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Food deserts? Healthy food access in Amsterdam

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ABSTRACT

Healthy food environments are imperative for public health. Access to supermarkets that offer wholesome food products at low prices varies across space and over socioeconomic status and ethnic neighborhoods. This research examined food inequalities in Amsterdam, the Netherlands. Supermarket accessibility was calculated and linked to property prices and the share of native Dutch people on a geographic micro-scale with a spatial resolution of 100 meters. Mann–Whitney tests and Spearman correlations were used to test differences and associations between accessibility, property prices, and the share of natives per area. The spatially explicit contextual neural gas approach was used for data clustering. The results show access differences in supermarkets in favor of areas with high property prices and those areas with a large share of native Dutch people. The correlations indicate that low-priced areas and those with a low share of native Dutch people have a lower supermarket density, but the results are the opposite when proximity to and variety of supermarkets are examined. The clustering revealed no evidence of undersupplied areas. Pronounced inequalities in access to healthy food could not be confirmed. On the basis of this analysis, there is no urgent need for policymakers to intervene in the geographies of supermarkets.

1. Introduction

Overweight and obesity have become pandemic and are considered global health challenges (Ng et al., 2014): 1.9 billion adults are now overweight, and 600 million of these adults are obese (WHO, 2015). These figures have doubled since the 1980s. The Netherlands is no exception to this trend: The proportion of overweight people increased between 1981 and 2013 from 22.9% to 31.5% (CBS, 2015), and that of obese people from 4.4% to 10.1%. This is alarming, because both overweight and obesity are closely associated with non-communicable diseases (e.g., diabetes, musculoskeletal disorders, and cardiovascular diseases) (Rubenstein, 2005).

Although the causes are complex and multifactorial, there are two major viewpoints concerning the epidemic pathway to overweight and obesity (Ball, Timperio, & Crawford, 2006). First, individuals are responsible for their own weight gain, food intake, and energy consumption. Second, it is assumed that external factors such as an obesogenic food environment[1] affect people's consumption behavior and diet (Ball et al., 2006; Glanz, Sallis, Saelens, & Frank, 2005). From the latter perspective, overweight and obesity are a normal response to an abnormal environment. Empirical results for the association between the physical food environment – here defined as the accessibility/availability of places that sell healthy food (i.e., supermarkets) in the local environment – and individual dietary intake or weight status are inconsistent (Black, Moon, & Baird, 2014; Caspi, Sorensen, Subramanian, & Kawachi, 2012; Cobb et al., 2015). Reviews (Beaulac, Kristjansson, & Cummins, 2009; Hilmers, Hilmers, & Dave, 2012) suggest that limited access to healthy food partially explains dietary inequalities across urban neighborhoods. Findings show that people living in neighborhoods with low socioeconomic status and those living in ethnic minority neighborhoods are more prone to unhealthy diets, compared to those living in high

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[1] Food environments refer to "the sum of influences that the surroundings, opportunities, or conditions of life have on promoting obesity in individuals or populations" (Swinburn, Egger, & Raza, 1999, p. 564).

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socioeconomic status neighborhoods (e.g., Ball, 2015; Cummins & Macintyre, 2006; Moore & Diez-Roux, 2006; Van Lenthe & Mackenbach, 2002; Walker et al., 2011; Zenk et al., 2005).

Those areas with inadequate access to food outlets offering affordable and healthy nutrition (i.e., supermarkets), while being socially distressed, are metaphorically labeled "food deserts" (Cummins & Macintyre, 2002; USDA, 2016). Supermarkets serve as suppliers of healthy and fresh food, offering them at more competitive prices than smaller grocery stores (Zenk et al., 2005). In contrast, convenience stores and corner stores offer more low-nutrient food and a limited range of healthy and fresh products (e.g., fruits and vegetables) at higher prices. People living in food deserts increasingly consume the energy-dense nutrition that is readily available in smaller convenience stores, which influences their dietary choices (Cummins & Macintyre, 2002; Morland, Wing, & Diez-Roux, 2002; Walker et al., 2011). Areas with a disproportionately high number of convenience stores are labeled as "food swamps" (Hager et al., 2016; Taylor & Ard, 2015).

Studies dealing with the identification of food deserts typically rely on analytics supported by geographic information systems (GIS; McKinnon et al., 2009; Peng et al., 2017). The concept of accessibility (Guagliardo, 2004) is central in such analyses and refers to the ease of access from an origin to a destination. The origins are primarily represented as centroids of administrative units (e.g., census tracts; Leete, Bania, & Sparks-Ibanga, 2012; McCracken, Sage, & Sage, 2013; Sadler, Gilliland, & Arku, 2013; Lu & Qiu, 2015). As administrative units vary in size and shape, area-based approaches are under debate (Ver Ploeg, Dutko, & Breneman, 2015). Accessibility measures vary greatly in complexity and their selection has proven to be challenging (Burgoine, Alvanides, & Lake, 2013; Charreire et al., 2010; McKenzie, 2014).

Because there are myriad ways of operationalization, a single measure is rarely sufficient to represent supermarket accessibility holistically (Charreire et al., 2010). Thus, Apparicio, Cloutier, and Shearmur (2007) call for a multidimensional perspective obviating an oversimplification of people's access to retailers of healthy food as, for example, in McCracken et al. (2013), through a single measure. Such multidimensional indicators are based on a combination of proximity to, and density and variety of, supermarkets (Apparicio et al., 2007; Russell & Heidkamp, 2011; Wang, Qiu, & Swallow, 2014, 2016). For each measure, ad-hoc and less theory-driven decisions need to be made, such as whether to employ Euclidean or street network distances (Charreire et al., 2010). Oliver, Schuurman, and Hall (2007) and Apparicio, Abdelmajid, Riva, and Shearmur (2008) showed that the latter represent actual distances more precisely. Similarly, buffers based on straight-line distances tend to overestimate food store availability and do not impose mobility restrictions where man-made features (e.g., railways) serve as impediments (Oliver et al., 2007). There is no agreement in terms of buffer width, but distances of around 1000 meters are common (e.g., Apparicio et al., 2007; Charreire et al., 2010; Cushon, Creighton, Kershaw, Marko, & Markham, 2013).

Besides accessibility, food deserts are frequently discussed in tandem with vulnerable population groups (Beaulac et al., 2009; McCracken et al., 2013). Yet, studies show that ethnic minorities and/or low income groups have insufficient access to healthy food (Gordon et al., 2011; Morland & Filomena, 2007; Powell, Auld, Chaloupka, O'Malley, & Johnston, 2007; Zenk et al., 2005). In order to identify food deserts, both the accessibility and neighborhood characteristics (e.g., income levels; Shavers, 2007) are frequently grouped by means of descriptive approaches (e.g., quartiles), although conceptually this is overly simple (Leete et al., 2012). A statistically more sound analytical procedure is clustering. This analytical procedure groups multivariate data into smaller groups that have similar accessibility and neighborhood characteristics (Hagenauer & Helbich, 2013a).

Taken together, while empirical evidence for food deserts in U.S. urban landscapes is extensive (Beaulac et al., 2009; Taylor & Ard, 2015; Walker et al., 2011), findings for Canada are mixed (Larsen & Gilliland, 2008; Lu & Qiu, 2015; Smoyer-Tomic, Spence, & Amrhein, 2006). For example, Apparicio et al. (2007) and Gould, Apparicio, and Cloutier (2012) found that socioeconomically deprived neighborhoods have in fact better access to affordable and healthy food, while Larsen and Gilliland (2008) found the opposite for Montreal. Others, including Cushon et al. (2013) and Smoyer-Tomic et al. (2006), did not confirm an accessibility–socioeconomic association. Cultural, economic, and regulatory differences or the provision of affordable and wholesome food make it difficult to transfer results from North America to Europe (Cummins & Macintyre, 2006). Shaw (2012), for instance, identified some areas in Nantes, France, that have both poor access to food outlets and low socioeconomic profiles. For the UK, Clarke, Eyre, and Guy (2002) found food deserts in Leeds/Bradford and Cardiff in neighborhoods with low socioeconomic status; in contrast, Macdonald, Ellaway, and Ball (2011) concluded that no population groups are significantly disadvantaged in British cities as a result of the spread and densification of food outlets. Křižan, Bilková, Kita, and Horňák (2015) confirmed these findings of satisfactory access to healthy food across the residents of Bratislava, Slovakia.

