69;1.01]). Only in intervention areas did this number increase over time (Models 1 and 2, variable 'area*years': sex and age corrected IRR 1.08 [95% CI, 1.02;1.15]). After including the interaction term 'period*area' (Model 3) these effects disappeared. Model 3 shows that in control areas the number of injuries did not change (Model 3, variable 'period': sex and age corrected IRR 0.94 [95% CI, 0.73;1.22]) during the month after implementation of the new alcohol policy. In contrast, intervention areas experienced a significant 43% additional increase (Model 3, variable 'period*area': sex and age corrected IRR 1.43 [95% CI, 1.00;2.05]) as compared to control areas. This effect remained present in Model 4, which includes the additional interaction term 'period*years'. The interaction term reveals that the trend (per year) in the number of injuries remained similar after implementation of the new alcohol policy (Model 4, variable 'period*years': sex and age corrected IRR 1.05 [95% CI, 0.91;1.21]), both in intervention and control areas (Model 5, variable 'period*area*years': sex and age corrected IRR 0.94 [95% CI, 0.71;1.24]).

Table 2. Change in levels and trends of alcohol-related injuries after implementation of the new alcohol policy in intervention versus control areas

	Incidence rate ratio (95% confidence interval)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Area:					
Level in control areas	1.00	1.00	1.00	1.00	1.00
Level in intervention areas	0.84 (0.69;1.01)	0.84 (0.69;1.01)	0.95 (0.76;1.19)	0.95 (0.76;1.19)	0.93 (0.72;1.19)
Years:					
Trend	1.03 (0.98;1.07)	0.99 (0.92;1.06)	1.04 (0.96;1.14)	1.03 (0.94;1.13)	1.02 (0.93;1.13)
Area*Years:					
Additional trend in contro areas	1.00	1.00	1.00	1.00	1.00
Additional trend in intervention areas	1.08 (1.02;1.15)#	1.08 (1.02;1.15)#	0.97 (0.86;1.10)	0.97 (0.86;1.10)	0.99 (0.86;1.14)
Period:					
Level after implementation		1.13 (0.95;1.35)	0.94 (0.73;1.22)	0.92 (0.71;1.20)	0.90 (0.68;1.19)
Period*Area:					
Additional level after implementation in control areas			1.00	1.00	1.00
Additional level after implementation in intervention areas			1.43 (1.00;2.05)#	1.45 (1.01;2.08)#	1.48 (1.02;2.17)#
Period*Years:					
Additional trend before implementation				1.00	1.00
Additional trend after implementation				1.05 (0.91;1.21)	1.09 (0.89;1.33)
Period*Area*Years:					
Additional trend after implementation in control\ areas					1.00
Additional trend after implementation in intervention areas					0.94 (0.71;1.24)
Model fit					
Residual Deviance	577.98	576.11	572.26	571.77	571.57

Incidence rate ratios and 95% confidence intervals are obtained with Poisson regression in R.

[#] P-value <0.05; corrected for sex (men, women, missing) and age (<18, 18-24, 25-34, 35-44, 45-54, 55+ years, missing).

The fit of Model 5 (residual deviance) was not significantly better compared with Model 3 (p=0.710).

Because trends did not differ between intervention and control areas (Model 5, Table 2) and the fit of Model 5 was not significantly better than Model 3, the latter model was used for our stratified analysis. Model 3 could be further simplified by excluding the interaction term 'area*years' because the IRR for this interaction term was approximately 1 (Table 2) and the model fit did not change after excluding this term (residual deviance 572.44 versus 572.26). This final simplified model is graphically presented in Figure 3.

Figure 3. Change in sex and age corrected level of alcohol-related injuries after implementation of the new alcohol policy

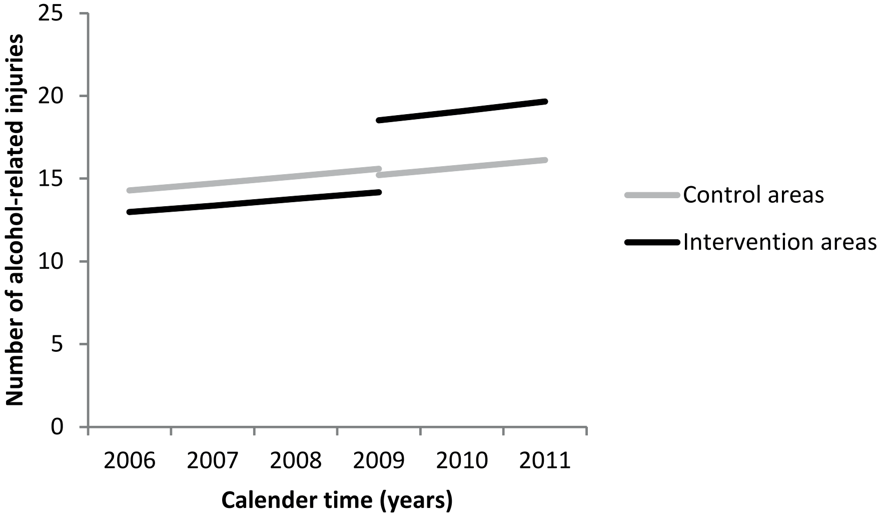


Table 3 shows the IRRs of the simplified model described above, including the IRR of 1.34 that implies a 34% larger change in injury incidence in intervention areas than control areas (variable 'area*period': sex and age corrected IRR 1.34 [95% CI, 1.12;1.61]). Although none of the interaction terms were statistical significant, we found that individual IRR estimates varied and were statistically significant only for the time period 2.00-5.59 am, for the weekend, in men, in individuals aged 25-34 years, and in subjects transported to a hospital (sex and age corrected IRRs are 1.39 [95% CI, 1.00;2.92]), 1.43 [95% CI 1.13;1.80], 1.41 [95% CI 1.11;1.77], 1.49 [95% CI 1.01;2.19], and 1.35 (95% CI 1.06;1.71] respectively). The sex and age corrected IRR was higher for alcohol-related injuries in which violence was involved compared to alcohol-related injuries in which no violence was involved (IRR 1.47 compared to 1.25) but the former IRR was not significant due to the low number of injuries related to violence.

Table 3. Change in levels of alcohol-related injuries after implementation of the new alcohol policy, in intervention versus control areas, stratified by time, day, sex, age, transportation to a hospital, and involvement of violence

	Incidence rate ratio (95% confidence interval)				
	Area: Level in intervention versus control areas before implementation	*Years*: Trend	*Period:* Level after versus before implementation in control areas	*Period**Area*: Additional level after versus before implementation in intervention areas	*P-value for interaction*
All[-]	0.91 (0.80;1.03)	1.03 (0.97;1.09)	0.98 (0.80;1.20)	1.34 (1.12;1.61)[#]	-
Time					
06.00 am-17.59 pm	0.81 (0.56;1.17)	0.97 (0.81;1.15)	1.04 (0.60;1.80)	1.14 (0.64;2.04)	0.858
18.00 pm-21.59 pm	0.83 (0.60;1.16)	1.03 (0.89;1.19)	0.83 (0.52;1.34)	1.22 (0.72;2.09)	*Ref*
22.00 pm-01.59 am	0.91 (0.74;1.12)	1.03 (0.93;1.14)	1.02 (0.73;1.43)	1.06 (0.78;1.44)	0.655
02.00 am-05.59 am	1.20 (0.97;1.50)	0.98 (0.89;1.09)	1.03 (0.70;1.49)	1.39 (1.00;1.92)[#]	0.693
Day					
Working week	0.91 (0.75;1.11)	0.99 (0.90;1.10)	1.02 (0.73;1.44)	1.16 (0.86;1.57)	*Ref*
Weekend	0.90 (0.77;1.05)	1.02 (0.95;1.10)	0.91 (0.70;1.18)	1.43 (1.13;1.80)[#]	0.294
Sex[§]					
Women	1.45 (1.15;1.82)[#]	1.03 (0.93;1.15)	1.06 (0.71;1.58)	1.19 (0.85;1.68)	*Ref*
Men	0.72 (0.61;0.84)[#]	1.03 (0.96;1.12)	0.95 (0.74;1.21)	1.41 (1.11;1.77)[#]	0.436
Age (years)[§]					
<25	1.62 (1.31;2.01)[#]	1.09 (0.99;1.21)	0.98 (0.69;1.41)	1.23 (0.89;1.70)	*Ref*
25-34	0.73 (0.56;0.95)[#]	1.02 (0.90;1.16)	0.95 (0.62;1.46)	1.49 (1.01;2.19)[#]	0.458
35-44	0.65 (0.47;0.91)[#]	1.15 (0.97;1.36)	0.82 (0.49;1.37)	1.16 (0.71;1.89)	0.836
45+	0.66 (0.50;0.88)[#]	0.96 (0.84;1.11)	0.83 (0.53;1.31)	1.26 (0.79;2.01)	0.933

Table 3. Change in levels of alcohol-related injuries after implementation of the new alcohol policy, in intervention versus control areas, stratified by time, day, sex, age, transportation to a hospital, and involvement of violence (*continued*)

	Incidence rate ratio (95% confidence interval)				
	Area: Level in intervention versus control areas before implementation	*Years*: Trend	*Period:* Level after versus before implementation in control areas	*Period*Area*: Additional level after versus before implementation in intervention areas	*P-value for interaction*
Transportation to a hospital					
No	1.02 (0.84;1.23)	1.00 (0.91;1.10)	1.12 (0.82;1.53)	1.10 (0.82;1.45)	*Ref*
Yes	0.85 (0.73;1.00)[#]	1.03 (0.95;1.12)	0.90 (0.69;1.17)	1.35 (1.06;1.71)[#]	0.275
Violence involved					
No	0.92 (0.81;1.04)	1.04 (0.97;1.10)	0.97 (0.79;1.20)	1.25 (1.04;1.51)[#]	*Ref*
Yes	0.79 (0.46;1.38)	1.04 (0.79;1.37)	0.73 (0.28;1.93)	1.47 (0.66;3.25)	0.704

Incidence Rate Ratios and 95% confidence intervals are obtained with Poisson regression in R.

~ The fit of the model without the interaction term Area*Years is not statistically different compared to Model 3 presented in Table 2, including this term (residual deviance 572.44 versus 572.26, p=0.674).

[§] Sex is missing for 70 out of 1880 individuals and age for 153 out of 1880 individuals.

[#] P-value <0.05; corrected for sex (men, women, missing) and age (<18, 18-24, 25-34, 35-44, 45-54, 55+ years, missing).

4.4 Discussion

Implementation of the new alcohol policy was associated with 34% more alcohol-related injuries in areas where alcohol outlets could extend their closing times by one hour, compared to control areas without extended closing times. This increase was statistically significant between 2.00 and 5.59 am, during the weekend, for men, for those aged 25-34 years, and also for people transported to a hospital. Furthermore, both types of alcohol-related injuries (injuries in which violence was involved and injuries in which no violence was involved) increased similarly.

Strengths and limitations

In previous studies investigating the impact of extended closing times without the inclusion of control areas, it was hard to distinguish whether changes in injuries were caused by the policies or by coinciding environmental changes (2, 3). During the last decade, several studies did include control areas (4-10), but two studies selected these areas from another city or country (9, 10), thereby introducing the potential for country- and city-level confounding. A great strength of our study is that we selected our control areas within the same city district as our intervention areas, thereby eliminating both confounding processes.

In our study, both intervention and control areas accommodate many restaurants, bars, clubs, and fast food venues, all areas are in the central district of Amsterdam, and all areas are within walking distance from the Central Station. Therefore, other policy changes focusing on the clubbing environment probably affected all areas to the same extent. Besides this, most of the other alcohol policies for the central district of Amsterdam in 2009 were 'gradual' long term plans, such as municipal investments to increase the capacity or number of bars, clubs, and restaurants, and plans to increase the number of cultural venues, such as theatres, that can legitimately sell alcohol alongside activities included in their cultural program. These gradual policy changes are likely to affect only longer term trends of health-related injuries and not to produce the immediate changes that were found in our study.

In our controlled before-and-after evaluation, three problems could have biased our results. First, the control areas (especially the Red-light district) likely attract different types of visitors, i.e. men and older individuals, than do the intervention areas (Table 1). However, this potential bias can be discounted because the IRRs presented in our paper are corrected for sex and age. Second, we only know the location of the ambulance attendances, but not the location of alcohol consumption. Because all nightlife areas are within walking distance, individuals can easily move between intervention and control areas. If any, this movement could have biased our results toward the null, as some people could have consumed alcohol during extended opening hours in the intervention areas and have an injury in the control areas, which are on the route towards the Central Station. Third, as no information was available on customer volumes of intervention and control areas, we cannot dismiss the possibility that visitors switched from control to intervention areas soon after the intervention.

In our study, we used data reflecting alcohol-related injuries from the ambulance database in Amsterdam. A limitation of these data is that free-text descriptions of injuries are relatively short, such that, in many cases, only the primary medical diagnosis is reported. In case of injuries leading to unconsciousness or bleeding, the fact that an individual was intoxicated may not be noted. In addition, the ambulance service has little time to report information about injuries at peak times, which could have led to greater underestimation of alcohol-related injuries between 2.00 and 5.59 am. It is unlikely that this underestimation, which probably occurred in both intervention and control areas, has biased our relative effect estimates but it precludes accurate estimation of the absolute risk of alcohol-related injury.

Comparison to literature and interpretations

Our study bears similarities to several other studies that investigated the health impact of changed closing times in Norway (9) and Australia (4, 5, 8). These studies investigated the impact of a less than two hour change in closing times on the number of assaults or alcohol-related traffic accidents. Studies investigating assaults found a 16% increase in Norway after a one hour extension (9), a 35.7% larger increase in Perth, Australia (4), and a 37% larger decrease in central district areas in Newcastle, Australia, with a one and a half hour restriction of closing times compared to areas without (8). In Western Australia the mean annual traffic crash rate increased by 47% after the introduction of extended trading permits (5). These results are in line with the 34% increase we found in areas with extended closing times. Although all effect measures point in the same direction, sizes are not exactly comparable due to different interventions, control groups, and outcome measures.

The number of alcohol-related injuries in intervention areas in Amsterdam may have increased because visitors drink more. Alcoholic beverages are available for a longer time period and extended closing times could delay the time to visit bars and clubs, thereby allowing for a longer time to “pre-drink” relatively cheap alcohol in private homes (13). This may result in more alcohol-related injuries, even when the number of visitors remains the same. An additional explanation could be that the number of visitors increased in the intervention areas, thereby increasing the total population at risk. A higher number of visitors also increases crowding of public areas, which may increase the frequency of conflict situations and resulting violence and assaults (14).

It is difficult to generalize the observed health impact of extended closing times to other Dutch cities or to other countries as the impact may depend on the environmental and policy context (2, 15). It is also difficult to predict what would happen if closing times are extended throughout the entire city of Amsterdam. First, our estimated impact may have been influenced by a shift of visitors – who would have experienced an injury in the control areas anyway – towards the intervention areas. However, this interpretation is not supported by our own data, as no change of alcohol-related injuries in the three control areas was present. We cannot completely dismiss this possibility as it is possible that a switch of visitors from intervention to control areas soon after the intervention occurred alongside an underlying increase of visitors over the time period of the study. Second, implementing this policy in the entire central district of Amsterdam could reduce the concentration of visitors to particular nightlife areas and hence reduce the risk of alcohol-related violence. However, such a city-wide implementation might as well increase the number of injuries in Amsterdam as more visitors may find a nearby opportunity to drink for a longer period.

Harmful effects of extended closing times could be reduced by preventive measures like better surveillance by police and arresting or evicting aggressive individuals (16). Another possibility is to implement measures that prohibit employees of alcohol outlets from selling alcohol to drunk individuals. However, there is no conclusive scientific evidence on the effectiveness of such measures (17). Such measures may only be effective when employees are extensively educated and when police enforcement is present (18).

Conclusion

This paper provided strong evidence that a one hour extension of closing times in two nightlife areas in the central district of Amsterdam increased the number of alcohol-related injuries during the night-time. It is important to consider this negative impact on public health when making policy choices about closing times of alcohol outlets.

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CHAPTER 5

Assessing associations between socio-economic environment and self-reported health in Amsterdam using bespoke environments

Abstract

Background: The study of the relationship between residential environment and health at micro area level has a long time been hampered by a lack of micro-scale data. Nowadays data is registered at a much more detailed scale. In combination with Geographic Information System (GIS)-techniques this creates opportunities to look at the relationship at different scales, including very local ones. The study illustrates the use of a 'bespoke environment' approach to assess the relationship between health and socio-economic environment.

Methods: We created these environments by buffer-operations and used micro-scale data on 6-digit postcode level to describe these individually tailored areas around survey respondents in an accurate way. To capture the full extent of area effects we maximized variation in socio-economic characteristics between areas. The area effect was assessed using logistic regression analysis.

Results: Although the contribution of the socio-economic environment in the explanation of health was not strong it tended to be stronger at a very local level. A positive association was observed only when these factors were measured in buffers smaller than 200 meters. Stronger associations were observed when restricting the analysis to socioeconomically homogeneous buffers. Scale effects proved to be highly important but potential boundary effects seemed not to play an important role. Administrative areas and buffers of comparable sizes came up with comparable area effects.

Conclusions: This study shows that socio-economic area effects reveal only on a very micro-scale. It underlines the importance of the availability of micro-scale data. Through scaling, bespoke environments add a new dimension to study environment and health.

5.1 Introduction

Since the mid-1990s, a great deal of research has been conducted with the aim to assess area effects on health (for an overview, see Smyth) [1]. A key aim in this research has been to demonstrate the independent effect, if any, that area-level socio-economic factors have on health. Most studies have concluded that living in a socio-economically disadvantaged neighbourhood is associated with only relatively small effects on health outcomes. Furthermore, the health effects shown in observational studies often disappear after extensive adjustment for individual socio-economic characteristics (see for example, Robert, Pickett et al., Reijneveld, Yen et al.) [2]-[5].

An explanation for this lack of strong association may be that area effects are difficult to measure. It is widely recognized that the selection of the spatial unit is an important consideration in accurately detecting area effects. However, the definitions of 'neighbourhood' used in most studies are not based on theoretical considerations but instead on data availability [6]. As a result, in many cases, administratively defined areas have been used to define the spatial units for analysis.

Using administratively defined areas poses two types of problems related to, respectively, scale effects and boundary effects. **Scale effects** refer to the influence of the spatial scale used on the measurement of area effects. It is commonly agreed upon that the existence and strength of area effects on health are scale dependent [7]-[12]. Generally, stronger effects may be found if a smaller spatial scale is used [13]. **Boundary effects** occur especially when administrative boundaries do not accurately reflect appropriate neighbourhood boundaries. Administrative borders may not be relevant in the daily lives of residents. Residents living near the border of administrative areas may relate more to neighbouring administrative zones [14]. Due to such effects, the use of administratively defined areas may underestimate or skew geographical effects that would otherwise be observed within more relevantly defined areas.

Scale and boundary effects could in principle be avoided when so-called "bespoke environments" are used. In this approach, separate neighbourhoods are created for each individual resident. These neighbourhoods are centered on each respondent's home and are independent of administrative boundaries. The size of these neighbourhoods can be determined flexibly in terms of distance (the radius of the buffer) or counts (e.g. the number of residents).

This methodology has been applied in several research fields. Bespoke environments were introduced in the 1990s in studies of voting [15] and of social exclusion [16]. Studies on voting behaviour observed clear links between the characteristics of local milieus and voting behaviour [15], [17]. Anderson et al. [11] used, aside from administrative units, bespoke environments of 100 meters around each individual's home to study area effects on income. They found area effects to be strong at this very local level while non-existent or weak at the municipal level. Bolster et al. [18], investigated the effect of neighbourhood disadvantage on income dynamics using bespoke environments of different scales. They too found that the local level had a stronger association with individual outcomes.

The concept of bespoke environments has been applied in epidemiology at only a limited scale. Frank et al. [19] used this approach to assess the effect of the neighbourhood environment on walking behaviour and obesity. Each household was designated an area of one kilometer around the home. They found that the greater the diversity in land use within the bespoke environment, the lower the risk of obesity. Propper et al. [20] also used bespoke environments in their study on local neighbourhood conditions and mental health. The bespoke environment consisted of the area around each individual that contained the nearest 500-800 people. They found that the prevalence of common mental disorders was related to the socio-economic composition of the surrounding population, although the impact was limited. Maas et al. [21] used bespoke environments to measure the amount of green space in people's direct residential environment. A weak positive relationship was found with levels of physical activity.

