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A geo-big data approach to intra-urban food deserts: Transit-varying accessibility, social inequalities, and implications for urban planning

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A B S T R A C T

Urban studies attempt to identify the geographic areas with restricted access to healthy and affordable foods (defined as food deserts in the literature). While prior publications have reported the socioeconomic disparities in healthy food accessibility, little evidence has been released from developing countries, especially in China. This paper proposes a geo-big data approach to measuring transit-varying healthy food accessibility and applies it to identify the food deserts within Shenzhen, China. In particular, we develop a crawling tool to harvest the daily travel time from each community (8117) to each healthy food store (102) from the Baidu Map under four transport modes (walking, public transit, private car, and bicycle) during 17:30–20:30 in June 2016. Based on the travel time calculations, we develop four travel time indicators to measure the healthy food accessibility: the minimum, the maximum, the weighted average, and the standard deviation. Results show that the four accessibility indicators generate different estimations and the nearest service (minimum time) alone fails to reflect the multidimensional nature of healthy food accessibility. The communities within Shenzhen present quite different typology with respect to healthy food accessibility under different transport modes. Multilevel additive regression is further applied to examine the associations between healthy food accessibility and nested socioeconomic characteristics at two geographic levels (community and district). We discover that the associations are divergent with transport modes and with geographic levels. More specifically, significant social equalities in healthy food accessibility are identified via walking, public transit, and bicycle in Shenzhen. Based on the associations, we finally map the food deserts and propose corresponding planning strategies. The methods demonstrated in this study should offer deeper spatial insights into intra-urban foodscapes and provide more nuanced understanding of food deserts in urban settings of developing countries.

1. Introduction

1.1. Background

As one of the basic human needs, food is broadly acknowledged as a cornerstone of health. It requires the access to nutritious and sufficient foods to sustain the functioning, development, and growth throughout the life course (Battersby, 2013). During the past decades, the scientific and political communities have placed increasing attention on the local food systems within neighborhoods (Apparicio, Cloutier, & Shearmur, 2007; Bader, Purciel, Yousefzadeh, & Neckerman, 2010; Caspi, Sorensen, Subramanian, & Kawachi, 2012; Taylor, 2015; Yeager & Gatrell, 2014; Zhang, Wu, Yao, Bai, & Xiong, 2014). More specifically, the number and types of food stores are not evenly distributed across space. Geographic access to healthy foods, like fruits and vegetables, has been associated with reduced morbidity and mortality of obesity and other diet-related diseases within urban areas (e.g., cardiovascular disease, diabetes, cancer) (Key, 2011). Urban planners and policy makers have widely acknowledged the rationale that greater physical access should improve the residential diet nutrition and subsequently enhance their well-being and health (Kent & Thompson, 2014; Story et al., 2008; Taylor, 2015). They thus emphasize the geography of food stores and particularly the issue

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of accessibility. A wealth of literature has reported the complex relationships between food accessibility, public health, neighborhood socioeconomics, and society as a whole (Barnes et al., 2016; Black, Moon, & Baird, 2014; Caspi et al., 2012; Duran, Diez Roux, Latorre, & Jaime, 2013; Maguire, Burgoine, & Monsivais, 2015; Ravensbergen, Buliung, Wilson, & Faulkner, 2016; Thornton, Lamb, & Ball, 2016; Wang, Tao, Qiu, & Lu, 2016). The access to food systems has therefore become an urgent topic that should be better understood so as to address the issues of urban well-being, health promotion, and food security (Battersby, 2013).

Food deserts are commonly defined as areas with restricted access to healthy and affordable foods as well as a variety of other nutritious options (Apparicio et al., 2007; Jiao, Moudon, Ulmer, Hurvitz, & Drewnowski, 2012; USDA ERS, 2013). More specifically, supermarkets and large grocery stores (SLGSs) offer a diversity of better quality vegetables and fruits at a reasonable cost. The access to healthy foods is thus typically measured by the accessibility to large and chain vendors that provide healthy food options (Duran et al., 2013; Engler-Stringer, Shah, Bell, & Muhajarine, 2014; Gould, Apparicio, & Cloutier, 2012; Smoyer-Tomic, Spence, & Amrhein, 2006). In this regard, the inherent characteristic of 'food deserts' is spatial, and the physical absence of SLGSs within existing administrative units (e.g., census tract, district, community) is particularly emphasized in urban planning. For example, many local governments in US and Europe (e.g., Baltimore, Chicago, New York, Philadelphia, San Diego) have adopted the concept of food deserts and developed analytical tools to identify the areal units with limited geographic access to SLGSs (Couzin-Frankel, 2012; Chicago Magazine, 2009). These analytical tools largely employ geographic information systems (GIS) to measure the accessibility of SLGSs. However, the GIS methodologies have received criticism as a limited conceptualization and oversimplification of accessibility (Krizan, Bilkova, Kita, & Hornak, 2015). It requires to develop more reliable and nuanced measures of healthy food accessibility by considering the complexity of actual situation (e.g., transportation systems, integrated space-time conceptualizations, and dynamic urban life).

Social justice theories hold that socioeconomically disadvantaged communities are more likely to experience greater adverse environment threats (Golub & Martens, 2014; Wan & Su, 2016; Weng, Pi, Tan, Su, & Cai, 2016; You, 2016). To understand the contextual injustices in food deserts, scholars have sought to explore the associations between healthy food accessibility and individual or aggregated neighborhood characteristics that describe socioeconomic disadvantage, including minority groups, senior populations, low income, single-parent families, poor education, and blue-collar occupation (Black et al., 2014; Caspi et al., 2012; Duran et al., 2013; LeDoux & Vojnovic, 2013; Maguire et al., 2015; Ravensbergen et al., 2016; Thornton et al., 2016; Wang et al., 2016). Related cases in general found that food deserts were more likely to be observed neighborhoods where disadvantaged groups concentrate (Black et al., 2014; Giang, Karpyn, Laurison, Hillier, & Perry, 2008; LeDoux & Vojnovic, 2013; Powell, Slater, Mirtcheva, Bao, & Chaloupka, 2007). In this regard, 'food deserts' has become an urgent concern beyond geographical science and gradually become a hot topic for a wide range of urban fields (USDA ERS, 2013). A growing body of literature has been documented in urban research, responding to the concern on the social inequalities associated with the "food deserts" issue (Apparicio et al., 2007; Barnes et al., 2016; Furey et al., 2001; Jiao et al., 2012; Larsen & Gilliland, 2008; McKenzie, 2014; Paez, Mercado, Farber, Morency, & Roorda, 2009; Smoyer-Tomic et al., 2006; Widener & Shannon, 2014; Yeager & Gatrell, 2014). However, prior studies paid overwhelming attention to developed nations. Intra-urban food deserts and the related social inequalities issue have been seldomly investigated for developing countries, particularly in China.

1.2. Literature review

1.2.1. Conceptualizations

Since the 1990's scholars have made attempt to examine the links between neighborhood food environment and health disparities. These studies have led to the phrase of "food deserts", which was first used by a public housing sector scheme in Scotland to indicate regions devoid of nutritious food options (Cummins & Macintyre, 2002). Since that time, researchers have put forward a variety of definitions in different disciplines. Furey, Strugnell, and McIlveen (2001) defined food deserts as avoid areas as a result of high competition from series of large chain supermarkets. Cummins and Macintyre (2002) defined food deserts as areas where healthy foods are relatively unavailable and expensive. Wrigley (2009) claimed that food deserts referred to the neighborhoods with limited access to healthy and affordable foods where the residents suffered from social exclusion and deprivation. Gregory et al. (2009) argued that food deserts represented the areas with poor provision of healthy food at reasonable price, which were primarily associated with absence of large retailers. According to the USDA, the food deserts were deprived communities and neighborhoods spatially distant from affordable foods venders that offered a diversity of nutritious options (USDA ERS, 2013). Other authors acknowledged food deserts as relatively disadvantaged areas where population had inadequate better retail food sources (Apparicio et al., 2007; McEntee & Agyeman, 2010; Russell & Heidkamp, 2011; Walker, Keene, & Burke, 2010). Though there remains considerable debate as to the exact definition, the nature of food deserts generally involves three key facets: (1) affordable nutritious foods; (2) spatial proximity; (3) close association with socioeconomic disadvantage.

With respect to the proxy of healthy foods, previous studies have reported different alternatives and majority of them focused on supermarkets (Duran et al., 2013; Engler-Stringer et al., 2014; Smoyer-Tomic et al., 2006; Yeager & Gatrell, 2014). It is argued that a full range of fresh products (e.g., vegetables, fruit, fresh meet) at reasonable price can be provided in supermarkets to meet residents' daily needs for nutrients. Local grocery stores are also incorporated in most studies (Engler-Stringer et al., 2014; Gould et al., 2012; Martin et al., 2014), since some types of fresh foods are available in these stores. Inhabitants with far distance away from full-service supermarkets can also get access to healthy foods. Some recent studies started to consider specialty stores and farmers' markets, depending on the actual conditions of the study area. A consensus has been reached among scientists that proxies of healthy food can be stores that can relieve fresh food deficiency to a temporary extent (Engler-Stringer et al., 2014; Gould et al., 2012; Martin et al., 2014; Widener & Shannon, 2014; Yeager & Gatrell, 2014).

Healthy food access is also a complicated concept and it involves various dimensions (e.g., physical quantity, geographic proximity, travel cost, food price, personal tastes, transportation systems, organizational barriers) (Charreire et al., 2010; Shearer et al., 2015). Earlier studies emphasized the availability dimension and typically calculated the physical quantity of SLGSs within the neighborhood (Thornton, Pearce, & Kavanagh, 2011). Following cases underlined the coverage dimension and employed the "service area" method (Larsen & Gilliland, 2008; Russell & Heidkamp, 2011; Smoyer-Tomic et al., 2006; Wang, Qiu, & Swallow, 2014). More specifically, a buffer zone around the SLGSs is first determined as "service scope" by a pre-specified distance or travel time. Then, the total number of SLGSs within that service area is calculated. Some researchers preferred the opportunity dimension (Thornton et al., 2011) and developed the cumulative opportunity index to measure healthy food access. Most recent literature focuses on the geographic accessibility dimension. These studies commonly use distance-based metrics to measure the physical distance between community and the closest SLGSs, considering the Euclidean distance, road networks, and travel time (Thornton et al., 2011; Walker et al., 2010). The scientific community has basically agreed that the accessibility is the most appropriate dimension to understand the complexity of healthy foods access.

