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Grocery store accessibility: Different metrics – Different modal disparity results and spatial patterns

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ABSTRACT

Most accessibility studies focus on within transport mode travel performance variations. However, modal accessibility disparity analysis adds value to the single-mode analysis by assessing the interaction between different transport modes and land use. A review of modal disparity studies shows that different accessibility metrics lead to different results, and so it is unclear how this impacts modal accessibility disparity variation. Moreover, the correspondence of the disparity spatial pattern between the different metrics is unclear. This research examines how three typical accessibility metrics (closest facility, cumulative opportunity, space-time constrained) impact modal disparity of grocery store accessibility in Warsaw, Poland. Further, local indicators of spatial association are used to identify areas of similarity and difference between the metrics. This study finds that cumulative opportunities during non-rush hours indicate the best car advantage for all travel times but indicate the best transit advantage during rush hours for 15 min. Generally, the space-time metric indicates better transit accessibility than the closest facility metric which in turn shows better transit accessibility than cumulative opportunities. The city center has significant spatial similarity while peripheral, especially dense, areas have significant spatial difference. Similarity areas have higher transit stop and population densities, while difference areas have average-to-low stop, population, road and store densities.

1. Introduction

Comparison between car and transit accessibility is critical to equity assessments of transportation planning and investments (Ben-Eliaa and Benenson, 2019; Kelobonye et al., 2019). Modal accessibility disparity analysis, first developed by Kwok and Yeh (2004), adds value to the single-mode analysis by assessing the interaction between different transport modes and land use. A review by Niedzielski and Kucharski (2019) shows that modal accessibility disparity varies from extreme automobile domination to extreme transit domination. Most of the variation may be attributed to differences in urban spatial structure which induces higher use of one of the modes. Sprawling low-density cities tend to be car-oriented places while compact and dense cities tend to be transit-oriented places (Kawabata and Shen, 2006). The modifiable areal unit problem is likely another cause of the variation (Niedzielski et al., 2013).

Intriguingly, Niedzielski and Kucharski's review also shows that different metrics lead to different results when measuring accessibility to the same destination type, and so it is unclear how this impacts modal accessibility disparity variation. It is reasonable to expect that modal accessibility disparity results should be consistent and not depend on the metric so that different conclusions are not reached. It is not helpful in the least for developing transportation plans and for policy interventions designed to redress unjust distributions of accessibility (Golub and Martens, 2014) if modal disparity results based on one accessibility indicator determine an urban area to provide substantial car accessibility advantage while results based on another indicator determine the same urban area to have modal accessibility balance or even a transit accessibility advantage. Having consistent disparity results is key, because the resulting conclusions have tangible outcomes. Erroneous conclusions from disparity results could lead to policy interventions in areas that do not need it or overlook areas that need it.

The sensitivity of modal disparity results to the accessibility metric used is particularly relevant in the case of grocery stores. First, poor food accessibility may increase poor dietary habits and subsequent risk of chronic diseases (Leal and Chaix, 2011; Morland et al., 2006). Second, food access research emphasizes the closest store in accessibility calculations, but also recognizes multiple store accessibility and the time

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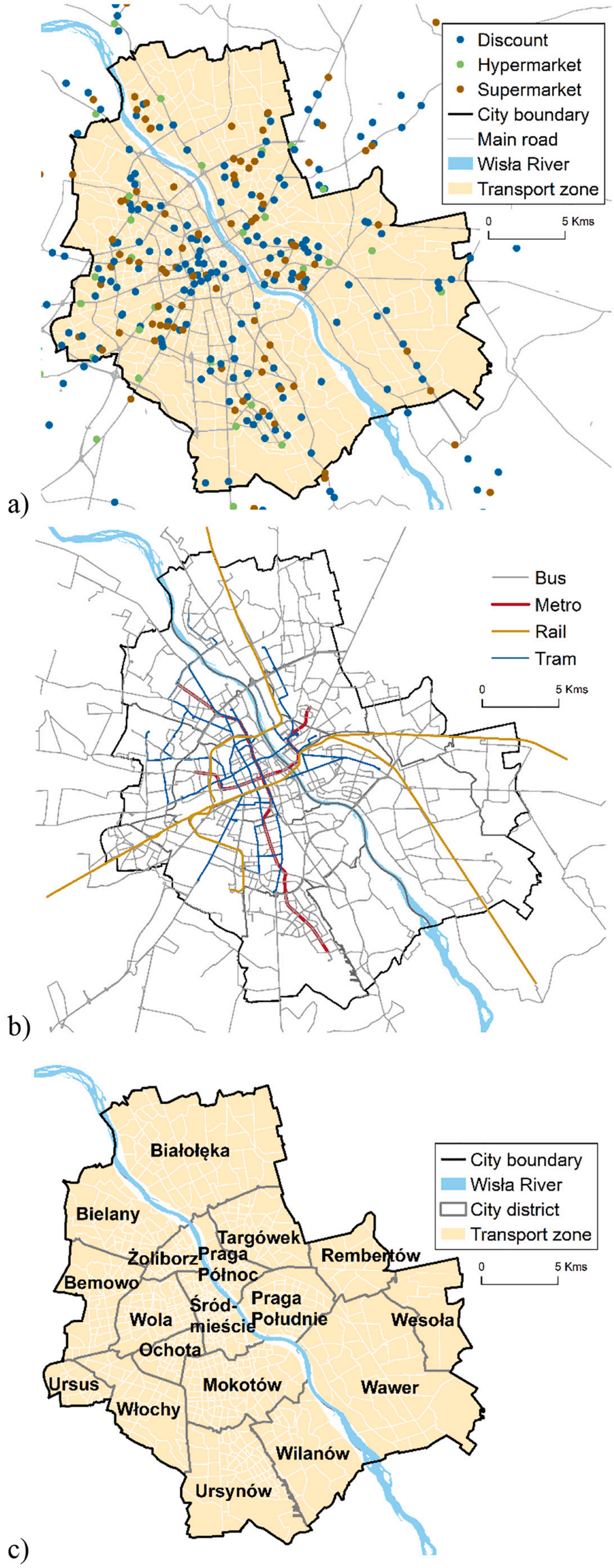

Fig. 1. a) Food store locations, b) transport lines, and c) city district boundaries in Warsaw.

spent shopping (Widener, 2017). How the three common accessibility metrics used in the food accessibility literature (closest facility, cumulative opportunities, and space-time constrained) impact modal disparity is unknown. Outstanding questions remain: Do the metrics produce similar results, and if not, what is the relative order of the metric results? Do the metrics produce similar spatial patterns, and if not, where are they similar and different? Comparative modal accessibility disparity analysis using the same urban area, data, and methods but different accessibility metrics has not been done before. Therefore, the aims of this paper are to explore: 1) how the choice of metric and its parameters impact the degree of modal accessibility disparity; 2) the correspondence between spatial patterns produced by the metrics; 3) the factors behind the spatial patterns.