To our knowledge, this study is the first in using bespoke environments to assess the association between socio-economic environment and self-reported health. The main aim of this study is to take into account scale effects and boundary effects when assessing the relationship between socio-economic environment and self-reported health in Amsterdam. The analysis consisted of three steps. First, we compared bespoke environments defined at eight different scales, with a radius ranging from 50 meters to 1500 meters, and assessed whether the association between socio-economic factors and self-reported health was strongest at smaller scales. Next, we distinguished between areas that were socio-economically homogeneous and heterogeneous and assessed whether the association between socio-economic factors and self-reported health was stronger among homogeneous areas. Finally, we compared the results with analysis based on administrative areas and assessed whether the bespoke approach showed a stronger association between socio-economic area and self-reported health.

5.2 Materials and Methods

Data

The data was obtained from the 2009 "State of the City" survey conducted by the Municipality of Amsterdam's Department of Research and Statistics. The State of the City surveyed 4351 inhabitants of Amsterdam. Stratified sampling was used to ensure that residents of all districts and ethnic groups within Amsterdam were represented, and respondents from five socially deprived neighbourhoods were oversampled. Data was collected by telephone (29 percent of all respondents), face-to face interviews (16 percent) and postal questionnaires (56 percent), with response rates of 34, 30 and 14 percent respectively (because the documentation of the source data mentions only rounded percentages the sum is not equal to 100). In the analysis we excluded respondents living in buffers with less than 10 inhabitants and/or less than 10 houses, because for these areas we could not obtain valid measures of the socio-economic environment. In the final analysis 4131 respondents were included.

The survey asked respondents about their living situation, such as housing and neighbourhood conditions, socioeconomic position and health. Perceived health status was measured by the response to the question, 'All in all, would you say your health is excellent, good, fair or poor?' The answers were classified into two categories: excellent/good and fair/poor. From the same survey, we obtained data on characteristics of the respondents that were used as control variables at the individual level. These include age, sex, ethnicity, household composition, educational level, income level, receipt of social benefits, home ownership and a measure of general wealth (whether the respondent experienced difficulties living on his or her current household income).

To measure the socio-economic characteristics of each respondent's environment, we used integral socio-economic registries maintained by the Municipality of Amsterdam. The registries were obtained by aggregating information from individual residents, households or houses to the level of 6-digit postcodes. A 6-digit postcode area, originally used for postal delivery, is the smallest geographical unit available. In urban areas, these units are sized approximately 50 x 50 meters and include 10 to 20 households. For each postcode area, we constructed three socio-economic variables: the percentage of residents receiving a social benefit (unemployment or welfare), the percentage of social housing, and the average property value of houses.

We constructed 'bespoke environments' or 'buffers' for each respondent using Geographic Information Systems (GIS) based on the central point location of the respondent's six-digit postal code. Buffers of eight sizes, with a radius ranging from 50 to 1500 meters, were created around each respondent. Finally, the socioeconomic characteristics of each of these buffers were estimated based on the data aggregated by postcode. Postcode areas that were only partially located within the buffer were weighted based on the percentage of the area contained. For this process, we performed an overlay operation, which joins data layers based on common geographical location. This approach is illustrated in figure 1 on the next page.

In addition, we optimized the geographic delimitation of the buffers, and the measurement of their socioeconomic characteristics, by taking into account natural barriers. These barriers included the Amstel River, the IJ River and the Ring Road (highway). The resulting, more strictly delimited areas were expected to correspond more closely to the mental map and the immediate living environment of the respondents.

For further analyses, we classified the buffers based on whether they were socioeconomically homogeneous or heterogeneous. This determination was made by calculating the standard deviation of each of the socioeconomic variables for the postcode areas within the buffer. The buffer was considered relatively homogeneous if the standard deviation was smaller than average for at least two socioeconomic variables. All other buffers were considered to be heterogeneous.

We also analysed respondents' administratively defined areas for comparison with the bespoke environment. We used three types of administrative areas: the 4-digit postcode area (on average 2.5 km^2, or approximately 1.6 km by 1.6 km); districts (referred to as 'wijken' in the Netherlands, on average 1.8 km^2); and wards ('buurten', on average 0.4 km^2). Wards and districts in Amsterdam are considered to be socioeconomically homogeneous. The boundaries for wards are primarily determined by physical boundaries and often correspond to specific periods of construction. Wards are a common unit of geographical analysis by statistical bureaus and municipal offices.

Figure 1. Data aggregation from 6-digit postcode areas to 50 meters radius bespoke environments

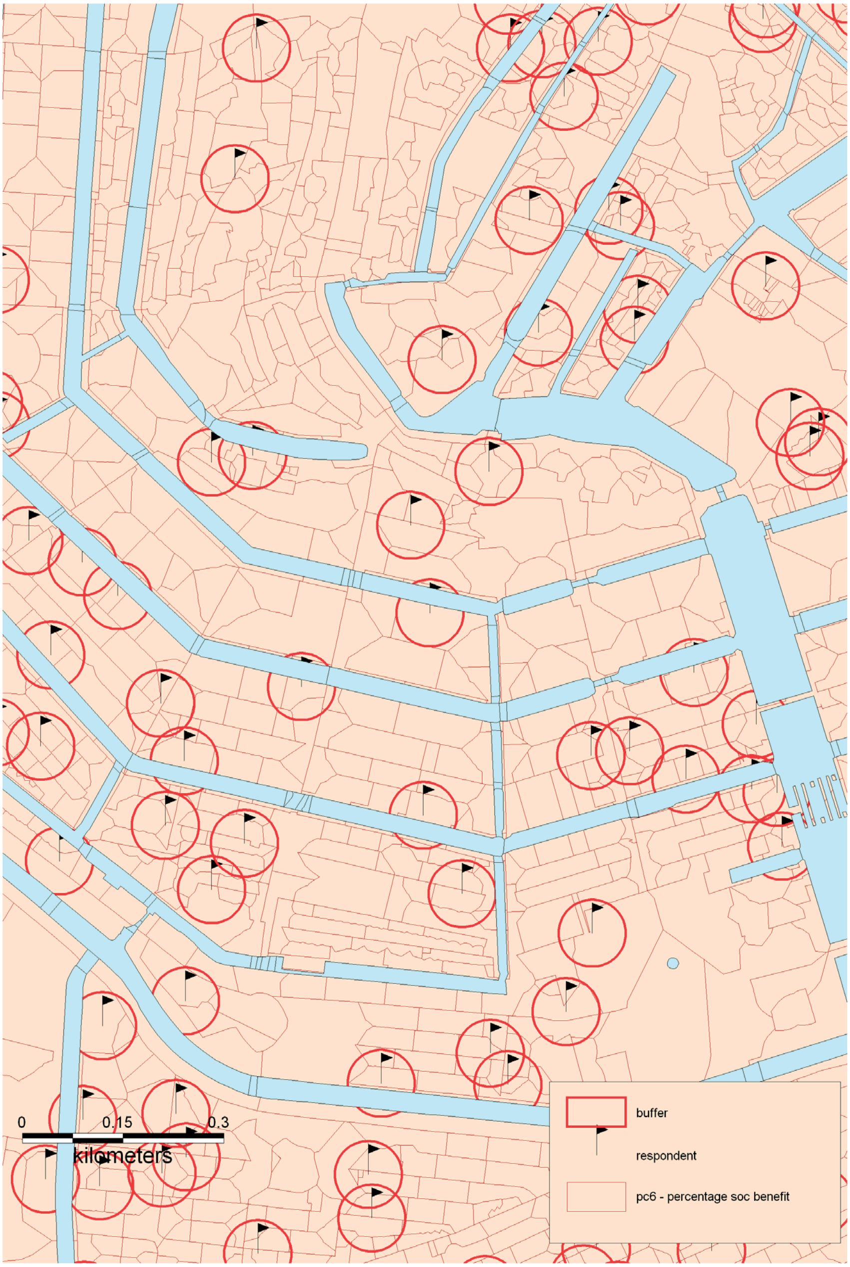


Table 1 shows the extent of geographical variation in the three socioeconomic variables based on the spatial unit (bespoke and administrative). If the size of the buffer increases, the standard deviation of socioeconomic variables decreases. The standard deviations for the percentage of the population receiving a social benefit decreased from 9.1 to about 3.6; the standard deviation for average property value decreased from 9.5 to 5.4. The standard deviations for the percentage of the population living in social housing are high at a small buffer size, but quickly decrease with increasing buffer size.

Table 1. Mean and variation of contextual variables

Spatial unit	Area (km^2)	Percentage receiving social benefit		Percentage of social housing		Average property value	
		mean	standard dev	mean	standard dev	mean	standard dev
Buffer 50	0.0078	15.37	9.05	56.55	37.28	23.35	9.47
Buffer 100	0.0311	15.49	7.81	56.70	33.52	23.96	9.05
Buffer 150	0.0699	15.49	7.15	56.82	30.59	24.51	8.75
Buffer 200	0.1244	15.53	6.71	56.94	28.24	24.99	8.53
Buffer 300	0.2798	15.61	6.08	57.04	24.92	25.77	8.22
Buffer 600	1.1191	15.52	5.09	56.85	20.45	27.66	7.39
Buffer 1000	3.1087	15.27	4.25	56.14	17.34	29.28	6.43
Buffer 1500	6.9945	14.77	3.57	54.48	15.42	30.35	5.43
Ward	0.4826	15.45	6.41	56.36	26.83	25.58	8.66
District	1.8573	15.58	5.53	56.89	23.11	26.89	7.92
Postcode 4	2.5104	15.25	5.12	56.34	20.99	29.40	8.03

Statistical analysis

The relationship between socio-economic characteristics of areas and self-reported health was assessed using logistic regression analysis, with fair/poor health as the dependent variable. We controlled for age, sex, ethnicity and household composition (model 1), as well as for education, income, receipt of social benefit, home ownership and the proxy for wealth (model 2). The results of these models are expressed in terms of odds ratios, which are derived from the regression coefficient for the socioeconomic characteristics. The 95 percent confidence intervals are derived from the standard errors of the regression coefficients.

To enable comparison between the different buffer sizes, we also present the odds ratios corresponding to standardized regression coefficients (which is equivalent to transforming the socioeconomic variables into z-scores before performing a logistic regression). These odds ratios can be interpreted as the increase in the odds of fair/poor perceived health if the socioeconomic level of a neighbourhood changes with one standard deviation. This measure takes into account the large differences in standard deviation according to buffer size (table 1).

In order to quantify the explanatory power of socioeconomic characteristics of areas, we also applied a regression strategy involving two steps: first we included only the individual-level characteristics, and next we added the socioeconomic characteristics of areas. Using Nagelkerke R^2 and AIC, we quantified the increase in explained variance by adding the latter terms.

5.3 Results

Table 2 illustrates the percentage of respondents reporting fair/poor health, broken out by the respondents' individual characteristics. Fair/poor health is more often reported by single parent families (33.9 percent), non-western migrants (on average 33.5), respondents with no education (55) or a low educational-level (33.5), lower income groups (about 50), those receiving social benefit (62.9) and those having difficulties in making ends meet (61.2).

Table 2. Number of respondents and percentage reporting fair/poor health by individual characteristics

Individual variable	N	% reporting poor health
Sex		
Male	1821	23.7
Female	2310	25.9
Age	4131	
Household composition		
Single-parent family	322	33.9
Two adults with child	1244	21.8
Two adults without child	1210	22.5
Single	1172	28.7
Other	183	23.0
Ethnicity		
Natives	2209	18.9
Surinamese	308	35.1
Atillean	63	31.7
Turks	343	38.5
Moroccans	461	33.6

Table 2. Number of respondents and percentage reporting fair/poor health by individual characteristics (*continued*)

Individual variable	N	% reporting poor health
Other non-western immigrants	192	30.2
Western immigrants	458	22.1
Rest of Asia	97	39.2
Education		
No education	496	55.0
Low	791	33.5
Medium	971	20.9
High	1578	10.6
Other	295	41.4
Income net (Euros)		
700	192	44.8
700-1000	442	50.0
1000-1350	503	38.2
1350-2050	831	20.6
2050-3200	757	14.8
3200 and more	590	6.3
Missing	816	25.9
Receiving social benefit		
Yes	267	62.9
No	3864	22.3
Home ownership		
No owner	2558	29.7
Owner	1518	16.7
Living on household income		
Very difficult	209	61.2
Quite difficult	660	44.8
Difficult	536	33.0
Quite easy	784	20.0
Easy	1327	14.7
Very easy	467	8.8
Missing	148	34.5

Table 3 quantifies the explanatory power of models including socioeconomic characteristics of areas, in terms of increase in percentage of variance explained and decrease of AIC. The explanatory power is strongest for small buffers, and it declines with increasing buffer size. For the percentage of residents living on social benefit, the percentage explained declines from 1.3 percent for 50 meter buffer size to 0.3 percent for 1500 meter buffer size. Notably, the percentage explained when the three socioeconomic variables are combined hardly exceeds the percentage that could already be explained by variable on residents living on social benefit.

Table 3. Changes in R^2 and AIC by inclusion of neighbourhood-SES variables compared to a model without neighbourhood-SES*

Buffer size	*Percentage receiving social benefit*		*Percentage of social housing*		*Average property value*		*Together*	
	R^2 (%)	Increase	R^2	Increase	R^2	Increase	R^2	Increase
50	18.5	1.3	18.4	1.2	18.0	0.8	18.8	1.6
100	18.3	1.1	18.2	1	17.8	0.6	18.5	1.3
150	18.1	0.9	18.1	0.9	17.7	0.5	18.2	1
200	18.1	0.9	18.0	0.8	17.6	0.4	18.2	1
300	17.9	0.7	17.8	0.6	17.6	0.4	17.9	0.7
600	17.7	0.5	17.7	0.5	17.5	0.3	17.8	0.6
1000	17.6	0.4	17.5	0.3	17.3	0.1	17.6	0.4
1500	17.5	0.3	17.5	0.3	17.3	0.1	17.5	0.3
	AIC	Decrease	AIC	Decrease	AIC	Decrease	AIC	Decrease
50	4120	38	4122	36	4134	24	4114	44
100	4124	34	4128	30	4140	18	4124	34
150	4130	28	4133	25	4143	15	4131	27
200	4131	27	4135	23	4146	12	4134	24
300	4139	19	4142	16	4148	10	4141	17
600	4143	15	4146	12	4152	6	4146	12
1000	4148	10	4150	8	4156	2	4152	6
1500	4151	7	4152	6	4158	0	4154	4

*base model without neighbourhood-ses (age, sex, household composition, ethnicity: Nagelkerke R^2 = .172; AIC = 4158)

Table 4 presents the effect of controlling for individual-level socioeconomic variables. We pay particular attention to the standardized odds ratio of columns 4 and 5. For example, the odds ratio in column 4 is 1.30 for the share of people living on social benefit within 50-meter buffers. This implies that if the share of people living on social benefit increases by 1 standard deviation (in this case 9 percent; see table 1), the odds of fair/poor health increases by 30 percent. After controlling for individual-level socioeconomic variables, this odds ratio declines to 1.10. Generally, after controlling for all individual-level variables, the association between health and socioeconomic factors is strongest at small buffer sizes. Statistically significant associations are found only for 50-meter buffers and 100-meter buffers (for the percentage of social housing). For buffer sizes larger than about 200 meters, the associations are not statistically significant. Moreover, above 200 meters, the odds ratios in columns 3 and 5 do not provide indications of a consistent relationship with buffer size.

Table 4. Comparison of the effects of the contextual variables between model 1 (base model) and model 2 (extensive model) at different scales

Buffer size	Odds ratio's (95% CI)		Standardized OR	
	Model 1	Model 2	Model 1	Model 2
	receiving social benefit (%)			
50	1.029 (1.018;1.039)	1.011 (1.001;1.022)	1.30	1.10
100	1.032 (1.022;1.043)	1.009 (0.997;1.021)	1.28	1.07
150	1.032 (1.020;1.045)	1.007 (0.993;1.021)	1.25	1.05
200	1.033 (1.021;1.046)	1.007 (0.993;1.021)	1.24	1.05
300	1.032 (1.017;1.046)	1.005 (0.989;1.021)	1.21	1.03
600	1.033 (1.017;1.050)	1.007 (0.989;1.023)	1.18	1.04
1000	1.032 (1.012;1.053)	1.008 (0.988;1.028)	1.14	1.03
1500	1.034 (1.011;1.056)	1.014 (0.991;1.038)	1.13	1.05
	social housing (%)			
50	1.007 (1.005;1.009)	1.002 (1.000;1.004)	1.30	1.08
100	1.007 (1.005;1.009)	1.002 (1.000;1.004)	1.26	1.07
150	1.007 (1.005;1.009)	1.001 (0.997;1.005)	1.24	1.03
200	1.007 (1.005;1.009)	1.001 (0.997;1.005)	1.22	1.03
300	1.007 (1.003;1.011)	1.001 (0.997;1.005)	1.19	1.03
600	1.007 (1.003;1.011)	1.001 (0.997;1.005)	1.15	1.02
1000	1.007 (1.003;1.011)	1.001 (0.995;1.007)	1.13	1.02
1500	1.007 (1.001;1.013)	1.001 (0.995;1.007)	1.11	1.02
	average property value (in 10.000 Euros)*			
50	1.023 (1.013;1.033)	1.006 (0.996;1.016)	1.25	1.05
100	1.020 (1.011;1.031)	1.004 (0.994;1.014)	1.20	1.04
150	1.019 (1.007;1.030)	1.003 (0.993;1.013)	1.18	1.03
200	1.017 (1.008;1.029)	1.002 (0.992;1.012)	1.16	1.02
300	1.017 (1.007;1.028)	1.003 (0.991;1.015)	1.15	1.02
600	1.015 (1.005;1.026)	1.006 (0.994;1.018)	1.12	1.04
1000	1.010 (0.999;1.022)	1.006 (0.992;1.020)	1.06	1.04
1500	1.009 (0.995;1.024)	1.006 (0.990;1.021)	1.05	1.03

*For average property value, the OR is inverted to make it more directly comparable to the other SES indicators. The OR represents the increase in odds of poor health if property value decreases with 10,000 Euro's.

In table 5, the results are compared across buffers that are relatively homogeneous in terms of the percentage of people receiving social benefits. In this sub-set of buffers, the association with health is stronger. Standardised odds ratios are highest for homogeneous buffers of 300-meters or less, up to an odds ratio of 1.15 for homogeneous buffers of 50-meters. No associations were observed in the larger buffers, irrespective of their degree of homogeneity. For the other two socioeconomic variables (percentage of social housing; property values), we also found that associations were evident only in relatively homogeneous buffers of 300 meters and smaller (results not shown).

Table 5. Comparison of neighbourhood effects between relatively homogeneous buffers and all buffers together

Percentage of people receiving social benefit					
Buffer size	Group	Odds ratio's (95% CI)		Standardized OR	
		Model 1	Model 2	Model 1	Model 2
50	homogeneous	1.035 (1.021;1.050)	1.018 (1.004;1.032)	1.37	1.15
	all	1.029 (1.018;1.039)	1.011 (1.001;1.022)	1.30	1.10
100	homogeneous	1.038 (1.021;1.054)	1.017 (0.999;1.035)	1.34	1.12
	all	1.032 (1.022;1.043)	1.009 (0.997;1.021)	1.28	1.07
150	homogeneous	1.027 (1.008;1.045)	1.009 (0.989;1.029)	1.21	1.06
	all	1.032 (1.020;1.045)	1.007 (0.993;1.021)	1.25	1.05
300	homogeneous	1.019 (0.999;1.040)	0.998 (0.978;1.020)	1.12	0.99
	all	1.032 (1.017;1.046)	1.005 (0.989;1.021)	1.21	1.03
600	homogeneous	1.026 (1.011;1.063)	1.016 (0.989;1.044)	1.13	1.08
	all	1.033 (1.017;1.050)	1.007 (0.989;1.023)	1.18	1.04

Table 6 explores whether analysis using administratively defined areas yields different results compared to analysis using bespoke environments. The results turn out to be similar: when socioeconomic factors are measured at the level of the smallest administrative unit, the ward, they can explain most of the variance in fair/poor health. The percentage explained at the ward level is about as large as when socioeconomic factors are measured at the level of buffers of 200 meters or smaller (cf. table 3). The AIC results indicate the same: the model improves if neighbourhood-SES variables are included and the effect decreases as administrative scales increase.

