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SAR-Gi*: Taking a spatial approach to understand food deserts and food swamps

He Jin[a,*], Yongmei Lu[b]

[a] School of Geosciences, University of South Florida, 4202 E Fowler Ave, 33620, Tampa, FL, USA
[b] Department of Geography, Texas State University, 601 University Dr., 78666, San Marcos, TX, USA

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ABSTRACT

Most existing food deserts/swamps studies adopted non-spatial approaches,overlooking the role of spatial dependence in the associations between food access and socioeconomic status. This study aims to fill the gap by examining this relationship with a spatial perspective. Using Austin, Tx as a case study, we adopted a multi-mode Huff-based 2SFCA method to measure the spatial access to food stores. Eight socioeconomic variables were represented by two indices per factor analysis:Economic Deprivation Index (EDI) and Sociocultural Deprivation Index (SDI). We proposed a SAR-Gi* model to characterize food deserts/swamps in Austin. Our analyses reveal that EDI is a significant predictor for access to healthy food (β = -0.054, p = 0.037), and SDI is significantly associated with access to unhealthy food (β= 0.160, p = 0.000). We also found that food deserts and swamps in Austin are concentrated in the east and northeast of Austin, respectively. The noticeable difference between the spatial patterns of food deserts and food swamps as identified by our study and those based on the USDA definition or other traditional methods speaks to the great potential of the SAR-Gi* model in reflecting geographical patterns and relations embedded in food access and socioeconomic status of neighborhoods.

1. Introduction

The development of food deserts in the cities of the United States began in the 1950s when suburbanization started. In the 1970s and 1980s, American cities went through an "urban crisis"(Wilson, 1996). Middle-class households moved to the suburbs and brought food retailers into the suburbs, leaving low-income families near or in the cities (Stein, 2011). Population and demographic changes in urban neighborhoods during this period also resulted in a significant loss of supermarkets and grocery stores. Meanwhile, the food swamp issue came into being with the rapid development of the fast-food industry in America (French, Harnack, & Jeffery, 2000). Food swamps refer to the areas where high calorie and energy-dense food swamps out healthy foods (Hager et al., 2017). Rose et al. (2009) articulated that the limited access to healthy foods is a useful metaphor for under-nutrition; the issue in the U.S. is over-consumption of nutrition, and food swamp is a more useful metaphor than food desert to depict this type of neighborhood food environment in the U.S.

The food access literature reports many ambiguities regarding the definitions of food deserts and swamps, and the definitions vary in different studies (Behjat, 2016). Accordingly, there are no standard variables nor methods to measure food deserts and food swamps (Stein, 2011). The lack of consensus on food desert definitions leads to different methodologies and terminologies. For instance, some researchers identified food deserts and swamps by considering food quality and costs (Cummins & Macintyre, 2002; Larsen & Gilliland, 2008); some considered the type and size of the food stores and the sales volumes (Hendrickson, Smith, & Eikenberry, 2006); others utilized spatial access to food stores to characterize food deserts and swamps (Coombs, Panther, Beye, & Fehrenbach, 2010); and still, others combined socioeconomic variables with spatial access to food stores when defining food deserts and swamps (Mulrooney et al., 2021; O'Dwyer & Coveney, 2006; Smoyer-Tomic, Spence, & Amrhein, 2006).

The consideration of both food access and socioeconomic deprivation is the conception and methodology we preferred in our study due to that several overarching theories are supporting this assertion. First, Macintyre's deprivation amplification hypothesis claimed that socially disadvantaged individuals are exposed to the contextual disadvantage in terms of access to affordable, nutritious food or physical facilities (Macintyre, 2007; Macintyre, Macdonald, & Ellaway, 2008). That being said, food access varies not only in spatial dimensions but also in non-spatial aspects such as income, race or ethnicity, education, and

* Corresponding author.
E-mail addresses: hjin1@usf.edu (H. Jin), yl10@txstate.edu (Y. Lu).

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employment (Dai & Wang, 2011; Kuai & Zhao, 2017). Second, Lytle's ecological model of individuals' eating behaviors provides another explaining the impacts of social marginalization and built environment (Luan, 2016; Minaker, 2013). Besides, Hillary Shaw identified three broad themes related to food access: ability, asset, and attitude (Shaw, 2006). Ability refers to the capability of physical access to healthy foods, whereas assets and attitudes reflect economic and sociocultural factors limiting healthy eating. Therefore, from the food equity and social justice perspective, only considering spatial access to food outlets may create bias in evaluating the retail food environment (Luan, 2016). Instead, we have to assume that the socioeconomically disadvantaged groups have reduced access to healthy food or excessive access to unhealthy food (Fleischhacker, Evenson, Rodriguez, & Ammerman, 2011; Hilmers, Hilmers, & Dave, 2012; Larsen & Gilliland, 2008). In this regard, we defined food deserts where residents have barriers to access healthy foods in deprived neighborhoods, that food swamps where residents are overexposed to unhealthy foods in deprived communities. Complying with our definitions of the two terms, the identification of food deserts and swamps should take into the spatial food access and socio-demographic deprivation simultaneously.

Understanding the relationship between food accessibility and socioeconomic deprivation is key to defining food deserts and swamps. In the past two decades, researchers have explored the relationship between food access and neighborhood deprivation extensively (Morland, Wing, Roux, & Poole, 2002; Pearce, Blakely, Witten, & Bartie, 2007; Powell, Chaloupka, & Bao, 2007; Zenk et al., 2005). These researches mainly focused on whether people in deprived areas have limited access to healthy foods or are overexposed to unhealthy foods (Galvez et al., 2008; Kwate, Yau, Loh, & Williams, 2009; Lisabeth et al., 2010). However, many studies have employed non-spatial statistics methods and models to analyze the association between neighborhood deprivation and food accessibility (Larsen & Gilliland, 2008; Matheson, Dunn, Smith, Moineddin, & Glazier, 2012). These non-spatial methods include, but not limited to, Ordinary Least Square (OLS) for continuous data (Kuai & Zhao, 2017), Poisson binomial regression for count data (Black, Carpiano, Fleming, & Lauster, 2011), logistic regression for binary data (Black et al., 2011; Smoyer-Tomic et al., 2008), etc. One assumption for non-spatial statistical methods is that each observation is randomly and independently distributed over geographic space. Food accessibility essentially is a 'spatial' problem (Dai & Wang, 2011; Kuai & Zhao, 2017); residuals from the non-spatial regression models are likely to be spatially auto-correlated, invalidating the results of the studies. The use of a spatial model could solve this problem potentially. Up to date, only a few studies have used the spatial model, including the spatial scan method (Baker, Schootman, Barnidge, & Kelly, 2006), spatial Bernoulli model (Lamichhane et al., 2013), spatial-temporal Bayesian hierarchical approach (Luan, 2016), Local Indicator of Spatial Association (LISA) (Garcia, Garcia-Sierra, & Domene, 2020), etc.