Recognizing that people shop at different times and on different days, and that congestion and transit schedules vary during the day and between days, accessibility is computed for four different times on a single weekday and for one time on Saturday. Accessibility is also calculated for different metric parameters such as the number of closest facilities or different travel times. Warsaw, Poland is chosen as the study site where grocery store locations are sourced from a spatial database of retail activities (DataWise, 2017). Although this study focuses on the car-transit comparison only, it does recognize the importance of walking to grocery stores, given the dense nature of the city, by including walking travel times which replace car and transit travel times if walking is faster.

2. Background

Poor dietary habits such as the lack of or limited intake of healthy food may increase the risk of obesity, cardiovascular disease, and diabetes (Walker et al., 2010). Such habits may result from non-spatial factors such as income, household characteristics such as education and race, transportation options in terms of car ownership and transit schedules, time use, availability of food stores in terms of their quantity and opening hours, and availability of food in terms of its price and cultural appropriateness (Widener, 2018; Zhang and Mao, 2019). Impacts of spatial factors on poor dietary habits include spatial accessibility in terms of the spatial pattern of food stores and transportation options (Widener, 2018), perception of the food environment (Caspi et al., 2012) and spatial dynamics of daily mobility (Niedzielski and Kucharski, 2019; Widener et al., 2013).

While accessibility tends to be overemphasized in research, relative to affordability and acceptability, and is inconsistent in its impact on diet and health, it nonetheless tends to have an impact at the margin (Widener, 2018). People living closer to grocery stores tend to consume more healthy food (Rose and Richards, 2004) and generally the spatial pattern of food accessibility tends to be inequitable (Beaulac et al., 2009). Part of the inequity may stem from locations of healthy food stores mostly in wealthier and whiter neighborhoods (Zhang and Mao, 2019). However, another part of the inequity may result from the availability of transportation options (Widener, 2017). Some people may not afford or may not able to drive a car, while transit, especially in U.S. cities, may not be available everywhere or may be too infrequent to be useful. Transportation mode is therefore an important component in indicators designed to identify areas for policy interventions.

One such indicator is modal accessibility disparity which reveals the complexities of accessibility between the triad of origin, destination, and transportation mode. Less dense and more dispersed cities lead to automobile dominated travel, while denser and more compact cities provide for good quality transit. How the two modes interact to produce food accessibility is understudied, as most food accessibility research considers within mode differences showing how accessibility is uneven by car or transit separately. Comparison of both modes is needed to properly assess the efficacy of spatial policy interventions so that transit resources are focused on areas that need it.

Modal accessibility disparity analysis aims to more accurately measure accessibility by incorporating modal interactions. At the local level, transit tends to provide better or equal accessibility than cars in central city areas and along major transit corridors (Tenkanen et al., 2016). Transit tends to result in better accessibility than cars in areas with high car congestion and large housing estates (Niedzielski and Kucharski, 2019). At the regional level, most cities have better car than transit accessibility, though that difference is negligible in Helsinki and Warsaw or even reversed in Hong Kong and Shanghai (Niedzielski and Kucharski, 2019; Wu et al., 2021). One potential source of the variation of disparity results is urban form as noted previously, but another is the use of different accessibility metrics.

Food accessibility research has used several accessibility metrics. Most early papers considered Euclidean distance or road network distance to the closest food store as a determinant of food accessibility (Apparicio et al., 2007). This approach has shortcomings because people do not always shop at the closest store, they cannot travel in straight lines, a store may be farther by distance but closer by travel time due to congestion, and they value travel time as part of their time budget (Tenkanen et al., 2016; Widener, 2017). Despite these issues, the closest facility metrics continues to be used, though with increasing availability of transportation data, travel time has replaced distance in calculations (Caspi et al., 2012). Another variant of this metric that tries to account for shopping behavior calculates the average travel time to the nearest three or ten grocery stores (Farber et al., 2014). A second popular metric is the cumulative opportunity approach which measures the number of healthy food stores within a predefined area. Initial studies using this metric counted stores within census units or a short, e.g. 1 km, distance buffer (Apparicio et al., 2007). However, these versions of the metric are arbitrary and disregard travel behavior and time use. More recent studies begin to incorporate simple travel behavior by using a predefined travel time, e.g. 30 min reflective of a typical one-way commute, as the isochrone in the cumulative opportunity metric (Widener, 2017). A third more recent development is the use of a space-time constraints-based metric, which incorporates a time budget in the cumulative opportunity metric by limiting the time for shopping and transport to and from the store (Niedzielski and Kucharski, 2019). This approach tries to account for the complexity of travel behavior and time use. A comparison of the impact of accessibility metrics on modal disparity of accessibility to grocery stores has not been done before, so this paper fills this gap. Three metrics are used: average travel time to the closest k^{th} supermarket, cumulative opportunity, and space-time constrained.

3. Methodology

3.1. Study area and data

Warsaw, the capital of Poland, with an area of 517 km^2 had a population of 1,764,615 in 2017, giving it a population density of 3413 (Zegar, 2018). The city is divided into 798 transport zones with an average area of 0.62 km^2 (minimum = 0.03 km^2 and maximum = 10.34 km^2). The focus is on calculating accessibility from zones within the city to grocery stores inside and outside the city to account for boundary effects. Accessibility is calculated from each zone centroid to 346 supermarket, hypermarket, and discount store locations (Fig. 1a) sourced from a 2017 business location database (DataWise, 2017). Store operating hours are incorporated in the analysis as the stores open between 6 and 8 am and close between 10 pm-12 m matching the five periods under analysis: 8-9 am, 12n-1 pm, 5-6 pm, and 9-10 pm on Wednesday, and 10-11 am on Saturday. Fig. 1b shows the bus, tram and metro lines while Fig. 1c depicts the 18 city neighborhoods.

