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Measuring segregation using patterns of daily travel behavior: A social interaction based model of exposure

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ABSTRACT

Recent advances in transportation geography demonstrate the ability to compute a metropolitan scale metric of social interaction opportunities based on the time-geographic concept of *joint accessibility*. The method we put forward in this article decomposes the social interaction potential (SIP) metric into interactions within and between social groups, such as people of different race, income level, and occupation. This provides a novel metric of exposure, one of the fundamental spatial dimensions of segregation. In particular, the SIP metric is disaggregated into measures of inter-group and intra-group exposure. While activity spaces have been used to measure exposure in the geographic literature, these approaches do not adequately represent the dynamic nature of the target populations. We make the next step by representing both the source and target population groups by space–time prisms, thus more accurately representing spatial and temporal dynamics and constraints. Additionally, decomposition of the SIP metric means that each of the group-wise components of the SIP metric can be represented at zones of residence, workplace, and specific origin–destination pairs. Consequently, the spatial variation in segregation can be explored and hotspots of segregation and integration potential can be identified. The proposed approach is demonstrated for synthetic cities with different population distributions and daily commute flow characteristics, as well as for a case study of the Detroit–Warren–Livonia MSA.

1. Introduction

Residential segregation refers to the sorted patterning of population groups into different neighborhoods, and measures of segregation attempt to quantify the degree of separation between two or more population groups (Massey and Denton, 1988). Decades of research have shown that residential segregation is associated with spatial inequalities in service provision causing racial disparities in health (Williams and Collins, 2001), economic outcomes (Massey et al., 1987), educational achievement of youth (Card and Rothstein, 2006), and spatial mismatch between the locations of low-wage workers and employment opportunities (Kain, 1968). Measuring the degree to which minority groups are concentrated in their own neighbourhoods (i.e. ghettoization) is an appropriate way to quantify segregation if the research goal is to identify the existence of segregation or to determine whether it is statistically associated with socioeconomic and health inequalities. For this reason, the Duncan Dissimilarity Index (DI) was the most commonly applied method for measuring racial segregation for many decades (Duncan & Duncan, 1955). The DI is interpreted as the percentage of the minority population that would need to relocate in order to perfectly integrate the residential distributions in a region. In addition to individual or neighbourhood level outcomes, segregation is also theorized to be associated with societal outcomes of the region like social cohesion (Tumin, 1953; Wilkinson, 2002). Defined as the degree to which different members of society work together for their common good (OECD, 2011), social cohesion depends on bridging network relations across social groups, requiring the existence of opportunities for communication and social interaction (Forrest and Kearns, 2001). Notwithstanding the societal implications of bridging social interactions, social networks may also be of interest for their production of social capital (Coleman, 1988). In either case, exposure has evolved as a dimension of segregation that is better suited to the measurement of interaction opportunities.

Following a decade of heightened criticism of the DI and the development of more than 20 new segregation indices, Massey and Denton (1988) determined that segregation could be explained by a set of five principal dimensions: evenness, exposure, concentration, centralization and clustering. Of these, we highlight the particular salience of exposure in this research. It “refers to the degree of potential contact, or the possibility of interaction, between minority and majority group members within geographic areas of a city” (Massey and Denton, 1988, 278).

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The interaction index is the archetypical measure of exposure cited in the literature (Bell, 1954; Lieberson, 1981). Massey and Denton eloquently describe it as "the minority-weighted average of each spatial unit's majority proportion" (Massey and Denton, 1988, 288). Borrowing notation from Wong and Shaw (2011) we can measure the exposure of group a to group b as:

$$P_{a\times b} = \sum_{i=1}^{n}\left(\frac{a_i}{A}\right)\left(\frac{b_i}{t_i}\right) \tag{1}$$

where a_i, b_i and t_i are the population counts of the two groups and the total population in zone i respectively, A is the total population of group a in the region, and n is the number of residential zones in the region. This interaction index evaluates the contact probability of the majority to the minority group within each residential zone, ignoring the potential for contact with members of the majority group living and working in different zones as people go about their daily activities. Importantly, this index is extendable to three or more population groups, and reversible, so that measures of isolation can also be obtained. A number of authors have sought to expand potential interaction spaces to areas outside of the residential zone by fusing segregation measures with spatial statistics (Morgan, 1983; Wong, 1993; Wong, 2002; Reardon and O'Sullivan, 2004), or by adopting more explicit activity–space approaches to measuring segregation (Schnell and Yoav, 2001; Wong and Shaw, 2011) and there is now a call for research that continues to move beyond measuring segregation within residential neighbourhoods to better capture people's experience of segregation over the course of their daily lives (Kwan, 2009, 2013).

The goal of this article is to draw on research developments in measuring metropolitan scale social interaction potential (Farber et al., 2012) and to quantify exposure using a time-geographic approach (Hägerstrand, 1970). Moreover, we are interested in developing a metric that is readily computable and comparable between regions so that hypotheses regarding the impacts of the spatial structure of regions (i.e. the patterns of where people live, work, and conduct their daily activities) on social contact opportunities can be explored. Specifically, we would like to extend this line of inquiry into an improved understanding of the relationship between spatial structure of regions and opportunities for between-group and within-group interaction potentials.

The rest of the article is organized as follows. First, we review the recent advances in segregation research, focusing on activity-based measurement approaches. Next we put forward our proposed measure of exposure that is based on the concept of social interaction potential. Following this, we describe the results of a simulation experiment designed to test the behaviour of the new metric with respect to its input parameters. After, the metric is applied in an empirical case study focussing on Detroit, Michigan, the most residentially segregated city in the US according to a recent study (Logan and Stults, 2011). Finally, we discuss the results, contextualize the knowledge gained through this research, and provide our thoughts on future research in this area.

2. Literature review

Our paper is part of a wider discourse aimed at using daily activity patterns to address the Uncertain Geographic Context Problem (UGCoP) which states that relationships between neighbourhood units and individual behaviours and outcomes are inherently fraught with errors associated with the unknown definitions of relevant spatial and temporal contexts (Kwan, 2012b, 2012a). By using activity patterns of individuals in a city, we are more succinctly defining a relevant spatiotemporal context in which to measure opportunities for social interaction between social groups.

Although this line of inquiry is recent, there has been a flurry of research activity using activity patterns to measure aspects of segregation. The existing research can be grouped into three categories. First are the papers that describe and visualize activity spaces belonging to members of different social groups in order to discover evidence of isolation, limited mobility, and ethnic partitions of activity spaces. For example, Lee and Kwan (2011) developed four visual methods to identify and describe socio-spatial isolation amongst South Koreans living in Columbus, Ohio. Similar work investigates three-way separation between activity spaces belonging to Palestinians, secular Jews and ultra-orthodox Jews living in Jerusalem (Greenberg Raanan and Shoval, 2014). Wang et al. (2012), for their part, visualize activity spaces of residents of different urban enclaves in Beijing and find statistical differences between spatiotemporal characteristics of activity patterns. These works are based on relatively small samples and are primarily visual and descriptive in nature. Importantly, there is no attempt to generalize findings into a replicable or transferable measure of segregation or exposure.