1.2.2. Methodologies of accessibility measurement

Fundamentally, accessibility measures the ease to a specified destination from an origin (Widener & Shannon, 2014). Within the foodscape research context, accessibility represents the accessed proximity between residents' address and SLGSs (Apparicio et al., 2007; Coveney & O'Dwyer, 2009; Larsen & Gilliland, 2008). Principle technologies include the GIS, GPS (global positioning systems), PDAs (hand held personal digital assistants), smart card technology, tablets, smart phones, and Google Maps (Boulos & Yang, 2013; Cetateanu & Jones, 2016; Hillier, 2008; Kerr, Duncan, & Schipperjin, 2011; Moore, DiezRoux, Nettleton, Jacobs, & Franco, 2009; Wang et al., 2011). An overwhelming body of literature uses the GIS to compute the measures of healthy food accessibility based on the location of residential neighborhoods. Some earlier studies were based on the straight-line or Euclidean distance. Such methodologies are rather straightforward but conceptualize the accessibility as an oversimplified term, since the actual travel environments are completely ignored. Some studies highlight the importance of considering the dynamics of urban life. For example, Burgoine and Monsivais (2013) found that healthy food accessibility estimated by the Euclidean distance method differed from, and sometime was lower than, that derived by the approach taking into account the everyday-commuting patterns. Widener, Farber, Neutens, and Horner (2015) also reported similar findings. Recent literature commonly uses the approaches based on road networks. While these papers establish a baseline to measure healthy food accessibility, they do not consider the differences associated with the use of different means of travel.

The methodologies are particularly preferred in the very recent literature to capture the separation between foods stores and communities, which consider the different transport modes. McKenzie (2014) conducted an intensive literature review with respect to the transport options in measuring healthy food accessibility. Primarily, two categories of transport modes are analyzed in related research. One category is the automobile or private car (Jiao et al., 2012; Paez et al., 2009), and the other is the public transportation (Bader et al., 2010; Widener et al., 2015). It is found that private vehicles play a key role in increasing the healthy food accessibility in western countries (Wang et al., 2014) and the public transits are critical alternative options in accessing healthy food for residents without private cars. In addition, other research recognizes the actual travel impedances (e.g., one-way roads, speed limits, restricted turns, traffic volumes). For example, Burgoine and Monsivais (2013) considered the transport mode and frequency and calculated the exposure to foodscape at home and work based on the shortest road network distance. Fuller, Cummins, and Matthews (2013) discovered insignificant role of travel means in moderating the relationship between healthy food consumption and accessibility. Widener et al. (2015) found increased healthy food accessibility after taking into consideration the limited time budget of transit commuters. While these works advance the understanding of healthy food accessibility, the issue of time-variability has not been adequately addressed.

Food acquisition is not only subjected to geographical restriction but also suffers from temporal constrains (Chen & Clark, 2013; Horner & Wood, 2014; Zenk et al., 2011). Kwan (2012) has pointed out the uncertainty in geographic context problem and highlighted the importance of spatiotemporal analysis into foodscape research. Widener and Shannon (2014) also argued that the temporal component should be incorporated into analysis of healthy food accessibility. Instead of determining the geographic distance, some very recent analysis calculated the travel time and the time spent on waiting, scheduling public transit, and transfers as an alternative approach to healthy food accessibility. For example, Farber, Morang, and Widener (2014) compared the traveling duration at different periods to measure healthy food accessibility. A three-dimensional approach was proposed by Chen and Clark (2013) to examine healthy food accessibility over the time of store operation. Widener et al. (2015) analyzed the spatiotemporal constraints to healthy food accessibility. Ravensbergen et al. (2016) compared the weekday vs. weekend accessibility to healthy food for children. While these studies have strengthened the space-time conceptualizations, the practice is still very lagged in ‘food deserts’ research. In addition, some scholars argued that SLGSs outside of residential neighborhoods should be considered (Boruff, Nathan, & Nijënstein, 2012; Kerr et al., 2011; Thornton et al., 2011) given that only a small proportion of residents' daily movement occurred within the residential neighborhood (Hillsdon, Coombes, Griew, & Jones, 2015).

1.2.3. Social equalities of healthy food accessibility

A number of studies, through the lens of social inequities, have explored the associations between healthy food accessibility and individual or neighborhood deprived characteristics (Black et al., 2014; Caspi et al., 2012; Duran et al., 2013; Maguire et al., 2015; Ravensbergen et al., 2016; Thornton et al., 2016; Wang et al., 2016). The literature reports that low healthy food accessibility is generally observed in neighborhoods with high poverty rate, low income, high unemployment rate, predominant minority, and dominant black population (Black et al., 2014; Giang et al., 2008; LeDoux & Vojnovic, 2013; Powell et al., 2007). However, most investigations simply compare the accessibility among neighborhoods with different deprivation levels or rely on descriptive analysis. Empirical investigations based on quantitative measurements are not common and generally employ the classic least square linear regression. Consequently, two critical issues are neglected: spatial autocorrelation and multilevel socioeconomic interactions. Spatial autocorrelation in SLGSs has been evidenced by economic literature. For one thing, greater profit can be achieved from the economies of agglomeration (Sage, McCracken, & Sage, 2013; Sanner, 2009), and retailers thus prefer to cluster together for possible declines in transaction costs. For another, competition can be increased as a result of rather similar business within one region, and retails may also disperse to maintain sustainable benefits (Jimenez & Perdiguero, 2011; Wang et al., 2016). Socioeconomic activities at different levels are interacted with each other. For example, the socioeconomic status of one neighborhood is not only related to community characteristics but also linked with macro administration characteristics at higher level (e.g., census track, block, county). Therefore, empirical analysis ignoring these two issues can generate biased estimations and leads to misleading urban planning recommendation. More sophisticated statistical tools should be developed to examine the social equalities of healthy food accessibility.

1.3. Current study

Considering the gap in the literature, our study aims to characterize the “food deserts” in developing countries using the case of

Shenzhen, China. Scholars have argued that Shenzhen should be an ideal example to examine the typical global issue, since it (1) mirrors the rapid socioeconomic development in many developed nations worldwide; and (2) illustrates the social and environmental problems commonly occurred in developing countries during the process of development (Su et al., 2016a). The Shenzhen city is situated in Pearl River Delta (Fig. 1), one of the most developed megacities in China. It covers an area of about 2000 km^2, and houses 10 million habitants. Shenzhen is the first Chinese Special Economic Zone and is regarded as China's open door to the outside world. It has experienced amazing socioeconomic development and large-scale immigration during the past decades. As China's largest migrant city, both the rich elite crowds and the disadvantaged migrant workers account for a large apportion of the total population. Great gaps exist between the two polarized groups in wealth, capital, and power. Socio-geographic segregation has been widely observed in residence, living environment, employment, education, public facilities and services, mobility, and medical care (Su et al., 2016a; Wan & Su, 2016; Weng et al., 2016; You, 2016). When such socio-geographic segregation is associated with neighborhood socioeconomic disadvantage due to being completely or partially unchosen, they are regarded as social inequalities. In Shenzhen, the 'food deserts' issue has not been recognized in urban planning and no official acts have been taken to relieve the associated social inequalities. It thus requires efforts to measure the healthy food accessibility and identify the food deserts within Shenzhen.

The purpose of this paper is twofold: to explore the healthy food accessibility and associated social equalities, and to provide recommends for urban planning by identifying the food deserts. Taking advantage of a geo-big data approach and multilevel regression model, we make a contribution to current literature by exploring the food deserts within Shenzhen and the potential associations with multilevel socioeconomic characteristics. More specifically, we attempt to: (1) measure the transit-varying accessibility to healthy food; (2) quantify the social inequalities of healthy food accessibility by considering multilevel socioeconomic interactions and spatial autocorrelation; and (3) identify the food deserts and discuss the implications for urban planning. The methods demonstrated in this study should offer deeper spatial insights into intra-urban foodscape and provide more nuanced understanding of food deserts. The empirical findings should provide new information for urban planners and other interest groups.

2. Methodology and data

2.1. Neighborhood geographic boundaries

Neighborhood is defined as a geographic unit of similar distinguishing or homogeneous characteristics with regard to development type, demography, housing, etc (Weng et al., 2016). Most researchers have selected postal code, census tract, community, block, and district as the geographic boundaries for defining neighborhood (Barnes et al., 2016; Shearer et al., 2015). Other scholars argue that neighborhood is a synonymous term of vicinity, and visualize their definitions by creating a predetermined buffer around residents' houses (Charreire et al., 2010; Leal & Chaix, 2011). However, the buffer-based neighborhood boundary varies greatly in size with studies and suffers from potential objective bias and lack of socioeconomic data (Charreire et al., 2010; Lebel, Pampalon, & Villeneuve, 2007). In China, community is the smallest geographic unit for residential management and census data collection. Hence, community ($N = 8117$) is used as the neighborhood geographic boundary in our study (Fig. 1). In addition, administration in Shenzhen is divided into three levels from community (lowest), to district and zone (highest). District ($N = 57$) has jurisdiction over community, and socioeconomics should interacted with each other. We therefore argue that socioeconomic status at the two levels should be considered when examining the social inequalities of healthy food accessibility.