3.2. Travel time calculation

A travel time matrix is calculated between 798 population-weighted zone centroids and 346 grocery store locations. Car origin-destination (OD) travel times are computed in three steps to account for congestion. Because real travel times were not available due to their high cost from providers like Google or TomTom, first free-flow travel times for each road segment are calculated in ArcGIS based on speed limits in a road file available from the local government. Then free-flow travel times are multiplied by the 2017 congestion factor available from the Warsaw traffic report on the TomTom (2021) website. To see how modal disparity varies by time of day and day of the week, five congestion factors are used: 76% for 8-9 am, 34% for 12n-1 pm, 85% for 5-6 pm, and 11% for 9-10 pm on Wednesday as a representation of a weekday, and 20% for 10-11 am on Saturday. Finally, ArcGIS Network Analyst is used to calculate OD travel times between each home-grocery store pair. In addition to the in-vehicle travel times, 10 min are added to each OD pair to account for the time walking between a car and origin/destination location, time spend searching for parking, opening/closing a car, buckling/unbuckling the seat belt, and loading/unloading groceries. Of the 10 min, six minutes is attributed to the average time walking to/from the car based on the 2015 Warsaw Traffic Survey (Kostelecka, 2015). The remaining four minutes is a reasonable estimate for the time to search for parking, to park the car, to load/unload groceries, to open/close the car, get in/out of the car, fasten/unfasten the seat belt and it is comparable to the time used in Salonen and Toivonen (2013). Walking times are also calculated to replace car travel times when walking is faster.

Transit OD travel times are calculated using three steps. First, the *Add GTFS to a network dataset* tool is used to create a network dataset based on General Transit Feed Specification (GFTS) data for Warsaw from April 8 (Saturday) and 12 (Wednesday), 2017 to match the year of the facility location dataset. The network dataset incorporates all door-to-door trip segments, such as in-vehicle travel time, transfer time, waiting at the transit stop, and stop access/egress time. Then, ArcGIS Network Analyst is used to calculate OD travel times four times (on the hour and at 5, 12, and 34 min past each hour) within each single-hour time period. The resulting OD matrix includes walking times if it is faster than transit. Finally, the average of the four OD travel times in each single-hour period is used in the accessibility calculations.

3.3. Accessibility measures

3.3.1. Travel time to closest facility (CF)

CF measures the average travel time to grocery stores using this formula:

$$A_{im}^{CF} = \frac{\sum_k t_{ikm}}{K} \text{ for } k = 1, \dots, K \tag{1}$$

where $A_{im}{}^{CF}$ is the average travel time from zone i by transport mode m to the closest K supermarkets, and t_{ikm} is the travel time in minutes from zone i by transport mode m to the k^{th} closest supermarket. When $K = 1$, then the result is the minimum travel time to the closest supermarket, and when $K \geq 2$, then the result is the average travel time to K supermarkets.

3.3.2. Cumulative opportunity (CO)

CO is a count of grocery stores available for shopping within a defined travel time threshold from each zone using this formula:

$$A_{im}^{CO} = \sum_{k \in N_i} O_k \tag{2}$$

where $A_{im}{}^{CO}$ is the count of grocery stores at zone i within a travel time t by transport mode m from i, O_k is a grocery store at location k, and $N_i = (k|\, t_{im} \leq T)$ is the subset of grocery stores (from set K) within the travel time threshold T in minutes from i.

3.3.3. Space-time constrained (ST)

ST considers travel time to and from the grocery store as well as shopping duration within a time budget threshold in calculating the minutes available for shopping. It is a two-dimensional representation of the three-dimensional potential path area based on space-time geography concepts (Miller, 2005). The formula is:

$$A_{ikm}^{ST} = max\left(0, B - \left(t_{ikm} + t_k + t_{kim}\right)\right) \tag{3}$$

where $A_{ikm}{}^{ST}$ is the number of minutes available for people living in zone i to shop at grocery store k using transport mode m given available travel budget B and minimum activity duration t_k, t_{ikm} is the travel time in minutes from zone i to grocery store k using transport mode m, t_k is the minimum required shopping time in minutes at k, t_{kim} is the travel time in minutes using transport mode m from grocery store k to zone i. From (3), the zonal average minutes available for shopping, $A_{im}{}^{ST}$, is derived by:

$$A_{im}^{ST} = \frac{\sum_{k \in K_{ii}} A_{ikm}^{ST}}{K_{ii}} \tag{4}$$

where K_{ii} is the set of grocery stores accessible within B minutes on the trip from and to home.

3.4. Modal accessibility disparity

Modal accessibility disparity (*MAD*) is a place-based indicator that quantifies the difference in accessibility between transit and cars (Kwok and Yeh, 2004). The sign of MAD depends on the accessibility metric. In CF, a smaller value indicates better accessibility while in CO and ST, a larger value indicates better accessibility. For consistency in the interpretation of modal disparity values, two ratios are used. The first is for the CF:

$$MAD^{CF} = \frac{A_{ikC}^{CF} - A_{ikT}^{CF}}{A_{ikC}^{CF} + A_{ikT}^{CF}} \tag{5}$$

and the second is for the other two metrics:

$$MAD^{CO,ST} = \frac{A_{ikT}^{CO,ST} - A_{ikC}^{CO,ST}}{A_{ikT}^{CO,ST} + A_{ikC}^{CO,ST}} \tag{6}$$

where $A_{ikT}{}^{CF}$ represents the two travel time transit-based accessibility metrics and $A_{ikC}{}^{CF}$ represents the two travel time car-based metric, $A_{ikT}{}^{CO,\ ST}$ represents the CO/ST transit-based accessibility metrics and $A_{ikC}{}^{CO,\ ST}$ represents the CO/ST car-based accessibility metrics. *MAD* ranges from −1 to 1, where negative values indicate car advantage over transit, positive values indicate transit advantage over cars, and zero indicates absolute balance between the two modes. Eqs. (5) and (6) are used to calculate modal disparity for zones, and to calculate regional disparity after aggregating the zonal accessibility values.