Table 6. Changes in R^2 and AIC for three neighbourhood-SES variables at different administrative scales compared to a model without neighbourhood-SES*

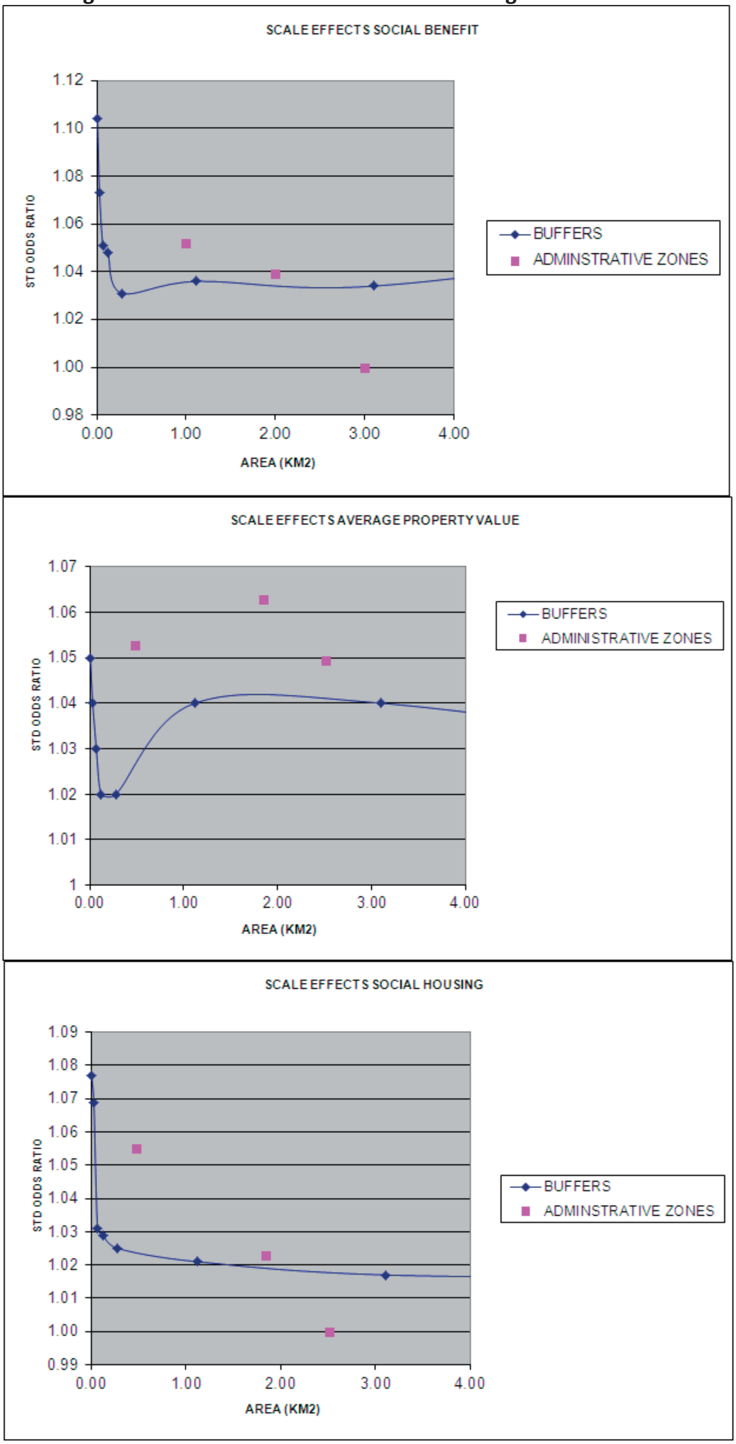
	% social benefit		% social housing		Average property value		Together	
administrative-zone	R^2 (%)	Increase	R^2	Increase	R^2	Increase	R^2	Increase
ward (0.4 km^2)	17.9	0.7	17.9	0.7	17.7	0.5	18.1	0.9
combination (1.8 km^2)	17.5	0.3	17.4	0.2	17.5	0.3	17.7	0.5
postcode 4 (2.5 km^2)	17.5	0.3	17.5	0.3	17.4	0.2	17.6	0.4
	AIC	Decrease	AIC	Decrease	AIC	Decrease	AIC	Decrease
ward (0.4 km^2)	4135	23	4137	21	4143	15	4131	27
combination (1.8 km^2)	4137	21	4138	20	4152	6	4132	25
postcode 4 (2.5 km^2)	4150	8	4151	7	4154	4	4148	10

*base model without neighbourhood-ses (age, sex, household composition, ethnicity: Nagelkerke R^2 = .172; AIC = 4158)

Figure 2 shows the standardised odds ratios, as estimated for different buffers. The odds ratios are plotted against the average size of the surface of the buffers. In general, the odds ratios decrease with increasing area surface of buffers. This implies that the association between health and socioeconomic factors is weaker when the latter are measured to larger buffers. For average property value, this trend is less consistent as odds ratios sharply increase for buffers smaller than 600 meter buffers. For the other two area characteristics, the association becomes consistently weaker with increasing area surface.

In addition, in Figure 2, a comparison can be made between buffers and administratively defined areas, while taking area surface into account. Analyses at the 4 digit postcode yield smaller effect estimates as compared to analyses using buffers of about similar size. However, when socioeconomic factors are measured at the level of districts, they perform equally well as socioeconomic variables measured at the level of buffers of a comparable size.

Figure 2. The strength of socioeconomic area effects according to scale



5.4 Discussion

Previous studies may have underestimated the association between health and socioeconomic characteristics of areas due to scale and boundary effects. We aimed to address these effects by using "bespoke environments" or "buffers" to study the relationship between health and the surrounding socio-economic environment. By comparing buffers of different sizes, we observed that the association between socio-economic environment and self-reported health could be demonstrated only for small buffers with a radius of 50 or 100 meters. Stronger associations were observed in analyses that only compared relatively homogeneous areas. When socioeconomic factors were measured to small administrative units (wards), they performed equally well as socioeconomic variables measured at the level of buffers of comparable size.

Evaluation of methodology

Our method and results should be considered in the light of the modifiable areal unit problem (MAUP). The MAUP states that area-level effects are dependent on the form, size and location of the sub-areas used. This dependency is particularly important when using administratively defined areas. Administrative zones have a form, size and location that are often quite arbitrary. In studies using administrative areas, the results therefore could be strongly sensitive to the precise delineation of these areas [22].

Theoretically, bespoke environments should solve some aspects of this problem. By using bespoke environments, all areas have the same form (distances are equal in all directions) and location (each area is based around the center point of individual respondents), thus avoiding potential boundary effects. In addition, the size aspect can be addressed by using bespoke environments of different sizes.

The use of bespoke environments as a geographic method might however bring new challenges as well. Because buffers overlap, especially the larger ones, observations for individual respondents are not entirely independent. Failure to take into account this dependency may result in overestimation of the precision and statistical significance of the area-effects. The use of multi-level models, using a restricted number of environments, would address this problem. However, when applying bespoke environments, such models cannot be easily integrated as respondents do not share identical environments and thus cannot be aggregated into the same high-order level category. We would like to note that, in our analyses, the strongest effects were observed at a smaller scale (50 meters) where buffers rarely overlapped.

We might have failed to control for potentially important confounders at the area level, such as land use mix, or noise nuisance caused by Schiphol Airport. We checked for area-level confounding by mapping the residuals of the regression analyses, with full control for individual-level variables. However, we did not observe spatial clusters of residuals, suggesting that there are no area-level confounders that could have biased our results to a significant extent.

In the analysis, we aimed to control for individual-level demographic and socioeconomic characteristics that could be considered to be potential confounders to the association between health and the surrounding socioeconomic environment. As controlling for these characteristics had an important effect on our effect estimates, we cannot exclude the possibility that more detailed control would remove even more of the area-level effect. At the same time, we would like to stress that we already had controlled both for education, income and wealth (by proxy), and that the potential for residual confounding by SES thus seems limited. However, we cannot exclude potential confounding by other factors and capabilities that may determine where people can choose to live [23].

The overall response rate to the survey was only 23 percent. It is documented that, in general, non-responders are often young, of non-Western origin and have a low income [24]. These characteristics were strongly related to self-perception of health. Given these relationships, we cannot exclude the possibility that selective non-response may have biased our estimates of the association between health and the socioeconomic environment. Most likely, we think that this association may have been underestimated to some extent.

Studies comparing administrative areas and alternative definitions of a neighbourhood found similar associations with health outcomes irrespective of the way in which the neighbourhood boundaries were defined [25], [26]. This corresponds to our finding that the analysis of wards yielded similar results as the analysis with similarly-sized buffers. However, we might have expected associations to be stronger with the buffers, as buffers may be a better representation of one's immediate living environment and activity space. Our results however suggest that administrative areas that are defined with regards to socioeconomic and geographic criteria, such as wards (in the case of Amsterdam), may function equally well.

By using GIS techniques we had the opportunity to construct residential areas on a very local scale. We observed this to be an important advantage, as the association between socioeconomic variables and health was found to be the strongest, and only demonstrable with statistical significance, at the level of very small buffers (50- or 100-meter). In addition, GIS techniques make it possible to perform additional geographic operations such as measuring the degree of homogeneity of areas. This offered the opportunity to restrict the analysis to a subset of areas with greater contrast in socioeconomic conditions.

Interpretation and comparison to previous studies

Other studies have also observed that the association between health and area-level socioeconomic characteristics was stronger in smaller areas. For example, one Dutch study assessed the effects of area-level socio-economic factors on mortality within postcode areas, districts, and wards. That study showed that differences in mortality chance of men were most pronounced at the lowest scale level of postcode areas [27].

We observed that the effect of area-level socioeconomic factors was small in comparison to the effects of individual-level socioeconomic variables on health (cf. table 2 and 4). A relatively small effect was also found in other Dutch studies[4], [28] and should possibly be considered in a national context. We postulate that effects of socio-economic conditions of areas may be small in a welfare state such as the Netherlands due to, among other factors, social housing policies and urban renewal schemes that that have limited sharp differences in living conditions amongst its population.

The fact that effects are observed only at the level of small (50-100 meter) buffers is suggestive of an effect of factors with a highly local reach. Among these, social networks might play an important role. In the case of voting behaviour, Johnston [17] and McAllistar [15] found clear links between local milieus and how people behave. Those who live in relative close proximity are more likely to think and act in similar ways. Other localized factors may include neighbourhood-level psychosocial stressors (e.g., nuisance from neighbours, feeling unsafe, drug abuse, etc.), many of which have been found to be related to self-rated health, including in Amsterdam [29]. Generally, these stressors may produce health effects on local scales, especially in socio-economically deprived areas [30].

Conclusions

To conclude, this study observed scale effects to be highly important when studying socio-economic area effects on health. The measurement of socioeconomic factors for large areas might result in a substantial underestimation, or even a negligence, of the effects of socioeconomic environment on health. The results stress the importance of using micro-scale data on the environment as well as health outcomes in order to study the relationship between these two. When such data are available, the methodology of bespoke environments could be applied to many environmental features and health-related outcomes. An important advantage of this methodology is that the buffer width can be tuned to the scale at which processes are expected to operate – whether a few meters or a few kilometres. The most relevant scale is likely to vary based on the health outcome and population group (e.g. children vs. middle-aged men) being measured. Through scaling, bespoke environments add a new dimension to study environment and health.

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CHAPTER 6

Association between self-rated health and the ethnic composition of the residential environment of six ethnic groups in Amsterdam

Abstract

Background: Studies on the association between health and neighborhood ethnic composition yielded inconsistent results, possibly due to methodological limitations. We assessed these associations at different spatial scales and for different measures of ethnic composition.

Methods: We obtained health survey data of 4673 respondents of Dutch, Surinamese, Moroccan, Turkish, other non-Western and other Western origin. Neighborhood ethnic composition was measured for buffers varying from 50–1000 m. Associations with self-rated health were measured using logistic multilevel regression analysis, with control for socioeconomic position at the individual and area level.

Results: Overall ethnic heterogeneity was not related to health for any ethnic group. The presence of other Surinamese was associated with poor self-rated health among Surinamese respondents. The presence of Moroccans or Turks was associated with poor health among some groups. The presence of Dutch was associated with better self-rated health among Surinamese and Turks. In most cases, these associations were stronger at lower spatial scales. We found no other associations.

Conclusions: In Amsterdam, self-rated health was not associated with ethnic heterogeneity in general, but may be related to the presence of specific ethnic groups. Policies regarding social and ethnic mixing should pay special attention to the co-residence of groups with problematic interrelations.

6.1. Introduction

In recent decades, urban societies in Europe have become more ethnically diverse as a result of large-scale immigration. Countries differ both in the composition of their ethnic populations and in the degree of ethnic residential segregation. Segregation rates in the Netherlands, the U.K. and Belgium are higher than in Germany, Austria and France [1]. Within countries, rates of segregation differ between cities and between ethnic groups.

Similar to most other countries, in the Netherlands, the largest cities are the most ethnically diverse. There are substantial differences in the ethnic composition of these cities. In Amsterdam, about half of the population is of non-Dutch origin. The largest ethnic minority groups are Moroccans (9.0 percent of the population), Surinamese (8.5 percent), Turks (5.2 percent) and Antilleans (1.5 percent). In its southeastern district alone, around 100 different nationalities live together [2]. Moroccans and Turks live generally more segregated than other ethnic groups [1].

Much research has been conducted to assess the effects of the ethnic composition of the residential environment on societal outcomes, such as social mobility [3] and integration [4,5]. It has been suggested that diverse neighborhoods would increase inter-ethnic contact, which would influence social mobility and integration positively. However, this suggestion is under pressure by a growing body of evidence contradicting this idea [6,7].

While mixing neighborhoods has been promoted in several European countries to prevent socioeconomic and ethnic segregation, such policies may also be important for their potential impact on population health. If living in ethnically-mixed neighborhoods has an independent effect on health, be it positive or negative, a reconsideration of these policies might be needed.

Many epidemiologic studies have aimed to assess the independent effect of ethnic composition on mental and physical health [8–10]. Previous studies have paid particular attention to the effects of ethnic diversity and own ethnic density. Ethnic diversity is defined in most studies as the degree of ethnic heterogeneity within the neighborhood. Bécares et al. [11] showed that, for ethnic minorities, living in heterogeneous neighborhoods is associated with improved mental health. A Dutch study in Rotterdam and studies conducted in the U.S. and the U.K. suggest that the mental health of ethnic minorities may be poorest in homogeneous "white" neighborhoods [12–15]. Gibbons et al. [16] came to the same conclusion with respect to self-rated health: in Philadelphia, minorities living in predominantly white communities were significantly more likely to report poor/fair health than those in segregated minority neighborhoods.

Own ethnic density refers to the percentage of co-ethnics in the neighborhood. Research has not yet provided consistent answers on the direction and strength of possible relationship between health and own ethnic density. Some studies, particularly on mental health, suggest own ethnic density to have a positive effect on health [17–19]. Other studies found higher own ethnic density to be associated with greater risk of mortality, poor self-rated health and low birth weight [20–22], while some studies found no association at all [23–25].

The impact of living among co-ethnics may differ by ethnic group, age and gender. Studies focusing on self-rated health found divergent results. Bécares [26] found high own ethnic density to have an inverse association with general health among black Caribbean people, but a positive association among black African people in the U.K. Patel et al. [27] reported a positive association among older Mexican Americans in the U.S. Effects may differ by gender, as well. Shaw et al. [28] found an inverse association in the U.S. among both black men and women, while among Hispanics, the association was positive among women, but inverse among men.

Previous research suggests that both ethnic diversity and own ethnic density may influence health through several mechanisms, such as effects on: (1) the quality of social support from neighbors; (2) social cohesion within the neighborhood; and (3) experiences of racism or discrimination [29–33]. The "classic" theory suggests better health if a high proportion of the own ethnic group lives in the neighborhood, because of increased social support and less discrimination. For example, Hunt et al. [32] showed that people reported less discrimination when living in areas with a high proportion of their own group.

No predominant theory exists on the effects of ethnic diversity. Some argue, in line with social contact theory, that diversity is associated with higher levels of social capital (in terms of social networks, social cohesion and social support) and with greater respect for ethnic differences [34]. Putnam, however, argued that, in line with conflict theory, ethnic diversity results in a pronounced decline in social solidarity and social capital; but he also asked that attention be paid to the "constrict theory": diversity might reduce both in-group and out-group solidarity and, thus, might impact bridging capital (ties to people unlike you) and bonding capital (ties to people like you) [35]. He found that "in ethnically diverse neighborhoods residents of all races tend to 'hunker down'. Trust (even of one's own race) is lower, altruism and community cooperation rarer, friends fewer" ([35], p. 137). Such mechanisms may also have negative consequences on health. In line with Putnam's argument, Neil and Neil [36] argue that diversity and community sense are inversely related, possibly because people strive for homophily and proximity. According to Putnam [35], in the long run, successful immigrant societies will create new forms of solidarity and more encompassing identities.

In the scientific literature, there is a lack of attention on the presence of specific ethnic groups (other than the own group) in the neighborhood. Most studies on the relationship between health and ethnic composition focus on relations between the majority group and the minority group as a whole. Some studies refer to more refined categories, such as blacks, whites, non-black minorities and mixed [16]. However, especially in cities where many different ethnic groups live together (like Amsterdam), it may be important to distinguish even more ethnic groups and to examine whether the co-residence of specific ethnic groups, in the neighborhood (and relations between these groups) influences social-support mechanisms, social cohesion, experiences of discrimination, and, ultimately, health.

Another potential limitation to previous studies is that the spatial scale used in most studies may be inappropriate [30,37,38]. The generally-used administratively-defined areas (such as counties, census tracts or electoral wards) may in many cases be irrelevant or too large to examine the relationship between ethnic composition and health. Experiences of discrimination and social support might not relate to ethnic composition as measured at the level of entire administrative areas. Frequently, the ethnic composition of residential environments may strongly differ between different parts of administrative areas. As people might be most confronted with people living nearby, ethnic composition measured at a smaller spatial scale may be more appropriate for identifying the effects of the ethnic composition of residential environments on health.

The main aim of this study is to assess associations of ethnic composition and self-rated health among different ethnic groups in Amsterdam. Different dimensions of ethnic composition will be addressed including ethnic heterogeneity, the presence of own ethnic group and the presence of other ethnic groups. We use a spatial approach that accounts for the possibility that observed effects are dependent on the spatial scale that is applied. More specifically, we use bespoke environments ("buffers" created around the respondent) defined at seven different scales, ranging from 50 up to 1000 m in radius, and we measure the ethnic composition of the residential environment according to each buffer size. To our knowledge, this is the first study to examine this relationship using this spatial approach and that therefore could assess potential effects at very small spatial scales.

6.2. Methods

Data

The data were obtained from the 2012 Amsterdam Health Monitor conducted by the Amsterdam Public Health Service. The Monitor surveyed 7218 adult inhabitants. Stratified sampling was used to ensure that residents of all districts and age groups within Amsterdam were represented. Data were collected by Internet (46 percent of all respondents), face-to-face interviews (4 percent) and postal questionnaires (50 percent), with an overall response rate of 38 percent. Male respondents between 19 and 34 and non-Western respondents aged 19–34 years showed particularly low response rates. Details of the survey design are described elsewhere [39]. We were allowed to use the data of the respondents that indicated the willingness to participate in future research (4756). After excluding respondents that lived at locations with less than 25 inhabitants within a buffer of 50 m (83), our sample comprised 4673 respondents.

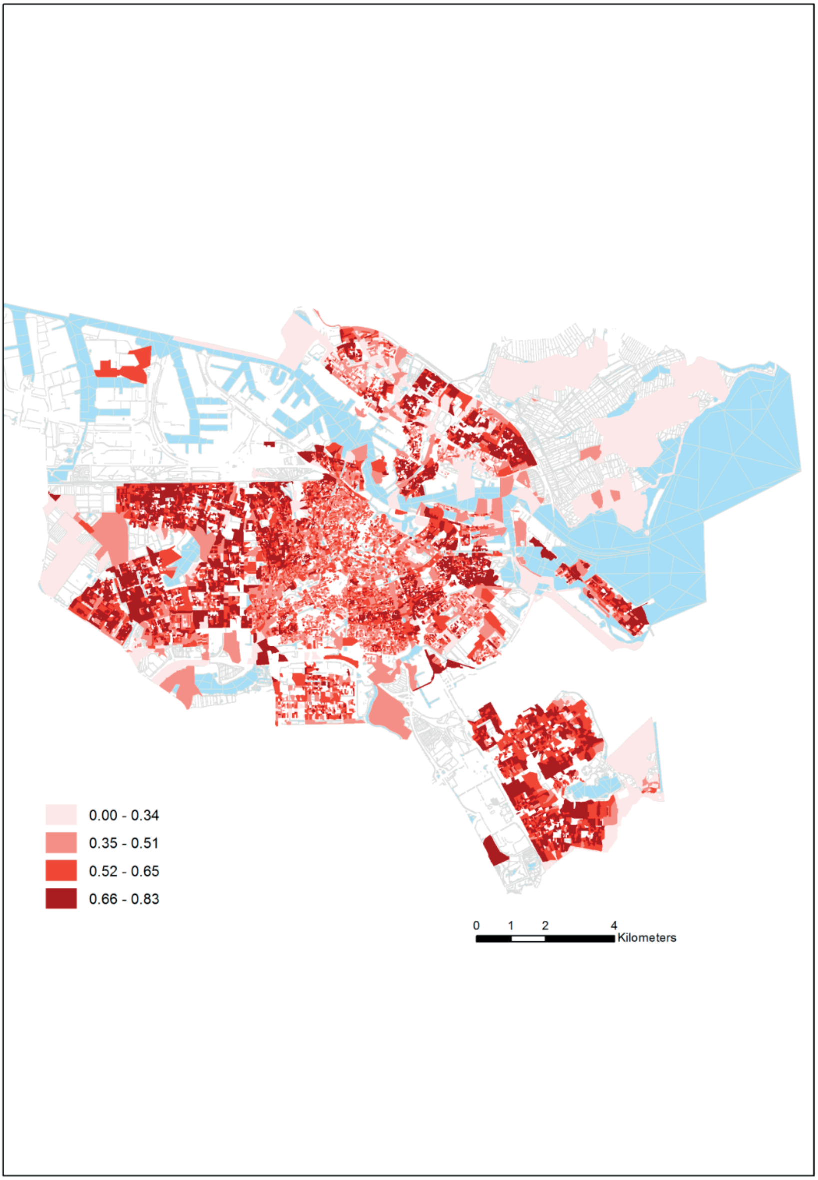
The survey asked respondents about health indicators, such as physical health and mental health, and health determinants, such as smoking, physical activity, housing and neighborhood conditions. Self-rated health was measured by the response to the question "All in all, would you say your health is very good, good, moderate, poor or very poor?" The answers were classified into two categories: very good/good and moderate/poor/very poor. From the same survey, we obtained data on respondent characteristics, including age, sex, ethnicity, marital status, household composition, educational level and a measure of making ends meet (whether the respondent experienced difficulties living on his or her current household income).