Even though these studies contributed significantly to our understanding of food deserts, several shortcomings remain. First, although there is compelling evidence for food deserts in North American cities (e.g., Apparicio et al., 2007; Larsen & Gilliland, 2008), investigations for continental Europe are scarce (e.g., Křižan et al., 2015; Shaw, 2012). Yet, to date, there is no research for the Netherlands. This is surprising for cities such as Amsterdam, where significant health disparities across neighborhoods are documented (GGD Amsterdam, 2013). Second, from a methodological point of view, studies largely remain at a coarse analytical level (e.g., census tracts) (e.g., Clarke et al., 2002; Cushon et al., 2013; Smoyer-Tomic et al., 2006). Inconsistencies in empirical findings might be caused by the way that geographic boundaries for neighborhood definitions are chosen (Barnes et al., 2016), whereas scale and zoning effects can be significantly reduced by employing at least aggregated data (Openshaw, 1984). Thus, local variations in food accessibility within a spatial unit call for micro-geographic analyses at a grid level. Third, with few exceptions (e.g., Apparicio et al., 2007), food deserts are rarely identified based on multivariate cluster analyses that group data objectively and coherently. Fourth, the review by Lamb et al. (2015) emphasized methodological flaws in most food desert studies (Wang et al., 2016). The fact that adjacent spatial units share similar attributes (i.e., are spatially dependent) is usually ignored, even though this has serious consequences for non-spatial statistical analysis, including clustering (Hagenauer & Helbich, 2013a). This calls the validity of the findings partially into question.

This research addressed the aforementioned shortcomings and was the first to investigate the associations between, on the one hand, the accessibility of supermarkets and, on the other hand, property prices and the share of native Dutch people (i.e., persons whose parents were born in the Netherlands) in Amsterdam, on a spatial micro-scale with a spatial resolution of 100 meters. Specifically, while also utilizing multivariate statistics, we used an innovative and spatially explicit clustering approach, namely contextual neural gas (CNG). An understanding of local food environments is an important first step toward combatting the increasing prevalence of population overweight and obesity (Ng et al., 2014). Our findings are essential for decision-makers to promote food equity and to formulate policies toward healthy food environments.

2. Study area and data

2.1. Study area

Amsterdam is the Netherlands' largest municipality (825,080 residents) (CBS, 2015). It was chosen for three reasons. First, approximately 40 percent of the residents are overweight, and 75 percent of the adults do not consume the recommended amount of fruit and vegetables (GGD Amsterdam, 2013). Second, the residents do not experience health problems equally. For instance, the health monitor reports that the prevalence of overweight and obesity differs significantly between ethnicities (e.g., Moroccan 60% vs. 35% Dutch). Third, there are distinct differences in overweight and obesity across space, with a higher prevalence in the central areas (22%) and a sharp increase toward the northern districts (34%) (GGD Amsterdam, 2013). These health inequalities are assumed to be translated into local food environments, which made Amsterdam ideal for this investigation.

2.2. Datasets

Following the majority of studies (e.g., Barnes et al., 2016; Križan et al., 2015; Larsen & Gilliland, 2008), we used supermarkets as food vendors offering a wide variety of healthy food. Supermarkets were defined as the standard grocery stores of the major chains operating in the Netherlands (e.g., Albert Heijn, Jumbo). Chain supermarkets have higher price competitiveness than small grocery shops (Zenk et al., 2005). Although organic supermarkets and farmers' markets provide healthy food (Lu & Qiu, 2015; Wang et al., 2014), their pricing is less competitive (Zenk et al., 2005). We thus excluded them from our analyses. “To go” stores were disregarded as they offer ready-to-eat products and are mainly located at places with high levels of commuter traffic.

The location of each supermarket was collected through the website of each chain. To avoid boundary effects (Van Meter et al., 2010), stores within a buffer zone of two kilometers around Amsterdam were taken into account. Of the 144 supermarkets considered, 122 are located within the administrative area. The store addresses were geocoded with the Dutch cadastral data “Basisregistraties Adressen en Gebouwen.” Fig. 1 shows the distribution of the supermarket locations.

To circumvent aggregation bias, scale, and zoning effects related to administrative areas (Barnes et al., 2016), this research conceptually followed Shaw (2012) in terms of using a grid representation but utilizing a more detailed spatial resolution of 100 meters. The grid was superimposed over the study area. Cells without any residents were excluded, resulting in $N = 5242$ cells. While Statistics Netherlands still provides socioeconomic data, such a microscale is already close to address-based analyses. Area-level socioeconomic characteristics were represented by a proxy variable reflecting the average value (in €1000) of all properties registered as residential (HOUS) within a cell for the years 2011 and 2012 (i.e., the higher the property prices, the higher the status; Fig. 2) (Braveman et al., 2005). Since neighborhood ethnicity was repeatedly associated with food deserts (Walker et al., 2011), the share of native Dutch people (NATI) within a cell for the year 2014 was also considered (Fig. 3). Both variables were available at an ordinal level.