3.5. Local indicators of spatial association

Local Moran's I_i is used to determine whether the spatial pattern of modal disparity values is similar or different between the metrics. The statistic measures the statistical significance of spatial clustering of similar values for each location. In this analysis, the value is the standard deviation of a set of modal disparity values, depending on the comparison (more below in Section 3.6). Zones that are significant at the 5% level are classified into one of four types: low-low cluster indicates similarity between metric values; high-high cluster indicates difference between metric values; low-high type indicates a zone with similar metric values surrounded by zones with different metric values; a high-low type indicates a zone with different metric values surrounded by zones with similar metric values.

Local Moran's I_i is defined as

$$I_i = \frac{x_i - \bar{x}}{\sum_{i=1}^{n} (x_i - \bar{x})^2 / n} \sum\nolimits_{j=1, j \neq i}^{n} w_{ij}\left(x_j - \bar{x}\right) \tag{7}$$

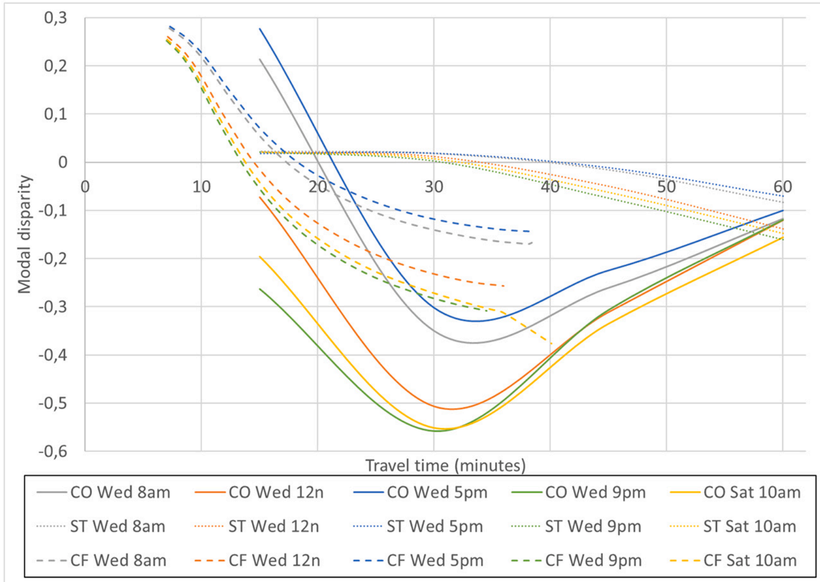

Fig. 2. Modal accessibility disparity results by travel time and time of day.

using a row standardized binary spatial weights matrix based on the eight nearest neighbors for each zone *i*. Statistical significance is obtained by repeating the analysis 10,000 times while varying the values around each zone using a randomization process. Calculations are performed using ArcGIS.

3.6. Study design

The analysis consists of five steps. The first step involves calculating congested travel times between zone centroids and grocery store locations in Warsaw for cars and transit. The next step consists of calculating accessibility to grocery stores using the three types of metrics. Since many different parameters of each metric are used in the literature, this study uses multiple parameters in the calculation of each metric to gauge the sensitivity of the modal disparity metric. For the CF metric, accessibility is calculated for all facilities in the set $K = \{1, \ldots 346\}$. For both the CO and ST metrics, accessibility is calculated for four different one-way travel time thresholds: 15, 30, 45, and 60 min. For the ST metric, a time budget of 150 min is used making the travel time thresholds equivalent to shopping times of 30, 60, 90, and 120 min. Third, modal disparity to grocery stores is quantified. Next, standard deviation of disparity values is calculated in four ways: a) for all above parameters (four travel time parameters in CO and ST; 10 of the 346 stores in CF, specifically, the 1st, 5th, 10th, 50th, 100th, 150th, 200th, 250th, 300th, and 346th) for each of the 15 metric-time of day combinations, b) for all parameters and metrics for each time of day, c) for all parameters and times of day for each metric; and d) for all parameters, metrics, and times of day. Finally, factors (transit stop, population, road, grocery store densities) that may influence the similarity or dissimilarity of disparity values are explored. Each density value is calculated by zone and then the mean and standard deviation are taken when summarized by each Moran's cluster. Sources for the previously unmentioned data are: GTFS for transit stops, and the 2011 National Census for population.

4. Results and discussion

Fig. 2 shows that each accessibility metric produces different modal disparity values and that they are very sensitive to parameter values. Across all metrics, times of day, and all parameters, modal disparity varies from a high of 0.282 (first CF at 5 pm) to a low of −0.557 (CO at 9 pm). Already, it is clear that depending on which metric is used, modal disparity conclusions spanning the range from transit advantage to car advantage can be reached. How modal disparity changes within these extremes is equally important.

Several trends are noticeable. First is the relationship between modal disparity and travel time. Generally, transit is competitive against the car at shorter travel times. As travel time increases, modal disparity decreases at an increasing rate for the ST metric, decreases at a decreasing rate for the CF metric, and it decreases then increases for the CO metric. Second is the impact of congestion during the morning and afternoon rush hours. The increased congestion and more frequent schedules during rush hours provide for transit's edge against the car. Rush hour modal disparity values are higher. In some cases this means the values are positive indicating transit advantage, while for others the values are negative but the car advantage is lower than at non-rush hour times. Interestingly, at 15 min travel time, the impact of rush hours leads to opposite conclusions about modal disparity within a single metric. This is true for both CF and CO; within each metric, transit has the advantage during rush hours, while cars have the advantage during midday, evening and on Saturday. Third, is the relative order of the metric results. In descending order of disparity values, the relative order of metrics at 15 min is: rush hour CO, rush hour CF, all ST, non-rush hour CF, and non-rush hour CO. At 30 min the order is: all ST, all CF, and all CO. At 45 min, ST is above CO, while at 60 min the order is: rush hour ST, rush hour CO, midday and evening CO, midday and Saturday ST, Saturday CO, and evening ST.