2.2. Healthy food accessibility measures

With respect to the proxy of healthy foods, previous studies have reported different alternatives. A consensus has been reached among scientists that proxies of healthy food can be stores that can relieve fresh food deficiency to a temporary extent. In our study, full-service supermarket, grocery store, fruit store and market, vegetable store and market, and seafood market are selected as proxies of healthy food. In total, there are 102 healthy food stores within Shenzhen (Fig. 1). Healthy food accessibility is defined as the ease to a certain healthy food store from a community in this paper. Travel time is used to indicate accessibility in our study, since it can more realistically reflect the ease of origin-destination travel determined by the character and quality of transportation service (Jiao et al., 2012; McKenzie, 2014). In particular, character and quality of transportation service is highly sensitive to the transport modes and time period of a day. We conducted a household survey in June and collected 1073 questionnaires in Shenzhen. Respondents reported four transport options (walking, private car, public transit, and bicycle) and majority of them chose to go to healthy food stores during 17:30–20:30. The Baidu Map (http://map.baidu.com) is employed to calculate the travel time associated with the four transport options during 17:30–20:30. The Baidu Map is the leading electronic navigation platform of Web GIServices in China. It uses a door-to-door approach (Salonen & Toivonen, 2013) to find the shortest traveling route in the road network and estimates the travel time based on the real-time transportation information (e.g., traffic volume, driving speed, sidewalks, one-way and restricted turns). Hence, the Baidu Map should provide a more realistic picture and reliable measurement of accessibility. In particular, we develop a crawling tool to harvest the daily travel time from each community to each healthy food store during 17:30–20:30 in June 2016. The crawling tool is written by Python from the web pages of Baidu Maps. It takes about 40 min to complete the data collection for one community. In total, we collect 827934 (8117×102) travel time calculations. The extremes and outliers are removed and we find consistent estimations among weekdays and weekends ($p = 0.12$). In order to confirm the data quality, we make a comparison between the Baidu Map the Gaode Map (another electronic navigation platform of Web GIServices in China) and find no significant estimations ($p = 0.08$). Based on the travel time calculations, we develop four baseline indicators to measure the healthy food accessibility for each community: the minimum (Min_time, the shortest travel time to park), the maximum (Max_time, the longest travel time to healthy food store), the weighted average (Mean_time, the weighted average travel time to all the healthy food stores), and the standard deviation (SD_time, the differences in travel time to all the healthy food stores). These indicators not only describe the 'closest' proximity to 'local' healthy food, but also provide comprehensive information for the cumulative accessibility opportunity to the 'global' healthy food. General statistics of the accessibility indicators are shown in Table 1.

2.3. Neighborhood socioeconomic indicators

Scholars have proposed a great diversity of indicators to measure neighborhood socioeconomics, and the applied indicators are generally case-specific in prior literature. Criteria for indicator

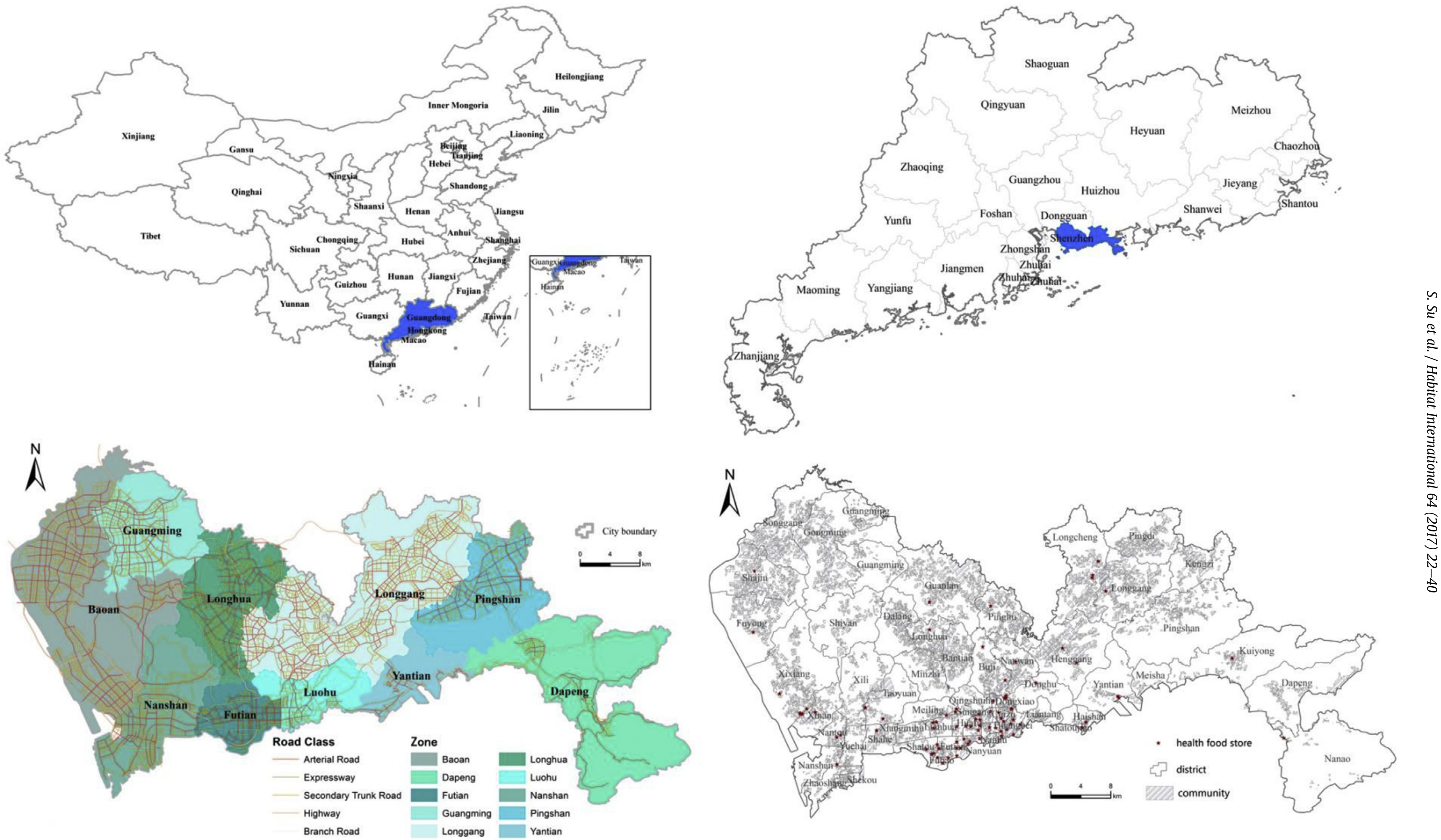

Fig. 1. Location and administrative division of Shenzhen city (China) as well as healthy food stores and communities within it.

Table 1
Descriptive statistics of healthy food accessibility indicators under different transport modes (N = 8117; unit: min).

Transport mode	Accessibility indicators	Maximum	Minimum	Standard deviation	Mean
Walking	Min_time	353.00	1.00	42.18	31.39
	Max_time	1418.00	57.00	165.86	950.87
	Mean_time	1035.00	11.00	127.99	290.99
	SD_time	753.00	35.00	27.76	159.15
Public transit	Min_time	179.00	1.00	17.00	9.20
	Max_time	390.00	54.00	41.36	221.55
	Mean_time	292.00	1.00	30.55	76.58
	SD_time	93.00	10.00	4.71	40.42
Private car	Min_time	17.00	1.00	0.86	1.33
	Max_time	236.00	56.00	19.07	104.78
	Mean_time	94.00	2.00	8.49	32.75
	SD_time	43.00	10.00	4.80	21.81
Bicycle	Min_time	205.00	1.00	12.88	7.43
	Max_time	1415.00	51.00	67.40	306.38
	Mean_time	334.00	1.00	42.79	94.63
	SD_time	1147.00	9.00	52.03	59.48

Abbreviations: the minimum (Min_time), the maximum (Max_time), the weighted average (Mean_time), and the standard deviation (SD_time).

selection can thus be summarized into four key points: (1) indicators should represent different dimensions of socioeconomic status (e.g., income, education, occupation, and housing); (2) they have potential to reveal the inequalities in healthy food accessibility; (3) they are not highly redundant; and (4) they are comparable with those in earlier related studies. We refer to previous studies (Wan & Su, 2016; Weng et al., 2016; You, 2016) and also consider data availability, and first select two sets of indicators at community level and at district level, respectively. Then, Pearson's correlation analysis and principal component analysis (PCA) are employed to reduce the redundancy (Su et al., 2016a; You, 2016). The standard for redundancy reduction is: (1) one of two highly correlated indicators (|r|>0.9) is discarded; (2) indicators of low loadings (|r|<0.75) in each component are discarded (Su et al., 2016a; You, 2016). Finally, we obtain 6 indicators at community level and 8 indicators at district level (Table 2). Data are provided by the local government.

2.4. Multilevel additive regression

Geographical data in urban studies typically presents clustered or hierarchical structure, in which aggregated groups at lower level are nested with units at higher level. The risk of type I error should possibly be increased without consideration of the hierarchical structure, since the standard error of the estimated coefficient would be inflated (Yamagata, Murakami, Yoshida, Seya, & Kuroda, 2016). In foodscape relevant applications, healthy food stores are embedded within sociodemographic units across different levels. Healthy food accessibility should be interacted with contextual socioeconomic conditions at different levels. Therefore, the estimations should be highly subjected to the explanatory variables with nested hierarchy. In this regard, we should incorporate the hierarchical structure when exploring the associations between healthy food accessibility and socioeconomic conditions. Multilevel regression represents the explanatory modeling in which independent variables are at two levels or more (Su, Zhou, Wan, Li, & Kong, 2016b). Scholars have proposed a variety of multilevel regression models, including the hierarchical linear model (Su et al., 2016b; Tso & Guan, 2014), the variance component model (Du, Xiong, Wang, & Guo, 2016), the random coefficient model (De Leeuw & Kreft, 1986), the mixed-effects model (Bagiella, Sloan, & Heitjan, 2000), the Bayesian model (Eastwood et al., 2016), and the spatially additive model (Yamagata et al., 2016). Considering the strong capability to handle the hierarchically structured aggregated data as well as the spatial autocorrelation, we employ the hierarchical linear additive model (Eq. (1)) to examine the association between healthy food accessibility and socioeconomics at community level and district level. Besides, we also perform the F test for variance homogeneity, the Shapiro–Wilk test for normality and the standard deviation model for standardization. The R software is used to perform the regression analysis.

$$Y_{ij} = \lambda_0 + \lambda_1 x_{ij} + \lambda_2 \beta_j + \varepsilon_{ij} + \theta_j + \lambda_3 W_{ij} + e \tag{1}$$

where Y_{ij} is the healthy food accessibility for community i within district j; x_{ij} and β_j are the explanatory variables at the level 1

Table 2
Selected neighborhood socioeconomic indicators at different geographic levels (unit: %).