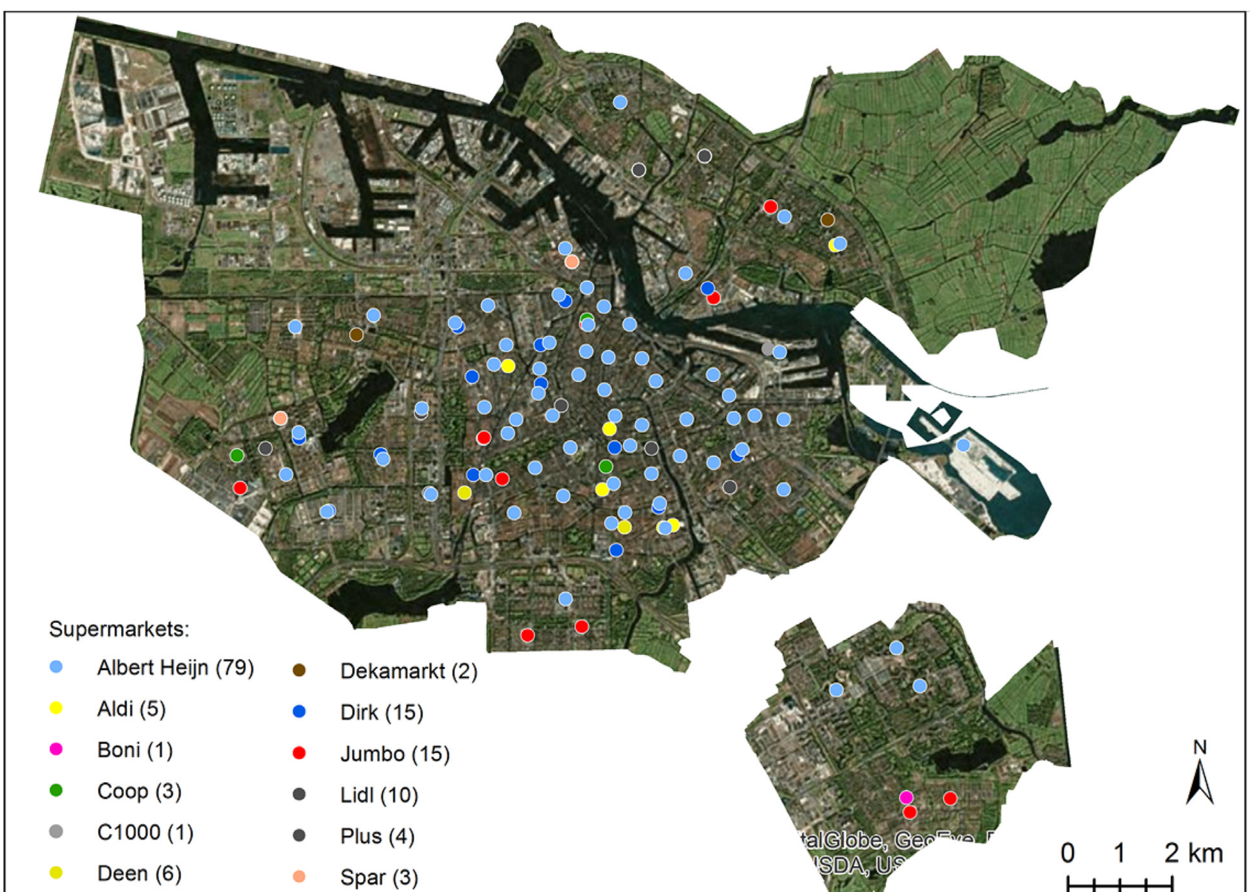

Fig. 1. Study area and the supermarket locations (in brackets: the total number of locations per supermarket chain within the buffered Amsterdam area; base map provided by ESRI).

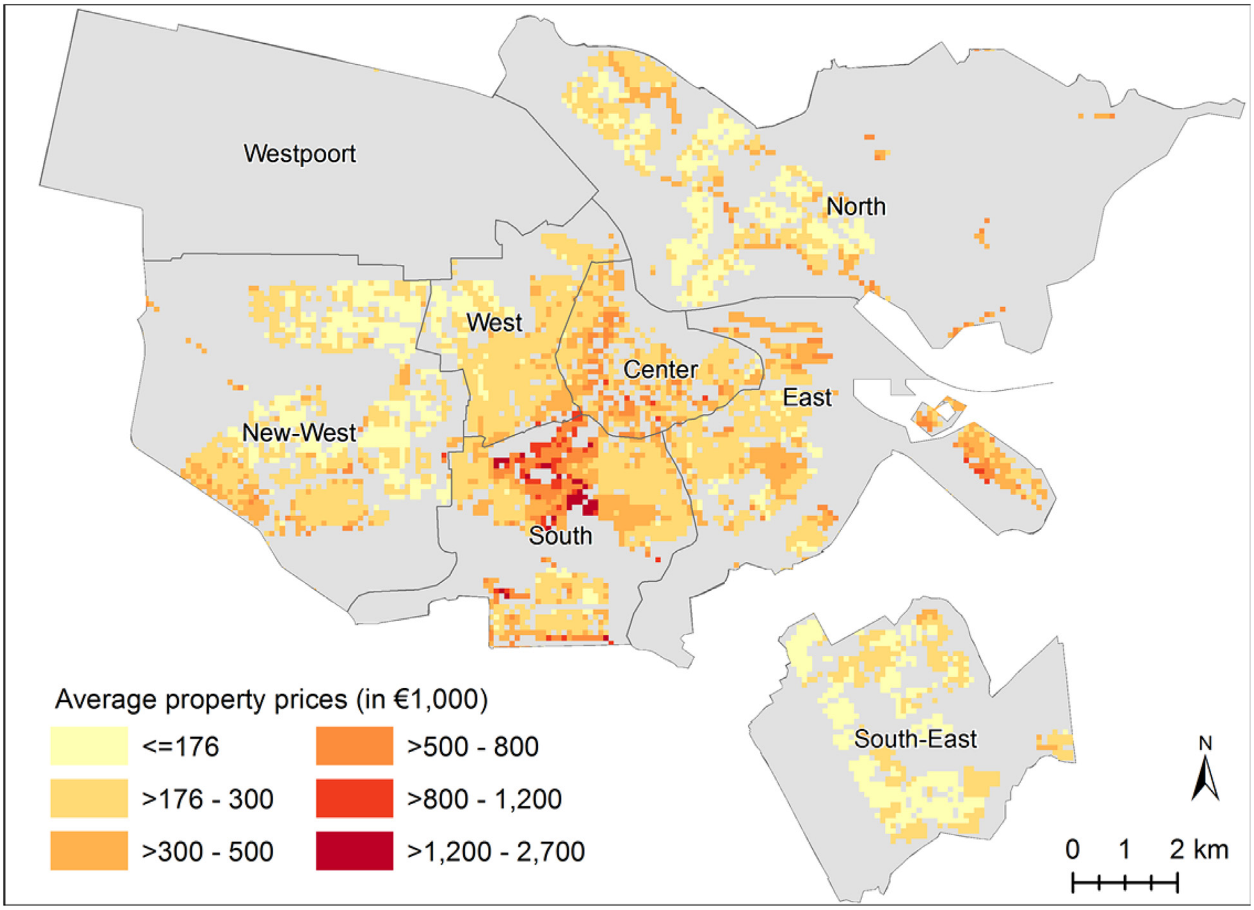

Fig. 2. Average property value per cell (in €1000).

3. Methods

3.1. Accessibility measures

Following Apparicio et al. (2007), Cushon et al. (2013), and Gould et al. (2012), the research design utilized the following three accessibility measures computed for each cell in a GIS using ESRI street data for the year 2008:

1) Proximity (PROX): This measure reflects the street network distance in meters from each cell centroid *i* to the closest supermarket *j* of any chain.
2) Density (DENS): This indicator represents the number of supermarkets *j* within a street network buffer around each centroid *i*. The threshold distance of 1000 meters (approximately a 12-minute walk for an adult in a city) was used, following previous studies (Charreire et al., 2010).
3) Variety (VARI): This measure represents residents' variety of choice in terms of both food products and prices, since not all supermarket chains offer the same goods at the same price (Drewnowski et al., 2014). Variety represents the mean street network distance from each centroid *i* to the three nearest supermarkets *j* from *k* different chains.

3.2. Statistical analyses

Key descriptive statistics were determined not only for each variable, but also for two stratifications representing neighborhoods with high/low property prices and a high/low share of native Dutch people, as in Lu and Qiu (2015). The threshold values were set through the lowest quartile of the property prices (€176,000). A neighborhood dominated by ethnic minorities was represented by a share of native Dutch people <40 percent. Non-parametric Mann–Whitney tests were conducted to establish whether both groups showed significant differences in accessibility. Bivariate Spearman correlations were computed to investigate the nature and magnitude of associations between the variables. Lamb et al. (2015) highlighted the importance of spatial autocorrelation for food accessibility studies, which has serious methodological consequences for statistics not explicitly developed for spatial data. To establish whether positive spatial autocorrelation (i.e., similar values are spatially close-by) was present, for each variable the Moran's *I* statistics with a neighborhood conceptualization based on an inverse distance weighting up to 1000 meters was utilized.