Recognizing that there are too many combinations of parameters, times of day and metrics to map and discuss all spatial patterns, and to generalize away from the specifics of Warsaw, the focus is on their correspondence. By using local measures of spatial association, areas in the city where results are similar/different are identified to understand whether the metrics are replaceable with one another. First, the correspondence between metric parameters is investigated (Fig. 3) showing two trends. One is obvious in that the spatial patterns between the three metrics differ in where the values of each metric agree or disagree. Disparity values between the 10 facilities in CF are similar (light blue) in small pockets around the edge of the city center, and in low density peripheral areas north and south. The city center is the place of similarity between the four travel times in both CO and ST, though it is much larger for ST and elongated along the north-south metro line. Dissimilar areas (light red) tend to be in the periphery in CO and ST, while there are also dissimilarity pockets around the city center in CF. The other trend is

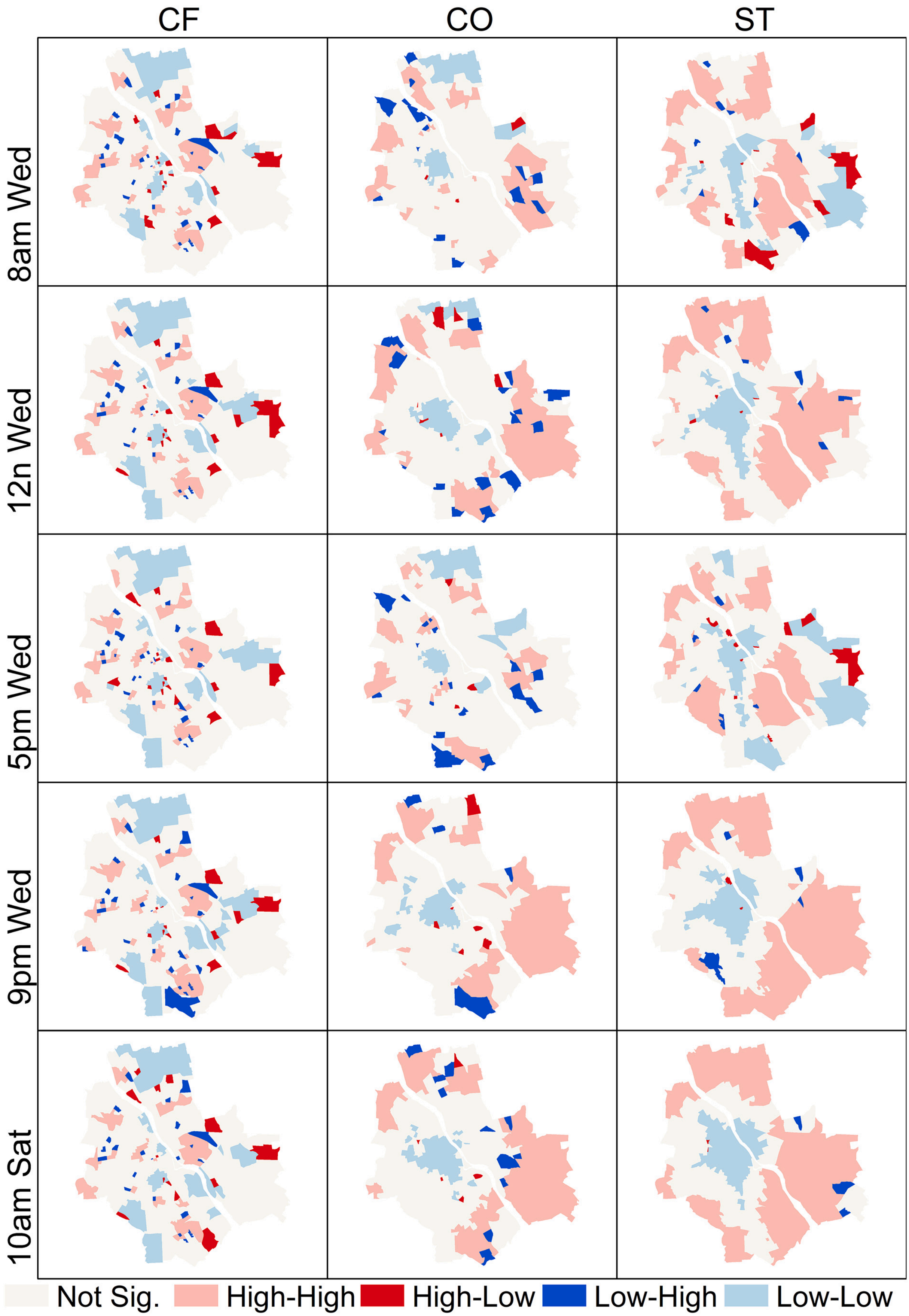

Fig. 3. Local Moran's I_i results by time of day and metric.