Of the different spatial approaches, spatial autoregressive models (SAR) is a method to deal with the problem of spatial dependence. There are two types of SAR models. The spatial lag model (SLM) is used when the dependent variable shows spatial autocorrelation. The spatial error model (SEM) is used when model specification fails to capture the impact of certain spatially clustered features on the spatial autocorrelation of the dependent variable. Dai and Wang (2011) employed SLM to account for the spatial autocorrelation effects of the food accessibility and socioeconomic variables in South-west, Mississippi. McKenzie (2014) examined the relationship between neighborhood supermarket access and socio-demographic factors in Portland, Oregon with SEM. Wang, Tao, Qiu, and Lu (2016) applied both SLM and SEM to analyze the relationship between spatial proximity to fresh food retailers and socioeconomic in two cities in Canada. These studies acknowledged the spatial dependence but did not further their research to the next level to define food deserts and food swamps.

When attempting to identify food deserts and food swamps, a classic non-spatial approach is commonly applied (Apparicio, Cloutier, & Shearmur, 2007; Blok, Scribner, & DeSalvo, 2004). Specifically, the spatial food access for multiple analysis units is ranked from low to high (e.g., 1 to 9), and each socioeconomic variable is also ranked in the same range. The rankings of all variables are added together to create a food desert index. The areas with the lowest index values are identified as food deserts. This type of approach seems straightforward, but it ignores the spatial dependence between food access and socioeconomic deprivation. Stein (2011) utilized *local bivariate Moran's I* to incorporate spatial dependence into defining food deserts and swamps. The specific method delineates food deserts as the census block groups located at the center of Low-High clusters measured by access to healthy foods, and food swamps as those at the centers of High-High clusters for accessing unhealthy foods. However, this method failed to capture the relationship between geographic food access and socio-demographic deprivation, which has been proved to be significantly and spatially dependent, as discussed above. Nevertheless, the use of Getis-Ord Gi* statistic[1] could solve the issue of *Moran's I* since it reveals spatial patterns in both neighboring and its own units. Gi* statistic, known as hot spot analysis, is commonly used in geography and other disciplines for spatial analysis (Cheng, Hsu, Li, & Ma, 2018; Chuai, Lu, & Li, 2020; Leitner, Glasner, & Kounadi, 2018). It calculates z-score and p value, which are used to identify whether the phenomenon under investigation have statistically significant hot spots (or cold spots). When significant "hot spots (or cold spots)" appear on maps, meaning that high (or low) values significantly cluster in specific areas.

For the purpose of delineating food deserts and food swamps, we propose a *SAR-Gi** method to account for the relationship between socioeconomic status and food accessibility, the spatial dependence of such a relationship, and the respective spatial autocorrelation patterns of food access and socioeconomic status. The SAR part in the SAR-Gi* model determines which socioeconomic variables are significant predictors for spatial food access when spatial autocorrelation is considered. It determines which socio-demographic deprivation variables will be analyzed using the Gi* statistics. Once the identified significant deprivation variables are specified, the Gi* statistic is applied to each deprivation variable as well as the spatial food access measures to identify areas as food deserts or food swamps.

Applying the *SAR-Gi** method to Austin, Texas in this research, we seek to relate socioeconomic disparities to access healthy (and unhealthy) foods with a spatial perspective, which is often missing in food environmental studies. The contributions of this study are twofold: (1) to examine and reveal the socioeconomic context for food access in Austin, and (2) to define the food deserts and swamps in Austin by considering both access to foods and the respective socioeconomic deprivation index.

2. Study area

The study area is the City of Austin (Fig. 1), the capital city and 4th-most populous city in Texas. It is across three counties of Travis, Hays, and Williamson. Austin has the second-largest population among the state capitals in the US, and it is the fastest-growing city in the nation. Approximately 947,890 people are living in Austin as of 2018. The median household income is $ 42,689, and per capita income is $ 24,163 per year. There are 9.1% of families and 14.4% of the population below the poverty line. The unit of analysis for this study is the census block group, the smallest unit that the US Census Bureau tabulates socio-demographic data. There are 555 census block groups in the study area.

3. Method & data preparation

The retail food stores in this study included healthy food sources —

[1] We shortened the Getis-Ord Gi* statistic as Gi* statistic in the remaining manuscript for a simplification purpose.

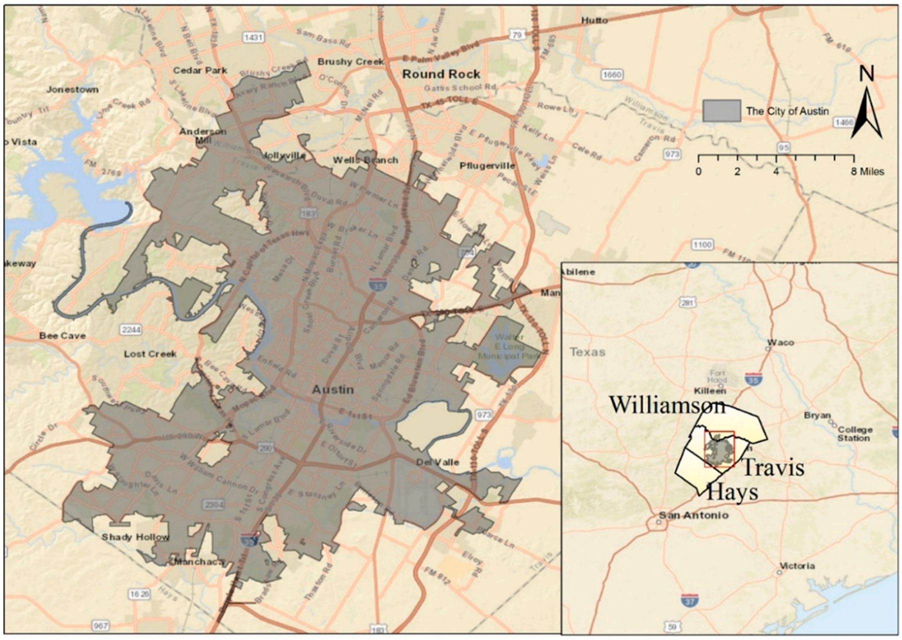

Fig. 1. Study Area — 555 census block groups in city of Austin, Texas.

supermarkets & grocery stores, supercenters, and specialty food stores (i.e., meat and fresh fruit vegetable markets) (Fig. 2); unhealthy food sources were convenience stores and fast-food restaurants (Fig. 2). Supermarkets and grocery stores are the reliable providers of healthy food because they consistently have greater variety and availability of healthy food options than other stores (Glanz, Sallis, Saelens, & Frank, 2007). Supercenters are also considered as reliable, healthy food sources (Krukowski, West, Harvey-Berino, & Prewitt, 2010). Some other studies included specialty stores as sources providing healthy food options (Moore & Diez Roux, 2006; Walker, Keane, & Burke, 2010). In contrast, convenience stores and limited-service fast food restaurants are classified as unhealthy food outlets since they primarily carry processed foods and high caloric food that do not meet people's nutrition needs (Glanz, Sallis, Saelens, & Frank, 2005; Saelens, Glanz, Sallis, & Frank, 2007). The data about these food outlets were collected from 2016 ReferenceUSA.[2]