We employed the contextual neural gas (CNG) approach for data clustering (Hagenauer & Helbich, 2013a). CNG consists of a set of prototype vectors. Each prototype vector maps the input data (i.e., PROX, DENS, VARI, HOUS, NATI) that is most similar to it and, hence, represents a distinct cluster. In order to obtain a meaningful clustering, CNG must be trained. For this purpose, the input data are iteratively presented and the prototype vectors are moved toward the direction of the inputs. The magnitude of movement depends on the prototype vectors' ranking order, the neighborhood range, and the learning rate. The last two typically decrease with time. What distinguishes CNG from basic neural gas (Martinetz & Schulten, 1991) is its two-step procedure for determining the

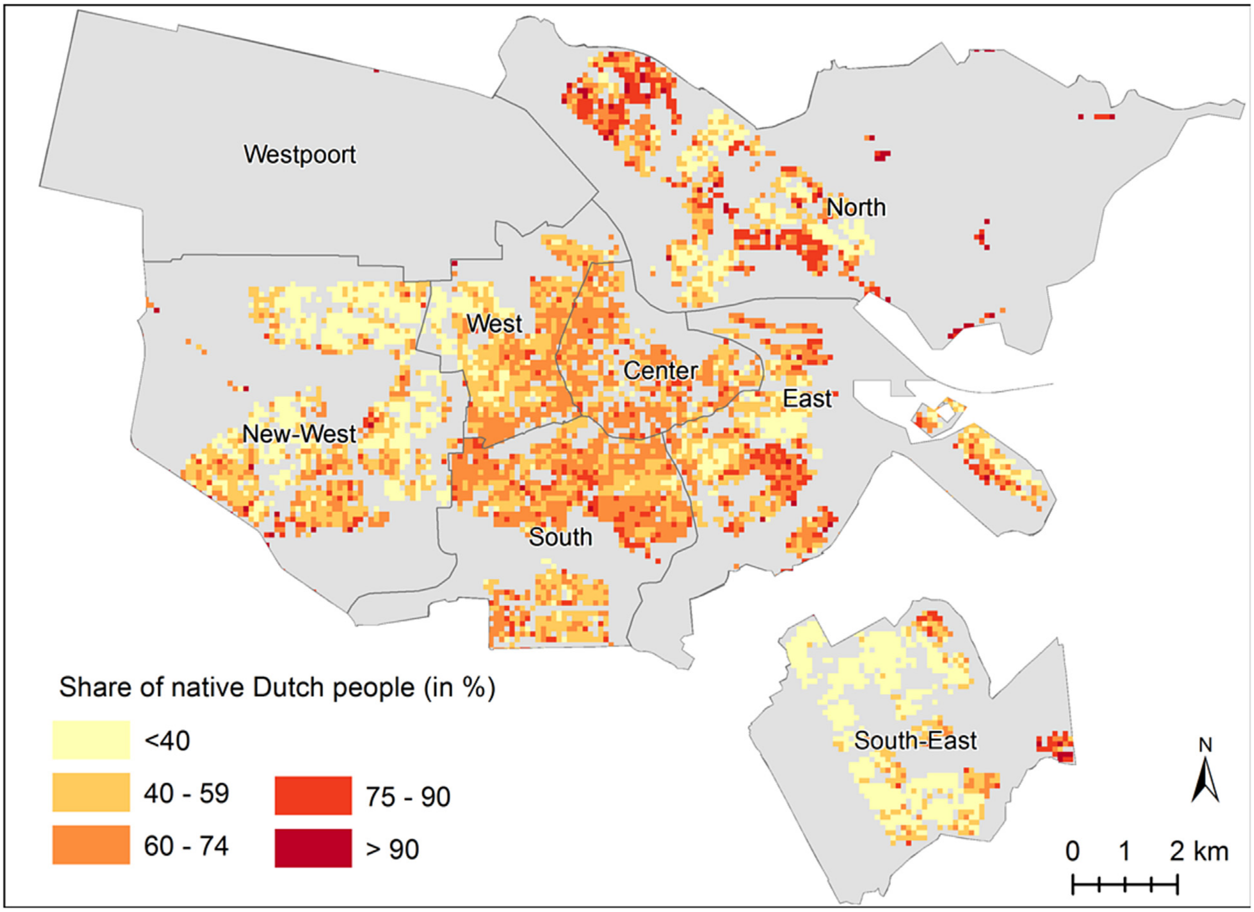

Fig. 3. Share of native Dutch people (in %).

rank ordering. This procedure is designed to take into account the spatial distance, besides attribute similarity. Briefly, first, the prototype vectors are ordered according to their spatial distance from the presented input data. Second, the first *k* prototype vectors of the resulting spatial ordering are reordered within their ranks with respect to attribute similarity. Thus, the smaller the chosen parameter *k*, the more the prototype vectors' rank order is determined by spatial distance and the more they will tend to approximate the spatial distribution of the input data after training. Generally, because the movement of the CNG's prototype vectors is not topologically restricted, the performance of CNG is superior to conceptually related algorithms based on self-organizing maps (Hagenauer & Helbich, 2013a). The CNG approach is implemented in the open-source toolbox called "SPAWNN" (Hagenauer & Helbich, 2016).[2]

4. Results

4.1. Descriptive statistics and bivariate analyses

Table 1 displays descriptive statistics. Of the 5242 cells, 25% showed low property prices, and 27% showed a low share of native Dutch people. Both conditions were fulfilled by 16% of the cells. To investigate accessibility differences across population groups, the indicators are stratified by low and high income and a low and a high share of native Dutch people. Cells with low property prices and a low share of natives had a median proximity of 629 meters, a median density of 2 supermarkets, and median variety of 1289.

Based on Mann–Whitney tests, cells with a low socioeconomic status (i.e., low housing values) are significantly further from the nearest supermarket ($p < 0.001$) and from three different chain supermarkets ($p < 0.001$), and have a significantly lower supermarket density ($p < 0.001$) compared to cells with high housing values. Similarly significant differences were found when the cells were split into a high/low share of Dutch people. The proximity, density, and variety measure showed significant differences ($p < 0.001$). Table 2 summarizes the results of the Spearman correlations. Among the accessibility measures, significant correlations ($p < 0.001$) were observed. Due to the identified spatial autocorrelation, these non-spatial analyses should be taken with care; however, they served as a rough indication of differences and associations between the variables.

4.2. Exploratory analyses

Exploring the spatial patterns of the proximity (Fig. 4), density (Fig. 5), and variety measures (Fig. 6), yielded two results. First, supermarket accessibility was best in the inner districts, which have a high supermarket density, namely at least three supermarkets within a walking distance of 1000 meters. The maps showed a concentric decline in accessibility toward the borders of Amsterdam in favor of the inner city. Second, the maps indicated similarities across the three measures. Cells having low proximity also

[2] SPAWNN can be downloaded via this link: https://sourceforge.net/projects/spawnn/.

Table 1
Descriptive statistics.

	Proximity measure (in meters)			Density measure (within 1000 meters)			Variety measure (in meters)		
	Not stratified	Low housing values	High housing values	Not stratified	Low housing values	High housing values	Not stratified	Low housing values	High housing values
5%	150	188	137	0.00	0.00	0.00	418	550	394
25%	349	421	329	1.00	1.00	1.00	707	857	664
Median	561	642	523	2.00	2.00	2.00	1068	1248	1011
Mean	685	735	667	2.65	1.65	2.99	1240	1333	1209
75%	891	971	861	4.00	2.00	5.00	1593	1768	1516
95%	1476	1541	1459	8.00	4.00	8.00	2530	2293	2674
Std. dev.	554	430	590	2.37	1.65	2.55	765	578	817
		Low share of native Dutch people	High share of native Dutch people		Low share of native Dutch people	High share of native Dutch people		Low share of native Dutch people	High share of native Dutch people
5%		185	137		0.00	0.00		552	391
25%		393	333		1.00	1.00		856	663
Median		615	539		2.00	2.00		1261	1002
Mean		677	687		1.87	2.95		1374	1190
75%		893	891		3.00	5.00		1805	1491
95%		1387	1527		5.00	8.00		2456	2562
Std. dev.		379	607		1.87	2.56		643	801

Note: A low housing values are ≤€176 (in €1000) and a low share of native Dutch people is <40%.

Table 2
Results of the Spearman correlations.

	Proximity measure	Density measure	Variety measure	Housing values	Share of native Dutch people
Proximity measure		−0.536	0.784	0.001	0.176
Density measure	0.000		−0.657	0.124	0.091
Variety measure	0.000	0.000		−0.031	0.041
Housing values	0.915	0.000	0.024		0.341
Share of native Dutch people	0.000	0.000	0.003	0.000	

The upper triangle shows the correlations and the lower triangle refers to the corresponding *p*-values.

