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A GIS-based spatial statistical approach to modeling job accessibility by transportation mode: case study of Columbus, Ohio

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ABSTRACT

Improving job accessibility based on transport connectivity helps to address equity issues. Spatial autocorrelation (SA) is also a focus of interest in transportation planning, but has been neglected in analyzing job accessibility in metropolitan areas. In this study, GIS-based job accessibilities by walking, transit, and car are computed for the metropolitan area of Columbus, Ohio, and three transport-based spatial autoregressive (SAR) models are estimated to account for the SA of job accessibility among neighboring block groups, while controlling for built-environment and socioeconomic factors. SA intensities and extents are compared in order to better understand local spatial clusters of job accessibility across the region. Direct and indirect spillover effects due to an investment change in transportation facilities are estimated and provide important transportation planning information. The results also show that walking-accessed jobs are primarily related to physical settings (e.g., land uses) at the local level. Locations with a higher share of zero-vehicle housing units have better job accessibility by transit. There is a spatial mismatch between Asian population clusters and transit-accessed jobs, possibly because of the car-oriented residential clusters around Honda of America Manufacturing in suburban areas. More importantly, locations with a higher share of single-parent households are at a disadvantage in overall job accessibility. Due to its complex transportation needs, a society friendly to single parents should spatially integrate accessible jobs with other needed activities via land-use and transportation planning. Alternatively, car-ownership programs and non-spatial social supports also might be effective to help secure job opportunities and perform daily life activities.

1. Introduction

Assessing accessibility to individual activities in metropolitan areas has been a long-standing interest in transportation geography (Chen et al., 2014; Karou and Hull, 2014; Le Vine et al., 2013; Lin et al., 2014; Martínez and Viegas, 2013). Transportation equity affects people's economic and social opportunities (Handy and Niemeier, 1997; Litman, 2002; Niemeier, 1997). Therefore, improving transport accessibility increasingly is used to cope with social inequality, particularly for socially disadvantaged groups (Sanchez et al., 2003). Job accessibility by transportation mode is a key theme among transportation equity issues (Cheng and Bertolini, 2013; Grengs, 2012; Holzer et al., 2003). The spatial patterns of jobs accessed by different transportation means result from a set of socioeconomic and built-environment factors (Bullard, 2003; Geurs and van Wee, 2004; Handy and Niemeier, 1997; Litman, 2002; Lubin and Deka, 2012). Therefore, it is important to understand more clearly the spatial relationships between transport-accessed jobs and these metropolitan factors (Bullard and Johnson, 1997; Klein, 2007). Spatial statistics increasingly are used to examine spatial autocorrelation (SA) in transportation planning (Goetzke, 2008; Wang et al., 2015). Therefore, this study tests the hypothesis that transport-accessed jobs in a given district spatially interact with those of neighboring districts, due to similar physical and socioeconomic conditions (Bolduc et al., 1997; LeSage and Pace, 2009). The SA intensity and extent may also vary across different transport-based job accessibilities. Therefore, transportation policies designed to enhance job accessibility should consider not only the direct effects of infrastructure investments but also the spillover effects when the SA is significant.

Job accessibilities by three different transportation modes (walking, transit, and car) are calculated for the metropolitan area of Columbus, Ohio. The census block group is selected as the

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geographical unit. Three spatial autoregressive (SAR) models for the three transportation modes are estimated to account for the SA of job accessibilities among neighboring block groups, while controlling for built-environment and socioeconomic factors. Accounting for SA, which has been infrequent in past research, should result in interesting insights when comparing different SA intensities and extents. Built-environment features include bus-stop density, street-junction density, distance from the city center, population density, and commercial and industrial uses. Socioeconomic factors are represented by race, single-parent households, zero-vehicle housing units, education, and owner-occupied housing units. The spatial patterns of these factors are compared to those of transport-accessed jobs to assess possible spatial mismatch.

The remainder of the paper is organized as follows. Section 2 provides background information. GIS-based calculations and the modeling methodology are discussed in Section 3. The GIS results are described in Section 4, while Section 5 presents the spatial statistical results. Section 6 summarizes the findings and outlines areas for future research.

2. Background

2.1. Social equity and accessibility

Transportation plays a pivotal role in shaping human interactions, economic mobility, and urban sustainability; therefore, transportation planning has significant impacts on social equity (Bullard, 2003; Delmelle and Casas, 2012; Klein, 2007; Litman, 2002; Sanchez, 1999). Social equity broadly refers to equally distributed social benefits and costs, which can be significantly affected by transportation accessibility. For instance, Kaplan et al. (2014) proposed using transit accessibility for assessing transport equity, and the results showed that lower-equity areas are linked to low transit connectivity, human interactions, and economic opportunities. In their study, accessibility is defined as the ability and ease of reaching activities, opportunities, services, and goods. Golub and Martens (2014) also reported that all neighborhoods in the San Francisco Bay Area suffer from a lack of car and transit accessibility, and showed that transportation investment can help reduce access poverty. Lack of fair and appropriate transport accessibility might result in a spatial mismatch between social groups and social benefits (Blumenberg and Shiki, 2003). Such spatial differences in accessibility could be across geographical areas, population groups, and time. Delbosc and Currie (2011), for example, used Lorenz curves to assess public transport equity across different age, income, and vehicle ownership groups.

Accessibility has been an essential measure for assessing cumulative opportunities reached by transport within a distance band (Castiglione et al., 2006; Delmelle and Casas, 2012; Fan et al., 2012; Handy and Niemeier, 1997; Litman, 2002; Niemeier, 1997; Páez et al., 2010, 2012). Job accessibility, a proxy for economic mobility, is an important equity focus. Numerous job accessibility concepts are comprehensively reviewed, together with their calculations, in Cheng and Bertolini (2013), Le Vine et al. (2013), Chen et al. (2014), Lin et al. (2014), Golub and Martens (2014), Karou and Hull (2014), where potential jobs within a certain travel time/distance and transportation impedance are the two factors used to assess job accessibility. Sanchez (1999) calculated labor participations for each block group subject to a certain walking distance from transit stops in Portland and Atlanta. In the case of transportation impedance, the lack of network connectivity between residential locations and employment workplaces results in low job accessibility (Ihlanfeldt, 1994; Sanchez, 1999). Moreover, Sanchez (1999), Lubin and Deka (2012) both reported the positive role of equitable transit in improving job accessibility for socially disadvantaged groups. Their research also found that some critical barriers still affect meeting the basic needs of these groups in terms of safety, reliability, affordability, and availability.