A *Multi-modal Huff-based 2SFCA* method was used to measure the spatial access to healthy foods (SAI_H) and spatial access to unhealthy foods (SAI_U) for each census block group (Jin, 2019). The *Multi-modal Huff-based 2SFCA* was proposed by Jin (2019), and it is based upon the Two Step Floating Catchment Area (2SFCA), which has been used in many accessibility studies since it not only accounts for the distance-decay effect but also emphasizes the interactions between service and population demands in neighboring analytical units (W. Luo & Wang, 2003). There are various improvements of the 2SFCA, including E2SFCA (W. Luo & Qi, 2009), Optimized 2SFCA (Ngui & Apparicio, 2011), Kernel Density 2SFCA (Dai & Wang, 2011), Three-step FCA (Wan, Zou, & Sternberg, 2012), Commuter-based 2SFCA (Fransen, Neutens, De Maeyer, &), and other variants (Mao & Nekorchuk, 2013; Vo, Plachkinova, & Bhaskar, 2015). Among them, the Huff-based 2SFCA is one of the successful modifications (J. Luo, 2014); it can reveal more variability of accessibility due to that it accounts for more realistic constraints (i.e., quantifying the probability of people's selection of a supply site with consideration of both travel cost and capacity of a supply site) in the measurement. Our *Multi-modal Huff-based 2SFCA* method, on the one hand, inherits the advantage of the Huff-based 2SFCA; on the other hand, it incorporates multiple transportation modes (i.e., driving, walking, and public transportation) into the Huff-based 2SFCA, overcoming the overestimation of the population demand in the Huff-based 2SFCA. It considers the transportation mode to food stores for low-income groups, especially for those who cannot afford personal vehicles. The Multi-modal Huff-based 2SFCA was implemented in ArcGIS 10.7. Network Analyst OD Cost Matrix solver was used to calculate the travel time of each mode for each census block/food store pair. The OD matrix uses Dijkstra's algorithm to find the shortest path through the network. Three transportation modes were utilized: 15-min for driving, 10-min for walking (Yang & Diez-Roux, 2013), and 30- min for public transits (Dai & Wang, 2011) as cut-offs for each travel mode catchment. One could refer to Jin (2019) for more details of the *Multi-modal Huff-based 2SFCA* method and the calculation of SAI_H and SAI_U. A low value of SAI_H means a lack of spatial access to healthy foods, and an increased SAI_U indicates elevated access to unhealthy foods. The SAI_H and SAI_U were both right skewed; hence, natural logarithm (ln) transformation was applied to generate $LnSAI_H$ and $LnSAI_U$ to represent the spatial access to healthy and unhealthy foods for the census block groups in the study area. The spatial patterns of the $LnSAI_H$ and $LnSAI_U$ are shown in Fig. 3.

Eight variables were carefully selected to represent the sociodemographic status of block groups. These variables include economic variables, such as median household income, the proportion of households below the poverty line, and unemployment rates (Harrington & Elliott, 2009); education (i.e., percentage of people without higher education) (Harrington & Elliott, 2009), linguistic barriers (i.e., the proportion of households in linguistic isolation) (Hsieh et al., 2015), home ownership (i.e., the percentage of households who rent homes) (Brown, Perkins, & Brown, 2004), race/ethnicity (i.e., the proportion of people who are Hispanic/Latino) (Galvez et al., 2008), and housing environment (i.e., households lacking complete kitchen facilities (Dai & Wang, 2011). We obtained the eight variables from the 2018 American Community Survey (ACS) 5-year estimates. The summary statistics are shown in Table 1.

Factor analysis (FA) was performed on the eight variables. The eight variables were reduced into two factors - Economic Deprivation Index (EDI) and Sociocultural Deprivation Index (SDI). The most important three variables contributing to the EDI were the unemployment rate (factor loading FL = 0.928), median household income (FL = −0.773), and the proportion of households below the poverty line (FL = 0.547).

[2] http://resource.referenceusa.com/.

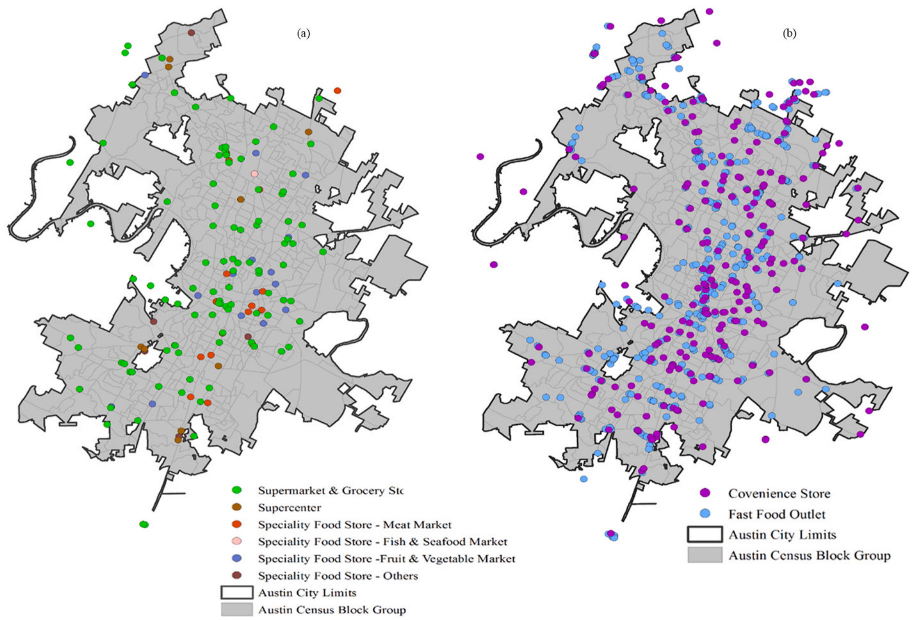

Fig. 2. Spatial distribution of healthy (a) and unhealthy (b) food stores in city of Austin, TX.