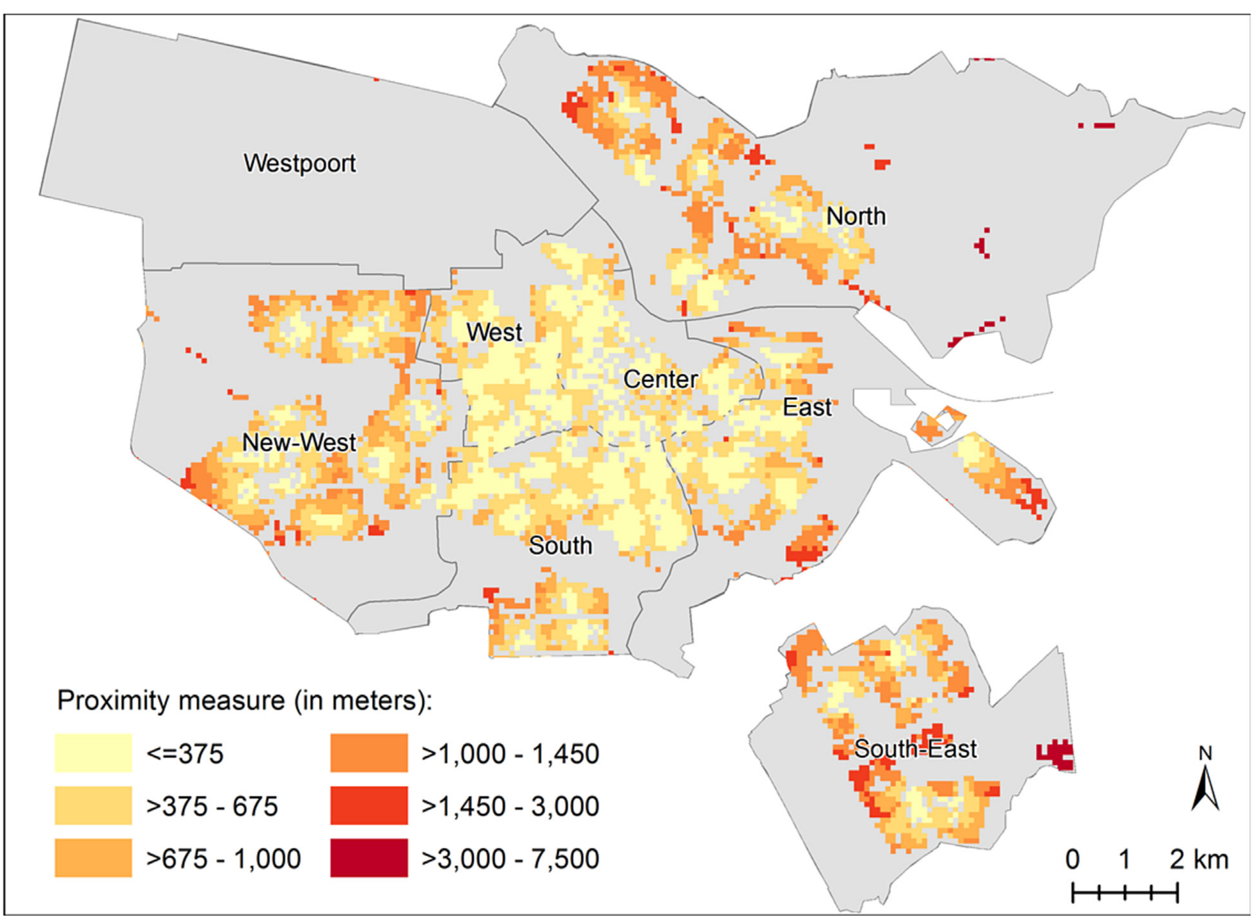

Fig. 4. Proximity to nearest supermarket per cell (in meters).

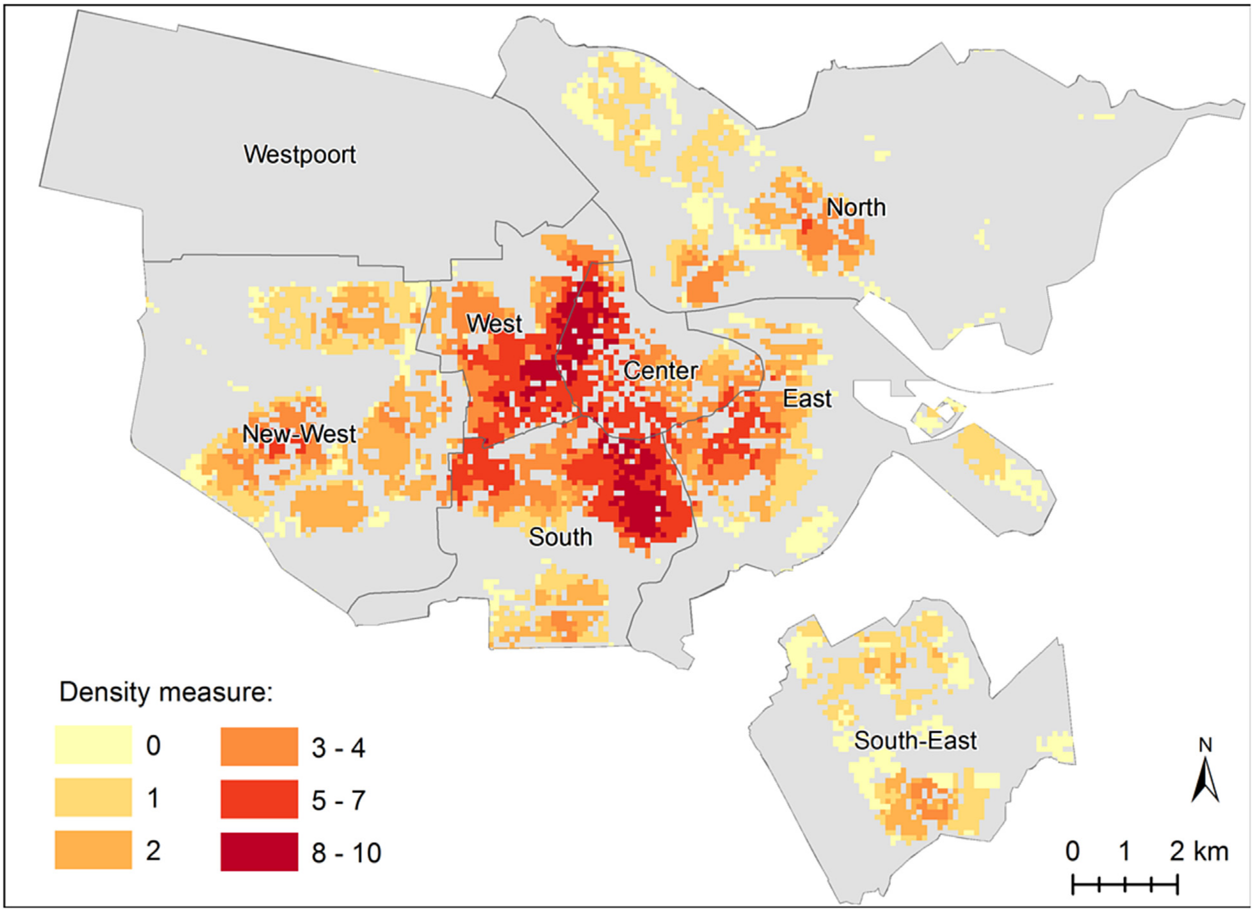

Fig. 5. Density of supermarkets within 1000 meters per cell.

showed a pronounced density and variety. Independent of the indicator, the areas Amsterdam North and Amsterdam South-East did not have adequate access to healthy food. Similar, but less clear, patterns emerged from Figs. 2 and 3. A concentration of high housing values appeared in the southern part of the inner city, while the share of native Dutch people was lowest in parts of Amsterdam New-West and Amsterdam South-East.