To measure the characteristics of each respondent's residential environment, we used integral demographic and socio-economic registries at the level of six-digit postcodes maintained by the Department of Research and Statistics of the Municipality of Amsterdam. A six-digit postcode area is the smallest geographical unit available. On average, these areas are 50 by 50 m in size and include 10–20 households. For each postcode area, we constructed several variables describing the ethnic composition: ethnic heterogeneity (described by the Herfindahl Index), the percentage of co-ethnics and the proportion of specific ethnic groups. We distinguish between six ethnic categories commonly used in Amsterdam's data registries: Dutch, Surinamese, Moroccans, Turks, those from other non-Western countries and those from other Western countries.

The Herfindahl Index represents the probability of two randomly-selected individuals from the same neighborhood to differ in ethnic origin. The theoretical range of the index runs from 0–1, with 0 representing an area in which every individual is from the same ethnic group and 1 representing an area in which every individual is from a different ethnic group. To calculate the Herfindahl Index, we sum the squared proportion of each ethnic group and subtract this total from one. Figure 1 shows a map of this index across the 18,111 six-digit postcode areas. The northern, western and (south-) eastern districts are the most ethnically diverse areas within Amsterdam.

To describe the socio-economic environment of each respondent, we constructed two socio-economic variables: the percentage of residents living on a minimum income and the average property value of dwellings.

Figure 1. Variations in the degree of ethnic heterogeneity within Amsterdam in 2012 (Herfindahl Index measured for six-digit postcode areas with at least 25 inhabitants)



Construction of Bespoke Environments

Bespoke environments for each respondent were constructed by buffer operations within a geographic information system (GIS). Buffers of seven different sizes, with radiuses ranging from 50–1000 m, were created around the central point of each respondent's six-digit postcode area as applied previously with similar attention to scale in Veldhuizen et al. [40]. Buffers of a 50-, 100-, 150-, 300-, 500-, 750- and 1000-m radius respectively comprise areas of 0.78, 3.14, 7.06, 28.26, 78.51, 176.69 and 314.12 hectares (one hectare is approximately 1.5 soccer fields). The ethnic composition and socioeconomic characteristics of each of these buffers were estimated by aggregating the data of all postcodes belonging to the buffers. More details on the procedure are given in Veldhuizen et al. [40].

Statistical Analysis

We assessed the relationship between neighborhood ethnic composition and self-rated health using logistic multilevel regression analysis, with the odds of having moderate/poor/very poor health ("poor health") measured at the individual level, as the dependent variable. In Model 1, we controlled for age, sex, marital status, household composition, education and a measure of making ends meet at the household level. In Model 2, we additionally controlled for the socio-economic environment at the buffer level, measured with the percentage of households living on minimum income and average property values. The results of these models are expressed in terms of odds ratios, which are derived from the regression coefficients for the ethnic compositional characteristics. The 95 percent confidence intervals are derived from the standard errors of the regression coefficients.

To enable a comparison between the different buffer sizes, we present the odds ratios corresponding to standardized regression coefficients. This procedure is equivalent to transforming the ethnic composition variables into z-scores, for each buffer size separately, before performing a multilevel logistic regression. These standardized odds ratios can be interpreted as the increase in the odds of poor perceived health if ethnic composition were to change with one standard deviation.

6.3. Results

Table 1 describes the characteristics of the study population according to ethnic group. In general, non-Western migrants, particularly Turks and Moroccans, report poor health more often than Western migrants and native Dutch people. Non-Western migrants show higher percentages of single parent families, low education levels and difficulties making ends meet. Western migrants and native Dutch respondents show a higher percentage of people above 65 years old.

Table 1. Characteristics of respondents and their socio-economic environment by ethnic group (in percentages)

	Moroccans	Turks	Surinamese	Other Non-Western Migrants	Western Migrants	Dutch
N	148	153	288	288	586	3210
Self-rated health						
Very good	11.6	11.1	13.7	16.1	24.4	20.1
Good	39.7	30.7	45.1	52.3	50.9	55.6
Moderate	30.1	39.9	32.4	22.8	20.1	20.2
Poor	15.1	15.0	7.0	6.0	3.8	3.5
Very poor	3.4	3.3	1.8	2.8	0.7	0.5
Sex						
Male	50.7	34.0	42.0	39.2	36.9	43.2
Age						
19–29	19.6	12.4	16.0	19.8	14.3	15.3
30–39	23.6	30.1	18.1	27.8	22.9	16.2
40–49	19.6	25.5	14.2	21.5	12.6	11.0
50–64	23.6	19.6	30.9	21.9	18.8	20.8
≥65	13.5	12.4	20.8	9.0	31.4	36.7
Marital status						
Married or unmarried couple	68.3	69.3	36.2	50.9	53.2	55.0
Never been married	16.9	12.7	39.1	30.9	28.8	26.5
Divorced	11.3	8.7	20.4	14.7	11.6	9.6
Widow/widower	3.5	9.3	4.3	3.5	6.4	8.9

Table 1. Characteristics of respondents and their socio-economic environment by ethnic group (in percentages) (*continued*)

	Moroccans	Turks	Surinamese	Other Non-Western Migrants	Western Migrants	Dutch
Household composition						
Two adults with children <18	33.6	37.1	15.7	26.1	16.8	12.2
Single-parent family children <18 years old	8.4	9.9	12.5	10.2	3.3	2.2
Single	12.6	9.9	31.8	22.9	28.8	31.2
Other	45.5	43.0	40.0	40.8	51.1	54.4
Education						
Low	39.5	47.2	11.0	20.1	4.5	6.1
Medium	21.1	18.1	35.3	19.7	17.0	22.8
Medium/High	19.0	22.2	30.4	24.0	23.5	23.9
High	20.4	12.5	23.3	36.2	55.0	47.2
Making ends meet						
Easy	17.7	15.1	14.9	20.4	34.5	37.8
Quite easy	26.5	18.4	32.6	33.7	37.6	39.8
Quite difficult	30.6	35.5	28.8	28.1	20.9	17.3
Difficult	25.2	30.9	23.6	17.9	7.1	5.1
Average property value of houses in postcode of residence	182,863	180,049	184,690	196,414	252,084	243,540
Average percentage of households living on a minimum income in postcode of residence	30.0	27.8	24.4	22.8	14.7	14.0

Table 2 shows, for different ethnic groups, the own ethnic density and ethnic heterogeneity of their residential environments as defined at different spatial scales. On average, Turkish respondents show the lowest share of co-ethnics in their immediate surroundings. The native Dutch respondents have the highest proportion of co-ethnics in their residential neighborhood; on average, Dutch respondents live among over 50 percent co-ethnic Dutch. Own ethnic density generally decreases as buffers increase. Only for the Surinamese group this decrease is modest. The standard deviations for own ethnic density are high, but quickly decrease with increasing buffer size, especially for Turks and Moroccans, indicating that residential environments differ most between respondents when these environments are defined at small spatial scales.

Findings on ethnic heterogeneity in the immediate surroundings show that, on average, respondents of Turkish and Moroccan origin live in the most heterogeneous neighborhoods, and Western migrants and Dutch in the least. Generally, larger buffers are more heterogeneous, especially for Western migrants and native Dutch. For Turks and Moroccans, however, heterogeneity slightly decreases beyond buffers of 500 m.

In further descriptions, we assessed the correlations between similar characteristics of the buffers. Because smaller buffers nest into larger buffers, high correlations could be expected. Correlations were highest among buffers of relatively similar sizes. For example, for Moroccans, the percentage of Turks in 50-m buffers was strongly correlated to the percentage of Turks in 100-m buffers (Pearson correlation of 0.854) and more weakly correlated to the percentage of Turks in 1000-m buffers (0.663).

Table 3 shows the associations of own ethnic density and ethnic heterogeneity with self-rated health, for each ethnic group. Only for the Surinamese and Dutch, own ethnic density results are statistically significant. For the Surinamese, we found the higher the percentage of co-ethnics in the neighborhood, the higher the chance they report poor self-rated health. After adjustment for socioeconomic environment (Model 2), the associations remain significant at all distances up to 500 m. Results are consistent for buffers less than 1000 m, and significances are highest for small-sized buffers. However, large buffers of 1000 m come to be important by showing the strongest association. Conversely, for the Dutch, we found that more co-ethnics (Dutch) in the neighborhood decreases the chances of reporting poor self-rated health, but b-coefficients were rather low. Significance decreases with increasing buffer size. After adjustment for socioeconomic environment, the significant results found in Model 1 disappear.

Table 2. Mean and variation of own ethnic density and ethnic heterogeneity (Herfindahl) per ethnic group and spatial scale (buffer size)

	Moroccans		Turks		Surinamese		Other Non-Western		Western		Dutch	
Buffer	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Own ethnic density												
50	23.13	14.42	16.38	10.50	20.04	15.67	#				57.73	18.25
100	21.00	12.45	13.76	7.48	18.73	14.63					55.96	17.13
150	20.18	11.62	13.44	7.15	18.32	13.98					55.04	16.56
300	18.46	10.23	12.08	6.00	17.95	13.56					53.58	15.28
500	17.32	9.20	11.29	5.45	17.85	13.20					52.30	14.15
750	16.18	7.88	10.74	5.18	17.62	13.10					51.52	13.05
1000	15.47	7.32	10.07	4.88	17.39	13.10					51.36	12.27
Ethnic heterogeneity												
50	0.72	0.10	0.72	0.09	0.68	0.11	0.67	0.11	0.59	0.14	0.56	0.16
100	0.73	0.08	0.74	0.08	0.69	0.09	0.68	0.11	0.61	0.13	0.59	0.15
150	0.73	0.09	0.75	0.07	0.69	0.09	0.69	0.11	0.63	0.13	0.60	0.14
300	0.73	0.08	0.75	0.06	0.70	0.08	0.69	0.10	0.64	0.11	0.62	0.12
500	0.73	0.08	0.75	0.06	0.70	0.07	0.69	0.09	0.65	0.10	0.64	0.11
750	0.73	0.07	0.74	0.06	0.70	0.06	0.69	0.08	0.65	0.09	0.65	0.10
1000	0.72	0.07	0.73	0.06	0.70	0.06	0.69	0.07	0.66	0.08	0.65	0.09

Because the other non-Western migrants and the Western migrants are very heterogeneous groups, it is impossible to measure own ethnic density in an accurate and meaningful way.

Table 3. Association of own ethnic density and ethnic heterogeneity with poor self-rated health [&], per ethnic group and spatial scale

	Own Ethnic Density		Ethnic Heterogeneity	
	Model 1 #	Model 2 ##	Model 1	Model 2
Buffer Size	Standardized OR $ (CI)	Standardized OR (CI)	Standardized OR (CI)	Standardized OR (CI)
		Moroccans		
50	0.82 (0.46; 1.47)	0.69 (0.37; 1.31)	1.11 (0.58; 2.11)	1.02 (0.50; 2.12)
100	0.85 (0.45; 1.61)	0.80 (0.44; 1.47)	1.15 (0.68; 1.97)	1.08 (0.56; 2.09)
150	1.04 (0.58; 1.86)	0.86 (0.44; 1.69)	1.11 (0.65; 1.88)	1.05 (0.55; 1.96)
300	0.82 (0.47; 1.44)	0.59 (0.30; 1.18)	0.96 (0.56; 1.62)	0.86 (0.47; 1.57)
500	0.75 (0.43; 1.30)	0.54 (0.27; 1.08)	0.94 (0.58; 1.58)	0.78 (0.41; 1.48)
750	0.85 (0.48; 1.48)	0.66 (0.33; 1.29)	0.98 (0.61; 1.64)	0.70 (0.36; 1.36)
1000	0.93 (0.53; 1.62)	0.73 (0.36; 1.47)	1.08 (0.63; 1.81)	0.76 (0.39; 1.50)
		Turks		
50	1.41 (0.86; 2.31)	1.31 (0.78; 2.22)	0.97 (0.56; 1.70)	0.86 (0.42; 1.71)
100	1.67 (0.98; 2.84)	1.66 (0.96; 2.84)	1.45 (0.80; 2.61)	1.27 (0.64; 2.53)
150	1.69 (0.99; 2.89)	1.70 (0.99; 2.91)	1.54 (0.90; 2.61)	1.55 (0.85; 2.82)
300	1.78 (1.04; 3.05) *	1.71 (0.98; 2.98)	1.52 (0.90; 2.60)	1.43 (0.77; 2.67)
500	1.53 (0.94; 2.50)	1.37 (0.81; 2.32)	1.34 (0.81; 2.24)	1.37 (0.73; 2.54)
750	1.48 (0.92; 2.41)	1.43 (0.85; 2.40)	1.42 (0.85; 2.37)	1.52 (0.81; 2.84)
1000	1.48 (0.92; 2.41)	1.34 (0.77; 2.32)	1.44 (0.87; 2.36)	1.60 (0.86; 2.97)
		Surinamese		
50	1.57 (1.13; 2.20) **	1.57 (1.12; 2.21) **	0.81 (0.55; 1.20)	0.73 (0.49; 1.07)
100	1.58 (1.12; 2.23) **	1.59 (1.12; 2.25) **	0.92 (0.63; 1.33)	0.85 (0.58; 1.25)
150	1.44 (1.03; 2.00) *	1.53 (1.06; 2.20) *	1.04 (0.71; 1.52)	1.02 (0.68; 1.53)

Table 3. Association of own ethnic density and ethnic heterogeneity with poor self-rated health [&], per ethnic group and spatial scale (*continued*)

	Own Ethnic Density		Ethnic Heterogeneity	
	Model 1 #	Model 2 ##	Model 1	Model 2
Buffer Size	Standardized OR $ (CI)	Standardized OR (CI)	Standardized OR (CI)	Standardized OR (CI)
300	1.40 (1.00; 1.96)	1.58 (1.04; 2.40) *	1.22 (0.83; 1.79)	1.40 (0.81; 2.44)
500	1.39 (0.99; 1.96)	1.55 (1.03; 2.33) *	1.33 (0.93; 1.89)	1.30 (0.87; 1.93)
750	1.36 (0.97; 1.92)	1.48 (0.96; 2.28)	1.28 (0.90; 1.83)	1.18 (0.79; 1.77)
1000	1.36 (0.97; 1.91)	2.10 (1.26; 3.48) **	1.40 (0.98; 2.01)	1.36 (0.89; 2.08)
		Other non-western migrants		
50			1.36 (0.98; 1.88)	1.14 (0.79; 1.65)
100			1.51 (1.07; 2.11) *	1.34 (0.91; 1.96)
150			1.47 (1.04; 2.06) *	1.36 (0.93; 1.99)
300			1.41 (1.00; 1.98)	1.24 (0.82; 1.87)
500			1.30 (0.93; 1.82)	1.20 (0.76; 1.88)
750			1.26 (0.90; 1.75)	1.25 (0.79; 1.99)
1000			1.22 (0.87; 1.70)	1.25 (0.79; 1.98)
		Western migrants		
50			1.24 (0.94; 1.62)	1.08 (0.80; 1.47)
100			1.10 (0.85; 1.42)	1.04 (0.77; 1.42)
150			1.04 (0.81; 1.33)	1.03 (0.75; 1.42)
300			1.00 (0.78; 1.28)	0.95 (0.68; 1.34)
500			1.00 (0.78; 1.28)	1.07 (0.75; 1.53)
750			1.02 (0.79; 1.30)	1.13 (0.77; 1.65)
1000			1.00 (0.79; 1.28)	1.03 (0.70; 1.51)

Table 3. Association of own ethnic density and ethnic heterogeneity with poor self-rated health [&], per ethnic group and spatial scale (*continued*)

	Own Ethnic Density		**Ethnic Heterogeneity**	
	Model 1 #	Model 2 ##	Model 1	Model 2
Buffer Size	Standardized OR $ (CI)	Standardized OR (CI)	Standardized OR (CI)	Standardized OR (CI)
		Dutch		
50	0.89 (0.81; 0.98) *	0.99 (0.89; 1.10)	1.14 (1.04; 1.26) **	1.04 (0.93; 1.15)
100	0.87 (0.79; 0.95) **	0.97 (0.87; 1.08)	1.17 (1.06; 1.29) **	1.05 (0.94; 1.17)
150	0.86 (0.78; 0.94) **	0.97 (0.86; 1.08)	1.17 (1.06; 1.29) **	1.05 (0.93; 1.17)
300	0.88 (0.81; 0.97) **	1.03 (0.91; 1.16)	1.14 (1.03; 1.25) **	0.98 (0.87; 1.11)
500	0.89 (0.81; 0.98) *	1.03 (0.91; 1.16)	1.12 (1.02; 1.23) *	0.97 (0.85; 1.10)
750	0.90 (0.82; 0.98) *	1.00 (0.88; 1.13)	1.11 (1.01; 1.22) *	0.98 (0.86; 1.12)
1000	0.90 (0.82; 0.99) *	0.99 (0.87; 1.12)	1.11 (1.01; 1.22) *	1.00 (0.87; 1.15)

& Defined as moderate/poor/very poor; # Model 1 adjusted for age, sex, marital status, household composition, education and difficulties making ends meet; ## Model 2 extended adjustment for socioeconomic environment, measured by the percentage of households living on minimum income and average property value; $ OR represents the standardized odds ratio (i.e., the change in odds with one standard deviation increase in the predictor variable); * significant at the 0.05 level; ** significant at the 0.01 level.

In Model 1, we found positive associations between ethnic heterogeneity and poor self-rated health: the more heterogeneous the environment, the higher the chance to report poor self-rated health. Weak, though significant, results were found only for the Dutch respondents at all buffer distances and for respondents belonging to other non-Western migrants at small distances. After adjustment for socioeconomic environment (Model 2), all significant results disappear.

Table 4 shows associations between the presence of other ethnic groups in the neighborhood and self-rated health among the different ethnic groups after adjustment of socio-economic environment (Model 2). For Turkish respondents, a higher percentage of Moroccans in the neighborhood is associated with a higher chance of reporting poor self-rated health. The statistical significance and strength of this association decreases with increasing buffer size (with the exception of very small buffers of 50 metres). For other non-Western migrants, a higher percentage of Moroccans, as well as a higher percentage of Turks is associated with a higher chance of reporting poor self-rated health. This association does not systematically vary according to buffer size.