The second category of work in this area includes attempts at measuring exposure by better defining individuals' geographic context using travel behaviour data, and measuring exposure through the intersection of the derived activity spaces of individuals with static census-based residential population counts. Wong and Shaw (2011) evaluated individual-level exposure measures using the collection of administrative zones visited by respondents of a travel diary survey. Each individual in the survey was considered potentially exposed to the residential population in the administrative zones visited. From this, an index of white–black exposure was built on the propensity of white respondents to visit zones in which black populations reside. Farber and Páez (2012) extend this approach by implementing a model-based activity space, and by placing the exposure measurement within a statistical inferential framework based on the G_i^* local statistic (Getis and Ord, 1992). While both approaches use sophisticated conceptualizations of the activity space, neither of them adequately represents the dynamic nature of the target population. In both cases, the measure of exposure is based on a simple static target population aggregated to zonal centroids. In other words, while activity spaces are used to generate more realistic representations of the geometries of the geographic context a person is exposed to, the context itself is still merely attributed with static residential population counts.

A third group of papers address this shortcoming by representing both source and target populations with detailed spatiotemporal activity patterns. In a methodologically innovative study, mobile phone location data was used to build activity spaces for ethnic Russians and Estonians living in Estonia (Silm and Ahas, 2014a, 2014b). Using location data of nearly half of the country's population, over a three-year period, the researchers developed a time series of Russian and Estonian concentrations in neighbourhoods throughout Estonia. This data was then analyzed for temporal shifts in segregation on daily, weekly, and seasonal scales. The research identified that workday levels of segregation are far lower than evening and weekend levels, when people have more discretion to self-sort themselves into households and discretionary activity locations. In a similar vein, Palmer (2014) developed a spatial proximity index for grouped GPS trajectory data. Importantly, through spatial Monte Carlo simulations, it was demonstrated that the small sample bias of the proximity estimator disappears when the sample of trajectories approaches several hundred.[1]

Analyzing spatio-temporal activity patterns using mobile phone and GPS data allows very accurate measurement of the spatiotemporal contexts of both source and target populations. However, these data are often semantically poor. Mobile phone and GPS trajectory data are seldom associated with socioeconomic attributes of the phone's owner or user. One could quite readily establish the phone's home location,

[1] Palmer computes a proximity index using a sample of GPS trajectories. The index is a sample estimate of the true population index that could only be computed if we had trajectories for the entire population of the city. Palmer shows that as the sample size gets larger and larger, the difference between the sample estimate and population index shrinks, and for samples of several hundred respondents, there is essentially no bias in the estimate.

and from that infer some neighbourhood socioeconomic data, but doing so within the context of a segregation study will almost certainly require the researcher to commit an ecological fallacy. Due to the phone users' selection of language used to communicate with the phone company in Estonia, the Estonian team has at least one identifier of ethnicity in their dataset. But this is not the norm for mobile phone based datasets, and, given the lack of spatial consistency in how mobile phone data are obtained and the types of social identifiers that are attached to observations, it is not currently possible to conduct rich socioeconomic investigations of mobile phone trajectories in a comparative study of segregation in cities.

More generally, it is possible to place segregation measures on a continuum of place vs. people based measures of segregation (Fig. 1) (Kwan, 2009), akin to the dichotomies drawn in accessibility research and GIScience (Miller, 2005b, 2007). On the one side, place based measures take advantage of readily available census data, are easy to calculate and usually quite straightforward to interpret. However, they ignore the UGCoP and for this reason do not offer theoretically valid measures of personal experience. On the other side, people based measures, while being far more theoretically valid, suffer from issues of reproducibility and transferability due to the costs of collecting primary data and the lack of consistency associated with commercially available data. This is a particular concern with respect to our research goal of comparing segregation across cities in order to better understand the role of spatial structure of different places. So, we call for development in the middle ground; a measurement approach that is readily interpretable and calculable across a wide array of regions, but at the same time takes the UGCoP into consideration by basing the measurement on activity patterns. Our solution is proposed in the next section.

3. A social interaction potential (SIP) based measure for potential exposure

3.1. The roots of SIP in time geography

Social interaction potential is a time geographical approach to measure opportunities for social contact between people in a region (Farber et al., 2012). Based on the concept of joint-accessibility (Neutens et al., 2007a, 2007b; Neutens et al., 2008) and the principles of time geography that govern interaction opportunities (Miller, 2005a), SIP is a computation of the average space–time prism intersection volume between all pairs of people in a region. The space–time prism is a geometric approximation of the set of all space–time paths an individual could potentially traverse between a pair of fixed anchors in space–time (Hägerstrand, 1970). The volume of the prism is traditionally interpreted as a measure of potential accessibility, as it intrinsically captures the amount of time an individual could participate at each opportunity location (Burns, 1979; Lenntorp, 1976; Miller, 1991, 1999). Following on this, the volume of intersection between two people's prisms can be interpreted as a measure of potential interaction opportunity between them (Farber and Páez, 2011). These concepts are further illustrated in Fig. 2 below. The space–time path in 2A depicts the movement of a person as they conduct their daily activities. In 2B, we present a space–time prism, which is anchored at two locations in space–time; in this case, the anchors are the results of *bundling* and *authoritative* constraints (Hägerstrand, 1970) that dictate when the individual is free to leave work, and what time they are required back at home to conduct mandatory household activities. The difference in time between these anchors is denoted as the person's discretionary time budget which when coupled with the individual's mode and speed of travel (an example of Hägerstrand's *capacity* constraints) results in the space–time prism, a volume representing the amount of time a person can conduct an activity at each reachable location, given one's time-geographical constraints. For two space–time prisms belonging to two different individuals, the volume captured by their intersection represents the amount of time two people can jointly conduct an activity at each jointly reachable location, given each person's constraints.

Provided this understanding of the fundamentals of time geography, Farber et al. (2012) show that averaging over all pairs of prism intersections in a region, we can obtain a global, regional measure of SIP:

$$SIP = \sum_{s}^{P}\sum_{t\neq s}^{P} V_{st} \times [P(P-1)]^{-1} \tag{2}$$

where V_{st} is the prism intersection volume between persons s and t and P is the total number of people in the region. This formula denotes the theoretical (and wholly unobtainable) value of SIP in a region based on individual space–time prisms. In practice, save for several highly detailed, but small sample datasets, individual level data are not available in the construction of personalized space–time prisms for a region's population, but origin–destination (OD) transportation datasets can be used to represent the most fundamental space–time constraints on the typical individual: their home and work locations. An OD matrix is an $N \times N$ matrix containing the number of people who live and work in each of the N zones in a region. We can therefore approximate SIP using zonal OD data with the following:

$$SIP = \sum_{i}^{N}\sum_{j}^{N}\sum_{q}^{N}\sum_{r}^{N} V_{ijqr} P_{ij} P_{qr} \tag{3}$$

where V_{ijqr} is the intersection volume between two prisms anchored at home and work zones Z_i/Z_j and Z_q/Z_r respectively, and P_{ij} is the percentage of the region's population that lives at Z_i and works at Z_j. The nested summations are used to iterate over all pairs of OD pairs in the region. Note that for the reflexive flows, P_{ii} is the percentage of people who live and work in the same zone, plus the percentage of people living in Z_i who do not go to work. Our measure therefore attempts to include

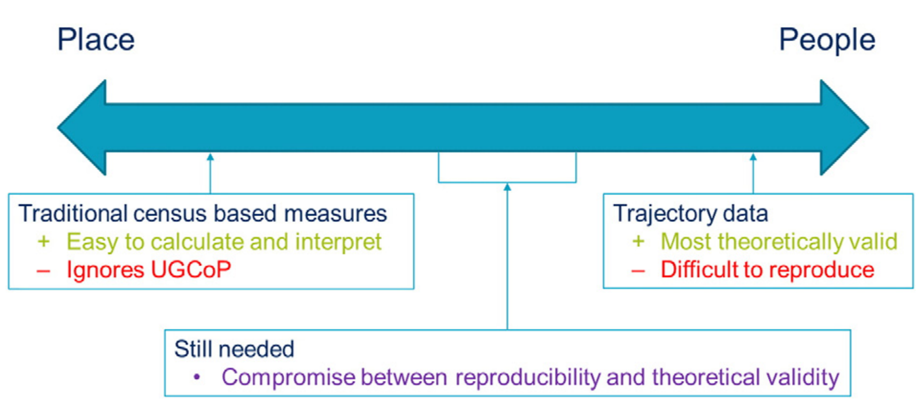

Fig. 1. Place vs. people based segregation.