Level	Variables	Abbr.	Explanation	Max	Min	SD	Mean
Community	Living alone	LAC	Proportion of people living alone	1.00	0.00	0.15	0.10
	No house property	NHPC	Proportion of people without house property	1.00	0.00	0.19	0.09
	Unemployment	UC	Proportion of unemployed people	1.00	0.00	0.15	0.08
	Less educated	LDC	Proportion of people with degree lower than middle school	1.00	0.00	0.10	0.04
	Elder	EC	Proportion of people aged 60 and above	1.00	0.00	0.08	0.04
	Blue-collars	BCC	Proportion of blue-collar workers	1.00	0.00	0.20	0.12
District	Low income	LID	Proportion of low income household	0.68	0.13	0.12	0.36
	Illiteracy rate	IRD	Proportion of people who are unable to read or write	0.03	0.00	0.01	0.01
	Jobless	UD	Proportion of adults without job	0.07	0.01	0.01	0.03
	Floating population	FPD	Proportion of floating population	0.28	0.05	0.04	0.11
	House without taping water	HTD	Proportion of household without access to taping water	0.09	0.00	0.01	0.02
	Divorce rate	DRD	Proportion of divorced couples	0.02	0.00	0.01	0.01
	Low-rent housing	LHD	Proportion of affordable house	0.38	0.01	0.07	0.09
	Elder	ED	Proportion of people aged 60 and above	0.08	0.01	0.02	0.04

(community level) and level 2 (district level), respectively; λ_1, λ_2, and λ_3 are the estimated coefficients; λ_0 is the intercept; random parts are ε_{ij} (level 1) and θ_j (level 2); W_{ij} is the spatial lag; e is the error term.

2.5. Spatial analysis

Overlay analysis is applied to identify the food deserts within the study area. More specifically, the coverage of healthy food accessibility is overlaid with the coverage of neighborhood socioeconomic indicators. We define the communities as food deserts that have lower healthy food accessibility and higher socioeconomic disadvantage. In particular, the socioeconomic disadvantage indicators are the significant exploratory variables of healthy food accessibility identified by the multilevel regression. We refer to the international standard (Community Guide: http://archived.naccho.org/topics/HPDP/commguide/) for public facilities accessibility to define lower healthy food accessibility: >20 min (public transit), >15 min (bicycle), >10 min (private car), and >30 min (walking).

3. Results

3.1. Transit-varying accessibility of healthy food

The transit-varying accessibility of healthy food is shown in Fig. 2 (walking), Fig. 3 (private car), Fig. 4 (public transit) and Fig. 5 (bicycle). The estimated healthy food accessibility varies greatly with transport modes and with accessibility indicators. Communities within the central zones (e.g., Luohu, Futian, and Nanshan) present lower values of the four accessibility indicators by walking (Fig. 2). It indicates that these communities not only have greater access to the nearest healthy food store but also have more opportunities to visit all the healthy food stores within Shenzhen by walking. The private car -based Min_time has no obvious spatial variations, while the other three indicators present lower values in northeastern and northwestern regions (Fig. 3). It suggests that communities across Shenzhen should have comparative access to the nearest healthy food store by private car. Lower values of the four accessibility indicators via public transit are observed in communities of the western region, while higher values are concentrated in the central part (Fig. 4). It can be inferred that inhabitants in the western areas have more restricted access to healthy food than those in the central places. Bicycle -based healthy food accessibility has similar patterns as the walking -based one (Fig. 5). We further visualize the typology of communities in regard to the nearest healthy food accessibility under different transport modes using the Gephi (Fig. 6). The large yellow dots represent the healthy food stores and the small color dots denote the communities. The lines connecting the dots indicate the accessibility and thicker lines represent better accessibility. It can be seen that the typology of the networks representing the accessibility from each community to each healthy food store varies with transport modes. It confirms the argument that healthy food accessibility should be highly subjected to transport modes.

3.2. Healthy food accessibility in association with neighborhood socioeconomics

Table 3 presents the associations between healthy food accessibility variables and neighborhood socioeconomic indicators. Coefficients of determination (R^2) reach approximately 0.6 and Moran's I for the model residuals approaches zero (no spatial autocorrelation). It suggests that the multilevel additive regression should be efficient to explore the associations between healthy food accessibility and neighborhood socioeconomics. Exploratory variables of healthy food accessibility vary with transport modes and with accessibility indicators. Under the walking mode, Min_time is positively associated with UC (proportion of unemployed people) and LDC (proportion of people with degree lower than middle school) at community level as well as LID (proportion of low income community). It suggests that the people in the socioeconomically disadvantaged communities and districts should spend more time to reach the nearest healthy food store by walking. Additionally, the socioeconomic variables also correlate positively with Max_time, Mean_time and SD_time. It indicates that inhabitants in the deprived communities and districts have fewer opportunities to reach all the healthy food stores in Shenzhen by walking. No significant relationships are identified between Min_time and neighborhood socioeconomic variables under the private car mode. Negative exploratory variables for Mean_time include the NHPC (proportion of people without house property) at community level and LID (proportion of low income household) at district level. In addition, the socioeconomic variables present negative relations with Max_time. These results denote that no social inequalities exist in reaching the nearest healthy food stores by private car. However, people in the socioeconomically advantaged communities and districts do face more time cost to visit all the healthy food stores in Shenzhen by private car. Under the public transit mode, the elder proportion at community level and socioeconomic variables at district level show positive relationships with the four accessibility indicators. It denotes that the elder concentrated communities, especially in the socioeconomically disadvantaged districts, have restricted access to healthy food stores (both in their neighborhood and in entire Shenzhen) by public transit. Under the bicycle mode, it is interesting to discover that Min_time and Mean_time are positively correlated with community level socioeconomic variables but negatively associated with district level socioeconomic variables. It implies that social inequalities, in terms of healthy food accessibility by bicycle, are obvious at community level within the socioeconomically districts.

3.3. Food deserts identification

Foods deserts are identified for the communities of lower healthy food accessibility with respect to unemployment rate (Fig. 7), elder proportion (Fig. 8), and proportion of less educated population (Fig. 9). The spatial heterogeneities of food deserts vary with socioeconomic contexts and with transport modes. However, majority of the identified food deserts are distributed in the socioeconomically disadvantaged districts. For example, food deserts are typically observed in the Pingdi, Longgang, Kengzi, Gongming, and Taoyuan districts. These findings not only confirm the obvious existence of food deserts within Shenzhen, but also identify the communities that require specific planning support.

4. Discussion

4.1. Healthy food accessibility and social inequalities

Prior studies have highlighted the importance of considering the non-physical conditions in measuring accessibility (Salonen, Broberg, Kytta, & Toivonen, 2014; Wang, Brown, Liu, & Mateo-Babiano, 2015), since rather simple measures (e.g., travel thresholds, dissimilar accessibility, Euclidean distance) can result in problematic and even contradictory conclusions (Salonen et al., 2014). This paper demonstrates that the geo-big data approach can easily overcome the problems. In particular, the Baidu Map based method is quite flexible and, most important, it moves beyond the presupposed logic of 'nearest available service' by incorporating the non-physical conditions (e.g., road networks,

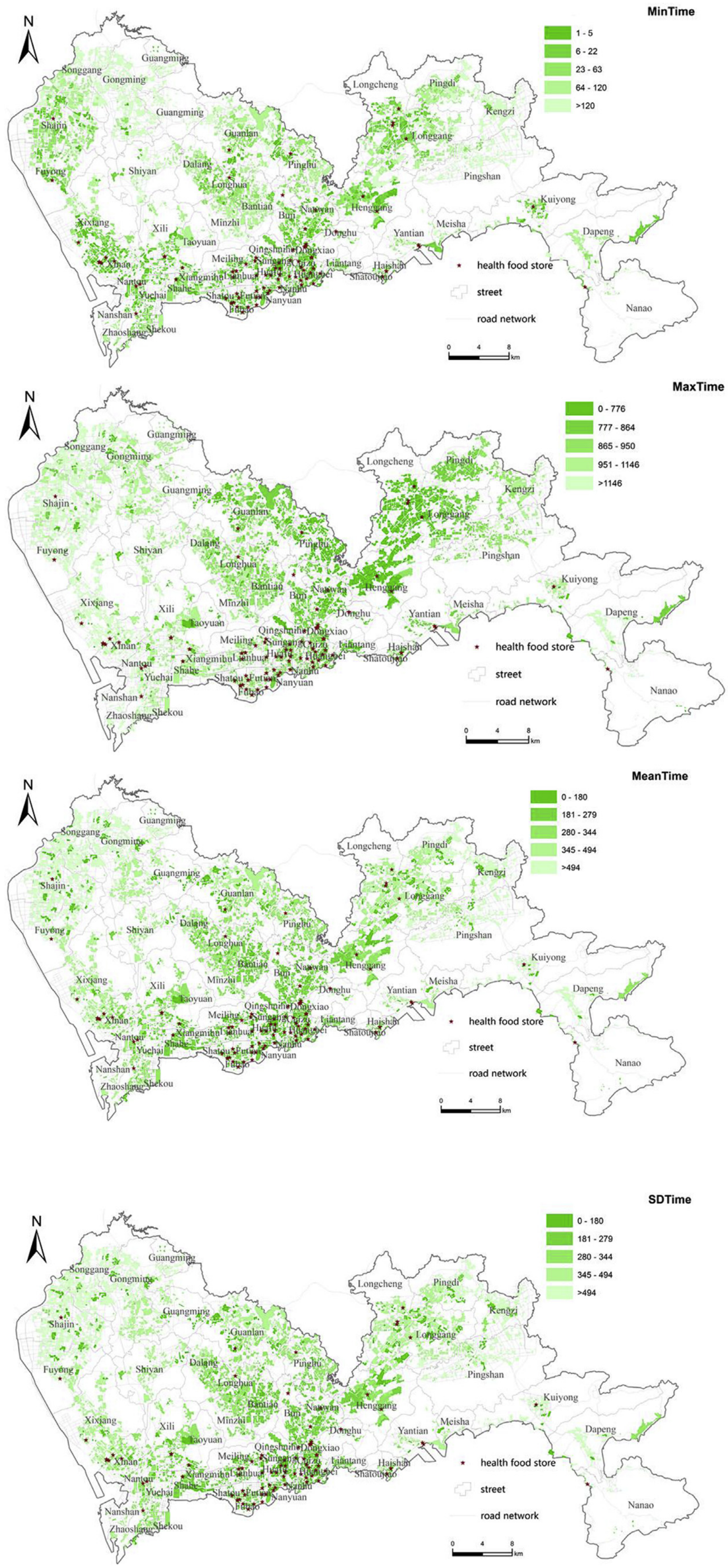

Fig. 2. Spatial heterogeneity of healthy food accessibility by walking (time based indicators) across communities in Shenzhen, China: Min, minimum time; Max, maximum time; Mean, weighted average time; SD, standard deviation time (unit: min).