2.2. Spatial analysis of job accessibility

There are two streams of research on the spatial relationships between job accessibility and built-environment and socioeconomic factors: graphical comparisons and the metropolitan structure and statistical regression modeling. Job accessibility, together with the associated transport connectivity, is graphically presented and compared to the metropolitan distributions of race, income, age, gender, single-parent households, car ownership, and household size (Chen et al., 2014; Cheng and Bertolini, 2013; Golub and Martens, 2014; Karou and Hull, 2014; Le Vine et al., 2013; Lin et al., 2014). A drawback of this approach is that the results do not provide comprehensive spatial relationships between job accessibility and the factors of interest. Using a spatial statistical approach to account for the effects of built environment features, Sung et al. (2014) found that land-use patterns and the transportation system intrinsically define the urban framework and, thus, influence transport accessibility. Páez et al. (2010) also reported that social exclusion regarding food accessibility is affected significantly by household income and car ownership. Fan et al. (2012) found that job accessibility is improved significantly by implementing light-rail systems, particularly in areas with high shares of Latinos, Asians, college graduates, and zero-vehicle residents. Foth et al. (2013) reported that most socially disadvantaged census tracts in Toronto have better job accessibility due to lower transit travel times and, therefore, concluded that Toronto has an equitable transit system.

Global spatial trends in metropolitan areas can be compared using ordinary regression models, but local spatial autocorrelation (SA) may remain in the residuals. Agglomeration economies generally refer to location-specific effects, which can help us understand SA effects (McCann, 2001; Park and von Rabenau, 2011). Agglomeration economies have been widely used to account for the urban structure and different city sizes through three economies-of-scale mechanisms: information spillovers, non-traded local inputs, and local labor pools (McCann, 2001). The concept of agglomeration can also be used to analyze the simultaneous effects of regional attributes on quality of life (Park and von Rabenau, 2011; Roback, 1982). Park and von Rabenau (2011) used a spatial autoregressive (SAR) simultaneous equation model to account for the effect of agglomeration factors on amenity, and calculated direct and spillover effects. It is worth noting that location-specific effects may decay rapidly with distance, at a scale smaller than a city (Duranton and Overman, 2005; Fu, 2007; Park and von Rabenau, 2011; Van Soest et al., 2006). Using the concept of agglomeration, the basic assumption is that the job accessibility of a given district is related not only to built-environment and socioeconomic factors, but also to the accessibilities of neighboring districts. Sung et al. (2014) demonstrated the existence of SA in accessibility in Seoul and its metropolitan area, using spatial error (SEM) models. In this study, SA intensities do not vary among different accessibility catchments. Conceptually, a transportation-facility investment in a given district can increase job accessibility not only for that district but also for neighboring districts, due to the spillover effects of improved local transport connectivity.

3. Methodology

3.1. Job accessibility calculations by transportation modes

The cumulative-opportunity approach, a location-based accessibility measure, has been widely used in accessibility studies because of calculation and interpretation convenience (Castiglione et al., 2006; Fan et al., 2012; Martens and Golub, 2011). It is selected here to calculate job accessibilities for three different transportation modes for each of the 887 census block groups (BG) in Columbus, Ohio, accounting for the number of jobs that someone in a given BG can reach by walking, transit, and car. The number of jobs at the BG level is the aggregated employment for workplace drawn from the Longitudinal Employer-Household Dynamics (LEHD) Origin–Destination Employment Statistics (LODES) database in 2010 (USCB, 2010).

Job accessibility for walking is calculated by counting the jobs within a quarter-mile buffer from a given BG centroid. A quarter mile has been widely used as the maximum walking distance to a workplace (Dill, 2004; Song and Knaap, 2004; Zhao et al., 2003). A buffer based on a given BG is first created to capture the neighboring BGs within a quarter mile, and then the jobs within the selected block group and its neighboring BGs are counted. The job accessibility by walking, therefore, is formulated as:

$$A_i^W = O_i + \sum_{j=1}^{J} G_j O_j \tag{1}$$

where A_i^W is the job accessibility by walking; O_i is the number of jobs in BG i; and G_j is a binary value, =1 if the centroid of BG j falls within the quarter-mile buffer of BG i, =0 otherwise.

Public transit provides an alternative low-cost travel mode for commuting, particularly for social groups with limited access to private vehicles. To account for time-dynamic transit service, job accessibility by transit is calculated based on the transit network dataset built by Network Analyst in ArcGIS, using the General Transit Feed Specification (GTFS) database (COTA, 2014). The GTFS is a recently developed database for storing public transit routes, stops, and schedules. The 30-min travel time for using transit in medium-sized U.S. cities has been used as a commuting threshold in related studies (COTA, 2009; Fan et al., 2012; Sanchez, 1999; Wang, 2003), and is selected here to count the jobs reachable by transit within a 30-min buffer. The availability of bus stops within walking distance is also determined. A quarter-mile is selected, based on studies of the acceptable walking distance to a transit station (Alam, 2009; Zhao et al., 2003). The equation for job accessibility by transit is:

$$A_i^T = O_i + \sum_{j=1}^{J} B_j O_j S_i \tag{2}$$

where A_i^T is the job accessibility by transit for BG i; O_i is the number of jobs in BG i; B_j is a binary parameter, =1 if the centroid of BG j is within the 30-mint buffer of BG i, =0 otherwise; and S_i is also a binary parameter, =1 if the centroid of BG i has at least one bus stop within a quarter-mile buffer, =0 otherwise.

Job accessibility by cars is calculated using the Ohio street network dataset (ODT, 2014). According to the Household Travel Survey for Central Ohio (FHA, 2009), the average commuting time by car is around 15 min. Therefore, a 15-min travel-time buffer from a given BG centroid is created, based on the street network dataset in ArcGIS. Jobs within the BG and its buffer-defined neighbors along the street network are counted for each of the 887 block groups. The equation for job accessibility by car is:

$$A_i^C = O_i + \sum_{j=1}^{J} D_j O_j \tag{3}$$

where A_i^C is the job accessibility by car for BG i; O_i is the number of jobs in BG i; and D_j is a binary parameter, =1 if the centroid of BG j is within the 15-min buffer of BG i, =0 otherwise.