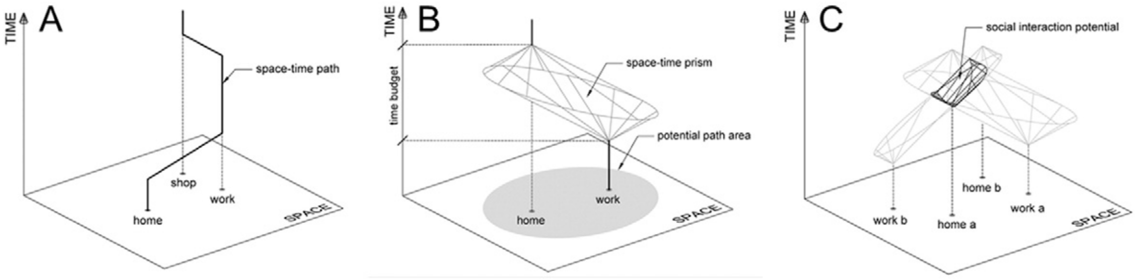

Fig. 2. Depictions of A) a space–time path, B) a space–time prism and C) the intersection of two space time prisms, forming the basis of the social interaction potential (SIP) metric (Source: (Farber et al. 2012)).

the experiences and impact of the non-working population. With this approximation, we assume that on a typical day, people are constrained by their work and home locations, and in the SIP model, which is clearly an abstraction and simplification of the far more heterogeneous activity patterns of people in a region, we quantify the potential opportunities for social contact subject to these constraints.

For computational reasons, the precise estimation of V_{ijqr} is very difficult to obtain. Our approach to computing an accurate approximation of the true intersection volume is to divide the study region into a regular grid. Then, by invoking the same principals used in Simpson's approximation to numerical integration, we find that:

$$V_{ijqr} = \lim_{\substack{K\to\infty \\ s_k\to 0}} \sum_{k}^{K} A_{ijqr}^{k} s_k \tag{4}$$

where A_{ijqr}^{k} is the amount of time a person travelling from Z_j to Z_i will have to participate in an activity at grid location k with a person travelling from Z_r to Z_q, s_k is the area of a grid cell, and there are $k = 1..K$ grid cells in the region. When the number of grid cells approaches infinity, and the area of each grid cell approaches 0, our numerical approximation in (4) approaches the theoretical value of V_{ijqr} in (3). In practice, sensitivity analysis has shown that a grid cell of 2.5 km provides an accurate approximation to V_{ijqr} when tested for a variety of regions across the United States (Li, 2015).

Finally, to explain how V_{ijqr} is computed, we must also define the activity time at location k as:

$$A_{ijqr}^{k} = \begin{cases} max(0, \min(b{-}t_{ki}, b{-}t_{kq}) - max(t_{jk}, t_{rk})) & if\ A_{ij}^{k}, A_{qr}^{k} \geq 0 \\ 0 & otherwise \end{cases} \tag{5}$$

where b is an exogenous parameter representing the duration of the evening after-work time budget, t_{ki} is the travel time from k to i, $\max(t_{jk}, t_{rk})$ is the beginning of the overlapping time period, $\min(b - t_{ki}, b - t_{kq})$ is the ending of the overlapping time period, and the max(0,-) function excludes the case where the two individuals have non-overlapping time availabilities at k. In practice, travel times in the region can be computed using a geographic information system (GIS) or extracted from a transportation model, and travel times for different modes of travel can be used to more accurately represent capability constraints. Simply put, for any location k, A_{ijqr}^{k} is the amount of time two individuals can spend together there provided they need to travel there from their work locations and return to their homes before their discretionary time budgets expires. If the combination of their travel times and discretionary time budgets do not allow for an activity to take place, we set the value to 0.

3.2. Extending SIP into measures of exposure and isolation

So far, everything described in this section on the derivation of the SIP measure has been review, and is already published in the following articles (Farber et al., 2012; Neutens et al., 2013; Farber and Li, 2013; Li, 2015). Next, we introduce the adjusted SIP measure that can account for potential interactions within and between social groups. The guiding principle of this measure is that total SIP can be decomposed into interaction potential within groups and between groups. Without loss of generality, suppose the population of a city is bifurcated into only two groups, *A* and *B*. Then:

$$SIP = SIP^{A/A} + SIP^{B/B} + SIP^{A/B} \tag{6}$$

such that the total SIP of a region, is the sum of the contributions of within-group social interaction potentials ($SIP^{A/A}$ and $SIP^{B/B}$) and the between-group interaction potentials ($SIP^{A/B}$). This identity is quite similar to Lieberson's isolation and interaction indices adding to 1 (Lieberson, 1981).

More explicitly, given the group specific OD probabilities, P_{ij}^{A} and P_{ij}^{B}, where $P_{ij} = P_{ij}^{A} + P_{ij}^{B}$, the SIP metric in (3) can be decomposed into group specific contributions as follows:

$$\begin{aligned} SIP &= \sum_{i,j,q,r}^{N} V_{ijqr} P_{ij} P_{qr} \\ &= \sum_{i,j,q,r}^{N} V_{ijqr} \left(P_{ij}^{A} + P_{ij}^{B}\right)\left(P_{qr}^{A} + P_{qr}^{B}\right) \\ &= \sum_{i,j,q,r} V\left(P_{ij}^{A} P_{qr}^{A}\right) + \sum_{i,j,q,r} V\left(P_{ij}^{B} P_{qr}^{B}\right) + \sum_{i,j,q,r} V\left[\left(P_{ij}^{A} P_{qr}^{B}\right) + \left(P_{ij}^{B} P_{qr}^{A}\right)\right] \\ &= SIP^{A/A} + SIP^{B/B} + SIP^{A/B} \end{aligned} \tag{7}$$

where the subscripts on V_{ijqr} have been omitted for ease of reading. Essentially, by decomposing the weights in the summation by each social group, we obtain the amount of interaction potential for each pair of population groups in the region.

The decomposition of the OD matrix into group-specific flows gives rise to three global measurements of potential exposure:

1. $SIP^{A/A}$—Potential exposure of A's to A's.
2. $SIP^{B/B}$—Potential exposure of B's to B's.
3. $SIP^{A/B}$—Potential exposure between A's and B's.

Each of these is easily decomposed into local measurements of exposure by holding locations of home, work or activity constant during the summations. This procedure is elaborated elsewhere (Farber et al., 2012; Neutens et al., 2013). Combined, we herewith refer to this family of potential exposure measurements as SIPSEG measurements.