Table 4. Association presence of other ethnic groups with poor self-rated health, per ethnic group and spatial scale (Model 2)

	Standardized OR $ (CI)					
	Moroccans	**Turks**	**Surinamese**	**Other non-Wes Migrants**	**Wes Migrants**	**Dutch**
% Sur						
50	1.35 (0.80; 2.29)	0.87 (0.51; 1.49)	1.57 (1.12; 2.21) **	0.97 (0.70; 1.36)	0.90 (0.69; 1.18)	1.03 (0.94; 1.13)
100	1.46 (0.91; 2.34)	0.81 (0.47; 1.40)	1.59 (1.12; 2.25) **	1.04 (0.75; 1.44)	0.91 (0.68; 1.20)	1.03 (0.93; 1.13)
150	1.46 (0.91; 2.36)	0.74 (0.41; 1.35)	1.53 (1.06; 2.20) *	0.98 (0.71; 1.36)	0.95 (0.71; 1.26)	1.01 (0.92; 1.11)
300	1.25 (0.79; 2.00)	0.55 (0.28; 1.07)	1.58 (1.04; 2.40) *	0.88 (0.63; 1.24)	1.02 (0.77; 1.35)	1.02 (0.92; 1.12)
500	1.26 (0.77; 2.06)	0.57 (0.28; 1.15)	1.55 (1.03; 2.33) *	0.90 (0.63; 1.26)	1.11 (0.84; 1.47)	1.00 (0.91; 1.11)
750	1.19 (0.71; 2.02)	0.60 (0.27; 1.32)	1.48 (0.96; 2.28)	0.84 (0.59; 1.20)	1.16 (0.88; 1.54)	0.99 (0.89; 1.09)
1000	1.19 (0.71; 1.97)	0.81 (0.34; 1.91)	2.10 (1.26; 3.48) **	0.74 (0.51; 1.08)	1.18 (0.88; 1.58)	1.00 (0.90; 1.11)
% Mor						
50	0.69 (0.37; 1.31)	1.89 (1.07; 3.39) *	0.83 (0.57; 1.19)	1.51 (1.08; 2.10) *	0.86 (0.65; 1.14)	0.98 (0.89; 1.09)
100	0.80 (0.44; 1.47)	4.29 (1.86; 9.92) **	0.73 (0.50; 1.06)	1.55 (1.12; 2.15) **	0.86 (0.62; 1.18)	0.99 (0.89; 1.11)
150	0.86 (0.44; 1.69)	4.58 (1.90; 11.1) **	0.73 (0.50; 1.06)	1.53 (1.09; 2.14) *	0.83 (0.59; 1.15)	0.98 (0.87; 1.09)
300	0.59 (0.30; 1.18)	2.94 (1.48; 5.85) **	0.76 (0.47; 1.23)	1.35 (0.96; 1.90)	0.79 (0.56; 1.11)	0.92 (0.82; 1.03)
500	0.54 (0.27; 1.08)	2.18 (1.22; 3.95) **	0.80 (0.55; 1.17)	1.34 (0.96; 1.87)	0.85 (0.62; 1.17)	0.95 (0.85; 1.06)
750	0.66 (0.33; 1.29)	2.03 (1.17; 3.50) *	0.87 (0.61; 1.25)	1.43 (1.02; 2.00) *	0.87 (0.64; 1.19)	0.99 (0.89; 1.10)
1000	0.73 (0.36; 1.47)	1.76 (0.99; 3.14)	0.77 (0.37; 1.60)	1.50 (1.07; 2.09) *	0.83 (0.62; 1.11)	1.00 (0.90; 1.11)
% Tur						
50	0.78 (0.46; 1.33)	1.31 (0.78; 2.22)	0.91 (0.65; 1.26)	1.36 (1.01; 1.83) *	1.00 (0.77; 1.30)	0.97 (0.89; 1.07)
100	0.64 (0.37; 1.11)	1.66 (0.96; 2.84)	0.85 (0.60; 1.20)	1.56 (1.15; 2.11) **	1.06 (0.81; 1.39)	1.04 (0.94; 1.14)
150	0.65 (0.37; 1.13)	1.70 (0.99; 2.91)	0.90 (0.63; 1.28)	1.40 (1.03; 1.89) *	1.07 (0.81; 1.42)	1.04 (0.94; 1.14)

Table 4. Association presence of other ethnic groups with poor self-rated health, per ethnic group and spatial scale (Model 2) (*continued*)

	Standardized OR $ (CI)					
	Moroccans	**Turks**	**Surinamese**	**Other non-Wes Migrants**	**Wes Migrants**	**Dutch**
300	0.60 (0.33; 1.11)	1.71 (0.98; 2.98)	0.96 (0.64; 1.43)	1.35 (0.99; 1.84)	0.97 (0.72; 1.30)	0.97 (0.87; 1.07)
500	0.62 (0.32; 1.19)	1.37 (0.81; 2.32)	0.98 (0.68; 1.41)	1.35 (0.99; 1.84)	1.03 (0.79; 1.34)	0.95 (0.85; 1.05)
750	0.73 (0.40; 1.33)	1.43 (0.85; 2.40)	1.01 (0.71; 1.43)	1.49 (1.08; 2.04) *	1.04 (0.79; 1.22)	0.97 (0.88; 1.07)
1000	0.76 (0.42; 1.37)	1.34 (0.77; 2.32)	0.95 (0.62; 1.43)	1.50 (1.09; 2.05) *	0.96 (0.75; 1.25)	1.00 (0.90; 1.10)
% Dutch						
50	1.45 (0.70; 2.96)	0.49 (0.24; 1.00)	0.67 (0.43; 1.03)	0.70 (0.46; 1.05)	0.98 (0.72; 1.32)	0.99 (0.89; 1.10)
100	1.20 (0.60; 2.37)	0.43 (0.21; 0.91) *	0.73 (0.47; 1.14)	0.64 (0.42; 0.97) *	1.03 (0.76; 1.40)	0.97 (0.87; 1.08)
150	1.17 (0.59; 2.34)	0.43 (0.21; 0.92) *	0.66 (0.39; 1.13)	0.73 (0.48; 1.10)	1.04 (0.76; 1.42)	0.97 (0.86; 1.08)
300	1.63 (0.83; 3.20)	0.52 (0.27; 1.01)	0.45 (0.26; 0.78) **	0.89 (0.58; 1.39)	1.02 (0.72; 1.43)	1.03 (0.91; 1.16)
500	1.73 (0.85; 3.53)	0.62 (0.33; 1.17)	0.49 (0.30; 0.80) **	0.93 (0.59; 1.47)	0.88 (0.62; 1.25)	1.03 (0.91;1.16)
750	1.57 (0.79; 3.15)	0.57 (0.32; 1.04)	0.47 (0.28; 0.79) **	0.97 (0.63; 1.50)	0.85 (0.60; 1.21)	1.00 (0.88; 1.13)
1000	1.40 (0.70; 2.82)	0.61 (0.33; 1.13)	0.34 (0.20; 0.61) **	1.10 (0.72; 1.67)	0.89 (0.62; 1.27)	0.99 (0.87; 1.12)

$ OR represents the standardized odds ratio; * significant at the 0.05 level; ** significant at the 0.01 level; Sur: Surinamese; Mor: Moroccans; Tur: Turks.

For Turkish, Surinamese and other non-Western respondents, the percentage of Dutch in the neighborhood was inversely associated with poor self-rated health (i.e., positively associated with good health). Among Turks and other non-Western migrants, this association was statistically significant only at smaller buffer sizes. In contrast, among the Surinamese, associations were strongest at larger buffer sizes.

6.4. Discussion

Current evidence on the relationship between neighborhood ethnic composition and health is mixed. For Amsterdam, we studied this relationship at different spatial scales and using different measures of ethnic composition. The results suggest that Putnam's findings regarding the negative impacts of ethnic heterogeneity on social capital and trust of the other and even of members of one's own group do not universally apply to reporting poor self-rated health. Ethnic heterogeneity and self-rated health were not statistically-significantly associated for any of the six ethnic groups that we distinguished after controlling for the socio-economic composition of the environment. However, the presence of own ethnic group was associated with higher odds of reporting poor health among Surinamese, but not among other groups. With respect to the presence of specific other ethnic groups in the neighborhood, several significant associations were found. For example, a high proportion of Moroccan-origin residents was associated with poor self-rated health of Turkish and other non-Western residents. A higher proportion of Dutch in the neighborhood was associated with a lower chance to report poor health by Turkish and Surinamese residents.

Special attention was paid to the role of spatial scale. In general, stronger relationships were found at lower spatial scales. For Turks, the effect of having Moroccans and Dutch around was most clear in 100- and 150-m buffers. For non-Western migrants, the influence of Turks, Moroccans and Dutch is most pronounced in 100-m buffers. However, there are some exceptions. Among the Surinamese, the influence of the own group is strongest in large, as well as small buffers.

Evaluation of Data and Methodology

One of the strengths of our study is that we could use detailed socio-economic and demographic data from registries at the level of six-digit postcodes, which is the smallest area of observation available, including no more than 10–20 households in urban areas. This level of geographical detail exceeds that of most previous studies on this topic. Moreover, by using bespoke environments instead of administrative areas, we not only address “scale effects”, but also avoid the problem of “boundary effects”, which are associated with the use of administrative areas [41]. While residents living near the boundary of administrative areas are assigned characteristics of the administrative area they reside in, they may be equally affected by characteristics of neighboring administrative areas.

Because larger buffers overlap, the environmental characteristics of respondents are not entirely independent. This may result in an overestimation of the precision and statistical significance of the associations. This problem may not have affected the levels of statistical significance at smaller scales, where buffers rarely overlapped. However, it might have influenced our findings for Surinamese, where we observed a number of associations, especially in larger buffers. As Surinamese are strongly concentrated in the southeastern district of Amsterdam (called “Bijlmer”), these associations may reflect an unidentified “Bijlmer effect”.

We found a higher non-response among lower educated respondents (42.3 percent compared to 20.6 percent among highly-educated respondents) and among non-Western migrants (on average 41.0 percent compared to 24.8 percent among Western respondents). In addition, we could only include those respondents who had indicated willingness to participate in future research. This might have resulted in a selective group of relatively active, engaged and trusting respondents. If these characteristics are associated with the ethnic composition of neighborhoods, selective inclusion of this group could have affected our estimates of the associations between ethnic composition and health.

The administrative classification of the Amsterdam population into “other non-Western migrants” and “Western migrants” (in addition to four defined ethnic groups) reduced the detail with which we could measure ethnic composition. Due to this, we may have missed more specific associations between ethnic composition and self-rated health. This especially applies to the potential effects of the co-residence with specific groups in the “other non-Western migrants” and “Western migrants” categories.

Because of the cross-sectional design of our study, the observed associations may reflect reverse causality or selection effects. Selective migration plays a role if people prefer to move to areas with specific ethnic composition and if this ability depends on health or related characteristics. For example, the inverse associations that we observed may be due to Surinamese preferring to move away from other Surinamese and to Turks preferring to move away from Moroccans. In Amsterdam, however, such selection effects may be modest because spatial mobility in Amsterdam is limited due to lack of appropriate housing for people willing to move as a result of upward social mobility [42]. Moreover, we controlled for a series of socioeconomic measures that may drive residential mobility. However, as there are other health-related factors that could influence neighborhood selection, selection bias and reverse causality could still have influenced the results.

Interpretation and Comparison to Previous Studies

Large ethnic inequalities exist in the overall prevalence of poor health. Good or very good health is reported by 75.8 percent of native Dutch compared to only 41.8, 51.3 and 58.8 percent of Turks, Moroccans and Surinamese (Table 1). These large inequalities contrast with the much smaller ethnic inequalities in mortality, which are driven by migrants' lower rates of mortality of most cancer types [43,44]. Instead, migrants have higher prevalence rates for most non-fatal diseases, including highly-disabling disease, such as diabetes and arthritis [45]. These inequalities in disease prevalence are not, or only to a minor extent, attributable to potential differences in access or quality of healthcare [46]. More importantly, these inequalities reflect to an important extent the migrants' lower socioeconomic position and related disadvantages, such as poorer living and working conditions [47]. In addition, disadvantages specifically related to the position of migrant or ethnic minorities, such as the experience of overt or covert discrimination, have been found to be related to poorer physical or mental health [48].

We found no influence of ethnic heterogeneity on self-rated health. This finding is not in line with the theories of Putnam [35] and Neil and Neil [36], which would suggest a higher chance to report poor self-rated health in heterogeneous neighborhoods because of lower social capital in these neighborhood. Our finding better fits into the recently-started debates on whether community connections (including social trust and social capital) are really weaker in ethnically-diverse communities [49].

The results of this study suggest that the other dimensions of ethnic composition are associated with self-rated health in Amsterdam only among particular ethnic groups. This is in line with other studies showing the associations between own ethnic density and self-rated health to differ between different ethnic groups, both in the U.K. [26] and in the U.S. [28].

A previous study of Surinamese, Turkish and Moroccans in the four largest Dutch cities (including Amsterdam) found no association between own ethnic density and psychological distress in any of the three ethnic minority groups examined [25]. Our results regarding Turkish and Moroccans are similar. However, unlike this previous study, we did find associations between own ethnic density and self-rated health among Surinamese. A possible explanation is that the former study used a spatial scale of four-digit postcode areas (on average 2.5 km2), whereas we observed these associations for Surinamese at smaller spatial scales.

Our finding that among the Surinamese respondents, the presence of their own group is associated with poor (instead of good) self-rated health is not in line with the classic ethnic density effect, which predicts better health for people living among co-ethnics. This unexpected association may have different causes. First, it is generally known that Surinamese wish to integrate and participate in the Dutch society. From this perspective, living in a district characterized by a high percentage of co-ethnics (the "Bijlmer" district) might represent an undesirable situation, associated with poor self-rated health. Second, residence in areas dominated by Surinamese may imply co-residence among Surinamese subgroups that have poor relations. The Surinamese group includes the Creoles, Hindustani, Javanese and Chinese, with each sub-group having their own organizations, events, meeting places and social networks [50].

The presence of Moroccans in the residential environment was associated with poorer self-rated health for Turks. This association is consistent with explanations derived from identity threat theory. According to this theory, similar groups evaluate each other negatively (compared to other groups) if they threaten each other's distinctive identities [51]. In the Netherlands, Turks and Moroccans have strong similarities in socio-economic circumstances, migration history, religion and culture [52]. As media attention and general public opinion in The Netherlands is negative about Moroccans, the Turks may perceive their presence as a threat to their position and identity as a minority group. We did not find a reverse association: the co-residence of Turks was not associated with self-rated health of Moroccans. This is consistent with Moroccans not seeing Turks as a threat: Moroccans judge mostly positively about the Turks, whereas Turks judge negatively about Moroccans [53].

Future Research Directions

For future research on relationships between health and the ethnic composition of the residential environment, we recommend a more detailed measurement of ethnic composition. In addition to measuring the general level of ethnic heterogeneity of an area, attention should be given to the presence of other specific ethnic groups, including the respondents' own group.

Moreover, it is important for future studies to measure the ethnic composition of the residential environment at different spatial scales. Not only should ethnic composition be measured in broad (often administratively defined) areas, such as city districts, but also in the immediate surroundings of respondents' home address. Different mechanisms may operate at different spatial scales: while integration and discrimination mechanisms may operate at larger spatial scales, social support mechanisms may operate at smaller scales [54].

Finally, extensive adjustment for socioeconomic environment is needed to better understand the role of neighborhood deprivation and to disentangle the effect of deprivation and residential ethnic composition. Our study shows that adequate control for the socioeconomic environment may noticeably alter the observed association between health and ethnic composition.

6.5. Conclusions

In Amsterdam, there is no general association between neighborhood ethnic composition and self-rated health. Instead, such associations are observed only for particular combinations of ethnic groups, especially when these occur in the immediate surroundings of the place of residence. These findings suggest that mixing policies addressing the ethnic composition of areas do not have generalized positive or negative effects on urban health. Instead, our analysis points to localized effects, sometimes positive and sometimes negative, depending on the combination of ethnic groups. Conflict situations in areas where specific groups with problematic inter-relations live together should be addressed for mixing policies to positively contribute to urban health.

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CHAPTER 7

The relationship between ethnic composition of the residential environment and self-reported health among Turks and Moroccans in Amsterdam

Abstract

Background: Previous studies from the US and UK suggest that neighbourhood ethnic composition is associated with health, positive or negative, depending on the health outcome and ethnic group.
We examined the association between neighbourhood ethnic composition and self-reported health in these groups in Amsterdam, and we aimed to explore whether there is spatial variation in this association.

Methods: We used micro-scale data to describe the ethnic composition in buffers around the home location of 2701 Turks and 2661 Moroccans. Multilevel regression analysis was used to assess the association between three measures of ethnic composition (% co-ethnics, % other ethnic group, Herfindahl index) and three measures of self-reported health: self-rated health, Physical and Mental Component Score (PCS,MCS). We adjusted for socioeconomic position at individual and area level. We used Geographically Weighted Regression (GWR) and spatially stratified regression analyses to explore whether associations differed within Amsterdam.

Results: Ethnic heterogeneity and own ethnic density were not related to self-rated health for both ethnic groups. Higher density of Turks was associated with better self-rated health among Moroccans at all buffer sizes, with the most significant relations for small buffers. Higher heterogeneity was associated with lower scores on PCS and MCS among Turks (suggesting worse health). We found spatial variation in the association of the density of the other ethnic group with self-rated health of Moroccans and Turks. We found a positive association for both groups, spatially concentrated in the sub-district Geuzenveld.

Conclusions: Our study showed that the association of ethnic composition with self-reported health among Turks and Moroccans in Amsterdam differed between the groups and reveals mainly at small spatial scales. Among both groups, an association of higher density of the other group with better self-rated health was found in a particular part of Amsterdam, which might be explained by the presence of a relatively strong sense of community between the two groups in that area. The study suggests that it is important to pay attention to other-group density, to use area measurements at small spatial scales and to examine the spatial variation in these associations. This may help to identify neighbourhood characteristics contributing to these type of area effects on urban minority health.

7.1. Introduction

European societies have become increasingly ethnically diverse over the last decades, and this demographic shift is likely to continue given the relatively high influx of immigrants. [1, 2]. Evidence indicates that ethnic minority groups overall tend to have worse self-rated health than the ethnic majority group in European countries [3]. This has been attributed to low individual socioeconomic status (SES) and psychosocial factors (e.g., discrimination, acculturation, social network) [4-7], amongst other factors.

Contextual factors such as characteristics of the residential environment may also shape the health of ethnic minority groups. One such characteristic is ethnic composition, which is conceptualized as ethnic diversity or as own-group density (i.e., the presence of the same-ethnic group in the residential environment) [8]. The association between ethnic composition of the residential environment and health presumably operates through social capital and exposure to discrimination [9]. However, evidence from the United States (US) and Europe is equivocal, in that the strength and direction (both negative and positive) of the association vary by ethnic minority group, spatial scale, and outcome measure [8-12].

Furthermore, the existing literature on this topic has three potential limitations. First, most epidemiological studies have focused on own-group density or ethnic diversity, while relatively few studies have assessed other-group density (i.e., co-presence of a specific other ethnic group). This might be particularly relevant for some cities in which two or more (large-sized) ethnic minority groups reside. Other-group density might affect health through material and psychosocial processes. The association could be either positive or negative, largely depending on the inter-relationship the groups have (e.g. mutual trust, discrimination, sharing job information) [13-15].

Second, previous studies have used large spatial scales (e.g., census tracts, electoral wards), making it potentially difficult to assess the associations with health outcomes accurately [16]. Most inter-ethnic interaction and the underlying material and psychosocial processes are likely to occur at smaller spatial scales in the direct environment. Hence using smaller spatial scales could possibly better capture the associations between ethnic composition of residential environment and health [16].

Third, most studies have presented the aggregated effects of ethnic composition on health at city-level [8-11]. This may possibly obscure the spatial variation within a city. Different parts of a city may differ in the opportunities they provide for social interaction between groups. These opportunities might be different due to differences in physical environments (e.g., built environment) and social environments (e.g., social cohesion, local institutions) [16]. So far, it is unknown whether the association between ethnic composition of residential environment and health differs within a city.

In the present study, we aimed to fill these gaps in the literature. First, we aimed to investigate the association between other-group density of the residential environment and self-reported health outcomes in two ethnic minority groups. We further considered other measures of ethnic composition of residential environment: ethnic heterogeneity and own-group density. Second, we assessed the associations at different spatial scales (both small and large). Third, we explored spatial variation, by assessing whether the associations differed within the city.

We focused on Turkish and Moroccan adults residing in Amsterdam, the Netherlands. These two groups are considered the largest ethnic minority groups in Europe, and tend to co-exist in many different cities (e.g. Paris, Berlin). Our study extended previous studies on this topic conducted in Amsterdam. A 2014 study found own-group density was not associated with psychological distress in Turkish and Moroccan adults living in the four largest Dutch cities (including Amsterdam) [12]. A more recent study from Amsterdam suggested that a high density of Moroccan residents was associated with poor self-rated health among Turkish residents, but not vice versa [13]. In the present study, we delve into these findings by using a much larger dataset, more health outcomes and different spatial scales, as well as by assessing variation within the city.