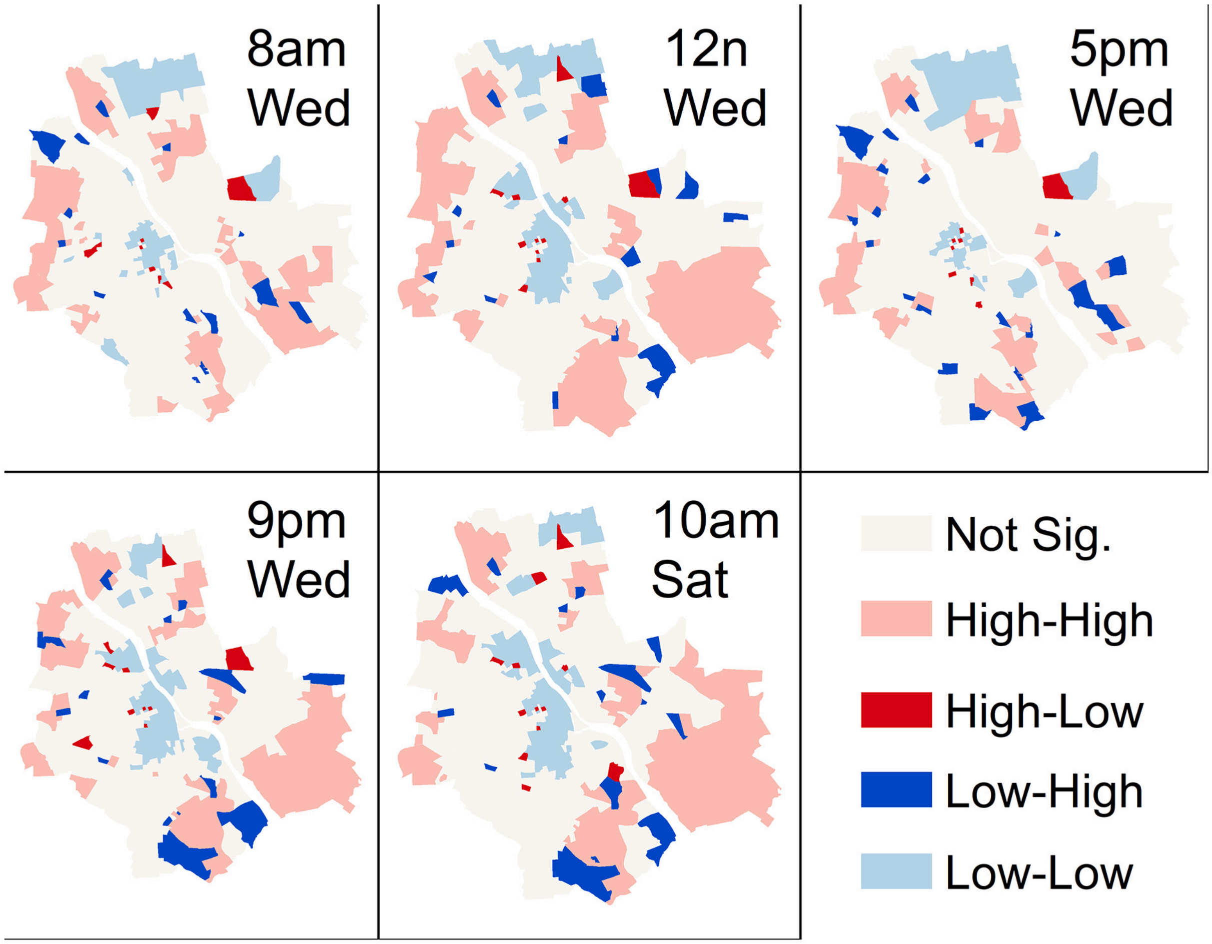

Fig. 4. Local Moran's I_i results by time of day across all metrics.

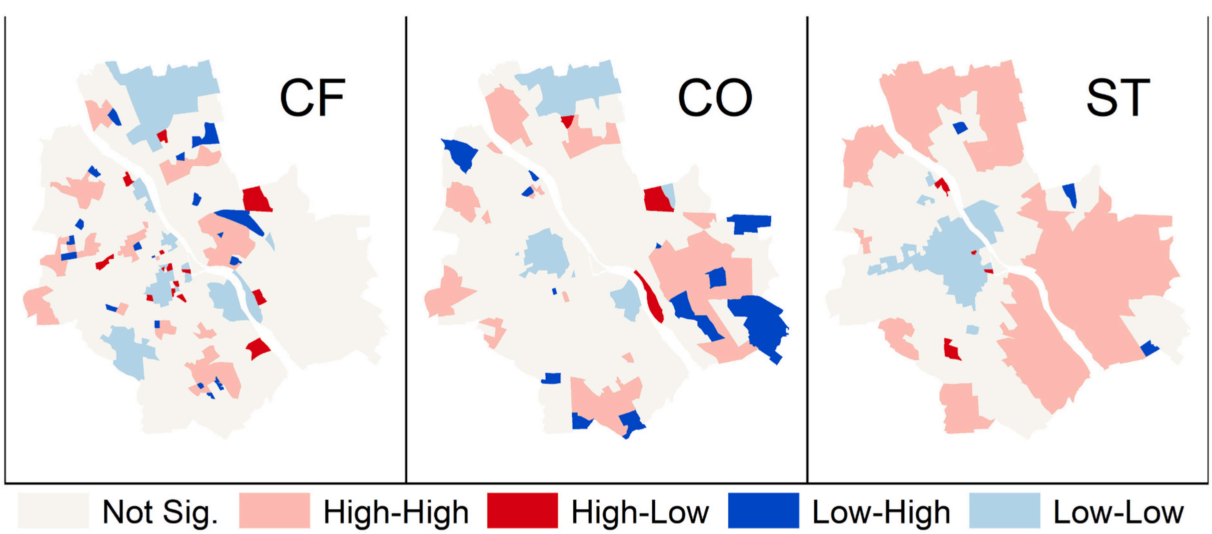

Fig. 5. Local Moran's I_i results by metrics across all times of day.

the impact of rush hours. In fact, the impact is essentially non-existent in CF, wherein the pattern is very stable across the five times of day with only subtle differences. In CO and ST the impact is most clearly seen in the city center and in the southeastern area (Wawer). In CO and ST, the central similarity area is smaller during both rush hours, probably because transit is faster due to better schedules compared to congested streets. Additionally, the central area of similarity in ST lacks the northern end in Żoliborz, probably for the same reason. Outside of rush hours, low density peripheral areas switch classifications. For example, the whole of Wawer is a dissimilarity area while during rush hours it is mostly or partly insignificant in CO or becomes an area of similarity in ST. The northern edge of Białołęka in CO is a similarity area in rush

Table 1
Average and standard deviation values for local Moran's I_i clusters based on Fig. 5, where LL = Low-Low, LH = low-high, HL = high-low, HH = high-high, and NS = not significant.

Metric	Local Moran's I_i cluster	Avg transit stop density (stops/km^2)	SD transit stop density (stops/km^2)	Avg road density (km/km^2)	SD road density (km/km^2)	Avg population density (pop./km^2)	SD population density (pop./km^2)	Avg grocery store density (stores/km^2)	SD grocery store density (stores/km^2)
	LL	32.46	32.68	22.09	12.24	5491.04	5713.58	0.16	1.28
	LH	31.87	36.36	31.28	14.21	9453.16	5070.61	3.76	6.02
CF	HL	34.77	32.46	22.28	8.46	6838.45	6667.70	0.97	2.38
	HH	28.43	17.72	28.81	11.20	10,155.87	4501.87	1.76	2.32
	NS	29.56	30.07	25.28	12.89	6150.76	4917.12	0.84	2.27
	LL	62.08	41.37	26.69	13.02	10,026.06	5955.30	2.05	4.67
	LH	10.70	16.54	20.37	13.41	1473.32	2214.57	0.00	0.00
CO	HL	4.31	2.03	7.45	3.95	430.70	171.23	0.00	0.00
	HH	11.94	9.88	23.88	11.54	3167.31	3300.25	0.58	1.28
	NS	28.36	24.91	26.04	12.66	7116.80	4959.49	0.96	2.10
	LL	57.27	33.94	28.99	12.61	10,417.12	4733.11	1.52	3.83
	LH	5.79	3.08	17.38	16.35	1055.04	936.52	0.00	0.00
ST	HL	27.13	23.15	29.07	14.33	4892.67	4966.48	0.15	0.33
	HH	11.14	10.28	21.85	11.82	3051.95	3922.98	0.53	1.37
	NS	25.98	22.63	25.90	12.58	7021.77	4734.16	1.01	1.99