3.3. Deriving expected values of SIPSEG under conditions of perfect integration

Importantly, under certain conditions, the expected values of the global exposure scores relative to the total SIP score can be derived. Let P(A) denote the percentage of the regional population in group A. Then P(B) = 1-P(A) is the percentage of the population in group B. Suppose that the flow between each OD pair in the city is split amongst groups according to the global split defined by P(A) and P(B). This implies that $P_{ij}^A = P(A)P_{ij}$ and $P_{ij}^B = P(B)P_{ij}$ for all OD pairs. This type of group distribution epitomizes complete integration; the various commuter flows are evenly distributed amongst the two groups according to their global shares of the regional population. Under these conditions, the DI for both the residential and workplace population distributions is equal to zero. In this scenario the relative contributions of the SIPSEG components to the total are:

$$\left(\frac{SIP^{A/A}}{SIP^T}\right)^* = \frac{\sum_{i,j,q,r} V\left(P_{ij}^A P_{qr}^A\right)}{\sum_{i,j,q,r} V\left(P_{ij}P_{qr}\right)} = \frac{\sum_{i,j,q,r} V\left(P_{ij}P_{qr}\right)P(A)P(A)}{\sum_{i,j,q,r} V\left(P_{ij}P_{qr}\right)} = P(A)^2 \quad (8)$$

$$\left(\frac{SIP^{B/B}}{SIP^T}\right)^* = \frac{\sum_{i,j,q,r} V\left(P_{ij}^B P_{qr}^B\right)}{\sum_{i,j,q,r} V\left(P_{ij}P_{qr}\right)} = \frac{\sum_{i,j,q,r} V\left(P_{ij}P_{qr}\right)P(B)P(B)}{\sum_{i,j,q,r} V\left(P_{ij}P_{qr}\right)} = P(B)^2 \quad (9)$$

and

$$\begin{aligned}\left(\frac{SIP^{A/B}}{SIP^T}\right)^* &= \frac{\sum_{i,j,q,r} V\left(P_{ij}^A P_{qr}^B\right) + \sum_{i,j,q,r} V\left(P_{ij}^B P_{qr}^A\right)}{\sum_{i,j,q,r} V\left(P_{ij}P_{qr}\right)} \\ &= \frac{\sum_{i,j,q,r} V\left(P_{ij}P_{qr}\right)[P(A)P(B) + P(B)P(A)]}{\sum_{i,j,q,r} V\left(P_{ij}P_{qr}\right)} = 2P(A)P(B).\end{aligned} \quad (10)$$

Since the expected values are derived under the assumption of perfect integration, they can be used as best-case benchmarks against which empirical realizations of component contributions will be compared.

Without loss of generality, if the population is partitioned into more than two social groups, the SIPSEG measures and their expected contributions can be easily derived. If G is the set of social groups in a region, then these expected contributions are easily extended to the case where there are $|G|>2$ social groups. In the general case for $|G|>2$, and given any pair of population groups, $g_1, g_2 \in G$, we have:

$$SIP^T = \sum_{g_1 \in G} P(g_1)^2 + \sum_{g_1 \in G} \sum_{\substack{g_2 \in G \\ g_1 \neq g_2}} P(g_1)P(g_2) \quad (11)$$

and

$$\left(\frac{SIP^{g_1/g_2}}{SIP^T}\right)^* = \begin{cases} P(g_1)P(g_2) & \text{if } g_1 = g_2 \\ 2P(g_1)P(g_2) & \text{if } g_1 \neq g_2 \end{cases} \quad (12)$$

4. Analysis of SIPSEG measures: numerical experiments

In this section we design and describe the results of a simulation experiment aimed at improving our understanding of how the SIPSEG metrics behave under controlled scenarios. For these scenarios, we designed a city of 1,000,000 people living and working in a city composed of 9 zones in a 3 by 3 grid. Each home and workplace zone is 12 km by 12 km, resulting in a 36 km by 36 km region. The social interaction locations consist of 81 zones in a 9 by 9 grid covering the same city region. In all scenarios, the home and workplace distributions are monocentric by design, and the OD flow matrix was fitted using a doubly-constrained gravity model. We control and test three parameters in the experiment. First, the percentage of the population that is of type B, P(B), is adjusted from 0% through to 100% in 5% increments. Second, the time budget, b, is tested at 0.5 h through to 2 h in 30 min increments. And third, the travel speed of people of type B is tested at 15 km/h to 60 km/h in 15 km/h increments. The travel speed of type A is set to 60 km/h and it is assumed that people travel between locations in the city in straight lines from zone centroid to centroid. This results in 336 combinations of parameter values for which the SIPSEG measurements are computed.

It is important to note that for all of these scenarios, $P_{ij}^A = P(A)P_{ij}$ and $P_{ij}^B = P(B)P_{ij}$. In other words, the Duncan Index (DI) which assesses the evenness of the racial distributions, computed on either the residential or workplace distributions, is equal to zero, and the expected values of SIPSEG contributions found in 8–10 above should be obtained in the simulation whenever people of type B travel at the same speed as those of type A.

Fig. 3 contains graphical depictions of the experiment results. The two columns of plots are for scenarios with 30 and 120 min budgets respectively. The results for the intermediate time budgets have been excluded for the sake of brevity. The three rows of plots are for $SIP^{A/A}$, $SIP^{B/B}$, and $SIP^{A/B}$ calculations respectively. For each plot, the vertical axis is the percentage of the total SIP contributed by the SIPSEG component for that row, and the horizontal axis is the percentage of the population that is of type B (%B). Each distinct curve pertains to scenarios where type B are travelling at the four different tested speeds: 15 km/h, 30 km/h, 45 km/h and 60 km/h. Recall that type A always travels at 60 km/h. One reason for including this variable in the experiment is that future empirical investigations may include multi-modal transport networks so that SIPSEG can be computed along divisions in users of different transport modes.

The plots tell several interesting stories. First, the scenarios where B travels at 60 km/h, denoted by the mustard curves, attain the expected values for SIPSEG contributions derived in Eqs. 8–10. When the two groups travel at the same speed, we obtain values predicted by Eqs. 8–10 because these scenarios epitomize perfect spatial integration of the populations both at home and the workplace. However, for each component, and especially for the 30 min time budget cases, decreasing the speed of group B results in reductions in total SIP and large shifts in relative shares of between-group and within-group interactions. In particular, when B's speed decreases we find that the relative contribution of A/A potential interactions increases while the share of B/B interactions decreases. Similarly, we also find that the share of A/B interactions drops below expected values except for several scenarios with very high values of %B. This indicates that the social opportunities in a city are most significantly held within groups with faster travel speeds, that groups with reduced travel speeds contribute very little towards the total number of social opportunities in a city, and that between group interaction is dramatically hampered by a reduction in speed of one of the groups.[2]

Finally, a comparison of plots between columns (30 min versus 120 min time budgets) reveals that increasing free time for social activities ameliorates the effect of declining velocity in all but the most extreme velocity-deprivation scenarios. This implies that time-use policies designed to create more opportunities for discretionary activity participation may improve levels of social cohesion in a region. Importantly, the SIPSEG measures are able to detect discrepancies in the levels of between and within-group potential exposure despite that DI = 0 in all cases.