7.2. Study population and methods

Study population

The data were obtained from the HELIUS (Healthy Life in an Urban Setting) study. The aims and design of the HELIUS study have been described elsewhere [17]. Briefly, HELIUS is a large-scale cohort study on health and healthcare among different ethnic groups living in Amsterdam. It included individuals aged 18–70 years from the six largest ethnic groups living in Amsterdam, i.e. those of Dutch, South-Asian Surinamese, African Surinamese, Ghanaian, Moroccan and Turkish origin. Participants were randomly sampled from the municipal registers, stratified by ethnicity. Data were collected by questionnaire and a physical examination. At the end of 2014, response rates were estimated between 20-40% with some variations across ethnic groups.

For the current study, baseline data collected from January 2011 until December 2014 were used, including 2962 Turkish and 3000 Moroccan participants. Individuals with missing data on self-reported health, individual characteristics, area ethnic composition or area socioeconomic position, and individuals living at locations with less than 25 inhabitants within a buffer of 50 metres were excluded from the analysis (n=600). Our final sample comprised 5362 participants: 2701 Turks and 2661 Moroccans.

Individual level measurements

Participant's ethnicity was defined according to the country of birth of the participant as well as that of his/her parents. Specifically, a participant is considered of Turkish/Moroccan origin if: 1) he or she was born in Turkey/Morocco and has at least one parent born in Turkey/Morocco; or 2) he or she was born in the Netherlands but both his/her parents born in Turkey/Morocco [18].

Three measures of self-reported health are used: self-rated health and generic physical and mental health (PCS and MCS). Self-rated health was measured by the response to the question, 'In general, would you say your health is excellent, very good, good, fair or poor?' The answers were classified into two categories: excellent/very good/good and fair/poor. In the remainder of the paper we refer to the first category as better self-rated health. Generic mental and physical health were assessed using the component summary measures of physical (PCS) and mental health (MCS) from the Medical Outcomes Study Short Form 12 (SF-12) [19]. Scores range from 0 to 100 with higher scores reflecting better health.

From the same survey, we obtained data on characteristics of the participants that were used as control variables at the individual level. These include age, sex, marital status, household composition, educational level, length of residence in the country and a measure of general wealth (whether the participant experienced difficulties living on his or her current household income). See table 1 for a description of these variables.

Area-level measurements

For area-level measurements we used integral demographic and socio-economic registries at the level of full 6-digit postcodes maintained by the Department of Research and Statistics of the Municipality of Amsterdam. Data on the spatial level of 6-digit postcode area is the most detailed data available. On average, these units are sized 50 x 50 metres and include 10 to 20 households.

To describe the ethnic composition for each participant, we constructed three variables: *own-group density* (i.e., percentage of co-ethnics), *other-group density* (i.e., percentage of the other ethnic group – Turks or Moroccans) and *ethnic heterogeneity* described by the Herfindahl-index. This index yields the probability of two randomly selected individuals from the same neighbourhood being of different ethnic origin. The theoretical range of the index runs from 0 to 1,with 0 representing an area in which every individual is from the same ethnic group and 1 representing an area in which every individual is from a different ethnic group. To calculate this index, we sum the squared proportion of each ethnic group (Surinamese, Antilleans, Ghanaians, Turks, Moroccan, other non-western migrants, other western migrants and Dutch) and subtract this total from one.

When studying the association between ethnic composition and health, it is not enough to control for individual characteristics only. Veldhuizen et al. [13] showed that it is necessary to control for the socio-economic environment as well, because this variable can act as a confounder. To describe the socio-economic environment we constructed two socio-economic variables: the percentage of residents living on a minimum income and the average property value of houses.

In general, the multicollinearity between the independent variables is not very high. Most correlations are 0,5 at most. Only the correlations between percentage Turks/percentage Moroccans/heterogeneity (Herfindahl index) and percentage of minimum income households are high for the larger buffers (0,7). However, because socioeconomic environment is an important determinant of self-rated health we cannot remove the variable from our model.

Within a Geographical Information System (ArcGIS) we created buffers of varying sizes, with radiuses ranging from 50 to 1000 metres, around the central point location of each participant's 6-digit postcode area. The ethnic composition and socioeconomic characteristics of each of these buffers were estimated by aggregating the postcode data to the buffers. For a more detailed description of the procedure see Veldhuizen et al. [20].

Statistical analysis

The associations between ethnic composition of the residential environment and self-rated health were assessed using multilevel logistic regression analysis, with better self-rated health as the dependent variable and 6-digit postcode as the variable indicating the higher level (participants living in the same postcode area have identical buffers). We adjusted for the individual characteristics age, sex, marital status, household composition, education, length of residence in the country and wealth and for socio-economic environment measured by the percentage of households living on minimum income and average property value.

To enable comparison of the results of these analyses between different predictors and the different buffer sizes, we present standardised odds ratios of the three measures of ethnic composition. These odds ratios can be interpreted as the change in the odds of better self-rated health if a predictor variable increases with one standard deviation. The odds ratios take into account the differences in standard deviation according to predictor and buffer size (table 2).

The associations between neighbourhood ethnic composition and PCS and MCS were assessed using multilevel linear regression analysis, adjusting for the same individual and environmental variables as mentioned above. We present standardised regression coefficients. These coefficients can be interpreted as the change in the standardised dependent variable in case the predictor variable increases with one standard deviation.

In total, 2251 postcode areas were included in the analysis; 1507 for the Turks and 1572 for the Moroccans. We applied random effects (intercept) estimators using STATA's melogit and mixed commands. Random effects appeared to be significant in all empty models and in approximately half of the models with variables. Because a significant number of postcode areas include only one or a limited number of participants, it was not possible to accurately measure both variations between and within the areas. As a result, likelihood ratio tests indicated that our random intercept models were not statistically significant in several models, implying limited meaning of random effects models compared to models without random effects. We present the parameters of the multilevel models because these models generated greater standard errors for our variables of interest than models without random effects.

The dependent variables show substantial variation over Amsterdam. For instance, across 22 administratively defined areas, for Turks the percentage of participants with good self-rated health varies between 44 and 77, for Moroccans between 50 and 73.

Geographical analysis

Additionally, we used logistic Geographically Weighted Regression (GWR) within the software GWR4 to explore whether the most important association we found from the multilevel regression analyses spatially differed within Amsterdam. GWR enables us to explore if the association varies within the city, without a priori assumptions with respect to the geographic scale at which these variations would occur. GWR is a local form of (in this case logistic) regression to model spatially varying relationships. It constructs a separate equation for every participant incorporating the dependent and explanatory variables of all participants living within a specific distance around the target participant. We used a bandwidth (Gaussian Kernel) of a fixed distance of 500 metres which means that a 500 metre kernel is used over the whole study area. The alternative for a fixed spatial kernel, an adaptive kernel, varies the size of kernel according to the spatial distribution of observation. This would mean that in areas with relatively few participants the kernel would become large which would obscure local relationships. We considered 500 metres as a reasonable compromise between two conflicting demands: (1) to include a reasonable number of participants in the analyses, and (2) to allow for the exploration of sufficient spatial variation. We mapped the resulting odds ratios to visually explore spatial patterns.

Based on the observation that the spatial pattern of the OR values more of less coincides with sub-districts of Amsterdam, we decided to perform an additional stratified multilevel analysis by sub-district. This allows us to assess the associations more accurately than within GWR because of the limited number of observations in the local regressions. We restricted the stratified analysis to Nieuw-West where most participants reside.

7.3. Results

Table 1 describes the characteristics of the study population in both ethnic groups. In general, no substantial differences in poor self-rated health, PCS and MCS were observed between Turkish and Moroccan participants. The two groups also had similar scores on most other characteristics although more Turkish participants were lower educated and had a little more difficulties in making ends meet.

Table 1. Characteristics of participants and their socio-economic environment, per ethnic group

Ethnic group	Moroccan	Turkish
N	2661	2701
Self-rated health (%)		
excellent	4.7	4.0
very good	9.7	10.8
good	48.1	49.6
fair	30.5	26.4
poor	7.1	9.3
Physical Component Score		
mean	46.0	45.3
standard dev	10.2	10.7
Mental Component Score		
mean	46.1	44.8
standard dev	10.9	11.3
Length of residence in the country (years)		
mean	28.6	28.2
standard dev	8.7	8.2
Age (%)		
18-29	28.3	25.0
30-39	22.3	21.1
40-49	22.4	29.5
50-64	24.4	22.7
>=65	2.6	1.7
Sex (%)		
Male	36.6	46.3
Marital status (%)		
married couple	57.6	62.6
unmarried couple	2.3	3.4
never been married	28.4	21.5
divorced	10.1	10.2
widow/widower	1.7	2.3
Household composition (%)		
single	7.2	9.2
couple without children	7.3	10.3
family	49.2	52.1
other (living with parents, parents in law, institution)	36.3	28.4
Education (%)		
no/elementary	33.1	33.3
lower secondary	18.0	25.5
intermediate/higher secondary	33.1	27.5
higher	15.9	13.6

Table 1. Characteristics of participants and their socio-economic environment, per ethnic group (*continued*)

Ethnic group	Moroccan	Turkish
Living on household income (%)		
no problems at all	22.3	16.8
no problems, but I have to watch what I spend	35.6	25.4
some problems	26.3	31.3
lots of problems	15.7	26.5
Property value of houses at postcode of residence (€)		
mean	198216	193880
standard dev	55915	53692
% Households living on a minimum income at postcode of residence		
mean	28.4	25.9
standard dev	14.4	15.5

Table 2 shows the average levels and standard deviations of own-group density, other-group density and ethnic heterogeneity by spatial scale for the two ethnic groups. Compared to Turkish participants, the residential environment of Moroccan participants was characterized by a higher share of co-ethnics. Levels and standard deviations of own-group density decreased with increasing buffer size, especially among Moroccans. Turkish participants had a higher percentage of Moroccans in their residential environment than vice versa. The difference between Turkish and Moroccan participants on the measures was approximately 10 percent points at all buffer distances. Levels and standard deviations of other-group density decrease with increasing buffer size, especially among Turkish participants. The level of ethnic heterogeneity of the residential environment of Moroccan and Turkish participants is comparable. Ethnic heterogeneity increases for buffers up to 500 metres.

Table 2. Characteristics of the participant's neighbourhood ethnic composition per ethnic group and spatial scale

Ethnic group	Moroccan		Turkish	
	mean	std dev	mean	std dev
Own ethnic density (%)				
Buffer50	26.6	16.5	17.2	10.5
100	23.5	14.9	15.0	8.6
150	22.2	14.1	14.3	7.9
300	19.7	11.7	12.9	6.8
500	18.3	10.3	12.2	6.3
750	17.2	9.0	11.7	6.0
1000	16.3	8.3	11.3	5.9
Other ethnic density (%) (Turks resp. Moroccans)				
50	12.6	9.9	22.9	15.3
100	12.3	8.6	22.6	13.4
150	12.0	8.1	22.2	12.6
300	11.1	7.1	20.7	10.5
500	10.5	6.5	19.7	9.0
750	10.0	6.1	18.7	8.0
1000	9.6	5.9	18.0	7.5
Ethnic heterogeneity (range 0-1)				
50	0.711	0.085	0.722	0.083
100	0.721	0.079	0.735	0.072
150	0.723	0.079	0.738	0.070
300	0.728	0.078	0.744	0.066
500	0.729	0.077	0.747	0.064
750	0.728	0.075	0.745	0.063
1000	0.725	0.073	0.742	0.062

Table 3 shows the association of own-group density, other-group density and ethnic heterogeneity with self-rated health per ethnic group. Overall, own-group density and ethnic heterogeneity were not significantly related to self-rated health in both groups. For other-group density, a higher percentage of Turks in the neighbourhood was associated with higher odds of reporting better self-rated health among Moroccans. These results were consistent with more significant relations found for smaller buffers. Self-rated health of Turks was not significantly associated with higher density of Moroccans in the neighbourhood.

Table 3. Association of density of Moroccans, density of Turks and ethnic heterogeneity with better self-rated health, per ethnic group and spatial scale

Ethnic group	Moroccan Standardised OR[$] (CI[#])	Turkish Standardised OR[$] (CI[#])
Density of Moroccans (%)		
Buffer50	1.01 (0.89;1.14)	1.05 (0.94;1.19)
100	1.08 (0.95;1.23)	1.08 (0.95;1.23)
150	1.10 (0.96;1.26)	1.05 (0.92;1.20)
300	1.09 (0.95;1.25)	1.05 (0.92;1.20)
500	1.09 (0.96;1.24)	1.04 (0.92;1.19)
750	1.11 (0.98;1.26)	1.08 (0.96;1.23)
1000	1.15 (1.02;1.30)*	1.08 (0.96;1.23)
Density of Turks (%)		
50	1.19 (1.07;1.33)**	1.10 (1.00;1.22)
100	1.16 (1.04;1.30)**	1.06 (0.95;1.18)
150	1.17 (1.04;1.31)**	1.07 (0.96;1.19)
300	1.15 (1.03;1.30)*	1.05 (0.94;1.17)
500	1.14 (1.01;1.28)*	1.08 (0.97;1.21)
750	1.14 (1.01;1.28)*	1.09 (0.97;1.22)
1000	1.16 (1.02;1.31)*	1.07 (0.95;1.21)
Ethnic heterogeneity		
50	0.98 (0.89;1,09)	0.98 (0.89;1.08)
100	1.03 (0.93;1.15)	0.97 (0.88;1.08)
150	1.03 (0.92;1.15)	0.99 (0.89;1.10)
300	1.10 (0.97;1.24)	0.97 (0.86;1.08)
500	1.15 (1.01;1.31)*	1.03 (0.92;1.16)
750	1.11 (0.97;1.26)	1.06 (0.94;1.20)
1000	1.14 (0.99;1.31)	1.09 (0.96;1.24)

[$] OR represents the standardised Odds Ratio (i.e. change in odds of having better self-rated health with one standard deviation increase in the predictor variable)

[#] CI represents 95% confidence interval

* significant at the 0.05 level

** significant at the 0.01 level

Table 4 shows the associations of own-group density, other-group density and ethnic heterogeneity with PCS and MCS per ethnic group. Among Moroccans a higher density of Turks within a 50 metre buffer was significantly associated with a healthier PCS. Among Turks, higher ethnic heterogeneity was significantly associated with worse PCS at buffer sizes up to 300 metres and with worse MCS from 150 to 500 metre buffers.

Table 4. Association of density of Moroccans, density of Turks and ethnic heterogeneity with Physical and Mental Component Score per ethnic group and spatial scale

Ethnic group	Moroccan		Turkish	
	Standardised b[$] (CI[#])		Standardised b[$] (CI[#])	
	PCS	MCS	PCS	MCS
Density of Moroccans (%)				
Buffer50	0.01 (-0.04;0.05)	0.03 (-0.02;0.07)	0.01 (-0.04;0.05)	-0.01 (-0.06;0.04)
100	0.02 (-0.03;0.07)	0.00 (-0.05;0.06)	0.01 (-0.04;0.06)	-0.02 (-0.07;0.04)
150	0.01 (-0.04;0.06)	0.00 (-0.05;0.06)	0.01 (-0.04;0.06)	-0.04 (-0.10;0.01)
300	0.00 (-0.05;0.05)	0.01 (-0.04;0.07)	-0.01 (-0.06;0.04)	-0.01 (-0.07;0.04)
500	-0.00 (-0.05;0.05)	0.01 (-0.04;0.06)	-0.00 (-0.05;0.05)	-0.03 (-0.08;0.02)
750	0.01 (-0.04;0.05)	0.00 (-0.05;0.05)	0.01 (-0.03;0.06)	-0.02 (-0.07;0.03)
1000	0.01 (-0.04;0.06)	0.00 (-0.05;0.05)	0.02 (-0.02;0.07)	-0.02 (-0.07;0.04)
Density of Turks (%)				
50	0.04 (0.00;0.08)*	0.01 (-0.03;0.06)	0.01 (-0.03;0.05)	-0.01 (-0.05;0.03)
100	0.04 (0.00;0.08)	0.01 (-0.03;0.06)	0.01 (-0.03;0.05)	-0.01 (-0.06;0.03)
150	0.04 (0.00;0.08)	0.01 (-0.04;0.05)	0.01 (-0.03;0.05)	-0.02 (-0.06;0.03)
300	0.03 (-0.02;0.07)	0.01 (-0.04;0.05)	0.01 (-0.03;0.05)	-0.02 (-0.07;0.02)
500	0.01 (-0.03;0.05)	0.01 (-0.04;0.05)	0.02 (-0.02;0.06)	-0.01 (-0.06;0.03)
750	0.01 (-0.03;0.05)	-0.01 (-0.05;0.04)	0.02 (-0.02;0.06)	-0.01 (-0.06;0.04)
1000	0.01 (-0.04;0.05)	-0.01 (-0.06;0.04)	0.03 (-0.01;0.08)	-0.02 (-0.07;0.03)
Ethnic heterogeneity				
50	-0.02 (-0.05;0.02)	-0.02 (-0.06;0.02)	-0.06 (-0.09;-0.02)**	-0.01 (-0.05;0.03)
100	0.00 (-0.04;0.04)	-0.01 (-0.05;0.03)	-0.05 (-0.09;-0.01)**	-0.02 (-0.06;0.02)
150	0.00 (-0.04;0.04)	-0.02 (-0.07;0.02)	-0.04 (-0.08;-0.00)*	-0.05 (-0.09;-0.01)*
300	0.04 (-0.01;0.09)	-0.01 (-0.06;0.03)	-0.06 (-0.10;-0.02)**	-0.07 (-0.11;-0.02)**
500	0.05 (0.00;0.09)	0.00 (-0.05;0.05)	-0.02 (-0.06;0.03)	-0.06 (-0.10;-0.01)*
750	0.03 (-0.02;0.08)	-0.02 (-0.07;0.04)	-0.02 (-0.07;0.02)	-0.05 (-0.10;0.00)
1000	0.03 (-0.02;0.08)	-0.01 (-0.06;0.05)	-0.00 (-0.05;0.04)	-0.03 (-0.08;0.02)

[$] b represents the standardised regression coefficient (i.e. change in the dependent variable with one standard deviation increase in the predictor variable)

[#] CI represents 95% confidence interval

* significant at the 0.05 level

** significant at the 0.01 level

Based on the results of table 3, we performed additional GWR-analyses to explore the spatial variation in the association of the density of Turks within 50 metre buffers with self-rated health of Moroccans. The map in Figure 1 shows some degree of spatial variation in this association, although most OR values were not significantly different from 1. In the district Nieuw-West, for example, the association of the density of Turks with self-rated health of Moroccans is more positive in the northern part of the district than in the southern part. In the district West mainly positive associations cluster and in East positive as well as negative associations were observed.

Figure 1. Association of percentage of Turks in buffers of 50 metres with better self-rated health of Moroccans (odds ratios)

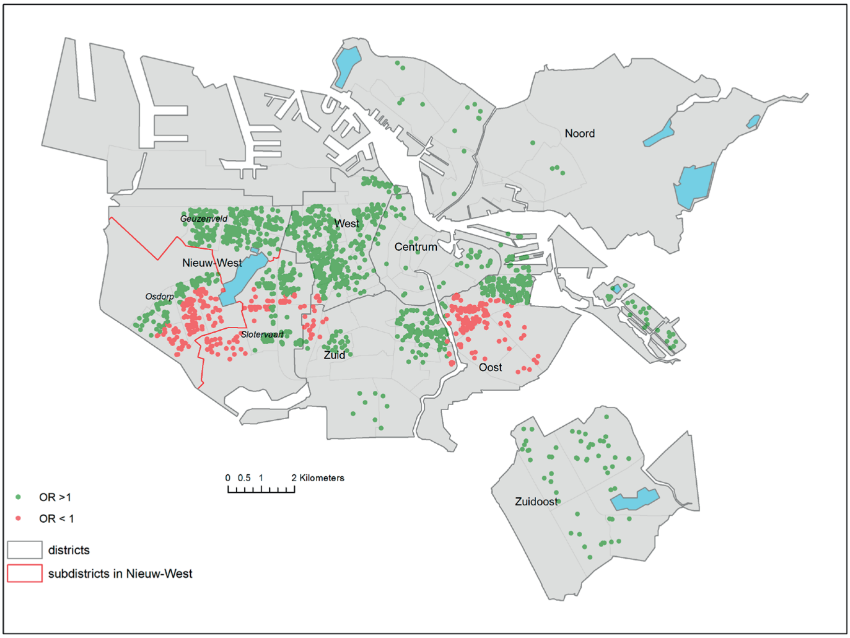

Table 5 assesses associations per sub-district in Nieuw-West. We stratified the additional MLR analyses by sub-district because the results of the GWR suggested variations at the level of sub-districts. We restricted the stratified analysis to Nieuw-West where most participants reside. Positive significant associations of density of Turks with self-rated health of Moroccans were found in the district Nieuw-West and mainly in the sub-district Geuzenveld. The density of Moroccans was significantly positively associated with self-rated health of Turks in Geuzenveld as well. For both groups, no significant association of own-group density with self-rated health was found in any district.