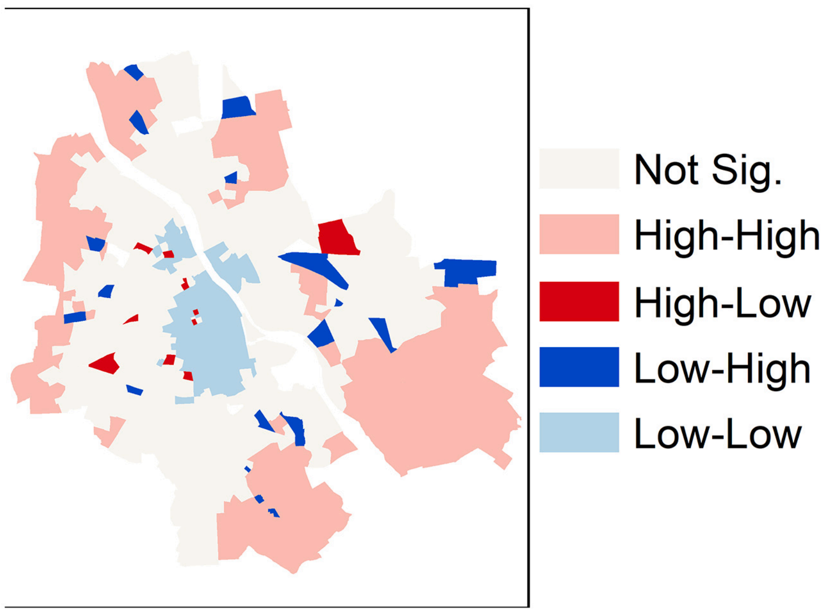

Fig. 6. Local Moran's I_i results across all parameters, all metrics and all times of day.

Table 2
Average and standard deviation values for local Moran's I_i clusters based on Fig. 6, where LL = Low-Low, LH = low-high, HL = high-low, HH = high-high, and NS = not significant.

Local Moran's I_i cluster	Avg transit stop density (stops/km^2)	SD transit stop density (stops/km^2)	Avg road density (km/km^2)	SD road density (km/km^2)	Avg population density (pop./km^2)	SD population density (pop./km^2)	Avg grocery store density (stores/km^2)	SD grocery store density (stores/km^2)
LL	57.94	34.74	28.92	12.52	9936.99	4534.19	1.16	3.18
LH	21.42	22.00	25.10	14.08	4761.20	4494.33	0.75	1.58
HL	37.68	28.96	21.78	10.74	6590.95	5464.49	2.07	4.01
HH	14.71	12.89	23.66	12.00	4875.64	4863.18	0.98	1.74
NS	26.00	23.80	25.92	12.63	6805.51	5058.54	0.99	2.41

hours (a small slither also during midday) while it is insignificant in other times. A similar improvement occurs in ST, in this case switching from dissimilar to insignificant in rush hours. Here again, better rush hour transit is driving this change as frequencies on buses and trains in these areas typically double, from 30 to 15 min (buses) or from 1 h to 30 min (trains).

Second, the correspondence between metrics and their parameters for each time of day is shown in Fig. 4. These maps are a spatial reflection of Fig. 2 showing the competitiveness of transit during rush hours. Both the 8 am and 5 pm maps show the smallest areas of similarity in the center and the smallest areas of difference in the periphery. Transit provides an advantage over cars in the center while it reduces the car advantage in the periphery. Interestingly, the north-south axis of similarity in the center outside of rush hours is remarkably stable. It encompasses Żoliborz, the city center, and north Mokotów, following the central portion of the first metro line. Here, transit loses its