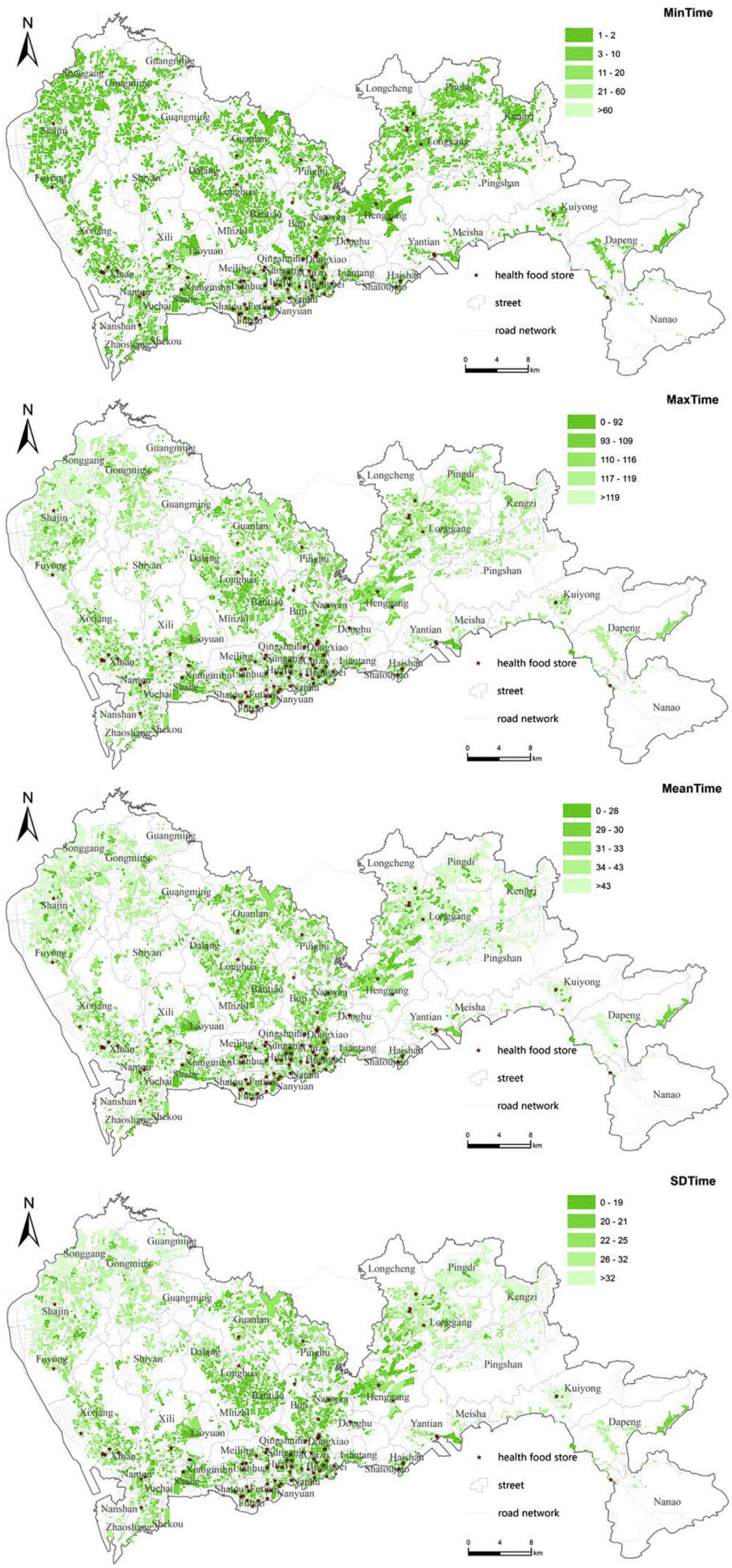

Fig. 3. Spatial heterogeneity of healthy food accessibility by private car (time based indicators) across communities in Shenzhen, China: Min, minimum time; Max, maximum time; Mean, weighted average time; SD, standard deviation time.

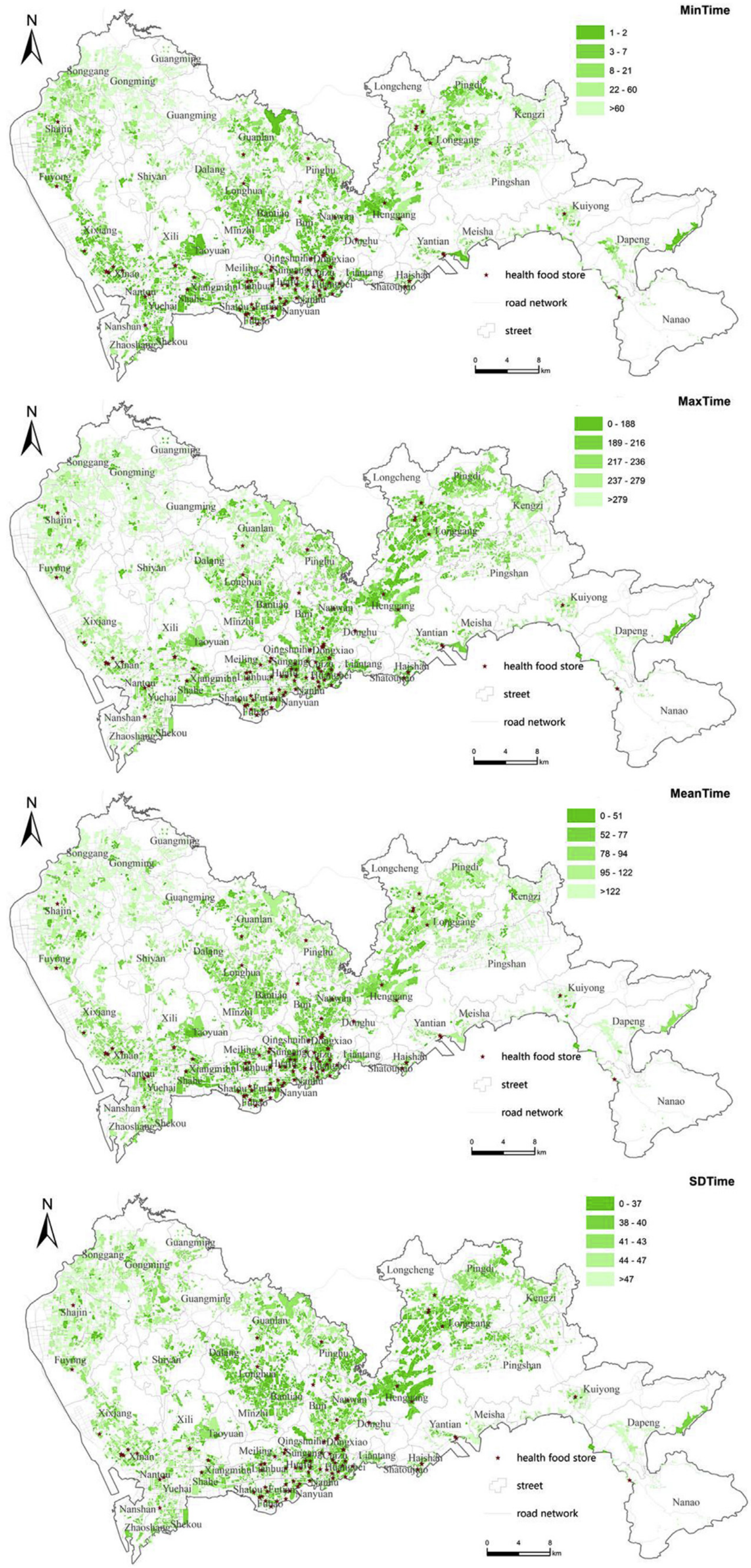

Fig. 4. Spatial heterogeneity of healthy food accessibility by public transit (time based indicators) across communities in Shenzhen, China: Min, minimum time; Max, maximum time; Mean, weighted average time; SD, standard deviation time (unit: min).

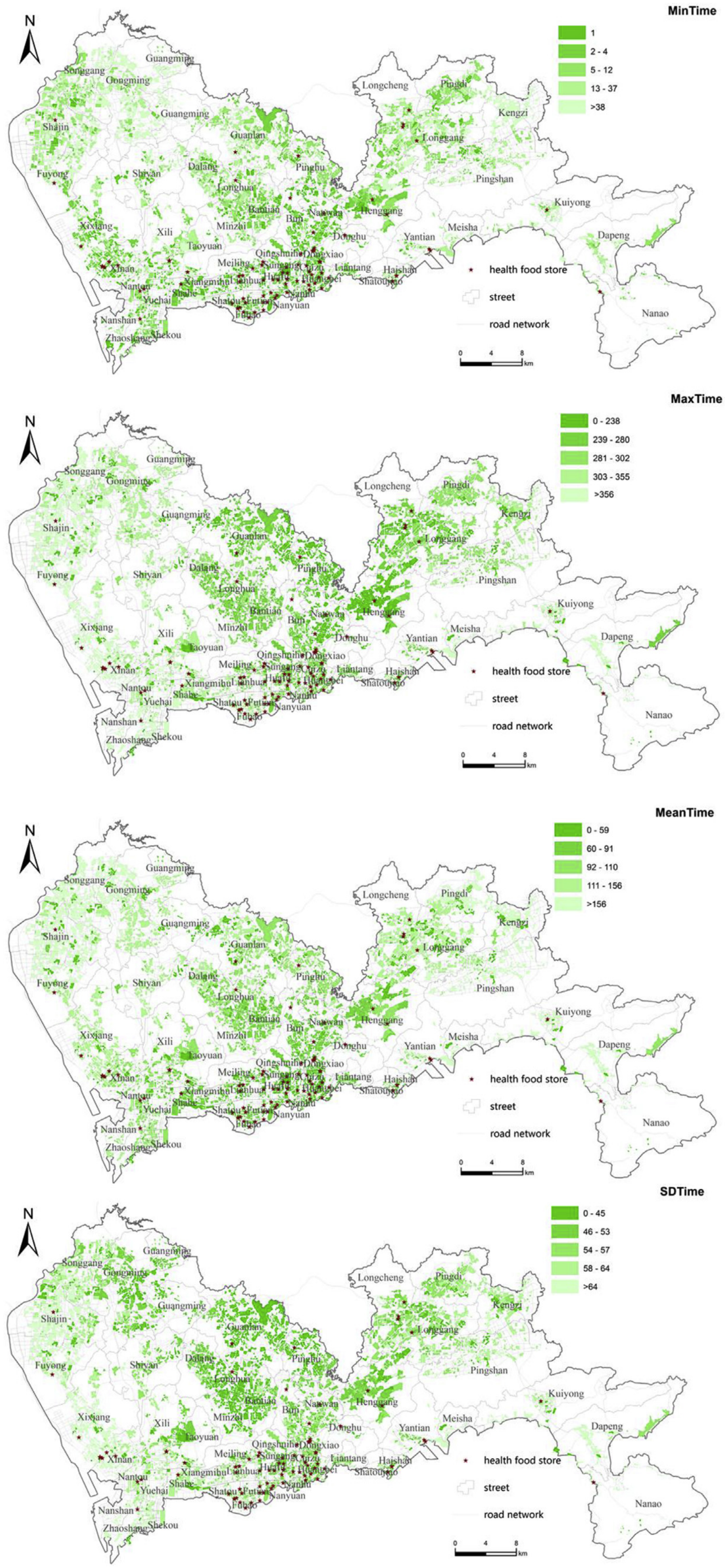

Fig. 5. Spatial heterogeneity of healthy food accessibility by bicycle (time based indicators) across communities in Shenzhen, China: Min, minimum time; Max, maximum time; Mean, weighted average time; SD, standard deviation time (unit: min).