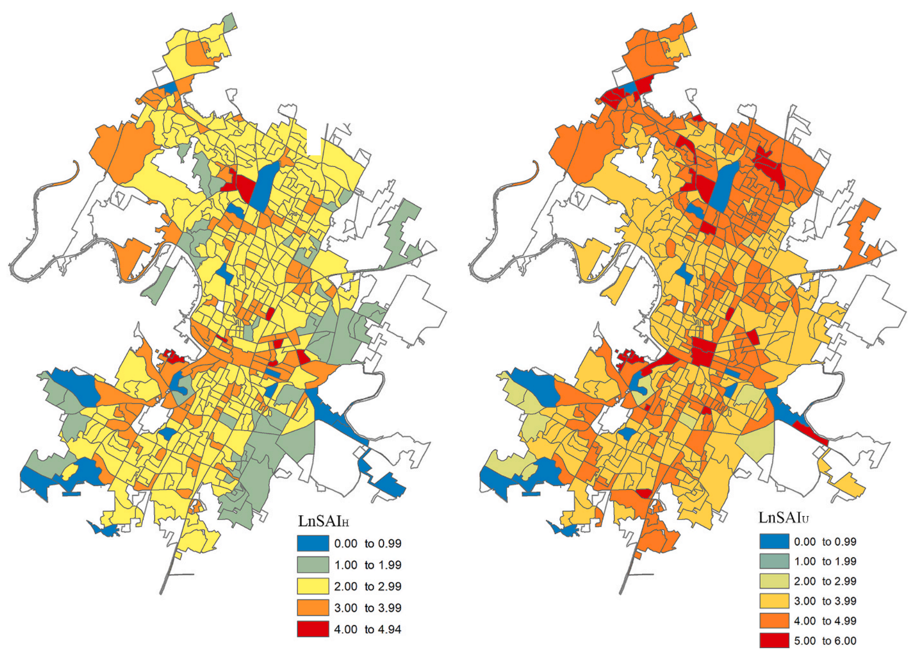

Fig. 3. The two logarithm-transformed accessibility measures: $LnSAI_H$ and $LnSAI_U$ in Austin.

Table 1
Description of the eight SES variables.

Variables	Min	1st Quartile	Median	3rd Quartile	Max	Mean	SD
Median Household Income ($1,000)	5.66	37.43	54.54	74.67	199.44	60.46	32.61
Unemployment Rate (%)	3.85	19.35	25.64	31.60	77.32	26.74	10.73
Below the Poverty Line (%)	0.00	5.14	11.79	21.80	100.00	16.28	16.58
Without a complete kitchen facility (%)	0.00	0.00	0.00	2.02	21.76	1.61	3.19
Home Renter (%)	0.00	29.47	51.03	74.06	100.00	52.50	28.63
Without Higher Education (%)	0.00	32.79	50.37	73.20	100.00	52.49	24.57
Hispanic People (%)	0.00	12.37	24.71	50.96	100.00	32.26	24.12
Linguistically Isolation (%)	0.00	0.00	3.43	8.76	46.62	6.81	9.38

Table 2
Component coefficient matrix of factor analysis.

Original Variables	Factors	
	Economic Deprivation Index	Sociocultural Deprivation Index
Median Household Income ($1,000)	**−0.773**	−0.460
Without Higher Education (%)	0.150	**0.897**
Hispanic People (%)	0.129	**0.937**
Below the Poverty Line (%)	**0.547**	0.368
Unemployment Rate (%)	**0.928**	0.085
Home Renter (%)	0.119	**0.947**
Without complete kitchen facilities (%)	0.142	−0.075
Linguistically Isolation (%)	0.211	**0.818**

The SDI is highly associated with home ownership, ethnical mix, education attainment, and language barriers (i.e., FL = 0.947,0.937,0.897, and 0.818, respectively). The EDI and SDI of each block group were computed using the coefficients in Table 2. Their descriptive statistics are shown in Table 3. The spatial patterns of the EDI and SDI are shown in Fig. 4. The higher of the index means the higher deprivation. The most economically deprived areas (i.e., > 2) were on the campus of the University of Texas at Austin and East Austin; the most sociocultural deprived areas are also found on the East side of Austin.

There are three steps in our proposed SAR-Gi* method (Fig. 5), and the rationale is explained below. The application of SAR model is to examine if economic deprivation (measured by EDI) and sociocultural deprivation (measured by SDI) are significantly related to spatial access to health food (measured as $LnSAI_H$) or unhealth food (measured as $LnSAI_U$). The SAR models adopted in this method are global models to assess how spatial access to (un)healthy food at census block group (CBG) level is or is not related to EDI or SDI. The p-value and its significant level of 0.05 is a standard approach as a cut-off value to assess a significant relationship. Since we define food desserts and food swamps as related to both spatial access to food and socioeconomic deprivation, our final identification of food desserts in the City of Austin is based on spatial interaction of the low spatial access to health food and high socioeconomic deprivation CBG. However, since $LnSAI_H$ is revealed by the SAR model to be only significantly related to EDI but not SDI, this final identification of food desserts includes those CBGs that have low LnSAIH and high EDI, and SDI is not considered for identification of food desserts. Similar explanation applies to the identification of food swamps. Therefore, although Fig. 5 uses the $LnSAI_H$ as the demonstration, the three-step procedure also applies to the $LnSAI_U$.

The first step of the SAR-GI* model is to employ SAR (SLM or SEM) to uncover whether the two deprivation indices (EDI and SDI) are significantly related to spatial access to healthy foods ($LnSAI_H$) (Fig. 5). The SAR analysis was performed using GeoDa 1.1.4. SLM model accounts for the spillover effects of the dependent variable on the regression model (see Eq. (1)); the SEM model captures the impact of error terms and omitted variables, especially when these omitted variables exhibit spatial autocorrelation (Eq. (2)).

$$\mathrm{Y} = (X\beta + \mathrm{u})(\mathrm{I} - \rho \mathrm{W})^{-1} \tag{1}$$

$$Y = X\beta + \varepsilon(I - \lambda W)^{-1} \tag{2}$$

Table 3
Descriptive statistics of the two indices.

	Min	1st Quartile	Median	3rd Quantile	Max	Mean	SD
EDI	−2.37	−0.64	−0.13	0.45	4.47	1.26E-07	1.00
SDI	−1.74	−0.81	−0.20	0.69	3.33	2.40E-04	1.00

where Y is the dependent variable $LnSA_H$ or $LnSA_U$; X is a vector of the independent variables: EDI and SDI; β is a vector of the estimated coefficients; W is the spatial weights matrix; ρ is a spatial lag parameter; u is the error vector; ε is a vector of spatially autocorrelated error; λ is the spatial error coefficient; $(I - \rho W)^{-1}$and $(I - \lambda W)^{-1}$ are both called the spatial multiplier. Lagrange Multiplier (LM) and Robust Lagrange Multiplier (RLM) statistics are utilized to determine which SAR model (SLM or SEM) to use. (Anselin, 2005) proposed a diagram to depict the decision process.