Table 5. Association of other- and own-group density within 50 metre buffer with better self-rated health, per ethnic group and sub-district

Ethnic group			**Moroccan Standardised OR[$] (CI[#])**		**Turkish Standardised OR[$] (CI[#])**	
Density of			Turks (%)	Moroccans (%)	Moroccans (%)	Turks (%)
(Sub-)district	N Mor	N Tur				
Nieuw-West	1238	1365	1.16 (1.00;1.35)*	0.93 (0.76;1.12)	1.03 (0.86;1.23)	1.10 (0.96;1.26)
Geuzenveld	433	626	1.39 (1.04;1.86)*	0.86 (0.62;1.20)	1.32 (1.02;1.71)*	1.05 (0.86;1.29)
Osdorp	388	383	1.11 (0.85;1.45)	0.97 (0.67;1.40)	0.87 (0.59;1.28)	0.99 (0.74;1.32)
Slotervaart	416	356	1.02 (0.76;1.37)	1.01 (0.70;1.45)	0.81 (0.53;1.25)	0.98 (0.72;1.33)

[$] OR represents the standardised odds ratio (i.e. change in odds with one standard deviation increase in the predictor variable)[#] CI represents 95% confidence interval

* significant at the 0.05 level

7.4. Discussion

In this study, we assessed associations between ethnic composition of the residential environment and self-reported health among people of Turkish and Moroccan origin living in Amsterdam. At the city-scale of Amsterdam, own-group density and ethnic heterogeneity were not associated with self-rated health for either Moroccan or Turkish participants. For Turks significant associations between ethnic heterogeneity and PCS and MCS were found, suggesting more negative health outcomes with increasing heterogeneity. With regard to other-group density, for Moroccans, greater density of Turks was significantly associated with higher odds of reporting better self-rated health and higher scores on PCS. Such associations were not found for Turks.

Additional geographical analyses suggest that the relationship between the density of the other group and self-rated health varies within Amsterdam. Associations were particularly observed in the sub-district Geuzenveld within the district Nieuw-West. In this specific area, other-group density is positively associated with self-rated health for both groups.

Evaluation of data and methodology

A major strength of our study is that the HELIUS data provides a large number of participants from different ethnic groups and detailed health measurements and socio-demographic data. We further derived precise data about place of residence using the 6-digit postcode of the home addresses of the participants, and we accessed detailed socio-economic and demographic data from registries at the level of 6-digit postcodes. On average, 6-digit postcode areas in Amsterdam include no more than 10 to 20 households and are sized 50 by 50 metres. The large number of participants and information on their precise place of residence enabled us to use advanced geographic techniques to explore varying associations within the city. The importance of using environmental variables at small spatial scales derives from the fact that most of the significant associations were found at small spatial scales. It suggests that no associations could have been demonstrated if the environmental characteristics of administrative areas were used because these areas may be too large to detect any health effects.

This study has some limitations as well. First, because buffers partly overlap, observations are not entirely independent. This results in a slight overestimation of significance levels. However, this problem of partial overlap applies particularly to larger buffers and less to smaller buffers, for which we found the most significant associations. Second, because our data are cross-sectional, our interpretations ought to refer to associations rather than to causal relationships. Nevertheless, we might interpret these associations as evidence for environmental influences on health. Reverse causality should refer to selective migration, which in our study would imply that healthy Moroccans would move to places with a lot of Turks or unhealthy Moroccans would leave such areas, which is not very plausible. Third, since we focused on two specific ethnic minority groups living in Amsterdam, our findings could possibly not be generalized to other populations or areas. Nonetheless, numerous large European cities have large migrant populations from Turkey and Morocco, so our findings might have relevance for these cities as well. Finally, PCS and MCS have not been validated among Turkish and Moroccan participants. However, these instruments have been positively validated across other cultures and countries [21-22].

Our conceptualization of the residential environment, buffers, can be associated with two discussions in the research field, referred to as the 'local trap' [23] and the 'residential trap' [24]**.** The local trap refers to the question whether the local scale is the best scale for analysis and the residential trap refers to the neglect of other environmental context besides the residential context. Because we use different buffer sizes in our study, we could evaluate the local trap problem. In fact, the results imply that this problem is not so relevant on our cases, as the strongest associations were observed in the smaller buffers.

With regard to the residential trap, we admit that other environmental contexts are also important in determining people's exposure to the own and other ethnic groups. To improve our understanding of the influence of other contexts, future research could try to combine different environmental contexts based on activity spaces. Activity spaces can be separated into domains such as a residential, transportation and work domain and for each domain the exposure to a certain environmental characteristic, for instance ethnic diversity, can be measured. Finally, the effects of the three exposure variables on a health outcome, such as mental health, can be assessed. This may yield new insights.

Interpretation and comparison with previous studies

For Turks and Moroccans in Amsterdam we did not find associations of own-group density with self-rated health, PCS or MCS. These findings are not in line with 'classic' ethnic density theory which suggests better health if a high proportion of the own ethnic group lives in the neighbourhood. This positive influence on health is presumably due to increased social support and less discrimination if your own group lives around [25-28]. Several studies in the US and UK found effects of own-group density on health, sometimes positive [9, 29, 30], but sometimes negative [31-33]. However, similar to our results, Schrier et al. [12] found no association between own-group density and psychological distress for Surinamese, Turks, and Moroccans in the four largest Dutch cities (including Amsterdam).

The absence of an ethnic own-group density effect especially among Turks is surprising considering that the Turks are known as a group with a strong orientation towards their co-ethnics. It might be explained by segmentation within the Turkish community. Turks are a heterogeneous group, divided along often crosscutting lines associated with political, ethnic, religious and geographical differences [34]. Our measure for own-group density, which is based on the country of birth of the participants or their parents, may fail to comprehensively capture the own-group effects. If the subgroups would have lived entirely segregated, an own-group density effect for the Turkish participants might be expected. However, probably the subgroups live mixed because most of the Turks and Moroccans depend on social housing which means little room for own choice regarding place to live [35]. Unfortunately we miss the essential accurate information about the home location of subgroups for further examination.

The negative influence of ethnic heterogeneity on PCS and MCS among Turks accords with conclusions of Putnam's study in the US [36] which suggested worse health conditions in heterogeneous neighbourhoods because of lower social capital in these neighbourhoods. For the Netherlands, Lancee & Dronkers [37] also found that more heterogeneous neighbourhoods are characterized by less social capital. However, our study did not find a negative effect of heterogeneity among Moroccans. Recently, it has been suggested that Putnam's theory may not be generalizable to all ethnic groups [38], but depend on ethnic group identities and specific inter-group relations. In Amsterdam, for Turks a heterogeneous environment might be experienced as negative, because Turks are known as a group with a strong orientation towards (some of) their co-ethnics. Moroccans are known to have lower levels of co-ethnic cohesion [39]. Hence it could be suggested that Turks rely more on 'bonding' social capital (relations within the own group), while Moroccans may find it easier to link with other ethnic groups and thus rely on 'bridging' social capital (relations with other groups).

We found a positive influence of density of Turks on self-rated health of Moroccans. A previous study, based on a smaller survey among six ethnic groups in Amsterdam [13], found a negative influence of the density of Moroccans on self-rated health of Turks. Although the findings of the two studies are not identical, both imply that co-residence with Turks has no negative effect on self-rated health of Moroccans, and the Moroccans have no positive effect on Turks. This asymmetric relation might be explained by a lesser positive opinion of Turks towards Moroccans, partly because Moroccans are more stigmatized in Dutch politics and media than Turks [39, 40]. In such a context it is less favourable for Turks to be associated with Moroccans living in the same neighbourhood than vice versa. Another reason might be that Turks seems more oriented on the own group unlike Moroccans as already mentioned in the previous paragraph.

The positive influence of other-group density in the direct residential environment on self-rated health of both groups in Geuzenveld might be related to specific conditions in this area. Geuzenveld is an area with a relatively strong sense of community among Turkish and Moroccan inhabitants. Compared to other administratively defined areas in Amsterdam, Geuzenveld is smaller in size and the ethnic composition is dominated by only a few groups. Turks and Moroccans together comprise almost 50 percent of the population. This implies a relatively high degree of dependency and interaction between the two groups, with possibly stronger social support systems between these groups. This is reinforced by a low number of relocations and outmigration among ethnic groups in ethnic concentration areas such as Geuzenveld [41]. Moreover, the two groups may have forged stronger alliances with each other, given the context of strong tensions between ethnic minorities and those of Dutch origin in Geuzenveld [42], and relatively low socio economic position of Geuzenveld residents as compared to most other parts of Amsterdam [43].

Our findings may give some direction to policy aimed to improve urban health. The health effects of residential ethnic composition we found in this study reveal generally at small spatial scales and varied within the city. This suggests that to improve urban minority (self-rated) health, area-based local interventions are more appropriate than global city-wide interventions; health benefits will be larger if interventions are adjusted to specific problem locations. For instance, in areas with negative associations between other group density or heterogeneity and health, policy interventions could aim to increase interactions and social cohesion at the very local level.

Conclusion

Our study suggests that in studies on the influence of neighbourhood ethnic composition on health three aspects are important. First, other-group density, the density of a specific ethnic group, deserves attention aside from common measures such as own-group density and ethnic heterogeneity. Additionally, it is important to use area measurements at small spatial scales. Finally, to improve our understanding of the underlying mechanisms, it might help to examine the spatial variation in the relationship within urban areas. The relationship between ethnic composition and health may depend on specific local factors influencing relations and ties between ethnic groups.

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CHAPTER 8

Summary and Discussion

Individual characteristics cannot completely explain health differences between places. Remaining differences can be partly the result of environmental characteristics. The main objective of this thesis was to employ spatial methodologies with the aim to provide a more accurate identification of environmental determinants of health in Amsterdam. To avoid the problems associated with the use of administratively defined areas (section 1.3), we employed two spatial approaches in order to define more relevant neighbourhoods, i.e. the hotspot and the bespoke environment approach. Part I of this thesis presented studies on the use of hotspots, whereas Part II presented studies on the use of bespoke environments.

The research questions of this thesis were:

- Can the clustering of health problems into hotspots be understood by environmental characteristics of these areas?
- Are individual health outcomes associated with specific area characteristics, after controlling for known individual-level determinants of such outcomes?
- At what spatial scale do these area characteristics influence health outcomes?

This concluding chapter starts with a summary of the main findings of each chapter of this thesis. In the next section the methodological considerations relevant for the interpretation of the results are addressed. Furthermore, we reflect on our findings and present some interpretations of our key findings. Finally, policy implications are discussed.

8.1 Summary of research findings

We applied two approaches aimed at identifying area characteristics that are associated with health outcomes of interest. One approach was to look for the *location of specific unhealthy areas (i.e. hotspots)* and to explore which area characteristics might explain the location of these hotspots. The other approach was to look at effects of *exposure to a specific area characteristic* on health outcomes. All studies applying the latter approach assessed associations with health at different spatial scales.

In **chapter 2** a mapping methodology is presented which goes beyond the use of traditional boundaries by introducing ‘data-driven dynamic geographies’. In today’s highly diverse urban settings, the commonly used maps based on administratively defined areas with fixed boundaries are too inaccurate to provide urban managers with relevant information on geographic variability. The presented mapping methodology, which is incorporated in the online GIS application Regiomonitor Amsterdam, provides accurate geographical information of concentrations of several urban phenomena. The spatial objects that are identified, a type of hotspots, are 'data-driven'; i.e. these objects are determined by the data of the phenomenon under consideration. In chapter 2, this tool is applied to the fields of demography, socioeconomics, housing, and employment. In its current state, the tool can be used to identify spatial concentrations of important determinants of health, such as unemployment, and spatial concentrations of populations at risk, such as ethnic minorities and groups with lower socioeconomic position. We found that these spatial concentrations were much smaller than administratively defined areas and that their demarcations were completely independent of formal administrative boundaries. We conclude that this mapping methodology produces *effective neighbourhoods* that recognize the varying spatial scale at which different urban phenomena occur.

In **chapter 3** we applied the mapping methodology described in chapter 2 to identify hotspots of alcohol-related ambulance attendances in Amsterdam. We aimed to characterise the hotspots outside the high outlet density areas in the centre of the city by creating victim and temporal profiles of the incidents and environmental profiles of these areas. Compared to victims in high outlet density hotspots in the centre, victims in these hotspots were older, more often male and lived closer to the incident location. Furthermore, incidents in these hotspots were less likely to take place during the night and at weekends. The victim and temporal profiles guided our search for relevant environmental characteristics. We applied a mixed methods methodology in order to identify combinations of area characteristics that might be responsible for the relatively large number of alcohol-related health incidents at these specific locations. In-depth analysis of four hotspots showed different combinations of contributing environmental factors, including (a) public parks bordering deprived neighbourhoods, (b) dance event facilities close to a traffic black spot, and (c) residential services for disadvantaged groups near 'hang-outs'. In summary, we found that hotspots were observed at locations where several environmental factors cluster, particularly in more deprived areas.

Chapter 4 applied the hotspot methodology to investigate the influence of policy on alcohol-related injuries in Amsterdam. In 2009 a new alcohol policy allowed alcohol outlets in two of the five nightlife areas to extend their closing times with one hour. First we identified five hotspots of alcohol-related ambulance attendances. These hotspots overlapped with the main entertainment/'plein'- areas with high outlet densities. Next we compared trends and levels of injuries in hotspots located in areas with extended closing times (intervention areas) to trends and levels in hotspots in areas without extended closing times (control areas). We found that after implementation of the new policy, intervention areas showed a larger increase in the level of alcohol-related injuries than control areas [incidence rate ratio 1.34, 95% confidence interval = 1.12, 1.61]. This increase was statistically significant and largest for incidents taking place between 2.00–5.59 a.m., on weekend days, involving men, involving individuals aged 25–34 years, or that resulted in victims being transported to a hospital. We conclude that these analyses provide strong evidence that a 1-hour extension of alcohol outlet closing times substantially increased the number of alcohol-related injuries.

In **chapter 5** we assessed associations between the socio-economic environment and self-rated health in a cross sectional study. The socio-economic environment was described by the percentage of residents receiving a social benefit (unemployment or welfare), the percentage of social housing, and the average property value of dwellings. We used the bespoke environment methodology to define neighbourhoods, i.e. individually tailored GIS buffers around survey respondents, and we explored associations at different spatial scales, including very local ones (50 to 1500 meter radiuses). An association between self-rated health and socioeconomic factors was observed only when these factors were measured in buffers smaller than 200 meters. After controlling for all individual-level variables, statistically significant associations were found only for receiving social benefit (50 meter-buffers) and social housing (50- and 100-meter buffers). For social benefit stronger associations were observed, in buffers up to 300 meters, when restricting the analysis to more homogeneous buffers, up to a standardised odds ratio of 1.15 for homogeneous buffers of 50-meters. The results implied that if the share of neighbours living on social benefit increased, the odds of fair/poor health increased as well. No significant associations were observed in the larger buffers, irrespective of their degree of homogeneity. Scale effects proved to be highly important but potential boundary effects seemed not to play an important role. Administrative areas and buffers of comparable sizes came up with comparable area effects. We conclude that associations between socio-economic environment and self-rated health in Amsterdam can be observed only at a micro spatial scale.

Chapter 6 has a similar approach but focuses on a different area characteristic: neighbourhood ethnic composition. We examined the effects of three aspects of ethnic composition: own ethnic density, ethnic heterogeneity and the presence of a specific ethnic group (other than one's own group). Own ethnic density was associated with higher odds of reporting poor health only among Surinamese. Ethnic heterogeneity and self-rated health were not significantly associated for any group. Self-rated health was associated with specific combinations of ethnic groups mainly in the immediate surroundings of the place of residence. Among Turks, the presence of Moroccans was associated with poor self-rated health. Among non-western migrants, the presence of Moroccans and Turks was associated with poor self-rated health. Among Turks, Surinamese, and non-western migrants the presence of Dutch was associated with better self-rated health. In general, stronger associations were found at local scales. We conclude that in Amsterdam, self-rated health is not related to ethnic heterogeneity in general, but that the co-residence of some specific ethnic groups may influence health in negative or positive ways.

In **chapter 7** we further explored the relationship between ethnic composition and health in a study among Turks and Moroccans using another, larger dataset. Ethnic heterogeneity and own ethnic density were not related to self-rated health for both ethnic groups. Higher density of Turkish people was significantly associated with better self-rated health among Moroccan participants, with the most significant relations for small buffers. Higher ethnic heterogeneity was significantly associated with lower scores on PCS (Physical Component Score) and MCS (Mental Component Score) among Turkish participants (suggesting worse health). We found spatial variation in the association of the density of the other ethnic group with self-rated health of Moroccan and Turkish participants. For both groups, we found a significant positive association (i.e. higher density, better health) in the north-western sub-district Geuzenveld. In summary, we found that the association between ethnic composition and self-reported health among Turks and Moroccans in Amsterdam differed between the groups and varied within the city and that associations reveal mainly at small spatial scales. Specific local circumstances contributed to varying associations within the city.

8.2 Methodological considerations

A main strength of this thesis is that none of the studies used predefined neighbourhood boundaries. This was possible because we could use detailed socioeconomic and demographic data from registries at the level of six-digit postcodes, which is the smallest area of observation available, including no more than 10 to 20 households in urban areas. In combination with the application of GIS techniques, we were able to define small-scale neighbourhoods in flexible ways and characterize these areas using detailed geographic measurements.

In the introduction, we identified three problems associated with the use of administratively defined areas: scale, zonation and boundary effects. In this thesis, these problems were overcome by using the hotspot and bespoke environment approaches. When using hotspots, these problems are solved automatically, as size, shape and boundaries are 'data-driven'. In the bespoke studies scale effects were avoided by using varying buffer sizes. Boundary effects were avoided by defining the neighbourhood using buffers such that respondents were located in the centre of their neighbourhood. Zonation effects were avoided because the neighbourhoods studied (buffers) have the same shape and size for all respondents.

We found that especially scale effects may be important as the association between environmental variables and health outcomes appeared to depend on the spatial scale used. In most cases, the association was most evident at a highly local scale: the hotspots that we identified were relatively small in size, and the associations that we found using bespoke environments were generally strongest at small spatial scales. This underlines that the most frequently used administrative areas, which are of relatively large size, may be too large to accurately identify area effects.

Even though our work has some main methodological advantages, there are at least seven methodological issues that remain (partly) unresolved; these are discussed below.

First, most of our studies use quantitative methods. However, the nature and impact of some environmental factors cannot be adequately captured by the use of quantitative methods only, such as the local cultural or historical context, or specific local circumstances. In one of our studies (chapter 3) we applied a mixed methods approach to reveal such subtle environmental factors and to create complete environmental profiles of hotspots of alcohol-related incidents. Future qualitative research is needed to reveal important area characteristics which cannot be captured by quantitative research. Furthermore, qualitative research might improve our understanding of how combinations of area characteristics influence the health of residents and which mechanisms are engendered by different environmental profiles.

Second, although the bespoke environments approach is key in solving some profound problems associated with the use of administratively defined areas, the use of bespoke environments introduces other problems. An important one is that common multilevel models have difficulty in incorporating bespoke environments that partly overlap. In the case of overlapping buffers the assumption of completely independent observations of the area characteristics is violated. Ignoring this dependence results in a slight underestimation of the standard errors of the area effects, which can lead to slightly too optimistic conclusions about levels of significance of these effects. This problem is less important for the smaller buffers where we found the most interesting associations. In future research, this problem should be overcome by building upon recent advancements in multi-level techniques that aim to solve the problem of partly overlapping buffers (Owen et al., 2016).

Third, in our analyses, a respondent's exact location was not derived from the full exact address information (street name plus house number) but equated to the central point of the six-digit postcode area. As a result, the buffers around these respondents were not perfect from a geographically point of the view, thus resulting in suboptimal measurement of their bespoke environment. However, we think that this did not have serious consequences for our results because most postcode areas comprise relatively few addresses. To further increase accuracy of area measurements, information on respondents' full addresses is needed. Access to full address information would require strict procedures to protect the privacy of respondents.

Fourth, the studies using the bespoke environment approach focused on the influence of the residential environment on health. However, the health status of people can be influenced by many different environmental contexts besides their residential environment. Their routes of travel, the places they visit (for example work or school), and the time they spend at these different places are also important in determining their exposure to specific environmental influences such as noise (Kwan, 2012). As a result, observed associations between health and the characteristics of the residential environment may be affected by the extent to which the residential environment deviates from other environments that people are exposed to. This problem is referred to as the so-called Uncertain Geographic Context Problem (UGCP) (Kwan, 2012). To address this problem, future research could aim to combine different environmental contexts. The concept of "*actual activity spaces*" may be useful in this context. Actual activity spaces comprise all locations where people stay. GPS technology can be used to collect data on locations visited and the time spent at these locations. It could be interesting to separate activity spaces into domains such as a residential, transportation and work domain. Then, for each domain the exposure to a certain environmental characteristic, for instance ethnic diversity, can be assessed. Based on these three scores a typology of exposure profiles can be created and applied to each individual.