5. Empirical case study: Detroit–Warren–Livonia MSA

In this section, potential exposure within and between racial groups in the Detroit–Warren–Livonia MSA is explored using the new SIPSEG measurements. The Detroit MSA is selected due to the rich study of racial segregation there (Kain, 1968; Farley et al., 1994; Darden and Kamel, 2000; Galster, 2012) and because it was recently found to be the most residentially segregated city in the United States with a DI of 79.6 between black and white populations (Logan and Stults, 2011). This means that 80% of the black population would need to relocate

[2] One additional and unexpected finding is that the contribution of $SIP^{A/B}$to total SIP peaks at higher levels of %B when B travels slower. This is a result of the interplay between relative population sizes and travel speeds, the exact nature of which cannot be explored analytically, but this is precisely why simulation studies are useful in this research.

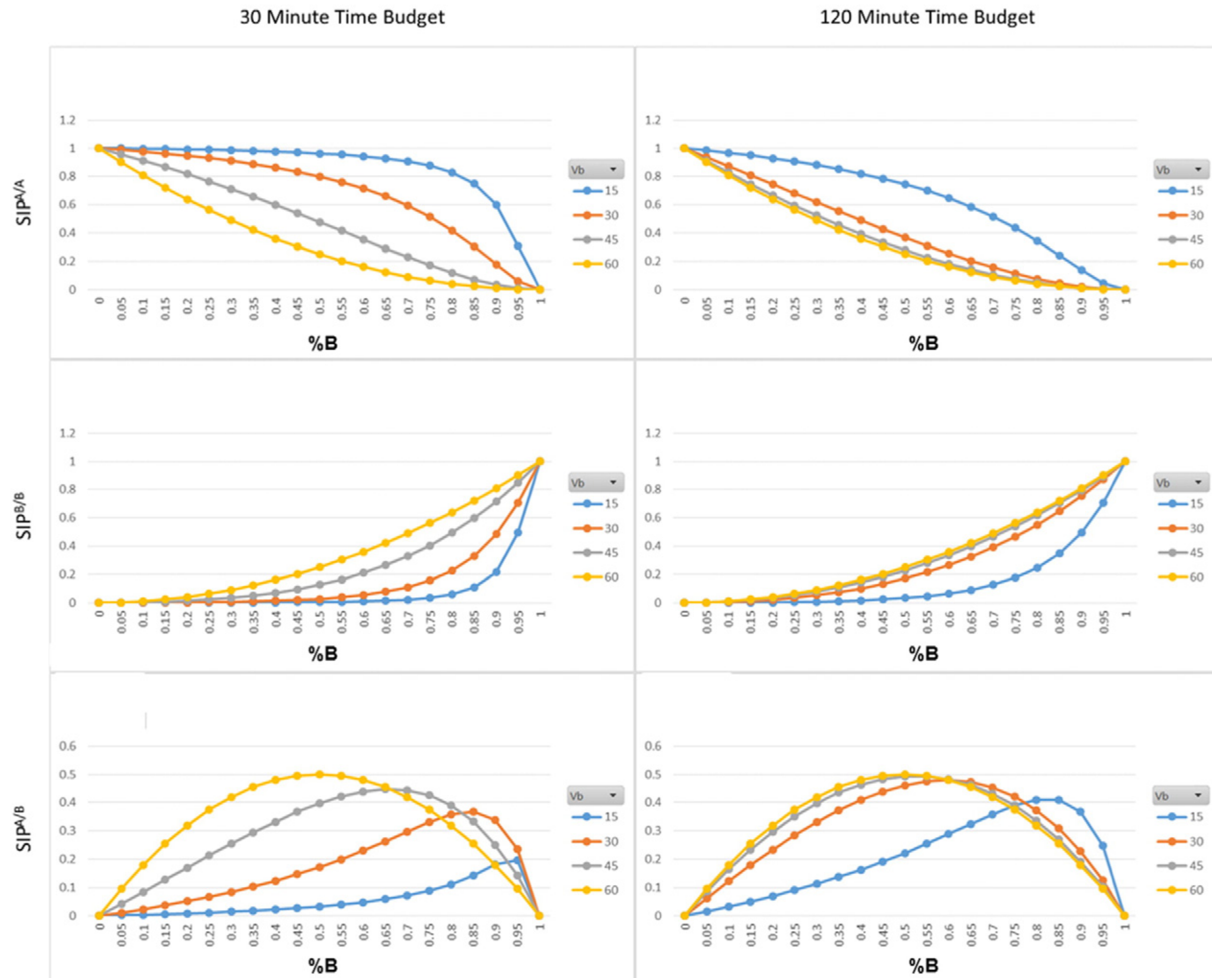

Fig. 3. SIPSEG contributions under controlled conditions.

in order to homogenize the residential mixing of races within neighbourhoods. The Detroit–Warren–Livonia MSA is a six county region of 3.7 million inhabitants. The racial divisions in Detroit are made clear in Fig. 4, where each dot of a different colour represents 25 inhabitants of a different race. There is a sharp north–south divide at the infamous 8 Mile line separating the inner city's predominantly black population (blue dots) from the suburban white population (red). Small pockets of Hispanic (orange) and Asian (green) can also be seen in the city.

The empirical SIPSEG measurements were computed using OD datasets obtained from the Census Transportation Planning Package (CTPP) 2006–2011 5-year average sourced from the American Community Survey (ACS). The non-working population was drawn directly from the same vintage ACS. Both the working and non-working populations are provided in the ACS for those aged 16 years and older. The study area covered the six counties in the region and the OD data were obtained at the census tract level of geography. Through a process of OD matrix disaggregation (more on this below), the resultant OD matrix contained race-specific flows between all pairs of census tracts in the region. Our definition of race follows Logan and Stults (2011) which accounts for multiple race responses in the census. In the end, our OD flows were disaggregated as White, Black, Hispanic, Asian, and Other.

The computation of SIPSEG requires the selection of input parameters and the creation of input data products. In the parameter case, we compare evening time budgets of 30 min to 120 min. The required data inputs include travel time matrices and the disaggregate flow matrix so that A^k_{ijqr} can be calculated. Two travel time matrices are required: $T^{w\to k}$ is the travel time from place of work to grid cell locations and $T^{k\to h}$ is the travel time from grid cell locations to place of residence. Here, places of work and residence are represented by census tract centroids, and the places of activity, k, are represented by the centroids of a square raster of grid cells with 2.5 km edge length. All travel times were based on computations of free-flow shortest paths by car using the Esri ArcMap Network Analyst extension and the StreetMap USA dataset. An additional travel time matrix from census tracts to census tracts was needed in the generation of the OD flow matrix.

The OD matrix needed to compute SIPSEG must be disaggregated by social groups, however, the OD data available from the CTPP is not available in this disaggregate form. We therefore employ the information minimizing trip distribution model developed by O'Kelly and Lee (2005) to synthesize the disaggregate OD matrix using known racial breakdowns at zones of residence and workplace. This method has been used by Kim et al. (2012), Sang et al. (2011), Lee (2012), and Jang and Yao (2014) in socioeconomic studies of commuting. More recently, the procedure has undergone quite substantial validation testing using the Longitudinal Employer-Household Dynamics dataset with results indicating an extremely high level of accuracy in reproducing known disaggregate OD flows using only marginal constraints (Niedzielski et al., 2015).