3.2. Job accessibility models

Ordinary regression models are first specified to measure the effects of the built environment and of socioeconomic factors on job accessibility by different transportation modes. Next, spatial autoregressive (SAR) models are used to capture the spatial autocorrelations (SA) of these accessibilities. The dependent variable, job accessibilities by transport means (A_i^m), is regressed on a set of explanatory factors (X_i^k), together with spatial lag terms ($W{\cdot}A^m$), with:

$$A_i^m = a + \rho \cdot W \cdot A^m + \sum_k b^k \cdot X_i^k + u_i \tag{4}$$

where A_i^m represents the number of jobs reached by transportation mode m for BG i, $W{\cdot}A^m$ represents the effects of neighboring jobs reached by transportation mode m for the BGs around BG i, ρ is the spatial scale, X_i^k is the explanatory variables k for BG i, and a and b^k are parameters to be estimated. The error term, u_i, is assumed to follows a standard normal distribution. The explanatory variables X_i^k (Casas, 2007; Fan et al., 2012; Niemeier, 1997; Páez et al., 2010) are:

1. Transportation facilities.
2. Metropolitan location-effects.
3. Population density.
4. Land uses.
5. Races.
6. Single-parent households.
7. Vehicle ownerships.
8. Education.
9. Owner-occupied housing units.

The transit variable is derived with data from the Central Ohio Transit Authority (COTA, 2014). The built-environment and socioeconomic variables are based on data from the 2010 Census, 2006–2010 Census Transportation Planning Products (CTPP), and the Franklin County auditor.

Eq. (4) indicates that job accessibility not only is related to the above variables but also to neighboring job accessibilities represented by the spatial lag term, $W{\cdot}A^m$. It is assumed that the relationship between the accessibility of a given BG and those of its neighboring BGs, measured by the spatial scale ρ, is positive. The larger ρ, the stronger the SA.

3.3. Spatial weight matrix (W) and marginal effects

In Eq. (4), a spatial weight matrix, W, must be created, based on a selected neighborhood structure. There are several methods to define neighborhood structures (graph-based, distance-based, and k-nearest neighborhoods), as suggested by LeSage (1998), Bivand et al. (2008). A graph-based neighborhood structure (NS) has been selected here, because the other methods failed to capture all the residual SA. A graph-based NS is defined based on the rule of adjacency, whereby districts are defined as neighbors when they share the same border. This first-order NS can be extended to a higher-order NS by including additional rings of neighboring districts adjacent to each other. The selected NS can be transformed into a spatial weight matrix (W). The standard spatial weight (SSW) is such that each row entry (0 or 1) is divided by the number of neighbors within the row. This normalization allows for the calculation of average neighborhood effects and treats every neighbor's effect equally.

LeSage and Pace (2009) proposed a method to interpret the marginal effects of the explanatory variables in the SAR model, showing that the coefficient of an explanatory variable does not represent the complete effect of that variable on the dependent variable. They proposed estimating both the average direct effect

(DE) and the average neighborhood effect (NE). The DE of X^k on A^m is the average own effect of a change in an explanatory variable across all n districts, with:

$$\mathrm{DE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\partial A_i^m}{\partial X_i^k} = \frac{b^k}{n}\cdot tr\left[(I-\rho\cdot W)^{-1}\right] \tag{5}$$

I is the identity matrix of dimension n. The average total effect (TE) of X^k on A^m represents the average of all effects on job accessibility caused by a change in the explanatory variable change, with:

$$\mathrm{TE} = \frac{1}{n}\sum_{i=1}^{n}\sum_{k=1}^{n}\frac{\partial A_i^m}{\partial X_i^k} = \frac{b^k}{n}\cdot l'\cdot\left[(I-\rho\cdot W)^{-1}\right]\cdot l \tag{6}$$

The average neighborhood effect of X^k on A^m, NE, is the difference between TE and DE.

4. Data

4.1. Job accessibilities by transportation modes

Table 1 presents descriptive statistics for all the variables. The average numbers of jobs are: 782 accessible by walking, 15,490 accessible by transit, and 335,547 accessible by car. The Columbus metropolitan area has a flat terrain, and has been regarded as a car-oriented city with a well-connected highway system.

The spatial distributions of job accessibilities by transportation modes, together with the location of the study region within Ohio, are illustrated in Fig. 1. The spatial pattern of job accessibility by walking (the top-right panel in Fig. 1) is characterized by clusters in the city center (along highways I-70 and I-71), and around the outskirts (along outer-loop Highway 270). Given the limit on travel distance by walking, one can expect that more jobs are reached in neighborhoods with higher shares of commercial or industrial land uses, where most workplaces are located.

Table 1
Variable definitions and descriptive statistics.

Variable	Definitions	Mean	S.D.
Job Accessibility			
JA_WAK	Number of jobs reached from a BG within a quarter mile walking buffer	782	2271
JA_TRS	Number of jobs reached from a BG within a 30-min transit commuting buffer	15,490	30,672
JA_CAR	Number of jobs reached from a BG within a 15 min driving buffer	335,547	115,973
Transportation facility			
BSDN	Bus stop density (# per square mile)	19	22
JCTN	Street junction density (# per square mile)	206	107
Metropolitan structure			
CBDS	Distance between a BG and the city center (mile)	6.50	3.15
PODN	Population density (people per square mile)	5568	4938
RES	Share of residential land use	55.64	28.23
IND	Share of industrial land use	4.20	11.32
COM	Share of commercial land use	22.37	21.89
AGR	Share of agricultural land use	4.13	12.79
UTI	Share of public utility land use	1.18	3.43
Races			
WHIT	Share of white population	67.05	26.94
BLAC	Share of black population	23.93	26.53
ASIA	Share of Asian population	3.37	4.83
OTER	Share of other populations	5.66	4.37
Socioeconomic characteristic			
SPAT	Share of single-parent households	11.88	8.50
VEH0	Share of housing units with zero vehicle	9.88	12.26
EDUC	Share of population with at least a Bachelor's degree	32.71	24.60
OWOC	Share of owner-occupied housing units	50.90	28.36
Number of observations: 887			

Job accessibility by transit, together with bus-stop distribution, is illustrated in the bottom-left panel in Fig. 1. The accessibility spatial pattern is linked to the distribution of bus stops. In addition to the jobs located within a given BG, one can reach more jobs in other BGs by using a bus along routes within a 30-min travel time. The clusters of jobs reached by bus are mostly located in the city center (along High street and Broad Street).