The second step is to apply Gi* statistic to the socioeconomic deprivation index (EDI or SDI) that is significantly related to spatial access to food (e.g., $p < 0.05$). Gi* statistic is also conducted to analyze the patterns of spatial access to healthy and unhealthy foods in Austin, $LnSAI_H$ and $LnSAI_U$. ArcGIS 10.7 was used to run G* Statistics. Three p -values (0.01, 0.05, and 0.10) are used to identify the significant hot and cold spots of variables. Based on the z-score and p-value, block groups are grouped into three types for the variables evaluated: not significant, hot spots, and cold spots. Block groups in significant hot (or cold) spots indicate that high (or low) values are clustering in a specific area. For example, the significant hot spots of EDI (or SDI) imply a severe economic (or sociocultural) deprivation in local areas; the significant hot (or cold) spots of $LnSAI_H$ depict that certain block groups with high (or low) access to healthy foods are clustered.

The third step is to define food deserts by identifying the spatial overlapped area between the hot spots of EDI or SDI (if they are significant factors) and the cold spots of $LnSAI_H$ (Fig. 3). This way, the block groups that fall within the areas of elevated socio-demographic deprivation and the areas lacking access to healthy foods are identified as food deserts. For the delineation of the food swamps, the same three-step procedure was used. First, we find out whether EDI (or SDI) is significant for predicting the $LnSAI_U$ by running the SAR model. If either index does, we then perform Gi* statistic on either index (EDI or SDI or both) and $LnSAI_U$. Last, we intersect the hot spots of EDI (or SDI) and those of $LnSAI_U$ to find block groups with elevated socio-demographic deprivation and excessive access to unhealthy foods.

4. Result

To specify which SAR model to use for predicting $LnSAI_H$ with our proposed SAR-GI* model, we ran the OLS first (see Table 4). SLM was chosen following the technical procedure explained in the previous section. For the dependent variable $LnSAI_U$, we followed the same procedure and selected SEM (Table 4).

The result of the SLM for $LnSAI_H$ is present in Table 5. The pseudo-R^2 of the SLM cannot be compared with the adjusted R^2 of the OLS (Anselin, 2005). More reliable measures of fitness are Log-Likelihood (LL), Akaike info criterion (AIC), and Schwarz Criterion (SC). A higher number Log-likelihood indicates a better model, while a lower number of AIC and SC indicates better goodness of fit of the model. The LL increases from −415.509 (the OLS) to −329.508, the AIC and SC both decrease, showing the improvement of model fit with the SLM relative to the OLS. The Breusch-Pagan (BP) statistic measures heteroscedasticity of the errors. The values of the BP test are 0.508 with p-value 0.776 (the SLM) and 1.082 with p-value 0.582 (the OLS), indicating that the heteroscedasticity is not an issue for the model. A Likelihood Ratio (LR) tests the significance of the spatial autoregressive coefficient. A high significance with LR value means the spatial effects in the data have not been removed entirely (Anselin, 2005). Also, we checked the spatial dependence of the residuals in SLM. The Moran's I index is 0.004 (p = 0.364), which indicates that including the spatial lag term in the model has effectively accounted for spatial autocorrelation or spillover of spatial accessibility to healthy food. These all confirm that the SLM is much more appropriate than the OLS.

The spatial lag (W_LnSAH) coefficient is 0.671 and is highly significant (t = 16.612, p = 0.000). The coefficient of the EDI is −0.054 with a

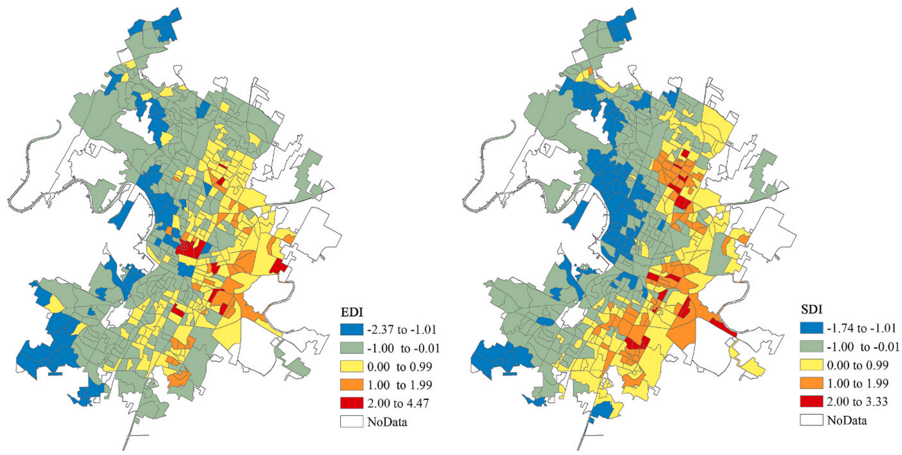

Fig. 4. Spatial distribution of the two indices — EDI and SDI in Austin, TX.

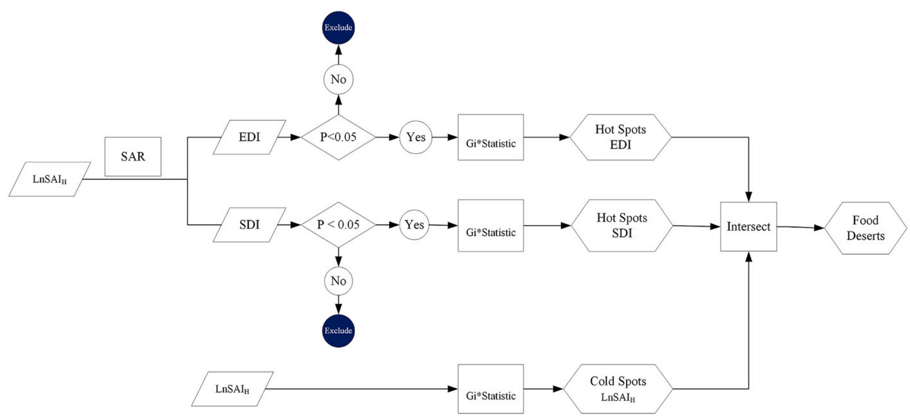

Fig. 5. The proposed SAR-Gi* model for the identification of food deserts (or food swamps).

Table 4
Statistics of Lagrange multiplier (lag) and Lagrange multiplier (error).

Test	MI/DF[a]	Value[a]	P[a]	MI/DF[b]	Value[b]	P[b]
Moran's I (error)	0.384	13.746	0.000	0.450	16.072	0.000
Lagrange Multiplier (lag)	1.000	193.471	0.000	1.000	173.158	0.000
Robust LM (lag)	1.000	18.013	0.000	1.000	0.958	0.328
Lagrange Multiplier (error)	1.000	179.800	0.000	1.000	246.694	0.000
Robust LM (error)	1.000	4.343	0.037	1.000	74.494	0.000
Lagrange Multiplier (SARMA)	2.000	197.814	0.000	2.000	247.652	0.000

Note.
[a] Indicates that the dependent variable is $LnSAI_H$.
[b] Indicates that the dependent variable is $LnSAI_U$.