With the travel time and OD matrices in hand, the last step in the SIPSEG computational process is to actually calculate the prism intersections. Due to the existence of five nested loops over i's, j's, q's, r's, and k's, for large regions such as Detroit, the computation of SIPSEG scales rather poorly. In fact, computing SIPSEG, as with other versions of SIP metrics, requires that we exploit the parallel

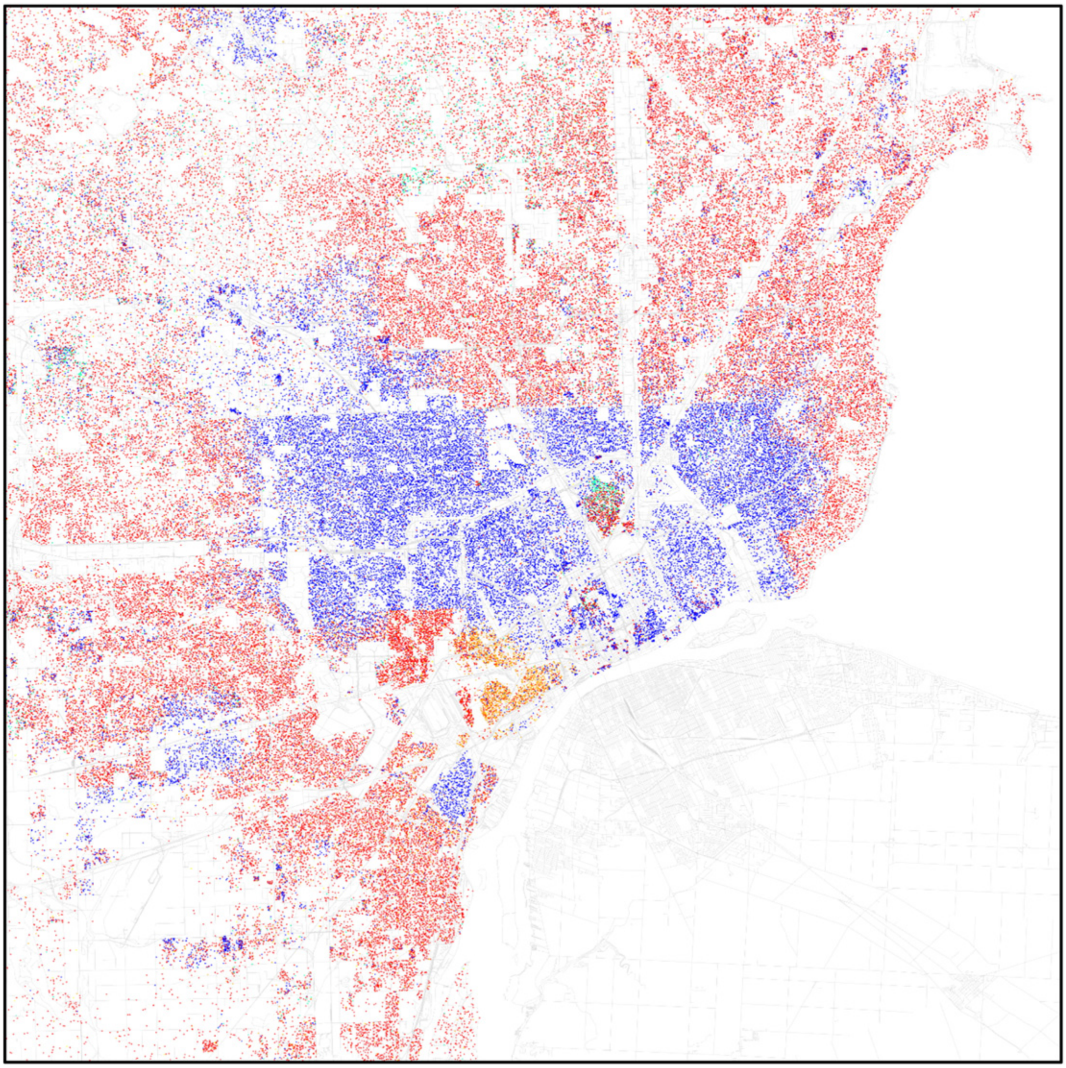

Fig. 4. Racial dot map of Detroit and its surrounding area. Each dot represents 25 inhabitants: blue dots for the black population, red dots for white, orange dots for Hispanic and green dots for Asian. (Source: Eric Fischer, "Eric Fischer's Photostream," Flickr, 12 December 2014, Data from Census 2010. Base map © OpenStreetMap, CC-BY-SA).

structure of the computational problem. Specifically, because the computations required to calculate intersection volumes for different pairs of prisms are independent, we are able to adopt a divide and conquer computation strategy to achieve massive runtime improvements. In this case, the CHPC developed code to compute SIPSEG in their cluster computing environment. The code was written so that each social group in a region is defined by a unique OD matrix, travel time matrix, and time budget parameter. This means that in future studies we can investigate questions of mobility-induced segregation between users of cars and public transit, or time–pressure based causes of segregation which are hypothesized to cause gender-based inequalities. In any event, for the present case study assuming equal travel speeds between races, one run through the Detroit MSA case study took two hours to compute using 160 simultaneous processors. What we computed in 2 h would take roughly two weeks to compute on a single processor.

The origins and destinations per census tract for the white, black and Hispanic populations appear in Fig. 5. It is convenient to think of these as the nighttime and daytime populations of census tracts since the destinations in this case also include adults who did not travel to work, roughly 50% of the adult population in the MSA. This explains the striking similarities between the daytime and nighttime population distributions. Fig. 6 shows the change between night and day, better capturing the spatial and racial dynamics in commuting patterns. We observe that white commuters tend to travel from the suburbs into commercial areas downtown, the surrounding inner city, and several white employment enclaves in farther out places. The black population leaves the inner city for downtown and inner suburb workplaces, and we observe less commuting to the more distant suburban employment centers. Finally, the Hispanic population leaves its residential enclave in southwestern Detroit for workplaces similar in distribution to the black population.

Given these trends in commuting, we expect that the commute to work should help increase opportunities for social interaction between racial groups, since workplace distributions are less segregated than the residential distributions (DI for residential distribution is 0.78 and for workplace distribution it is 0.65). At the same time, the white population is travelling great distances from the outer suburbs to their workplaces, suggesting that the time associated with their travel may actually hinder opportunities for interaction. Next we explore these types of effects in the SIPSEG results.

Fig. 7 summarizes the results of the global SIPSEG measures. For the sake of clarity, and in recognition that the two dominant racial groups in this region are white (68%) and African–American (23%), the rest of our discussion focusses just on these two groups, and lumps the remaining races and their interaction potentials into an "Other" category. The first column in Fig. 7 displays the expected contributions of each type of