The bottom-right panel of Fig. 1 presents the highway system and the spatial distribution of job accessibility by car. Highways include the east–west I-70, the north–south I-71, and the outer-loop 270, with a clear job cluster around the city center. The average number of jobs reached by car is 7.5 times greater than by public transit.

4.2. Built-environment and socioeconomic variables

The average bus-stop density (BSDN) is 19, and the average number of street junctions per square mile (JCTN) is 206 (Table 1). The study region is clearly a monocentric city. The distance between each BG and the city center represents the metropolitan location effect, with an average distance of 6.5 miles. The population density (PODN) has an average value of 5568. High-density clusters are located along the main streets out of the city center (the top-left panel in Fig. 4).

The land-use-share variables, presented in Table 1, are related to residential, commercial, industrial, agricultural, and utility land uses. Residential land use, with an average share of 56%, is the most intensive use in the region, followed by commercial land use, with an average share of 22%. Only commercial (COM) and industrial (IND) land uses are considered in the statistical model, since they represent employment workplaces. The spatial distributions of COM and IND are illustrated in Fig. 2. Commercial land uses are evenly distributed along the highway system and the main street network, while industrial land uses are concentrated along highways I-70 and I-71.

Table 1 shows that the average share of whites is 67%, of blacks 24%, of Asians 3%, and 6% for the other groups. The racial shares spatial distributions are illustrated in Fig. 3. The white population is primarily concentrated in the outskirts, while the black population is concentrated in the city center (the top two panels in Fig. 3). The Asian population is located around The Ohio State University (OSU) and Dublin, Ohio (the bottom-left panel in Fig. 3). OSU accommodates many international students and faculty members, while Dublin is the home of many Honda of America Manufacturing employees. Other racial groups are located along highways I-70 and I-71 away from the city center (the bottom-right panel in Fig. 3).

The average share of single-parent households (SPAT) is about 12%, with clusters located along highways I-70 and I-71 toward the southeast (the top-right panel in Fig. 4). As a car-oriented city, only 10% of housing units, on average, have no access to private vehicles (VEH0), and are concentrated in the city center (the bottom-left panel in Fig. 4). For education (EDUC), about 33% of the population, on average, has at least a bachelor's degree. The average percentage of owner-occupied housing units (OWOC) is about 51%, located around the outskirts of the city.

5. Results

5.1. Neighbors and weights

Based on the Lagrange Multipliers (LM) tests in Eq. (4), the SAR model of job accessibility by car captures all the spatial

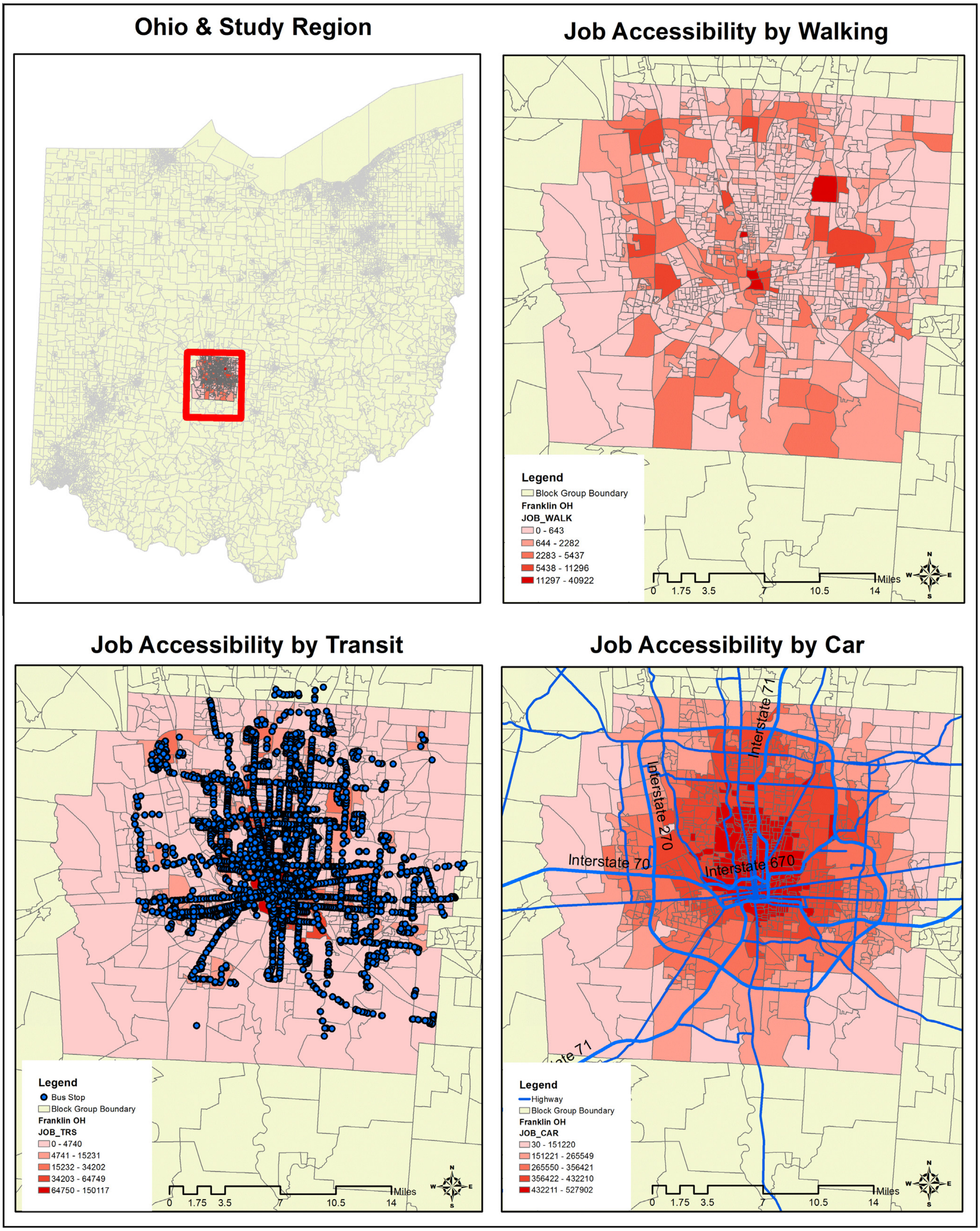

Fig. 1. Job accessibilities by transportation mode.