Table 5
The estimation of SLM for $LnSAI_H$ and the comparison between SLM and OLS.

	SLM			OLS		
R^2	0.390 (Pseudo- R^2)			0.015 (adjusted R^2)		
LL	−329.508			−415.509		
AIC	667.017			837.018		
SC	683.568			849.432		
BP	0.508 ($p = 0.776$)			1.082($p = 0.582$)		
LR	172.002 ($p = 0.000$)					
Moran's I	0.004 ($p = 0.364$)			0.384 ($p = 0.000$)		
	Coef.	t	p	Coef.	t	p
W_LnSAH	0.671**	16.612	0.000			
C	0.865**	8.002	0.000	2.634**	95.160	0.000
EDI	−0.054*	−2.089	0.037	−0.049	−1.496	0.135
SDI	0.025	0.958	0.339	−0.045	−1.384	0.167

Note: C: Constant; LL: Log-Likelihood; AIC (Akaike Info Criterion); SC: Schwarz criterion; BP: Breusch-Pagan test; LR: Likelihood Ratio Test.

p-value of 0.037, which indicates that EDI is negatively related to the spatial access index to healthy food outlets. Whereas the coefficient of the SDI is 0.025 with a p-value of 0.339 (>0.05), meaning that the SDI is not significantly related to healthy food outlets accessibility. Besides, the absolute value of the coefficient EDI is larger than the SDI, and it depicts that economic deprivation has more influence on healthy food accessibility.

Table 6 shows the result of the SEM with the dependent variable, $LnSAI_U$. The increase of LL value, the drop of AIC and SC values, confirming that SEM improves the model fit compared with OLS. The BP value is not significant ($p = 0.193$), suggesting that the heteroscedasticity is not present in the SEM. The spatial error (LAMBDA) coefficient is 0.693 and is highly significant ($t = 16.780$, $p = 0.000$). The constant term is significant ($t = 59.98$, $p = 0.000$). The coefficient of the EDI is −0.043 with a p-value of 0.206, which indicates that the EDI has an insignificant negative effect on spatial access index to unhealthy food outlets. The coefficient of the SDI is 0.160, with a p-value of 0.000, indicating that the SDI is significantly associated with unhealthy food outlets' accessibility.

Fig. 6(a) shows the result of the Gi* statistic analysis on $LnSAI_H$. Hot spots of healthy food access are in the city center and the southwest of

Table 6
The estimation of SEM for $LnSAI_U$ and the comparison between SEM and OLS.

	Spatial Error Model (SEM)			Ordinary Least Square (OLS)		
Adj.R^2	0.409(Pseudo- R^2)			0.014(adjusted R^2)		
LL	−312.262			−430.720		
AIC	630.524			813.440		
SC	642.937			825.853		
BP	3.285 (p = 0.193)			2.202 (p = 0.333)		
LR	182.916 (p = 0.000)					
Moran's I	−0.004 (p = 0.213)			0.450 (p = 0.000)		
	Coef.	t	p	Coef.	t	p
C	3.992**	59.980	0.000	4.022**	149.055	0.000
EDI	−0.043	−1.262	0.206	−0.071*	−2.220	0.027
SDI	0.160**	4.147	0.000	0.089 **	7.011	0.006
LAMBDA	0.693**	16.780	0.000			

Austin, while cold spots are found in the periphery and east of Austin. The block groups classified as cold spots indicate that these areas and their adjacent units have low access to healthy food outlets. The hot spots of unhealthy food access ($LnSAI_U$), as shown in Fig. 6(b), are mostly located in the north and northeast parts of Austin. The hot spots of the SDI and EDI are both located in the east of Austin (Fig. 6(c)–(d)).

The cold spots of $LnSAI_H$ and the hot spots of EDI were intersected to define food deserts. The result is illustrated in Fig. 7(a); food deserts are mainly located in the east of Austin near Austin International airport (i. e., the block groups in orange color). We also intersected the block groups with hot spots of $LnSAI_U$ and SDI to delineate food swamps; they are mainly located in the northeastern tip of Austin, next to the Walnut Creek Metropolitan Park (Fig. 7(a)).

For comparison purposes, we also map out the food deserts and food swamps defined by other methods. Fig. 7(b) shows the result of the bivariate Moran's I method (as in Stein, 2011), which is also a spatial measure. As discussed early in the paper, this method inappropriately associates spatial food accessibility of a geographic unit with social deprivation of the neighboring units. Fig. 7(c) is the USDA's food desert locator in Austin. The USDA developed a "food desert locator" to map food deserts at the census tract level across the United States. It uses two criteria — low income and low access to delineate food deserts. The