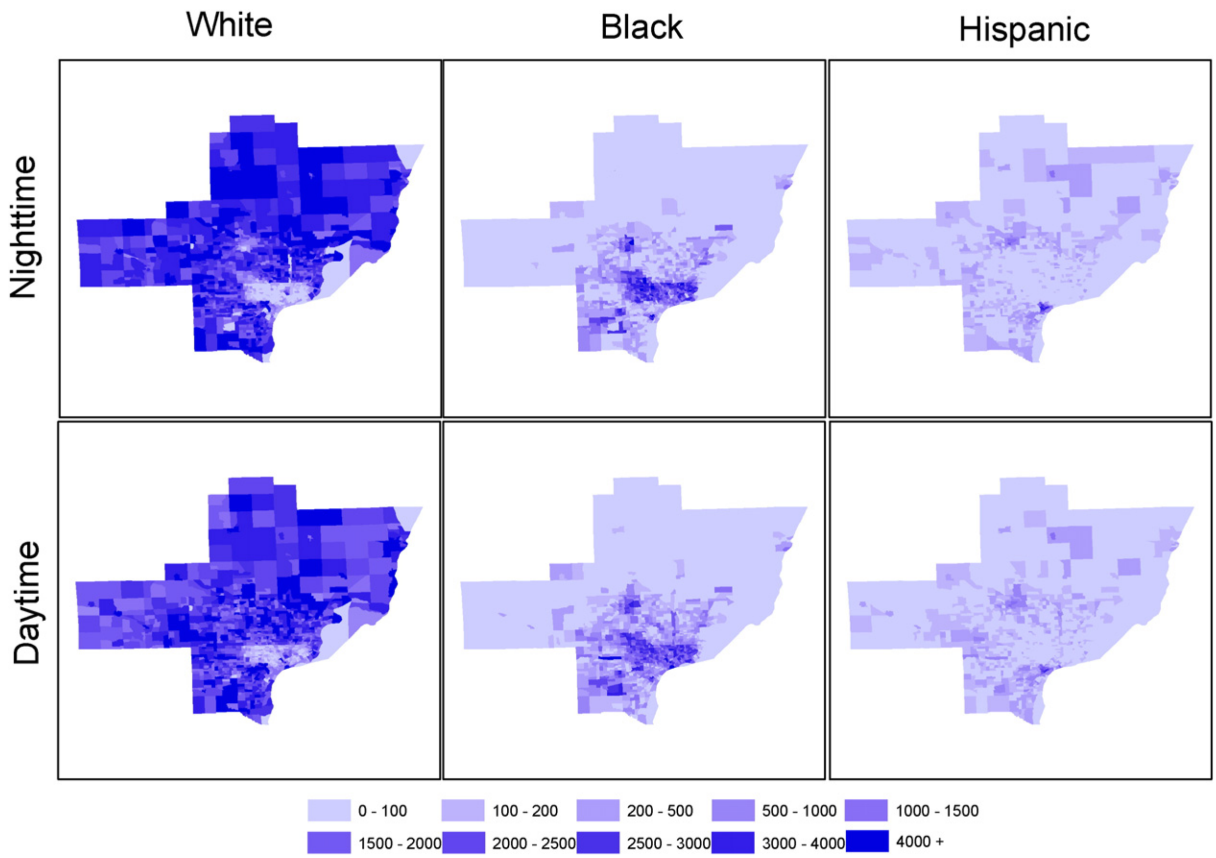

Fig. 5. Origins and destinations by race in the Detroit MSA.

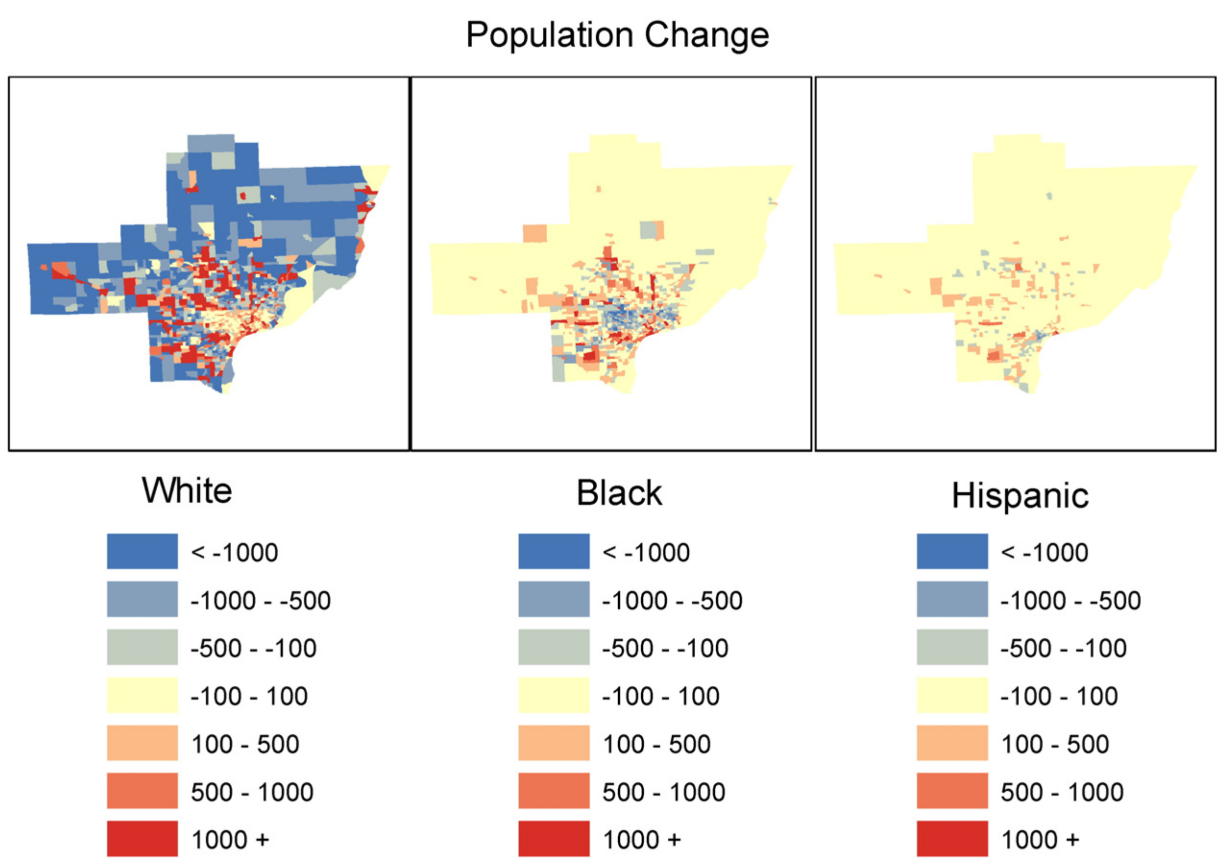

Fig. 6. Population change from nighttime to daytime.

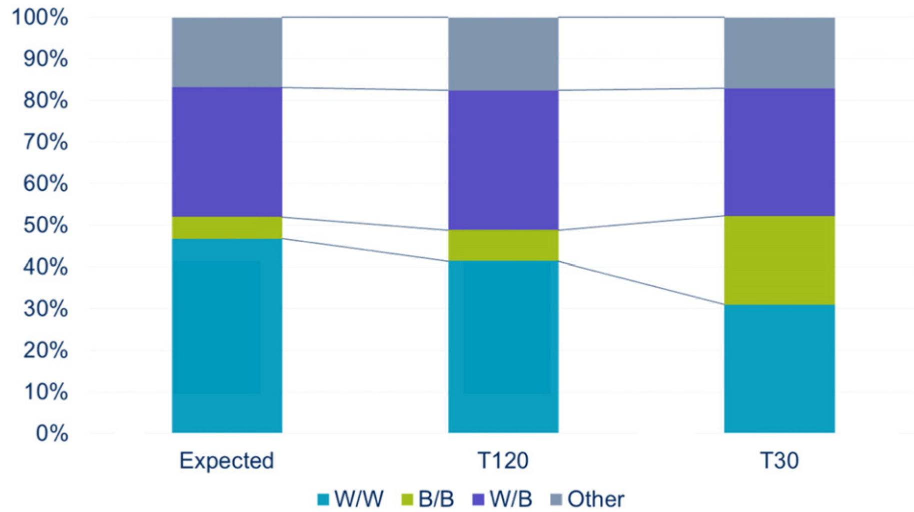

Fig. 7. Expected versus observed global SIPSEG measures relative to total SIP.