Fifth, there is uncertainty regarding the shape of the residential environment. For some people the perceived residential environment will not be a circle but a long narrow rectangle, the street in which they live. These people are not influenced by characteristics of the circle but by the characteristics of the rectangle. To improve our knowledge regarding the usefulness of buffers, it would be interesting to study characteristics of perceived neighbourhoods, especially the shape and average size and how these aspects relate to circles and different buffer sizes.

Sixth, our studies do not pay attention to residential histories of people. Exposure to factors in the residential environment will change as people change address. This mobility makes it difficult to determine whether exposure measurement should focus on the environments in the current neighbourhood or in past neighbourhoods (Owen et al., 2016). Studies on socioeconomic outcomes found that exposures in the most recent environment had most impact on people's income and employment. Exposure to a certain neighbourhood in the past has diminishing effects, i.e. smaller effects when an exposure happened further back in time (Musterd et al., 2012). For health, the importance of past environments will differ according to health outcome and type of exposure. It can be hypothesized that effects of ethnic composition or noise on mental health may rapidly disappear after moving to a new environment, while the effect of other exposures, for instance air pollution, may be manifest until many decades after migration. The creation of datasets that combine longitudinal measurement of residential histories with exposure data at small spatial scales will enable future studies to include residential history in fine-grained geographical analyses. Although we addressed the consequences of people changing address, comparable remarks apply to the situation in which characteristics of the neighbourhood change.

Seventh, we must recognize that observed associations between area characteristics and health outcomes may not just reflect causal effect of the environments, but they might as well reflect selection effects. Residents may be selected into neighbourhoods based on individual characteristics that are themselves also important to health (Owen et al., 2016). For example, unhealthy persons belonging to an ethnic minority group may prefer to live among co-ethnics for support, and to live near services that are tailored to their own culture and needs (e.g. doctors from their own ethnic group who speak their own language). Similarly, active elderly may want to move to neighbourhoods which facilitate their active lifestyle such as areas with much green space and bicycle lanes. Such residential self-selection based on health-related individual characteristics may result in association between health and neighbourhood characteristics. Therefore, causal inferences based on such association should be made with caution. Yet, previous Dutch studies (Van Lenthe et al., 2007; Jongeneel-Grimen et al., 2011) concluded that the geographical association between health and socioeconomic characteristics are not substantially influenced by selective migration flows. Moreover, in Amsterdam we think that selection effects may be restricted to residents with substantive purchasing power, because the housing market does not offer much choice regarding where to live for people with a low income.

Finally, we would like to stress that our findings relate to Amsterdam and that these findings cannot automatically be extrapolated to other cities. However, our key finding that associations can be identified at the very local spatial scale suggests that experiencing stress or support from neighbours might be one of the underlying mechanism. Therefore it is likely that this finding applies to other cities as well because this mechanism will operate similar in other cities. However, we do recognize the important role of local context, and the fact that associations observed at one place may not be observed elsewhere. A prime example from our own studies is from chapter 7 where we observed that the co-residence of specific ethnic groups is important to the health of Turkish and Moroccans especially in one specific district of Amsterdam.

8.3 Reflection on the main findings

The objective of this thesis was to employ spatial methodologies with the aim to provide a more accurate identification of environmental determinants of health in Amsterdam. Three additional research questions were posed. First, can the clustering of health problems into hotspots be understood by area characteristics? Second, are individual health outcomes associated with specific area characteristics? Third, at what spatial scale do these area characteristics influence health?

The studies in this thesis have shown that health may be most strongly related to environmental exposures in the direct surroundings of the house. Our hotspot approach revealed how some *area characteristics* and the local *policy context* may create a concentration of health problems within specific areas. The relatively small-scale hotspots of alcohol-related ambulance attendances illustrate the importance of circumstances/contexts at a very low geographic level. Our bespoke environment approach revealed that exposure to the *residential socioeconomic environment* and *ethnic composition* were relevant for self-reported health of (some subgroups of) the population and that the influence of these factors was in most cases strongest at small spatial scales, e.g in direct neighbouring streets.

We found that sometimes area characteristics only matter in combination with the presence of other area characteristics. E.g., we saw that the presence of a homeless shelter alone was not enough to create a hotspot of alcohol-related incidents, but only when it occurred within an anonymous environment with hang out areas. The influence of neighbourhood composition appeared to depend on other specific local circumstances as well. For example, we found that the influence of the co-residence of Turks and Moroccans on self-reported health differs within Amsterdam, and that its beneficial effect was reinforced within a district with a relatively strong sense of community.

In most of our studies, the observed association between health and characteristics of the residential environment was not strong. Generally, studies on neighbourhood effects on individual outcomes do not find large effects (Lupton, 2003). Individual health outcomes are the result of a combination of factors and it is generally acknowledged that the impact of environmental influences is modest as compared to influences at other levels (individual, household, network). However, unlike individual characteristics, such as gender, age and ethnicity, a lot of environmental characteristics can be changed in order to improve health conditions (Whitehead, 1995), for example, polluting industries can be moved and population compositions can be altered. Therefore, even the observation of small neighbourhood effects can be important.

It was not an aim of this thesis to investigate the mechanisms linking residential environmental to health. Yet, results of our studies may be interpreted to suggest that social cohesion is an important mechanism linking area characteristics to health. Social cohesion refers to a sense of community, with a focus on trust, shared norms and values, positive and friendly relationships, and feelings of being accepted and of belonging (Forrest & Kearns, 2001). Social cohesion influences health offering a source to mitigate the experience of stress and its negative influence on health, while it may enhance the positieve effects of social support. Similar to our study on alcohol hotspots, previous research found that the absence of social cohesion is an important precondition for hotspots of violence (e.g. Sampson et al., 1997). Observed associations were mostly found at very local scales. This suggests that social cohesion between people living close to each other is more important to self-reported health than social relationships with people living further down the street or neighbourhood.

If direct neighbours are the most important sources of stress and support, we may expect that people will try to optimize the level of social cohesion in their direct neighbourhood. Research has confirmed that individuals strive for homogeneity in their local environment in socio-economical, socio-cultural, ethnical and demographic terms (McPherson et al. 2001; Musterd et al 2016; Van Gent et al. 2017). This is reflected in higher probabilities of a residential move when the 'distance' between one's own position on these dimensions and the position of the neighbourhood is larger; and is also reflected in the fact that this distance usually has shrunk significantly after migration (Musterd et al 2016; Van Gent et al. 2017). This strive for local homogeneity emerges from two principles of relationship formation: homophily and proximity. Interaction between people is easiest if they share similar characteristics and if they live nearby, simply because it offers more conversation subjects and opportunities to meet (Neal & Neal, 2014).

8.4 Policy implications

An increasing number of cities aim to become a 'healthy city'. Our findings may give some direction to policies aimed to improve urban health.

The health effects of area characteristics studied in this thesis are generally found at small spatial scales, i.e. within specific hotspots and within residents' immediate environment. Furthermore we found that effects may vary within the city. These findings suggest that policy intended to improve urban health should think and act locally instead of globally. In fact, oftentimes policy makers should act *very locally*: not entire neighbourhoods but 'local pockets' should be the focus of attention and interventions. Environmental interventions may be more effective when adjusted to specific problem locations. In order for local policy to be effective, several conditions should be met.

First, 'very local acting' requires problem identification and monitoring. Therefore detailed information about the spatial distribution of health and health-related phenomena is needed. Maps of spatial concentrations derived from GIS applications that allow for such detail, such as the Regiomonitor Amsterdam, can be used to explore potential intervention areas based on health-related phenomena. For instance, spatial concentration areas of older people may require specific health promoting interventions in the neighbourhood, like improvement of safety in order to promote walking. Detailed geographical information on actual health conditions would be helpful to identify underlying causes such as specific combinations of adverse environmental exposures. For example, in areas with a concentration of people with overweight, special attention may be given to the role of environmental stress, food outlets and lack of opportunities for recreational physical activity. To date such small scale health information is not yet routinely available in Amsterdam. However, with some revisions, the mapping methodology applied in the Regiomonitor, could also be applied on survey data such as the

Amsterdam Health Monitor and registries of health insurance companies. As such, geographic health data can be combined with other register-based individual-level data, such as the social statistical database of Statistics Netherlands.

Second, it is important to integrate local urban planning and design. We found that spatial clustering of specific environmental characteristics was related to localised health problems. Policy interventions could aim to reduce negative effects of harmful clusters by removing one of the contributing environmental factors, for instance preventing comfortable anonymous places for drinking or using drugs in public places close to functions used by groups at risk. Similarly, the creation of healthy places requires close cooperation between planners and designers. For example, to encourage public parks to be used for physical acitivty purposes, the design of the park may play a crucial role. In order to simulate walking in the park among older people, the presence of sufficient comfortable benches may be important and to attract boot camps, runners and skaters in the evening during the winter period sufficient street lights are important. Safety will be an important environmental factor for most people in their decision to use the park . Safety can be increased by a well-advised mixing of specific functions (attracting other people resulting in 'eyes' in the park) and design (for example sufficient street lights in order to avoid dark spots).

Finally, our findings suggest that improvements in health might be achieved particularly by stimulating interaction between individuals living in the same street. More should be known about how interventions and programs can stimulate social cohesion at very local levels. At first sight, recent initiatives such as urban gardening seem to promote interaction and a sense of community. However, such initiatives have been found to increase social differences and thus to weaken social cohesion. For example, urban gardening is often initiated and used mainly by the more wealthy and white residents (Glover, 2004). More generally, health related initiatives may increase segregation rather then cohesion when norms regarding healthy living differ between sub-groups of residents, and when some groups tend to impose their norms upon others (Guthman, 2008).

Negative outcomes of initiatives which are expected to be positive might be explained by the spatial scale at which initiatives are being undertaken. The scale of the above mentioned initiative may not be sufficiently local and the target population too heterogeneous. Here again, the spatial scale may be the vital element and we argue that this should be a key focus of future research. If we know that a certain level of homogeneity may be helpful for building strong communities at the very local level, and that this would help creating healthier people, questions related to the scale at which residential mixing should be aimed for to realise other objectives, becomes highly relevant too. We recognise that this may conflict with policy efforts aimed at mixing the population, based on the assumption that this will enhance mutual understanding, 'integration' and respect for diversity. Recent work of community psychologists refers to this issue as the community-diversity dialectic: while residential mixing promotes respect for diversity by providing opportunities for intergroup contact, it prevents a sense of community by diminishing homogeneity (Neal & Neal, 2014). Perhaps local social homogeneity at street level can be combined with heterogeneity at slightly higher levels, creating more mixed, larger and less tight communities at a higher level of scale, perhaps the neighbourhood level, where people still see each other, meet when using services, and get together when they bring their children to school.

To conclude, environment matters to health. Creating healthy environments is an important part of policies aimed to improve the health of urban residents. While it is generally recognised that action at neighbourhood levels are important to reach this goal, our work goes one step further by pointing to the importance of working at the level of streets or blocks. It is at this highly local level where urban design and relations between residents may make a difference between healthy and unhealthy environments. A refined geographical identification of health problems and solutions may help municipalities to formulate integrated policies to improve the health and well-being of residents most in need.

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SAMENVATTING

De grenzen voorbij
Geografische aspecten van stedelijke gezondheid

In dit proefschrift wordt met een geografische blik naar gezondheidsvraagstukken gekeken. Het richt zich specifiek op omgevingsinvloeden op gezondheid in Amsterdam.

Op verschillende ruimtelijke schaalniveaus zijn geografische verschillen in gezondheid waarneembaar, zo ook binnen de stad Amsterdam. Die verschillen kunnen komen door individuele *kenmerken van mensen*; als oudere mensen vaker ziek zijn en er op bepaalde plekken relatief veel ouderen wonen, dan kan het individuele kenmerk leeftijd er de verklaring voor zijn.

Gezondheidsverschillen kunnen echter vaak maar deels worden verklaard door individuele kenmerken van mensen. Ook *kenmerken van de omgeving* kunnen een rol spelen. Dat worden contextuele verklaringen of effecten genoemd. Daarover gaat dit proefschrift. Contextuele verklaringen of effecten kunnen vele vormen hebben. De aanwezigheid van een stinkende en vervuilende fabriek, veel lawaai, criminaliteit of een groot aanbod ongezonde voeding kunnen je gezondheid negatief beïnvloeden. Maar ook de mensen die in je buurt wonen kunnen gevolgen hebben voor je gezondheid: van andere mensen kun je stress of juist steun ondervinden. Ook kunnen mensen je gezondheidsgedrag positief of negatief beïnvloeden: als veel mensen om je heen sporten, ga je misschien zelf ook eerder sporten en als veel mensen in je buurt roken ga je misschien zelf ook roken.

In dit proefschrift proberen we met behulp van geografische gereedschappen en micro data beter op het spoor te komen van '(on)gezonde' plekken en van mogelijke omgevingsaspecten die de gezondheid beïnvloeden. Kenmerkend voor de studies in dit proefschrift is dat de omgeving niet wordt gedefinieerd aan de hand van vooraf vastgestelde vaste administratieve gebieden. Op deze manier proberen we schaal- en grenseffecten te vermijden.

We hanteren twee benaderingen om relevante omgevingskenmerken te identificeren. De studies in **deel 1** van het proefschrift (hoofdstukken 2 tot en met 4) kijken hoe *'ongezonde' gebieden (hotspots) kunnen worden geïdentificeerd, waar ze liggen* en *waarom* ze daar liggen – c.q. welke omgevingskenmerken de locaties van de hotspots kunnen verklaren. De studies in **deel 2** (hoofdstukken 5 tot en met 7) kijken naar *effecten van blootstelling aan een specifiek omgevingskenmerk* op gezondheid.

Deel 1 – Hotspot benadering

Hoofdstuk 2 laat zien hoe je met behulp van micro data op zespositie postcode niveau en met Geografische Informatie Systemen (GIS) interessante, afwijkende micro-gebieden (hotspots) in kaart kunt brengen. De methodologie introduceert 'data-driven dynamic geographies'. Dergelijke gebieden trekken zich niets aan van formele, vaste administratieve gebieden, zijn veel kleiner en variëren in vorm en grootte, afhankelijk van het verschijnsel dat in kaart wordt gebracht. We laten zien dat de methodologie nuttige informatie oplevert omdat uitgegaan wordt van het voor een verschijnsel relevante schaalniveau. De methodologie wordt toegepast in een online GIS applicatie, de Regiomonitor Amsterdam. Momenteel is er nog geen gezondheidsthema structureel in het instrument opgenomen, maar indien geschikte data beschikbaar komen, kunnen op een dergelijke manier 'ongezonde' gebieden opgespoord worden.

In **hoofdstuk 3** worden hotspots gemaakt van alcohol-gerelateerde ambulanceritten in Amsterdam op basis van deze methodologie en wordt er gekeken welke omgevingsfactoren de locatie van de hotspots buiten de uitgaansgebieden kunnen verklaren. De studie laat zien hoe *een specifieke combinatie van omgevingskenmerken* kan zorgen voor het ontstaan van 'ongezonde' hotspots. Niet alleen de functionele omgeving is van belang maar ook de inrichting van de openbare ruimte en sociale controle spelen een rol; een daklozenopvang alleen is niet voldoende om een hotspot te doen ontstaan. Verder suggereert de kleinschaligheid van de hotspots de belangrijke rol van *zeer lokale omstandigheden*.

Hoofdstuk 4 beschrijft een experimentele 'controlled before and after' evaluatie waarin hotspots van alcohol-gerelateerde ambulanceritten in de uitgaansgebieden van Amsterdam met elkaar worden vergeleken. Er wordt onderzocht wat het effect is van het verruimen van de openingstijden met 1 uur van horecagelegenheden in een aantal van deze hotspots. De studie toont aan dat deze beleidsverandering leidt tot een extra stijging van alcohol-gerelateerde incidenten met 34 procent in de betreffende hotspots.

Deel 2 – Blootstelling via 'bespoke environments' benadering

De hoofdstukken 5 tot en met 7 kijken naar *de samenhang tussen blootstelling aan een specifiek omgevingskenmerk in de woonomgeving* (sociaaleconomische positie en etnische compositie) en gerapporteerde/ervaren gezondheid. Een belangrijke vraag in dergelijke studies is hoe de woonomgeving gedefinieerd moet worden. Vaak worden administratieve buurten gebruikt, maar dat levert een aantal problemen op. Die administratieve buurten zouden te groot kunnen zijn om bepaalde omgevingseffecten te kunnen meten en mensen die aan de rand van een buurt wonen zouden weleens veel meer gericht kunnen zijn op een aangrenzende buurt dan de eigen buurt waardoor de aan deze respondenten toegeschreven omgevingskenmerken niet relevant zijn. Daarom maken de studies in dit proefschrift geen gebruik van administratieve buurten om de woonomgeving te definiëren maar worden er buffers ('bespoke environments') van verschillende grootte om respondenten heen gemaakt. Buffers zijn flexibel in grootte en plaatsen respondenten altijd in het midden van hun woonomgeving. Voor die verschillende buffers worden nauwkeurige omgevingsmaten berekend op basis van data met betrekking tot de complete populatie op het allerlaagste schaalniveau van zespositie postcodes. Met behulp van (multilevel) regressieanalyses wordt de samenhang van die omgevingsmaten met gezondheid bepaald op verschillende schaalniveaus en controleren we voor relevante individuele en omgevingskenmerken.

Hoofdstuk 5 presenteert een studie naar associaties tussen de sociaaleconomische omgeving en ervaren gezondheid in Amsterdam. De sociaaleconomische omgeving is geoperationaliseerd via het percentage mensen met een uitkering, het percentage sociale woningbouw en de gemiddelde woz-waarde. We zien dat het percentage mensen met een uitkering net iets belangrijker is dan het percentage sociale woningbouw en dat de gemiddelde woz-waarde het minst belangrijk is. We concluderen dat significante associaties alleen waarneembaar zijn op het microniveau van 50 en 100 meter buffers. Daar geldt dat als het percentage mensen met een uitkering of het percentage sociale woningbouw toeneemt, de kans op slechte gezondheid ook toeneemt. Buffers en administratieve omgevingen van vergelijkbare grootte bleken vergelijkbare resultaten op te leveren. Dit geeft aan dat schaaleffecten heel belangrijk zijn, maar grenseffecten niet.

Hoofdstuk 6 beschrijft associaties tussen de etnische compositie van de woonomgeving en de ervaren gezondheid van zes etnische groepen in Amsterdam. Etnische compositie is geoperationaliseerd via de aanwezigheid van de eigen etnische groep, etnische heterogeniteit en de aanwezigheid van een specifieke andere etnische groep. We concluderen dat er in Amsterdam geen verband is tussen ervaren gezondheid en etnische heterogeniteit, maar dat specifieke combinaties van etnische groepen invloed uitoefenen op ervaren gezondheid, met name op het lage schaalniveau.

In **hoofdstuk 7** wordt dit onderwerp verder onderzocht met een andere en grotere dataset. De focus in deze studie ligt op Turken en Marokkanen in Amsterdam.

We vinden dat de aanwezigheid van Turken geassocieerd wordt met een betere ervaren gezondheid van Marokkanen en dat dat omgekeerd niet geldt. De samenhang blijkt het sterkst significant in de kleinste buffers, dus in de directe woonomgeving. Bovendien vinden we ruimtelijke variatie in de samenhang tussen de aanwezigheid van de andere groep en de ervaren gezondheid van Turken en Marokkanen. Geuzenveld bleek een opvallend gebied; we vinden in dit deel van Amsterdam een positieve significante samenhang voor *beide* groepen.

Conclusies van het proefschrift

De omgeving heeft invloed op gezondheid. In het algemeen zijn de gevonden samenhangen niet heel sterk maar in een aantal gevallen wel significant. Resultaten suggereren dat beleidsinterventies om de gezondheid van bepaalde plekken of groepen te verbeteren lokaal gericht zouden moeten zijn en niet stad-breed. De studies laten zien dat zelfs de buurt niet lokaal genoeg is en dat straten en straatblokken een beter schaalniveau zijn voor interventies. Op dit hele lokale schaalniveau kunnen stedelijk ontwerp en contact tussen buren het verschil bepalen tussen 'gezonde' en 'ongezonde' gebieden. Micro data en ruimtelijke analyse technieken kunnen door het genereren van nauwkeurige geografische informatie helpen om effectief geïntegreerd gezondheidsbeleid te formuleren om zo de gezondheid en het welzijn van de meest kwetsbare inwoners te verbeteren.

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