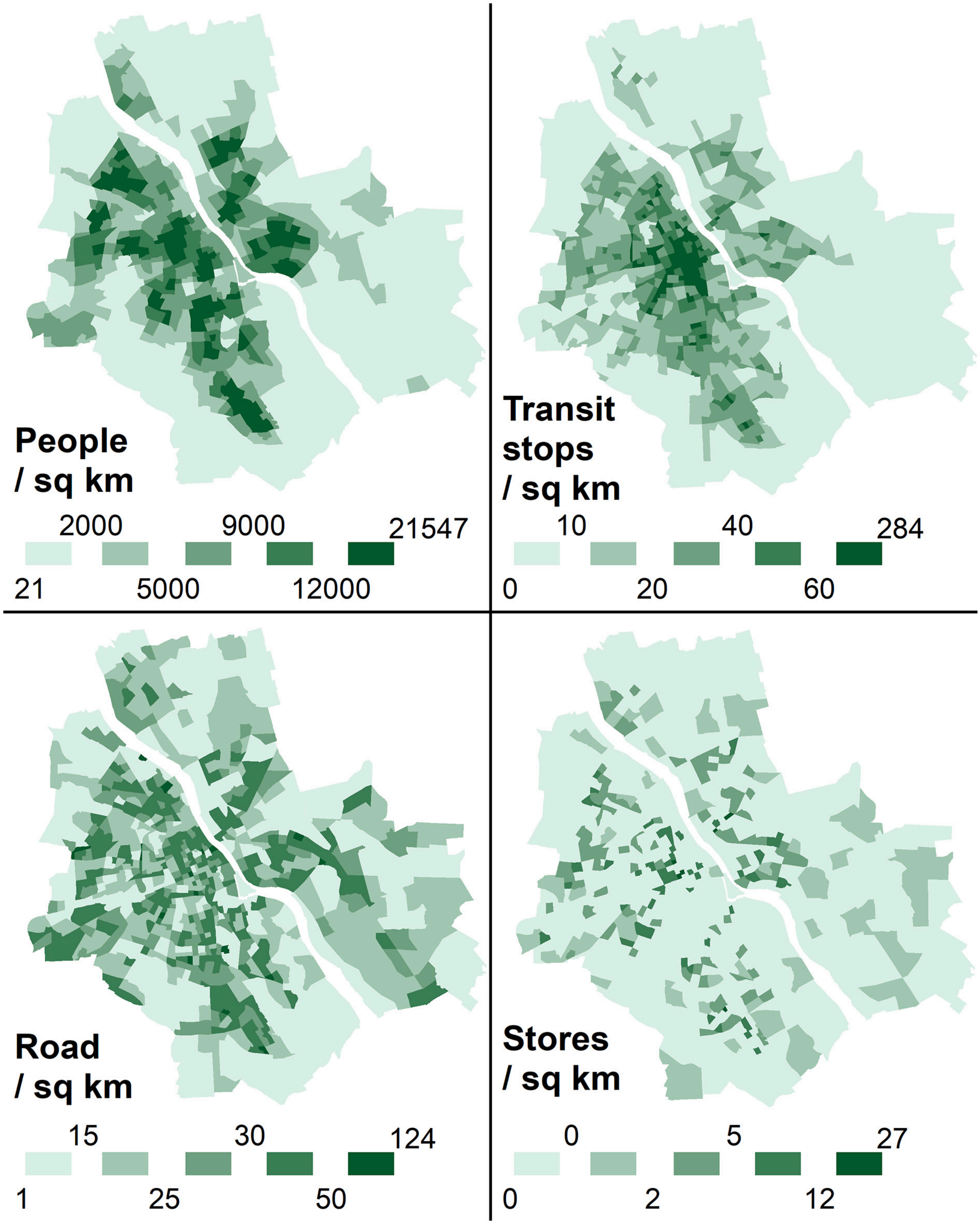

Fig. 7. Densities of population, transit stops, roads, and grocery stores.

advantage due to lower congestion in the off-peak.

Third, the correspondence between metric parameters and times of day for each metric is shown in Fig. 5. When comparing the spatial patterns of the metrics with the patterns of the four factors (Fig. 7, Table 1), there are stark differences between CF and the other two while there are noticeable similarities between CO and ST. The CF pattern is a mix of similarity and difference pockets throughout the city, while the CO and ST especially show a similarity center surrounded by an inner ring of insignificance and an outer ring of difference and insignificance. The CO and ST patterns are not identical as the ST similarity core is stretched along both axis due to both metro lines and northeastern Białołęka being in opposite clusters. The factors behind the patterns (Table 1) are contrary. Similar disparity values in CF are driven by average density of transit stops, and low density in the other factors. Different disparity values in CF are driven by high density of roads and population and low density of transit stops and grocery stores. Similar disparity values in CO and ST are driven by very high density of transit stops and population and higher density of roads and grocery stores. Low density in all four factors drives different disparity values.

Fourth, taking the standard deviation of all disparity values makes it possible to explore whether the metrics, their parameters, and times of day can be substituted amongst each other (Fig. 6). In other words, the level of mismatch across all variables is shown. Similarity exists in the city center following the north-south metro line between Żoliborz and north Mokotów and east into Praga Północ along the second metro line. Conversely, difference exists mostly in high density areas (Bemowo, Ursus, Ursynów, western Białołęka) but also low density areas (Wawer). According to Table 2, similarity areas are driven by very high density of transit stops and population, higher road density and average grocery store density. Difference areas are characterized by very low transit stop density, low population density, and average density of roads and grocery stores.

5. Discussion and conclusions

This research systematically explores the impact of three metrics on modal accessibility disparity to food stores, focusing on Warsaw, Poland. The analysis considers different metric parameters (travel times, number of facilities, times of day), and uses realistic door-to-door car and transit travel times. Results shed light on how the three metrics can be used by planners to assess transportation investments and plans. This study's approach shows where modal disparity values match or not along different dimensions, by metric parameters, by time of day, by metric, and across all of these variables. The two overarching simplified trends are that transit advantage decreases with increasing travel time and that the high density city center is where disparity values across all variables tend to be similar, while they are different in high and low density peripheral areas. The medium density inner ring around the center tends to be insignificant meaning that the disparity spatial pattern is not different from the random process null hypothesis.

The density of population, stores, and transport infrastructure play a role in the modal disparity spatial pattern. Clearly, more frequent and dense transit networks enhance transit's role relative to the car. This study's approach can be used to identify areas (and times) prime for transit investment. Transit investments are needed to connect the city to the suburbs to balance the center-focused network (a potential reason of difference in peripheral high density areas) and in non-rush hours. Interestingly, grocery store locations do not play an important role in disparity spatial patterns, probably because they are already ubiquitous. Importantly, the central similarity area is where metrics could be used interchangeably or together without introducing significant error. That the similarity areas are small in area and difference areas are larger and more of them suggests that any single metric should not be a single source for grocery store modal accessibility disparity analysis. Given the different disparity spatial patterns, the three metrics should be used together because each metric measures different aspects of food accessibility, namely local proximity (CF), maximizing opportunity choice (CO), and maximizing shopping time (ST). This has not been the case in the literature thus far, as each study uses a single and different metric. The focus on a single metric is a potential reason why the literature has concluded that food accessibility plays an uncertain role in health.

There are several limitations of this study. First, the findings are unique to Warsaw and may not apply to other cities with different land use and transportation patterns. Second, the analysis focuses on only two modes, car and transit, neglecting an independent walking mode and cycling, which provide alternative means of purchasing groceries. Third, the analysis uses a single out-of-vehicle time of 10 min for the entire city. Clearly this is a simplification given that distances between homes/grocery stores and parked cars and parking search time vary by location in a city. However, detailed data is not available for Warsaw and is generally difficult to find. Using a city-wide value is preferable to not using one at all, which would overestimate car accessibility. Further, it is beyond the scope of this paper to test the sensitivity of the findings to different input data values. Fourth, the analysis uses a single city-wide congestion factor in each of the four time periods. This creates uncertainties because such an approach is not a true representation of actual travel times. However, crowd-sourced travel times like Google Maps and others are also not true representations of actual travel times because of uncertainties arising from different data, assumptions and algorithms used in their creation. Wu (2019) shows that Google travel times are systematically higher than Uber data, on average by a factor of 1.262. Furthermore, Banke-Thomas et al. (2020) find that Google underestimates real travel times by 10 min on average. Importantly, they also show that speed-limit based travel times underestimate the actual on average by 40 min. Considering the inherent uncertainties in all travel time estimates and the prohibitive cost of crowd-sourced road link level congested travel times, using a single congestion factor is the next best option rather than just using free-flow travel time which would generate misleading results due to overestimating car accessibility.

Author statement

I have no competing interests.

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