The Moran's *I* value for the proximity measure was, at 0.778, highly significant ($p < 0.001$). The same applies to the Moran's *I* of the density measure ($I = 0.797$; $p < 0.001$), the variety measure ($I = 0.912$; $p < 0.001$), the housing values ($I = 0.458$; $p < 0.001$), and the share of native Dutch people ($I = 0.410$; $p < 0.001$). Even though the strengths of the Moran's *I* values varied slightly with alternative neighborhood specifications, sensitivity analyses clearly confirmed a pronounced spatial grouping of values across the accessibility indicators. These results called for a spatially explicit clustering.

4.3. Clustering

CNG was trained with 9 prototype vectors and data were *z*-score transformed to the same range. The initial value for neighborhood range declined from 6 to 1 over time, and the learning rate from 0.2 to 0.005. The parameter *k* of CNG was set to 3 so that the resulting clusters were mostly spatially compact. For sensitivity tests, the CNG was trained with different parameters, but no differences were found.

The clusters (Fig. 7) show a rather compact spatial pattern, but they vary in size. Cluster 5 has the largest size and is located in the central areas; cluster 3 is the smallest one and is located primarily in peripheral areas. The boxplots (Fig. 8) characterize cluster 3 as a potential food desert. To be labeled such, cells must be coherent and have, in theory, the following properties: high proximity, low density, large distances from different supermarket chains (variety), low housing prices, and few native Dutch people.[3] While the latter was not fully in accordance with expectations, the remaining four indicators fitted. The mean proximity value was 883 meters (median: 634), the mean variety was 1517 meters (median: 1481), and the mean density was 1.36 supermarkets (median: 1). However, cluster 3 comprised only a few isolated cells located far from the city center.

5. Discussion

5.1. Key findings

The objective of this study was to gain insights into inequalities in healthy food access in Amsterdam, a city with pronounced differences in overweight and obesity. When discussing our findings in the context of other studies, it must be kept in mind that, as Cummins and Macintyre (2006) critically noted, cultural, economic, and regulatory differences among countries are reflected in food accessibility. This makes cross-comparisons challenging. Still, based

[3] Note that these food deserts criteria deviate slightly from the definition provided by the United States Department of Agriculture (USDA).

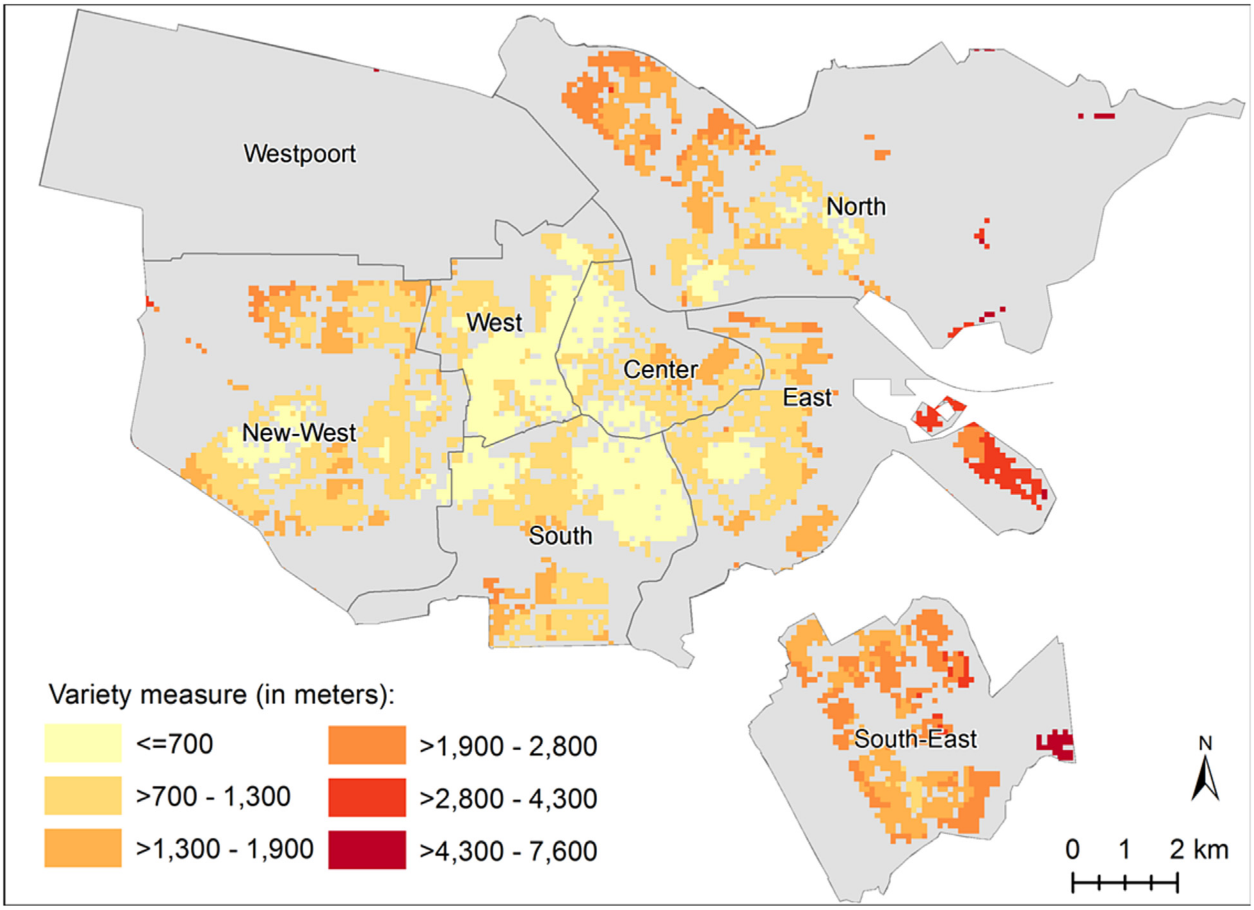

Fig. 6. Total distance (in meters) to the three nearest supermarkets from different chains per cell.

on our findings, a number of important conclusions can be drawn.

First, this study demonstrated the complexity of supermarket spatial accessibility. In the Amsterdam case, correlation analyses between accessibility measures referred to moderate associations, confirming that limiting accessibility to only one measure might be insufficient (Charreire et al., 2010). Only multiple indicators frame the comprehensive picture of supermarket accessibility, echoing Apparicio et al. (2007), Cushon et al. (2013), and Gould et al. (2012). Mapping the accessibility measures showed that especially in the city center, supermarkets were readily accessible independent of the considered indicator. A certain distance decay in accessibility was observed, with worse access toward the city edges. Smoyer-Tomic et al. (2006), for example, found a roughly similar pattern for the proximity measure in Edmonton, Canada.

Second, as opposed to other studies (e.g., Larsen & Gilliland, 2008), the proximity to the nearest supermarket was low (median: 561 meters). Good accessibility is important, because poor accessibility can be a critical barrier to purchasing healthy nutrition (Macintyre, 2007). However, even though the Mann–Whitney tests found significant disparities between the spatial accessibility, as well as between low and high property prices and the share of native Dutch people, the differences were far less evident when looking at the descriptive statistics. We therefore believe that the found discrepancy (i.e., a difference of approximately 120 meters for the proximity measure) has only marginal relevance for people's daily lives. The correlations of both the housing values and the share of native Dutch people were only partially in line with the initial food desert hypothesis (Beaulac et al., 2009). For instance, a counterintuitive positive correlation between housing values and proximity was found, which is an initial indication against food deserts, or a challenge to the utilized variables.