autocorrelation (SA) in the residuals, when only using the first-order neighborhood structure. However, the residuals remain spatially auto-correlated when using the first-order spatial weight matrix W^1 in the SAR models of job accessibility by walking and transit. The SA disappears when using the second-order spatial weight matrix (W^2). A block group, on average, is directly adjacent to six

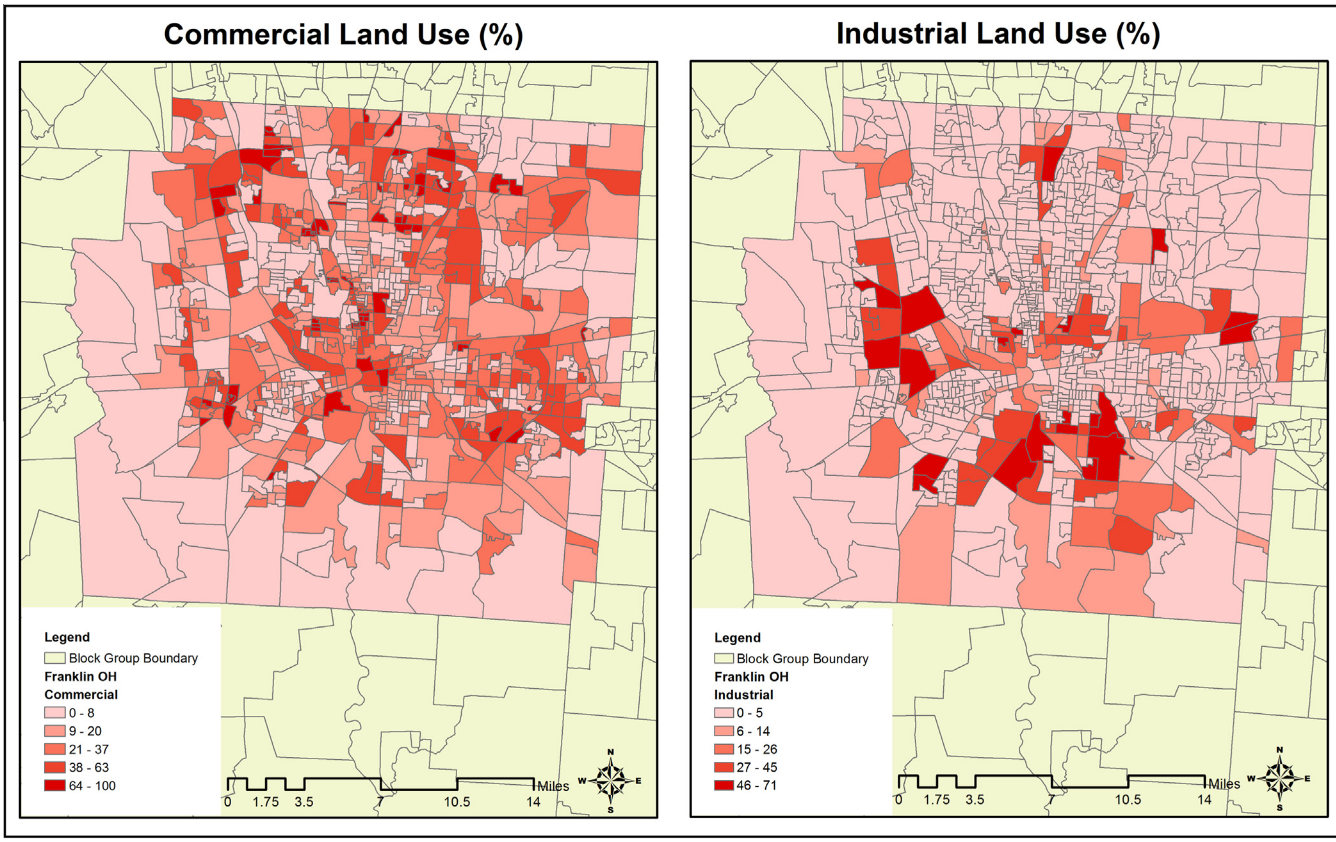

Fig. 2. Commercial and industrial land-use shares.

block groups (non-zero weights: 0.7%) in the first-order (W^1) case, and to 22 neighbors (non-zero weights: 2.4%), when using the second order (W^2) matrix. The need to consider a higher-order neighborhood is reasonable, because the average area of a BG is only about 0.6 square miles. Therefore, the spatial lag term ($W{\cdot}A^m$) with a second-order matrix (W^2) captures SA within an approximately 1.1 miles buffer around a given BG. This also indicates that the SA extent varies across different job accessibility catchments.

5.2. SAR model for job accessibility by walking

The estimates of the SAR model of job accessibility by walking (WAK2), with the second-order spatial weights (W^2), are presented in Table 2 ($R^2 = 0.17$), together with the OLS estimates (WAK1) without spatial effects ($R^2 = 0.16$). The coefficients of COM, IND, PODN, SPAT, and OWOC are significant at the 5% level and similar to those of the OLS model, implying a robust estimation. The spatial factor ρ is also significant at the 5% level. The positive signs of COM and IND are as expected. Most jobs reachable by walking a quarter mile or less are mostly likely located around the BG residence. Industrial and commercial land uses represent locations of secondary and tertiary employment. The coefficient of PODN is negative, indicating that the higher the population density the higher the competition among residents to access jobs around the neighborhood.

The negative sign of SPAT implies that the higher the share of single-parent households the lesser their access to jobs by walking. The share of owner-occupied housing units (OWOC) is significant and negative. The bottom-right panel in Fig. 4 shows that OWOC clusters spread out from the outer-loop Highway 270 toward the outskirts. The residents of these suburban BGs are less likely to access jobs by walking. The positive sign of ρ implies the existence of job clusters within a quarter-mile walking distance, which is illustrated in the top-right panel in Fig. 1.

The calculation of walking-accessed jobs does not depend on transportation facilities and metropolitan location effects and, therefore, the variables BSDN, JCTN, and CBDS are not used in models WAK1 and WAK2. It is also worth noting that all racial and socioeconomic variables (except SPAT and OWOC) are insignificant, which may imply that job accessibility by walking is primarily related to the physical setting (e.g., land uses) at the local level, rather than to metropolitan-scale variables.