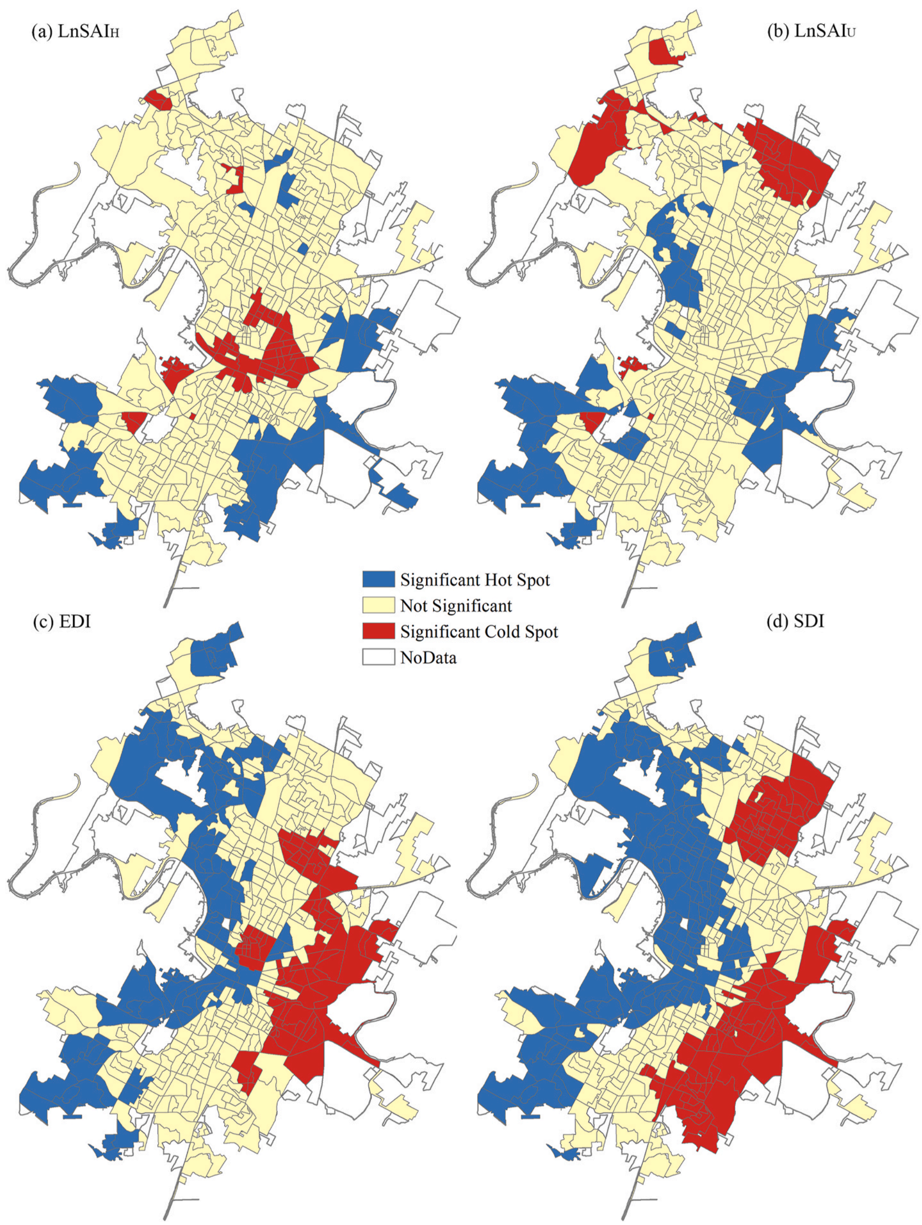

Fig. 6. Result of Getis-Ord Gi* analysis on (a) LnSAIH (b) LnSAIU (c) EDI (d) SDI.

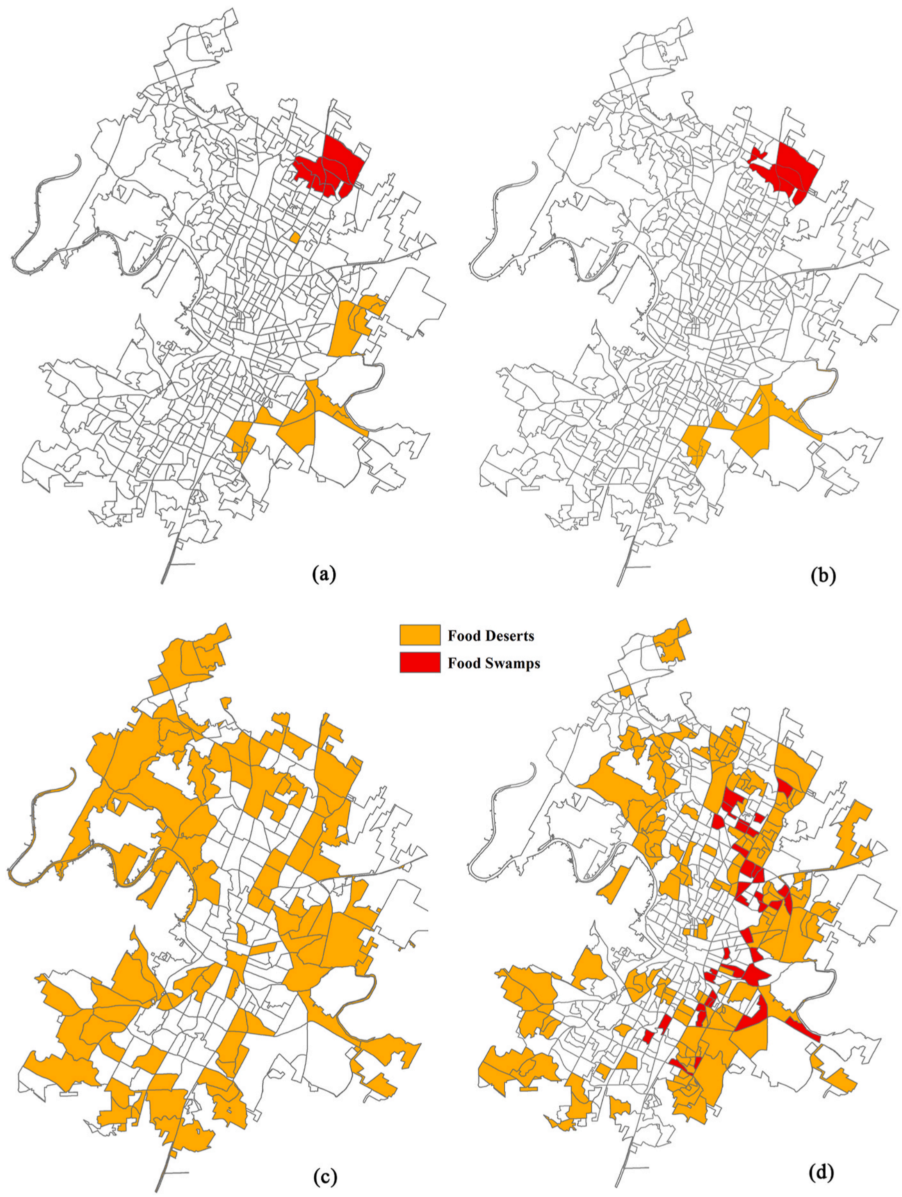

Fig. 7. Identified food deserts and food swamps in Austin with (a) SAR-Gi* method (our proposed one); (b) Bivariate Moran's I method; (c) USDA method; (d) classic statistical methods.

low-income census tracts are defined as 20% or higher poverty rate or a median family income at (or below) 80% of the area's median family income. The low-access census tracts are at least 33% of the population who reside more than one mile from a supermarket (or large grocery store) in urban areas and 10 miles in rural areas. Note that its original delineation is at the census tract level; we did the intersect analysis and derived food deserts at the block group level. The description of the classic statistical method was explained in the Introduction, and its result is illustrated in Fig. 7(d). The USDA and classic statistical methods are non-spatial methods. Their difference is that the classic method characterized multiple socio-demographic deprivation variables, but USDA counted only one income variable. The non-spatial delineations include more block groups into food desert/swamps than the spatial counterpart. Food deserts spread across Austin. Food swamps (Fig. 7(d)) are dispersed throughout East Austin. Compared to the other three methods, the SAR-Gi* method (Fig. 7(a)) not only characterizes the multifaceted nature of socioeconomic deprivation but also solves the spatial dependence issue.