All accessibility measures were positively associated with the share of native Dutch people. This conclusion is in contrast to findings in the U.S. (Beaulac et al., 2009). Whereas Zenk et al. (2005) reported racial differences in favor of the white population over the African–American population in accessibility for Detroit, the opposite was true for Amsterdam, which has only a minor proportion of African–Americans. Our research did not find indications, unlike Burns and Inglis (2007) and Alviola, Nayga, Thomsen, and Wang (2013), that neighborhoods with a larger share of minorities (and that are less economically strong) have worse spatial access to healthy food. A potential explanation is that socioeconomic polarization and segregation fueled by income and ethnicity is more distinct in U.S. and Canadian cities (Moore & Diez-Roux, 2006; Smoyer-Tomic et al., 2006).

Third, because the interaction between the considered variables was more complex than bivariate analyses can reveal, spatial clustering was employed to pinpoint food deserts. The results showed differences in spatial accessibility and socioeconomic characteristic across Amsterdam, but these differences were less conclusive. We were able to identify individual pockets that showed some typical characteristics that are representative of food deserts. However, looking at the geographical extent, these areas comprised only a few, scattered, and isolated areas located in the urban periphery. Therefore, although these areas were problematic due to a lack of critical spatial extent and coherence, they should

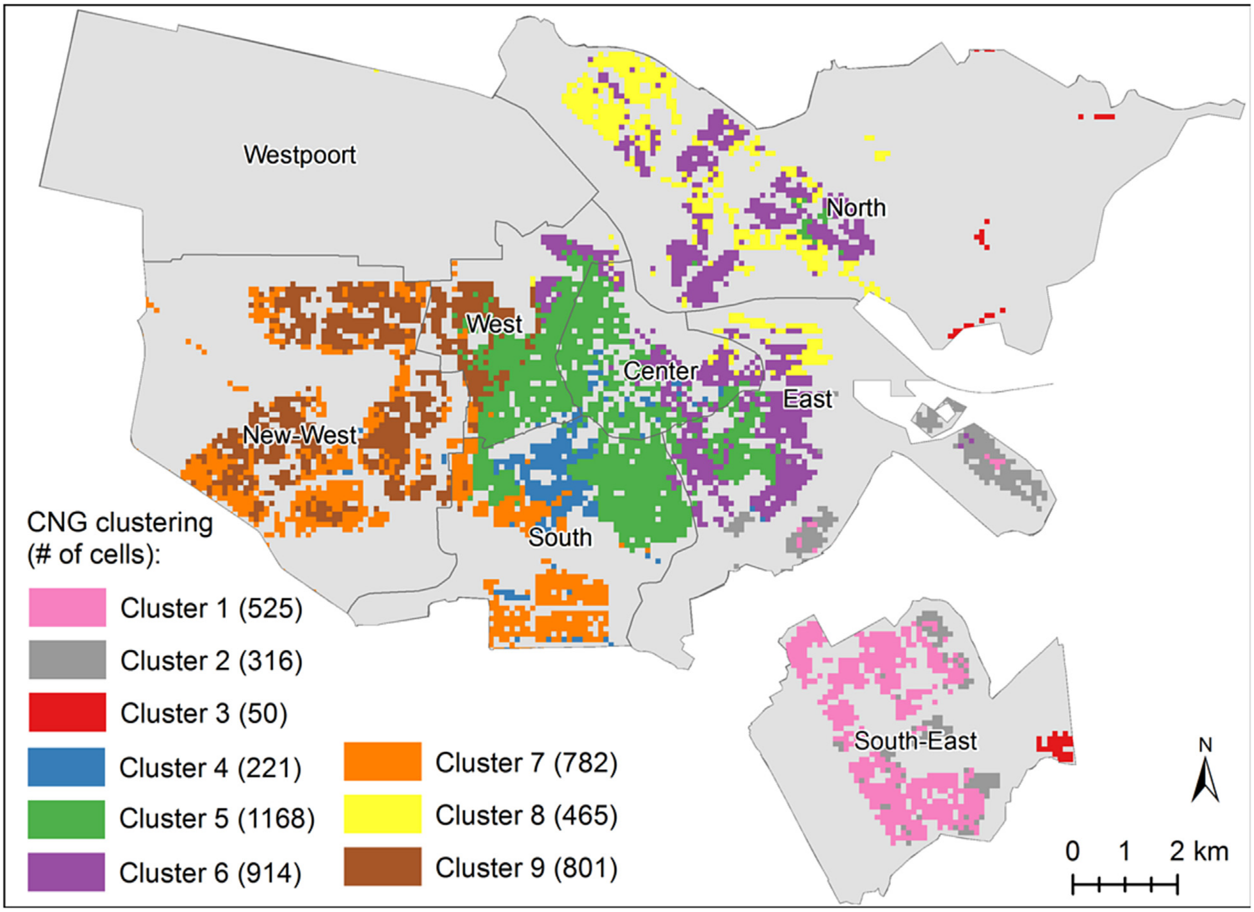

Fig. 7. Results of the CNG clustering.

not be labeled food deserts in the classic sense. A similar conclusion was reached by Cummins and Macintyre (2006) for Glasgow and Apparicio et al. (2007) for Montreal. Likewise, Križan et al. (2015) reported that most residents of Bratislava–Petržalka, Slovakia, live in areas where healthy food is readily accessible. In Amsterdam, poor access to supermarkets that offer healthy food was more prevalent in areas with a higher share of native Dutch people. As residential segregation is a more pronounced matter of concern in U.S. than in European cities (Van Kempen & Priemus, 1999), it was not surprising that several studies reported fewer supermarkets in lower-income and predominantly African–American neighborhoods (Walker et al., 2011; Zenk et al., 2005), while others did not (Morland et al., 2002). Reasons for the absence of food deserts in Amsterdam compared to North America include suburbanization in North America that eroded the inner-city supermarket accessibility in favor of "XXL stores" located on the edge of cities (this is also common in Europe, but to a smaller extent; e.g., Helbich & Leitner, 2009), different transport patterns (i.e., a more walking/cycling oriented society versus an automobile oriented society in North America) (Bassett, Pucher, Buehler, Thompson, & Crouter, 2008), a more well-balanced socioeconomic urban diversity in Amsterdam (Van Kempen & Priemus, 1999), and the stronger regulatory power of central and local governments in the Netherlands (e.g., strict zoning plans, social mix).

5.2. Policy implications

Better access to healthy and affordable food translates into an environment with increased opportunities to purchase and consume healthy products (Brug, 2008). As central governments and local municipalities are constantly searching for strategies to improve citizens' health, attention should be paid to food environments that could contribute to people's health. Our results for Amsterdam show that supermarkets are readily accessible via (health promoting) active transport modes such as walking and cycling. Past retail planning aimed for well-accessible supermarkets for urban residents in the Netherlands. These policies limited the growth of big supermarkets on the edge of Dutch cities (Bolt, 2003) and supported the absence of food deserts in Amsterdam. As the average distance from the closest supermarket in the Netherlands (~900 meters; CBS, 2015) is comparable to the average in Amsterdam (686 meters), we expect that food deserts are also absent from other urban areas in the Netherlands. Yet, we lack empirical confirmation of this.