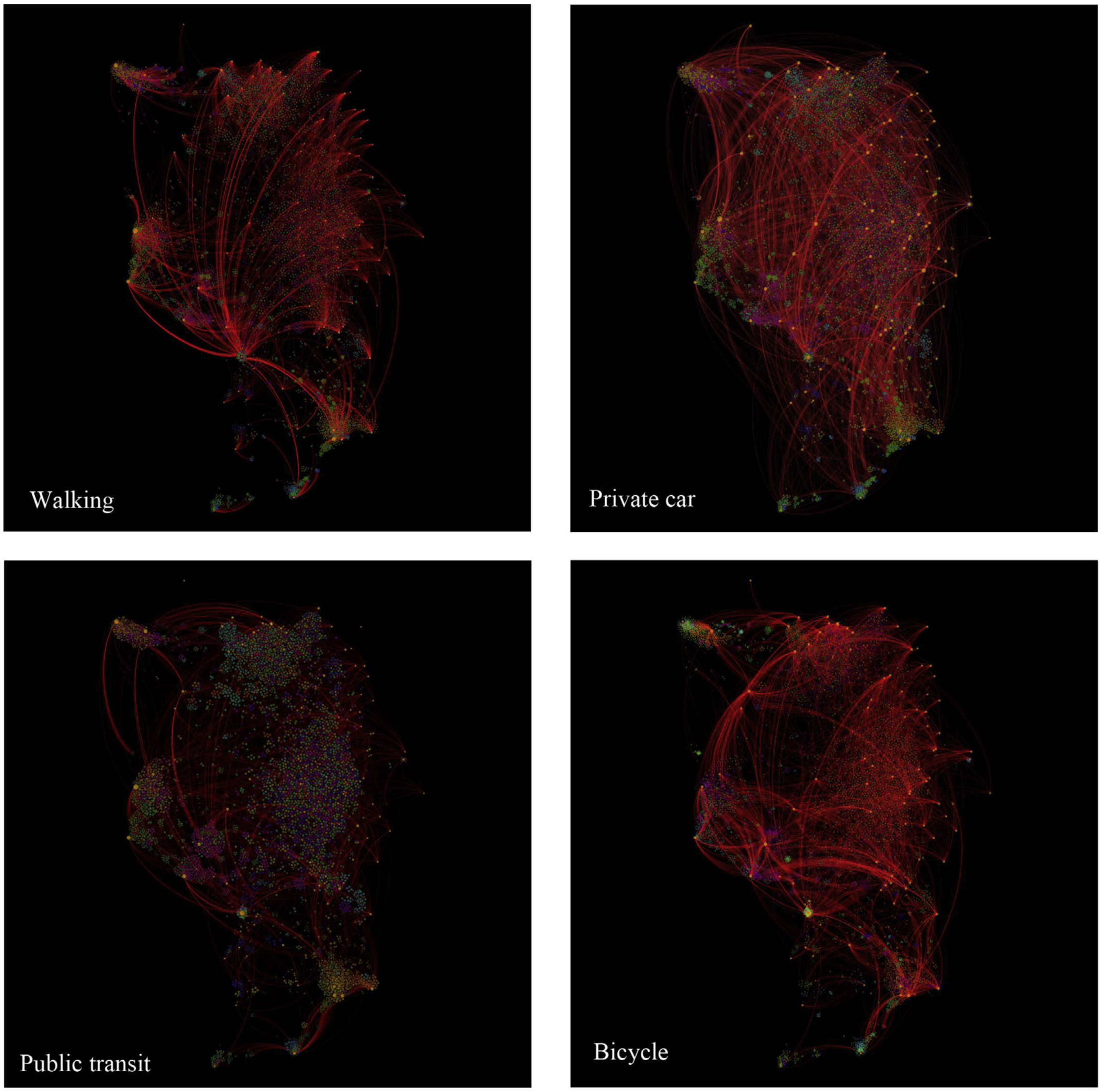

Fig. 6. Visualization of community varying minimum time accessibility to healthy food: small points represent communities, large points denote healthy food stores, and lines indicate accessibility.

traffic characteristics, transport modes, optimized travel routes) at a spatially aggregated level. Compared to the Euclidean distance, the applied methodology calculates actual travel time based on the optimized door-to-door journey under real-time traffic status for each transport mode. It could produce comparable accessibility measures among different communities and transport modes. In addition, we employ four indicators to measure the healthy food accessibility: minimum time, maximum time, average weighted time, and stand deviation time. These four indicators provide a full picture of the opportunities to access local and global healthy food. It has been argued that the actual travel time and personal visit preference do not necessarily depend on the proximity to the nearest healthy food stores in one's neighborhood. For various reasons (e.g., price, product diversity, quantity, quality), the healthy food stores would not be desirable or interesting for the nearby inhabitants. Our results demonstrate that the four accessibility indicators generate different estimations and the nearest service (minimum time) alone fails to reflect the multidimensional nature of healthy food accessibility. With respect to healthy food accessibility, more specifically, the communities within Shenzhen present quite different typology under different transport modes. It supports the argument that accessibility is a thorough consideration rather than a straight forward process (Charreire et al., 2010; Shearer et al., 2015).

Through our analyses, we examine the potential existence of social inequalities in healthy food accessibility. In addition, the nested socioeconomics at two geographic levels and the spatial autocorrelation are incorporated. We discover that the associations between healthy food accessibility and neighborhood characteristics are divergent when different transport modes and geographic levels are considered. Lower healthy food accessibility is observed in deprived communities by walking and elder concentrated communities by public transit within socioeconomically disadvantaged districts. These findings evidence the significant social equalities in healthy food accessibility via walking and public transition in Shenzhen. Non-poor population due to mobility constrain tends to reside close to public transport where a diversity of chain supermarkets concentrate. To the contrary, the deprived population typically settle in communities with lower apartment rent or house price. These communities are thus expected to see

Table 3
Associations between healthy food accessibility and neighborhood socioeconomic characteristics under different transport modes estimated by multilevel regression (N = 8117 for community; N = 57 for district).

Transit mode	Indicators	Exploratory variables (standardized coefficients)	W_y	R^2	Moran's I (residuals)
Walking	Min_time	UC (0.16), LDC (0.37), LID (0.46)	2.42	0.63**	0.07
	Max_time	BCC (0.58), HTD (0.07), IRD (0.19)	0.85	0.46**	0.00
	Mean_time	NHPC (0.39), LDC (0.22), LID (0.48)	1.98	0.57**	0.05
	SD_time	BCC (0.41), LHD (0.25)	0.43	0.28**	0.01
Private car	Min_time	NS (no significant exploratory variables)			
	Max_time	UC (−0.04), LHD (−0.51)	0.29	0.35**	0.00
	Mean_time	NHPC (−0.23), LID (−0.38)	0.67	0.29**	0.07
	SD_time	NS (no significant exploratory variables)			
Public transit	Min_time	EC (0.22), FPD (0.06)	1.54	0.55**	0.09
	Max_time	EC (0.19), DRD (0.05)	0.62	0.36**	0.04
	Mean_time	EC (0.14), IRD (0.11)	1.77	0.60**	0.08
	SD_time	EC (0.08), LID (0.20)	1.05	0.35**	0.02
Bicycle	Min_time	UC (0.19), UD (−0.31), LHD (−0.23)	1.39	0.55**	0.00
	Max_time	NS (no significant exploratory variables)			
	Mean_time	LDC (0.24), LHD (−0.11), LID (−0.26)	1.47	0.62**	0.04
	SD_time	NS (no significant exploratory variables)			

**$p < 0.01$.
Abbreviations: the minimum (Min_time), the maximum (Max_time), the weighted average (Mean_time), the standard deviation (SD_time), proportion of people living alone (LAC), proportion of people without house property (NHPC), proportion of unemployed people (UC), proportion of people with degree lower than middle school (LDC), proportion of people aged 60 and above (EC), proportion of blue-collar workers (BCC), proportion of low income household (LID), proportion of people who are unable to read or write (IRD), proportion of adults without job (UD), proportion of floating population (FPD), proportion of household without access to taping water (HTD), proportion of divorced couples (DRD), and proportion of affordable house (LHD).

higher percentage of unemployed or less-educated people. However, these communities generally have quite lower density of healthy food stores and limited transportation convenience. This accounts for the social inequalities in healthy food accessibility by walking and public transit in the socioeconomically disadvantaged districts. Different from walking and public transit, lower healthy accessibility by bicycle is expected to be observed in the socioeconomically advantaged districts, especially the deprived communities. The socioeconomically advantaged districts are mainly located in the old city center, where the lanes are narrow and disorderly. Moreover, the deprived communities in old central place are blind spots of municipal construction, and lanes are absent or broken to a large extent. No significant association is observed between neighborhood socioeconomics and accessibility to the nearest healthy food store by private car. However, people in the socioeconomically advantaged communities and districts do have a long journey to visit all the healthy food stores in Shenzhen by private car. The traffic congestion in the socioeconomically advantaged districts should pose great obstacles for driving to healthy food stores during 17:30–20:30 in Shenzhen. It should be mentioned that approximately 70% population has no private car in Shenzhen. Majority of the inhabitants have to visit the healthy food stores by walk or public transit and face the difficulty of buying heavy groceries. Therefore, we should be not too optimistic about the insignificant social inequalities in accessibility to the closest healthy food stores by car.