5.3. SAR model for job accessibility by transit

The estimates of the OLS and the SAR models of job accessibility by transit, TRS1 and TRS2, are presented in Table 2. Model TRS2 ($R^2 = 0.71$) improves over model TRS1 ($R^2 = 0.53$) by 18%. The spatial scale, ρ, is significant with a positive value of 0.91, which is much larger than $\rho = 0.32$ in model WAK2, pointing to a much stronger SA. This is also illustrated by the more intensive spatial clustering of transit-accessed jobs, as compared to walking-accessed jobs (the bottom-left panel in Fig. 1).

As expected, bus-stop density (BSDN) is significant and positive in both models. CBDS has a significant negative sign in model TRS1, indicating that metropolitan location-effects on transit-accessed jobs decrease from the city center. However, CBDS is insignificant in model TRS2. PODN has a significant positive sign in model TRS1 because population density has a clustering spatial pattern similar to that of transit-accessed jobs (see the bottom-left panel in Fig. 1 and top-left panel in Fig. 4). However, PODN is no longer significant in model TRS2. The local land-use variables, COM and IND, are not significant in model TRS2, as more jobs are reachable from any BG by transit. Regarding the no-longer-significant

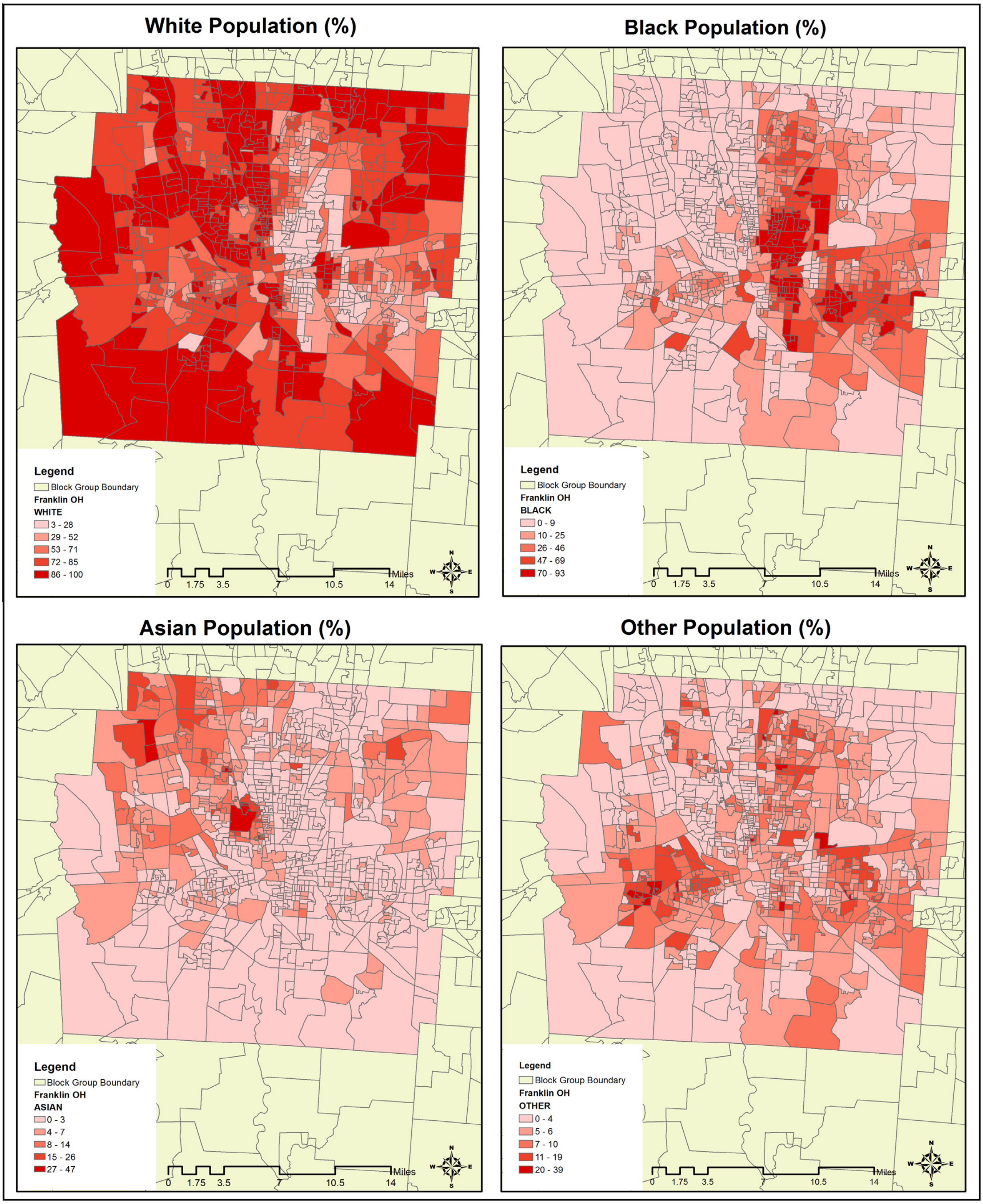

Fig. 3. Ethnic population shares.

variables in model TRS2, it is worth noting that all three OLS models have significant SA in their residuals, based on Moran's I tests. Their results are likely to be biased because SA effects are not considered.