Although fresh and healthy food is easily accessible, unhealthy foods are even more accessible and therefore dominate the availability of healthy alternatives. Therefore, the municipality of Amsterdam as well as public and private parties are implementing strategies to improve access to healthy food while reducing access to unhealthy products. Making high-quality food spatially more accessible is currently being investigated by the city administration through food-trucks selling fresh, organic, and sustainable food. Amsterdam put both nutrition and health prominent on urban agendas to counteract obesity in the city (Agenda Stad, 2016). In addition, the Municipality of Amsterdam (2016) is going to implement strategies aimed at,

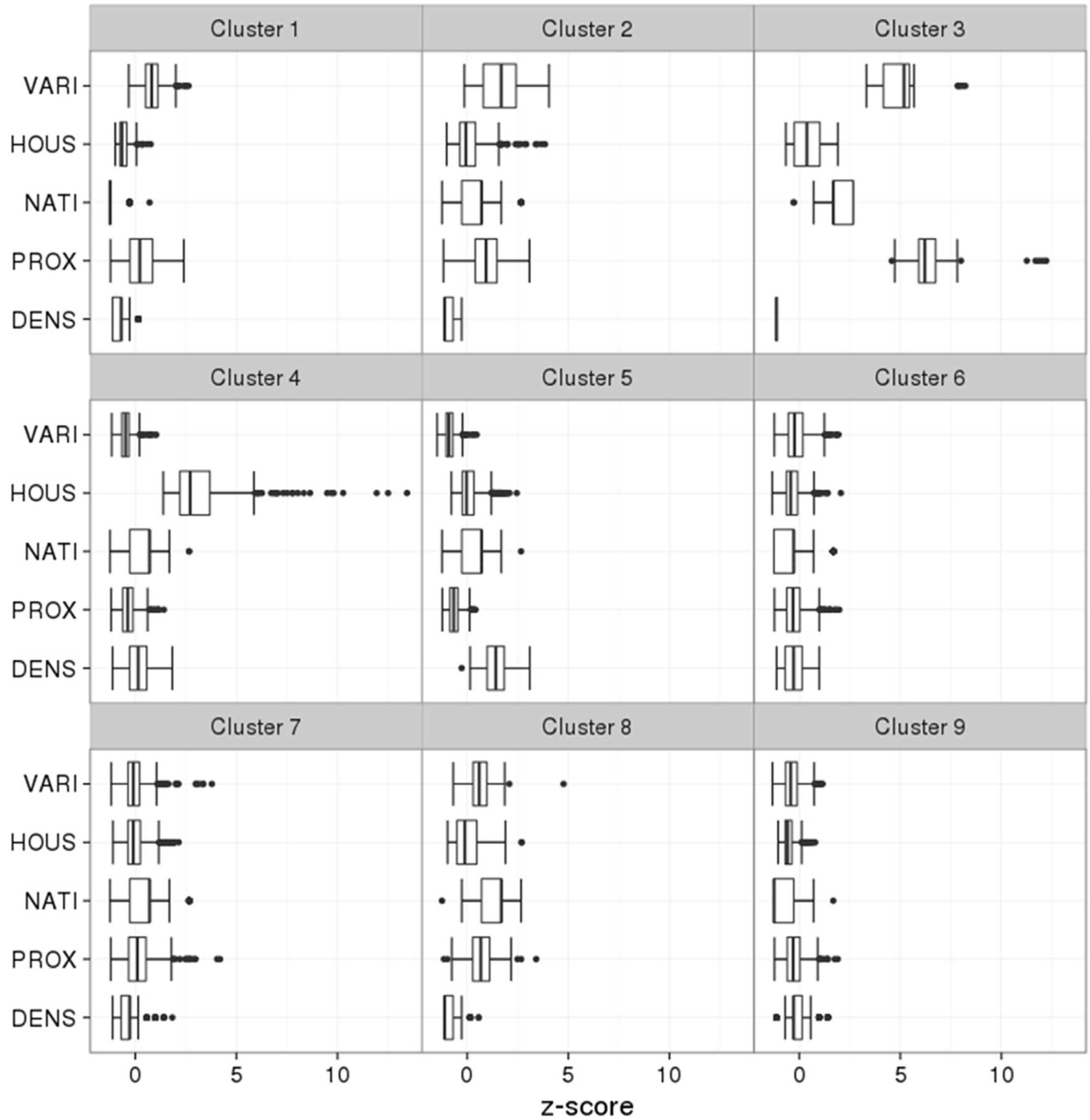

Fig. 8. Boxplots of the cluster-specific characteristics.

for example, banning food marketing in public spaces, creating healthier food options in shopping squares, and promoting healthier work and college canteens. Environmental and policy interventions (e.g., food taxes, subsidizing healthy foods) that go beyond the spatial accessibility of healthy food are also recommended to support healthy environments (Sacks, Swinburn, & Lawrence, 2009).

When a food desert is identified, policymakers often intervene by opening a new store. However, it is believed that this strategy is too shortsighted and does not improve the population's diet; multiple individual and environmental strategies seem more effective (Dubowitz et al., 2015). Furthermore, supermarkets are also a key source of unhealthy food containing high levels of sugar, saturated fat, and salt, although so far this has mostly been disregarded in the food desert debate. Consequently, it can be doubted that simply improving supermarket accessibility translates directly into improving the population's diet. It is likely that policies to improve dietary behavior should be directed to other factors that can lead to an unhealthy diet. From this viewpoint, policy agendas that guarantee access to healthy nutrition should be focused not only on lack of access to healthy and fresh food, but also on access to unhealthy food.

5.3. Strengths, limitations, and future work

This study was among the first to explore the existence of food deserts in Europe in general and, to the best of our knowledge, the first one to focus on the Netherlands. The accessibility indicators were computed along the street network, which is an improvement compared to Cushon et al. (2013), who simply used Euclidean distances (Apparicio et al., 2008). In tandem with multiple accessibility measures that reflect supermarket access more holistically (Charreire et al., 2010), a prime contribution of the research is that it went beyond arbitrarily defined spatial units, toward a grid representation at a geographical micro-level. This study is unique in that it successfully incorporated spatial autocorrelation in the clustering process through the CNG approach (Hagenauer & Helbich, 2016), otherwise biasing non-spatial methods — an issue stipulated by Lamb et al. (2015), but disregarded entirely in empirical studies (Apparicio et al., 2007). Finally, the underlying data are available in a data repository (Helbich & Hagenauer, 2017). This facilitates the application of alternative analytical approaches, serves as basis for follow-up studies, etc.

However, several limitations need to be acknowledged. Although the considered socioeconomic and ethnical variables are frequently reported, only a limited set of proxies were utilized because other theoretically sound variables were not available at the grid level. As Statistics Netherlands provided the socioeconomic and ethnical data at an ordinal level, we cannot exclude that the results are sensitive to the pre-defined class breaks. Like most food desert research (e.g., Križan et al., 2015; Lu & Qiu, 2015; Zenk et al., 2005), this study was restricted to a single timestamp. Longitudinal measures would allow an investigation of the emergence and disappearance of food deserts over time, which could be realized through space–time clustering (Hagenauer & Helbich, 2013b). We focused only on supermarkets. Particularly in Amsterdam, small stores selling ethnic groceries are important sources of healthy food. As such, the results may underestimate the overall exposure to healthy food, but also allow better comparability with other studies. No conclusions about individuals can be drawn. Further work is needed to grasp the associations between access to healthy food, people's food choices, and people's purchasing patterns (Fuller, Engler-Stringer, & Muhajarine, 2015). We cannot rule out people's temporal access constraints due to opening hours etc. (Chen & Clark, 2015; Widener & Shannon, 2014). Both issues call for individualized spatiotemporal food research in which access to healthy food at daily activity places outside the home is central (Kestens et al., 2012).

6. Conclusions

This was the first research on food deserts in Amsterdam carried out on a micro-geographic scale. The research also addressed spatial autocorrelation in the clustering when locating food deserts. The found accessibility differences among areas with high/low property prices and a high/low share of native Dutch people are primarily of a statistical nature, but are not seen as barriers to the purchase of affordable and healthy food by people residing in those areas. Although there is a decline in supermarket access along a central–periphery gradient, areas that have worse accessibility are not located in socially-distressed areas in ethnic minority neighborhoods. This conclusion is supported by the cluster analyses. The results suggest that only a few, spatially isolated areas have poor access to wholesome food supply, which de facto refutes the existence of food deserts in Amsterdam. Our findings are important for policymakers who wish to identify areas that are undersupplied with healthy food. For decision makers, however, we do not see an urgent need to intervene in the geography of supermarkets; nevertheless efforts to promote the consumption of healthy food should be maintained.

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