Our findings may partially answer for the controversial empirical conclusions in earlier case studies across different places. For example, most studies in foodscape research have discovered lower access to healthy food in less advantaged communities compared to non-poor neighborhoods (Apparicio et al., 2007; Giang et al., 2008; Larson, Story, & Nelson, 2009; Powell et al., 2007; Walker et al., 2010). However, some studies report no indication of restricted healthy food accessibility in deprived neighborhoods (Cummins & Macintyre, 2002; Giskes et al., 2011; Larsen & Gilliland, 2008). Other cases also demonstrate that higher healthy food accessibility is generally observed in high-poverty, less-educated, low-income communities (Barnes et al., 2016; Bertrand, Therien, & Cloutier, 2008; Sharkey & Horel, 2008; Sharkey, Horel, Han, & Huber, 2009; Wang & Qiu, 2016). It has been pointed that socioeconomically disadvantaged communities under some western jurisdictions are primarily clustered around public transit centers, where a number of healthy food stores are located (Wang & Qiu, 2016). The poor population who cannot afford private car tend to reside in these neighborhoods and thus has elevated access to healthy food. It is speculated that car dependence, neighborhood boundary, institute, historical context, urbanicity, and physical environment should have potential contribution to the case-specific discrepancies (Larson et al., 2009; Walker et al., 2010; White et al., 2004). Our study evidences the relationship between healthy food accessibility and neighborhood socioeconomics is sensitive to transport mode, geographic level, and measurement indicator. When taking these factors into consideration, we can obtain quite different or even contradictory estimations.

4.2. Food deserts and implications for urban planning

It has been argued that urban planning is closely related to well-being and public health (Kent & Thompson, 2014), particularly in three domains: community interaction, physical activity, and healthy eating (Kent & Thompson, 2014). With respect to healthy eating, urban planning can influence the location and density of healthy food stores through land use regulation and zoning. However, there is no special clause in China's urban planning that regulates the healthy food stores and targets at the food deserts. It would require the cooperation between the central government and local government to formulate the ‘food deserts’ oriented planning mechanism. The local planners should be entitled with more power to favor the establishment of healthy food stores in the food deserts. The central government has set the goal of ‘a well-off society’ in China. In response, the Shenzhen government has placed the priorities of helping the deprived residents to achieve such a sustainable goal. Our empirical results reveal the significant existence of food deserts within Shenzhen. Based on the findings, we map the food deserts in respect to overall socioeconomic disadvantage (Fig. 10), which can help identify the communities that require specific planning support. The critical implications for urban planning are summarized as follows.

First, neighborhoods with higher percentage of elder people have restricted access to healthy food. The aging has become a

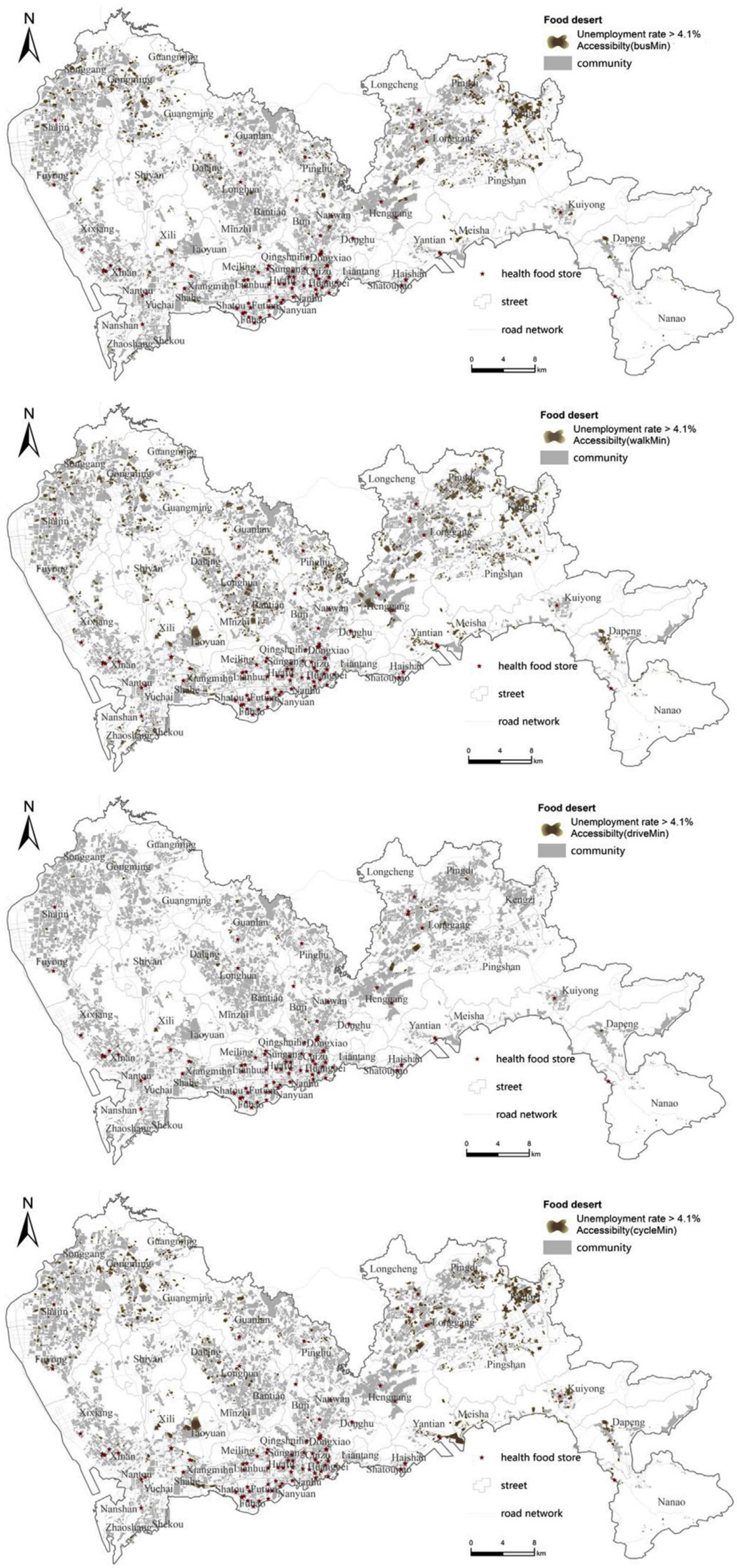

Fig. 7. Food deserts with regard to unemployed population under different transport modes within Shenzhen.

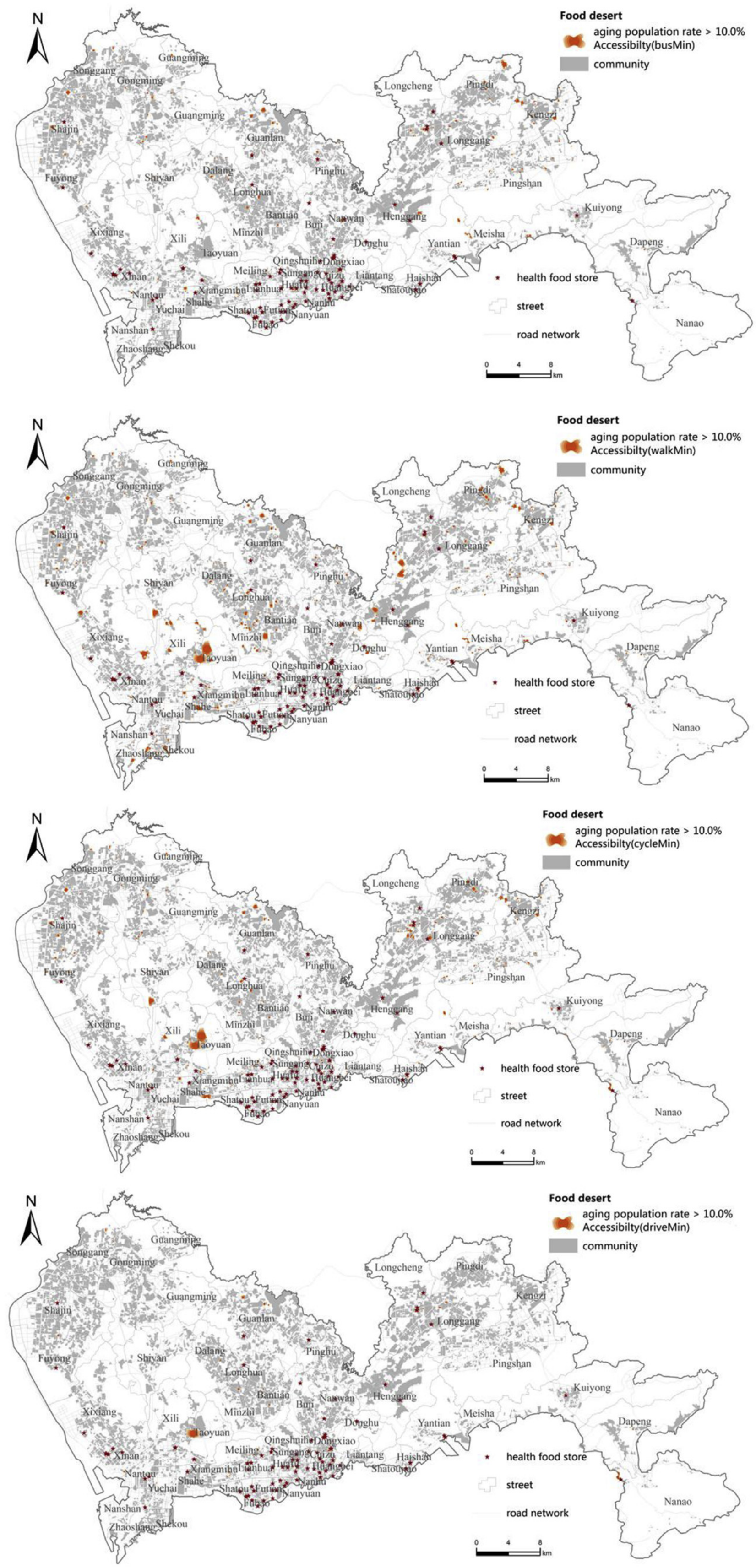

Fig. 8. Food deserts with regard to elder population under different transport modes within Shenzhen.