ASIA is significant and negative in both models, possibly because of the car-oriented residential clusters around Honda of America Manufacturing in suburban areas. This finding is also supported by comparing the two bottom panels in Fig. 3 and the

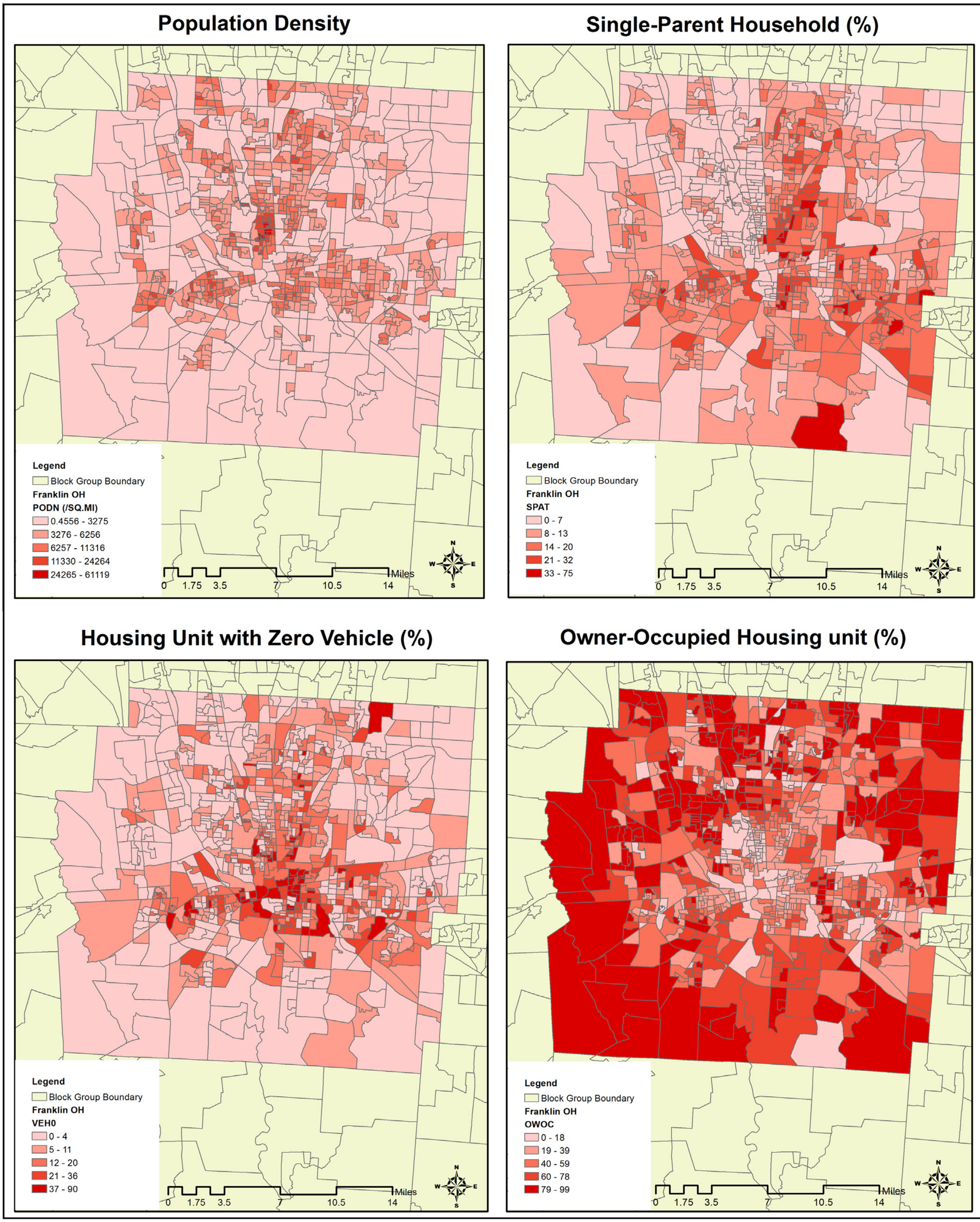

Fig. 4. Socioeconomic characteristics.

bottom-left panel in Fig. 1. As in models WAK1 and WAK2, SPAT is significant and with the same negative sign in models TRS1 and TRS2. As expected, the share of housing units with zero vehicles (VEH0) is significant, with a positive sign. BGs with a high share of housing units with zero vehicles are located around the city center, where transit service is widely available (see the bottom-left

Table 2
Estimations of job accessibility SAR models.

Variables	WAK1	WAK2	TRS1	TRS2	CAR1	CAR2
Constant	**1863**[a] **(3.9)**[b]	**1530 (3.2)**	**32,997 (6.3)**	**−624 (−0.2)**	**458,300 (33.9)**	**69,089 (5.5)**
Transportation Facility						
BSDN	–	–	**353 (8.4)**	**219 (7.4)**	–	–
JTCN	–	–	–	–	**91 (4.5)**	**52 (4.6)**
Metropolitan structure						
CBDS	–	–	**−2363 (−7.4)**	367 (1.5)	**−30,940 (−38.7)**	**−5694 (−7.5)**
PODN	**−0.1 (−5.6)**	**−0.1 (−5.5)**	**1.2 (6.8)**	0.2 (1.4)	0.2 (0.5)	−0.2 (−0.8)
COM	**20 (4.4)**	**18 (4.1)**	**−107 (−2.3)**	−12 (−0.4)	**392 (3.1)**	**235 (3.4)**
IND	**36 (5.5)**	**35 (5.3)**	105 (1.5)	−5 (−0.1)	−233 (−1.3)	61 (0.6)
Races (WHIT as benchmark)						
BLAC	−1 (−0.3)	1 (0.2)	−10 (−0.2)	−27 (−0.9)	**642 (6.1)**	89 (1.5)
ASIA	−3 (−0.2)	−5 (−0.3)	**−550 (−3.1)**	**−359 (−2.9)**	91 (0.2)	−85 (−0.3)
OTER	−36 (−1.7)	−27 (−1.3)	**−530 (−2.5)**	114 (0.8)	**160 (2.9)**	525 (1.7)
Socio-economic characteristics						
SPAT	**−45 (−3.3)**	**−47 (−3.5)**	**−544 (−3.9)**	**−296 (−3.0)**	**−954 (−2.6)**	**−473 (−2.3)**
VEH0	10 (1.4)	7 (1.0)	289 (3.7)	**109 (2.0)**	−28 (−0.1)	−85 (−0.8)
EDUC	5 (1.2)	3 (0.7)	226 (5.3)	**41 (0.2)**	**861 (7.7)**	42 (0.7)
OWOC	**−12 (−2.8)**	**−11 (−2.5)**	**−246 (−5.3)**	**−53 (−1.6)**	183 (1.5)	77 (1.2)
Spatial weights (W^p)	–	$\mathbf{W^2}$	–	$\mathbf{W^2}$	–	$\mathbf{W^1}$
Spatial scale (ρ)	–	**0.32**	–	**0.91**	–	**0.85**
LM test of residual SA	–	3.5	–	1.2	–	2.6
R-square (%)	16.0	16.6	52.9	71.1	77.4	89.3
AIC	16,099	16,086	20,203	19,640	21,912	21,028

[a] Significance: 0.05 in Bold.
[b] t-value in parenthesis.

panel in Fig. 4). In model TRS1, a block group with a high share of educated people (EDUC) is likely to have better access to jobs that can be reached by public transit. However, EDUC became insignificant in model TRS2. The share of owner-occupied housing units (OWOC) is significant and negative in model TRS1, but not significant in model TRS2.