5. Discussion and Conclusion

To gain an in-depth understanding of food issues in Austin, we identified food deserts and swamps by examining the association between inequality in spatial accessibility to food outlets and the two deprivation indices with our proposed SAR-Gi* model. The SAR is fundamental to our proposed SAR-Gi* method as it provides a primary investigation of the significant predictors of spatial food access. In this study, the SAR was applied to explore the relationship between food access and economic and social deprivation in Austin at the census block group level. With the spatial lag model (SLM), access to healthy food outlets in Austin, Tx was found to be significantly associated with economic deprivation. By contrast, the non-spatial method OLS did not find any significant relationship between access to healthy food outlets and the two socio-demographic factors in Austin, Texas. The magnitude of economic deprivation was more substantial when spatial effects are considered than as revealed by OLS. The negative relationship (−0.054) indicates that residents with a high economic disadvantage (i.e., high EDI) would have reduced access to healthy food outlets. This finding aligns with many previous studies that residents from low-income and high-poverty neighborhoods were less accessible to healthy foods (Beaulac, Kristjansson, & Cummins, 2009; Canto, Brown, & Deller, 2014; Chung & Myers, 1999; Drewnowski & Specter, 2004; Fleischhacker et al., 2011; Hilmers et al., 2012; Larsen & Gilliland, 2008; Leibtag & Kaufman, 2003; Morland et al., 2002). But it does not support Dai & Wang's (2011) finding that areas with higher urban economic disadvantages had better spatial food accessibility to healthy food stores.

With the SAR-Gi* model, only the sociocultural factor was a significant predictor of unhealthy food access in Austin, Tx. However, both economic and sociocultural deprivations are significantly related to access to unhealthy food outlets by the non-spatial OLS model. The magnitude of the sociocultural deprivation with the SAR-Gi* was more substantial than the OLS. The positive relationship (0.160) suggests that neighborhoods in high sociocultural deprivation (i.e., high SDI) had excessive access to unhealthy foods. The correlation between race/ethnicity and unhealthy food access has been widely recognized in America and other countries (Galvez et al., 2008; Hargreaves, Schlundt, & Buchowski, 2002; James, 2004; Kumanyika et al., 2007; Lisabeth et al., 2010; Morland et al., 2002; Pearce et al., 2007). Many studies showed that neighborhoods with predominantly minority (i.e., Hispanic or African America) had higher access to convenience stores or fast-food restaurants (Galvez et al., 2008; Lisabeth et al., 2010; Morland et al., 2002; Pearce et al., 2007). The findings agreed with these studies that Hispanic/Latino neighborhoods (Galvez et al., 2008; Lisabeth et al., 2010) and low education neighborhoods (Barker, Lawrence, Woadden, Crozier, & Skinner, 2008; Lawrence et al., 2009) were more exposed to unhealthy foods.

Furthermore, the SAR-Gi* model depicts an authentical picture of characterizing food deserts and swamps with the consideration of spatial dependence between an analysis unit (e.g., census block group for this study) and its neighbors, which is often missing in the bivariate Moran's I and non-spatial methods. Our proposed method revealed that food deserts are clustered in East Austin, and food swamps are in Northeast Austin. Both food deserts and food swamps were along the east side of the major highway IH-35. Food desert areas have not only scarce healthy food outlets but also high economic and sociocultural deprivation. In these areas, the less-dense population makes it hard for any new grocery stores and supermarkets to be profitable; opening small, independent, non-chain grocers have great potential to alleviate the problem (Bao, Tong, Plane, & Buechler, 2020). Other alternative is to promote farmers' markets, develop community gardens, and plant fruits and vegetables in backyards (Sage, McCracken, & Sage, 2013; Wang, Qiu, & Swallow, 2014). For example, Wang et al. (2014) articulated that community gardens and farmers' markets would increase access to healthy food and promote other social benefits for local communities even though they were not the cure-all for food deserts issues. Also, any investment to promote economic opportunities for people living in East Austin and help them improve income and eliminate poverty will help strengthen their affordability for healthy foods. For instance, increasing the numbers of grocery stores and supermarkets that accept the WIC (Women, Infants, and Children) and food stamps in food deserts, as suggested by Sage et al. (2013), is an effective measure to improve residents' healthy food affordability. It is worthy to note that the University of Texas at Austin campus was not identified as a food desert by our method because multiple grocery stores are surrounding and near the campus. Students in this area have the advantage of enjoying better spatial access to healthy food stores. However, we questioned whether this spatial advantage could indeed transfer to serving the students. Students often have less mobility because of low car ownership and poor food affordability. They are likely to purchase cheap and unhealthy diets nearby because of the burden of carrying heavy grocery bags via public transit or walking. Therefore, food issues on and surround the UT campus are of concern. For food swamp neighborhoods, zoning laws, or policies to limit the development of fast-food restaurants and convenience stores may be an effective option. Moreover, sociocultural deprivation in food swamps may result in inadequate nutrition intake and health disadvantages, especially for Hispanic and linguistically isolated families with low-level education. Therefore, intervention programs that help the marginalized groups adopt a healthy lifestyle, as well as enhance their literacy and knowledge on food nutrition, are essential to improve healthy food access in the food swamps.

This research implies that spatial accessibility is not the only essential factor in the understanding of food accessibility; deprived economic and sociocultural conditions can exacerbate the situation. Deprived conditions can influence people's dietary behavior; disadvantaged people may have no choice but to purchase energy-dense, nutritionally inferior, but cheap food, even with sufficient healthy food supply around their neighborhoods (Helling & Sawicki, 2003; Larson, Story, & Nelson, 2009). Furthermore, this paper aims to address the methodological gaps in previous research on the food environment in Austin, Texas. It emphasizes the importance of examining spatial effects in evaluating food access. Ignoring spatial effects in food environment assessment could lead to biased results. In the present study, the absolute values of coefficient estimates are generally larger in SAR-Gi* models than in the OLS model. The underestimated impacts of economic and sociocultural deprivation by the non-spatial model could mislead policy, recommendations, and interventions. Moreover, it is worth emphasizing that one of the important contributions of our study is that the spatial access to health food is significantly related to economic deprivation at census block group level in Austin, whereas the spatial access to unhealth food is significantly related to sociocultural deprivation. While this relationship is worth further examination for other study areas, but it points to a very promising direction to understanding the different socioeconomic context for different aspects of food access, lack of access to healthy food and over-exposure to unhealth food in particular.

As with any empirical studies, this research is not without limitations. First, this research emphasizes the importance of spatial effects; however, the technique of constructing the composite deprivation index (i.e., factor analysis) is a non-spatial approach. Luan (2016) applied its alternative spatial approach — spatial latent factor analysis to account for the spatial dependence of associated constructs. Future studies should explore a spatial approach when generating the deprivation indices. Second, we did not investigate food access for several population groups that potentially are vulnerable to access food outlets; these groups include but are not limited to the senior population and African American groups. Last, the food affordability, social preferences, and other measures of food access were not considered in the delineation of food deserts and food swamps in our present study.

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Author contribution statement

He Jin: Conceptualization, Methodology, Formal analysis, Software, Data curation, Visualization, Validation, Writing-Original draft preparation.

Yongmei Lu: Supervision, Writing-Reviewing and Editing.

All authors reviewed the results and approved the final version of the manuscript.

Declaration of competing interest

No potential conflict of interest was reported by the author(s).

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