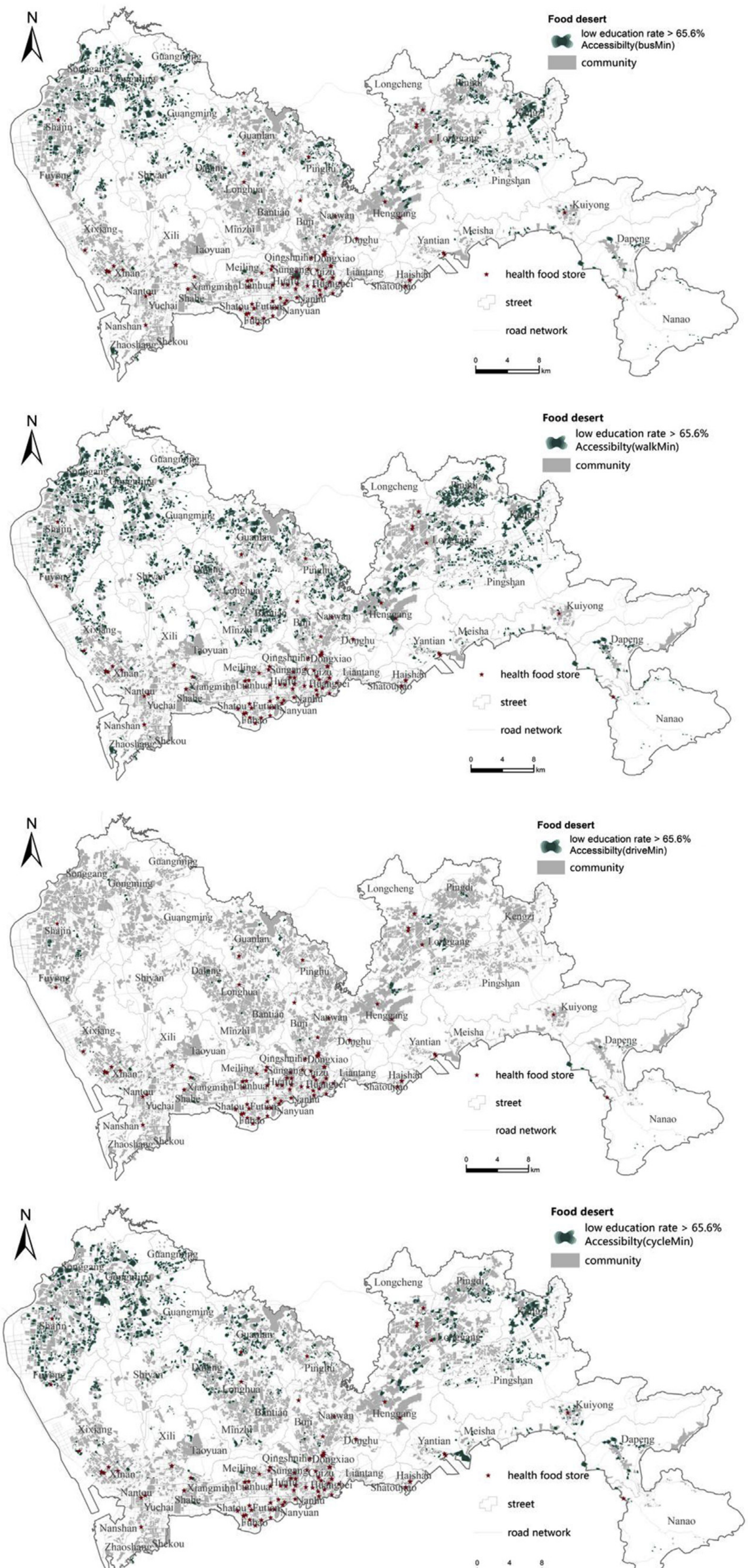

Fig. 9. Food deserts with regard to less-educated population under different transport modes within Shenzhen.

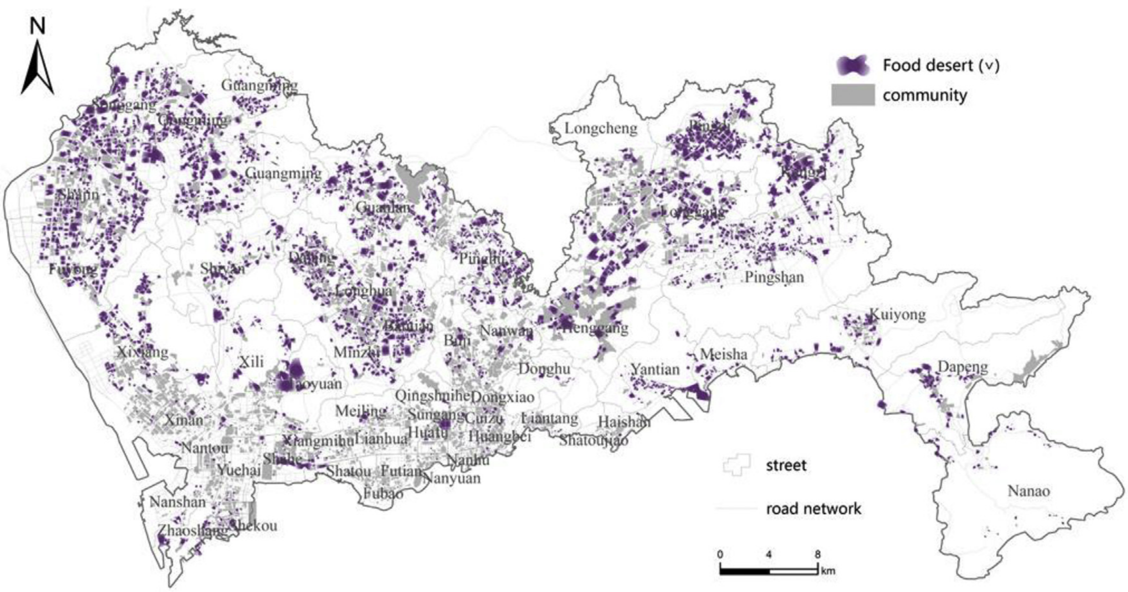

Fig. 10. Food deserts in respect to overall socioeconomic disadvantage within Shenzhen, China.

serious urban issue in China, and our findings highlight the necessity for placing more emphasis on healthy food opportunities for the elder. The elder people are acknowledged as a concerned group given their relatively poorer mobility and physical ability to reach destinations. It is noteworthy that the elder concentrated communities with less healthy food accessibility are particularly clustered in the socioeconomically disadvantaged districts. These districts may not be the ideal business locations for chain supermarkets, since potential profitability would not be constrained by the lower purchasing power. Large quantities of capital inputs (e.g., labor, infrastructure, and land) are required for these big business. Therefore, it should not be feasible to attract new supermarkets or superstores through planning interventions. Rather, formulating favorable strategies that encourage community-level local grocery stores should be a more realistic alternation.

Second, improving the public transportation for deprived communities is of great concern for urban planners. Convenient public transportation provides options for visiting healthy food stores far away from communities. A well-established and mature network of public transportation can also reduce the operation costs of retailers. Therefore, communities with convenience in a diversity of transport modes are expected to enjoy more access to healthy food. Urban planning should design and implement essential measures to increase the integrity of public transportation in the socioeconomically districts. Meanwhile, urban planners should emphasize the affordability of public transportation for visiting healthy food stores. One possible solution is to lower or subsidize the ticket fare for certain socioeconomically groups (e.g., unemployment, jobless, blue collars, and low-income). Another possible solution is to encourage the chain supermarkets to offer free regular bus service for the deprived communities.

Last, establishing more walkable sidewalks and special bicycle tracks should also effect. In Shenzhen, the sidewalks and bicycle tracks are very narrow and even absent in some districts. Such situation poses great obstacle to healthy food accessibility, since most local inhabitants prefer to visit the healthy food stores by walking and bicycle instead of public transit. Further urban planning should not only outline the quantity aspect, but also stresses the quality dimension. For example, walkability can be improved by greenbelts provision, pavement maintenance, lighting supply, and security fence establishment. Most important, the width of sidewalks should be matched with the main roads. Widening the main roads for relieving the traffic jam should not be at the cost of sidewalks.

5. Conclusions

This paper proposes a geo-big data approach to measuring transit-varying healthy food accessibility and applies it to identify the food deserts within Shenzhen, China. In particular, we develop a crawling tool to harvest the daily travel time from each community (8117) to each healthy food store (102) from the Baidu Map under four transport modes (walking, public transit, private car, and bicycle) during 17:30–20:30 in June 2016. Based on the travel time calculations, we develop four travel time indicators to measure the healthy food accessibility: the minimum, the maximum, the weighted average, and the standard deviation. Results show that the four accessibility indicators generate different estimations and the nearest service (minimum time) alone fails to reflect the multidimensional nature of healthy food accessibility. The communities within Shenzhen present quite different typology with respect to healthy food accessibility under different transport modes. Multilevel additive regression is further applied to examine the associations between healthy food accessibility and nested socioeconomic characteristics at two geographic levels (community and district). We discover that the associations are divergent with transport modes and with geographic levels. More specifically, significant social equalities in healthy food accessibility are identified via walking, public transit, and bicycle in Shenzhen. Based on the associations, we finally map the food deserts and propose corresponding planning strategies.

The methods demonstrated in this study should offer deeper spatial insights into intra-urban foodscape and provide more nuanced understanding of food deserts in urban settings of developing countries. Strengths of this study include incorporating real-time traffic volume on road networks, considering multiple transport modes, developing various accessibility measures, involving the nested socioeconomic characteristics and spatial autocorrelation, and quantifying the food deserts subjected to different socioeconomic characteristics. To our knowledge, this is the first study to examine the food deserts in China using a geo-big data approach. The present methodology can be generalizable to other populations and study areas worldwide. However, out study is not without limitations. First, the specific information is not collected regarding the food type, food price, consumed amount, actual visit number, and nutritional value of foods. As such, the healthy food accessibility cannot be described with more precise figures. Second, potential 'edge effect' is ignored, since the healthy food stores outside the Shenzhen are incorporated into analysis. Third, we employ the hierarchical linear additive model to explore the social inequalities. However, whether or not this model has advantage over other multilevel regression models remains unknown. Fourth, we do not compare the efficiency of Baidu Map with other navigation maps. Last, our finding would not stand for all populations and study areas, as the relationship between healthy food accessibility and neighborhood socioeconomic characteristics are highly sensitive to the contextual factors. Following studies should consider more categories of geo-big data and develop more sophisticated models to measure the healthy food accessibility. In particular, theoretical and actual linkage between healthy food accessibility and neighborhood socioeconomic characteristics as well as the mediators should be further understood.

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