5.4. SAR model for job accessibility by car

The OLS (CAR1) and the SAR (CAR2) models of job accessibility by car are also reported in Table 2. Model CAR2 (R^2 = 0.89) captures all the residual SA, using only the first-order spatial weights (W^1), implying smaller-extent SA as compared to the SA in the other two SAR models (captured by W^2). Model CAR2 (R^2 = 0.85) improves over model CAR1 (R^2 = 0.77) by 12%. As in model TRS2, the spatial scale (ρ) is significant, with a high positive value (0.85), pointing to a strong SA for job accessibility by car.

In parallel to the variable BSDN in models TRS1 and TR2, the street-junction density (JCTN) variable is significant and positive, as expected, in both CAR1 and CAR2. In both models, the metropolitan location effect (CBDS) is significant and negative. With a much larger job catchment by car, the SAR model captures not only the large spatial-scale effects but also the local SA effects in the region. Another metropolitan structure factor, PODN, is not significant in either model. Only commercial land use (COM) is significant and positive, most likely due to the fact that commercial activities are located along main streets.

The black (BLAC) and other (OTER) racial share variables are significant and positive in CAR1, but insignificant in CAR2. The right two panels in Fig. 3 show that these population groups are mostly clustered along highways I-70 and I-71. The black population is concentrated in the city center, while the other population is slightly spread out toward the outskirts. Therefore, there is, as expected, a positive spatial relationships between car-accessed jobs and the two variables in model CAR1, but the SAR model CAR2 captures these effects through its spatial lag factor. SPAT is significant with the same negative sign in models CAR1 and CAR2. The share of housing units with zero vehicles (VEH0) is no longer significant, as compared to models TRS1 and TRS2. Note that jobs reached by car from a given BG, based on Eq. (3), are limited to a 15-min driving buffer. More driving time is required if residents living in the outskirts (i.e., BGs with low job accessibility by car) want to reach more car-accessed jobs. As in model TRS1, EDUC is significant and positive in model CAR1, but not significant in model CAR2. The variable OWOC is insignificant in both models.

5.5. Marginal effect analysis

Table 3 presents the average direct (DE), neighborhood (NE), and total (TE) effects resulting from changes in the explanatory variables. The calculations of these marginal effects are based on Eqs. (5) and (6). With a smaller spatial lag (ρ = 0.32) in model WAK2, a 1% increase in commercial and industrial land use in a given BG increases the number of walking-accessible jobs for that BG directly by 18 and 35, respectively, and indirectly by 9 and 16 via spillover effects through neighboring BGs. The ρ scales in models TRS2 (0.91) and CAR2 (0.85) are larger, leading to stronger spillover effects (i.e. NE). A unit increase in bus-stop density (BSDN) increases transit-accessible jobs by 247 directly, and 2189 indirectly. Similarly, car-accessible jobs would directly increase by 66 with a unit increase in street-junction density, and by 298 with a unit increase in commercial land use, but would directly decrease by 7241 with a unit increase in the distance from the city center.

Table 3
Average marginal Effects.

Variable	Direct effect (DE)	Neighborhood effect (NE)	Total effect (TE)
Model WAK2			
COM (%)	18	9	27
IND (%)	35	16	51
Model TRS2			
BSDN (per square mile)	247	2189	2436
Model CAR2			
JCTN (per square mile)	66	278	344
CBDS (mile)	−7241	−30,718	−37,959
COM (%)	298	1266	1564

These changes in transportation facilities and metropolitan structure factors would also significantly change the number of car-accessible jobs through indirect effects. The neighborhood effects (NE) are much larger than the direct effects (DE) in models TRS2 and CAR2, due to the stronger SA intensities. Therefore, spillover effects on job accessibility through transportation-facility investments are much larger than their own effects.

6. Conclusions

The spatial results of calculating job accessibilities by transportation modes have been presented using buffering and network analysis operations. The estimations of three spatial autoregressive (SAR) models point to different SA intensities and extents. The larger the transport catchment of jobs, the stronger the spatial interactions between neighboring BGs. Understanding such SA effects may be helpful in solving related social-equity issues through transportation planning. The results also show different spatial relationships between metropolitan structure factors and job catchments by transportation means. Small job catchments by walking are positively related to local physical conditions, including population density (PODN) and commercial and industrial land uses (COM and IND). However, large job catchments by public transit or car are related to global metropolitan settings. For instance, bus-stop density (BSDN) and street-junction density (JCTN) have positive effects on transit-accessed jobs and car-accessed jobs, respectively.

More importantly, the share of single-parent households (SPAT) has a significant negative sign in all six statistical models, indicating the existence of spatial mismatch between high SPAT locations and transport-based job accessibilities. Single-parent families are likely to be more car-dependent due to their complex transportation needs. A society friendly to single parents should spatially integrate walking- and transit-accessed jobs with other needed activities via land-use and transportation planning, together with other non-spatial social supports (e.g., child care, education, and social support). Alternatively, car-ownership programs might be an effective way to help these disadvantage groups secure job opportunities and perform daily life activities (Fan, 2012). The location of Asian populations has a negative spatial relationship with transit-accessed jobs, possibly because of the car-oriented residential clusters around Honda of America Manufacturing in suburban areas. The locations with a higher share of zero-vehicle housing units (VEH0) have better job accessibility by transit. Education (EDUC) has a positive effect on job accessibility by public transit or car. However, residents in suburban areas (i.e., BGs with a high share of owner-occupied housing units (OWOC)) are less likely to access jobs by walking.

The proposed modeling approach has several limitations. First, the calculation of transport-based job accessibilities could be disaggregated by different job categories (e.g., manufacturing, services, etc.), and/or by different social groups (e.g., race, income, etc.). The effects of built-environment features (e.g., transport facilities and land uses) on job accessibilities by different social groups might be of particular interest. These are certainly avenues for future research, depending on data availability.

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