between-group and within-group interaction potential under the hypothetical case of perfect integration. Given that the white population makes up 68% of the total, we expect to see the white/white interaction potential contribute 46% (i.e. 0.68^2) of the total. Similarly, we expect that the black/black SIP would contribute about 5% (i.e. 0.23^2) of the total, and that white/black SIP would contribute 31% (i.e. $2[0.68 \times 0.23]$) of the total. The remaining 18% is due to interaction with and among "others". The second and third columns indicate the observed SIPSEG contributions under the scenarios with 120 and 30 min time budgets respectively. The most striking finding is that the level of segregation heavily depends on the time budget selected. Thus, we must interpret our results with respect to this important input parameter. In the very flexible case of 120 min, there are few discrepancies between the observed and expected levels of SIPSEG contributions. However, there are large differences in the 30 min case. We observe a large decrease in white/white SIP due to that population's large degree of residential dispersion in the suburbs, and large increase in black/black SIP due to that population's concentration in the inner city. There is only a minor decrease in white/black SIP, indicating that the relative level of interaction potential between these groups is not very sensitive to varying time budget constraints. It is of crucial importance to keep in mind that these results pertain to relative contributions of SIPSEG measures. There is an extremely large difference in total SIP and SIPSEG measures between scenarios in absolute terms. This is further investigated next.

Fig. 8 shows the average prism intersection volume for different combinations of race for the two time budgets investigated. This shows us the typical amount of SIP between pairs of people of the different races. First, and quite remarkably, we see a three order-of-magnitude difference between the total SIP for 120 min and 30 min. This is quite striking, and speaks to the near elimination of social contact opportunities when time budgets do not allow for much else than the daily commute. Next, we see that white/white intersection volumes are smaller than average, again a result of this population being very geographically dispersed. We also see that black/black intersections are much larger than average, a result due to the intensive clustering of this population. Moreover, we see that black/black SIP is far more resilient to the drop in time budget, also due to the clustering of this population in the inner city. While the overall prism intersection volume declines by three orders-of-magnitude, the black/black volume only declines by two orders. In terms of inter-group interactions, we see that the average white/black exposure drops by three orders-of-

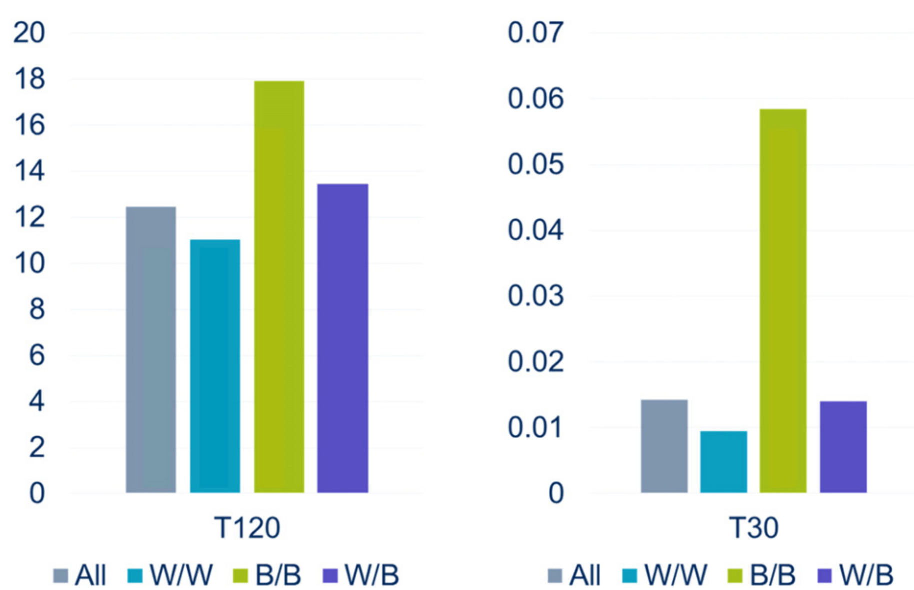

Fig. 8. Average prism intersection volumes by race.

magnitude, and in relative terms declines more than average. This result shows that declining time budgets will impact opportunities for between-race interaction potentials much more than black/black potentials. This is again largely driven by the dispersion of the white population who travel farther distances to work and therefore have less free time for social interactions amongst themselves or with people of other races.

Next we turn to the local indicators of SIPSEG to explore the spatial patterns in social contact opportunities. Fig. 9 displays the decomposition of the SIPSEG measures over the grid cells in the region. The colour of each grid cell represents the aggregate volume of prism intersections occurring at each grid location, k. For the 30 min time budget case, we observe that areas with high opportunities for black/black interactions are more spatially concentrated in the inner city, while white/white opportunities are more dispersed and peaking to either side of the inner city. The pattern for white/black interactions appears to be a mix of the other two with a high concentration in the inner city, but also spreading further out from the city. In general, the 120 min time budget smoothes out the interaction potential surfaces, leaving little ability to discern separate spatial patterns between the three types of opportunities mapped. For this reason, we limit our investigation to the 30 min scenario for the next two types of social interaction local decompositions.

Figs. 10 and 11 contain the home and work-based SIPSEG opportunity maps. Here, areas are coloured by the interaction opportunity associated with living in or working in each area from the perspective of a particular racial group. Keep in mind that these maps depict contributions to total SIPSEG scores, and are therefore dependent on the source population density in each zone. So, the top-left map in Fig. 10 depicts the opportunities for white people to interact with other white people provided their home residential zone. The pattern is one that demonstrates the importance of centrality in providing social contact opportunities. At the same time, because there are few white people living in the inner city, this region appears as a white/white cold-spot in the map. The top-right map depicts opportunities for whites to intersect with blacks, and we see that the pattern, while similar to the white/white map, is far more concentrated in areas closer to the inner city. This indicates a positive, integrative effect of compact urban form. The bottom-left map shows where blacks live with the highest levels of opportunity to socialize with whites. Thus, the black/white map is concentrated in the inner city, where the most black people live, but is more spread out in comparison to the black/black map, which is more concentrated in the inner city. In all cases, the work-based interaction potentials in Fig. 11 show similar but more centrally concentrated patterns to the home-based maps in Fig. 10. This is clearly due to the greater degree of spatial concentration of workplaces in the downtown and inner suburbs surrounding the urban core.

6. Conclusions

In this article, the social interaction potential metric is extended to capture within-group and between-group interaction potentials. This is framed as a novel method for measuring exposure (and its mirror measurement, isolation) based on basic commuting patterns readily available for cities around the world. The behaviour of the metric is explored using controlled simulations and an empirical case study and it is found to be sensitive to activity locations, travel times, and the spatial organization of homes and workplaces. Importantly, the measurements are comparable between study areas, or between uses of different time budget parameters given the ability to analyse absolute and relative contributions of within-group and between-group interaction potentials. The relative contributions are furthermore comparable to expected values which are derived analytically, and shown only to depend on the global breakdown of the population into different groups.

At the beginning of this article, we argued that SIP-based measures of potential exposure achieve a middle-ground balance between traditional place-based measurements, and the current state-of-the-art activity based approaches. The advantage over place-based measures are clear, SIPSEG provides a way to augment exposure measures with basic spatiotemporal population dynamics, while keeping the

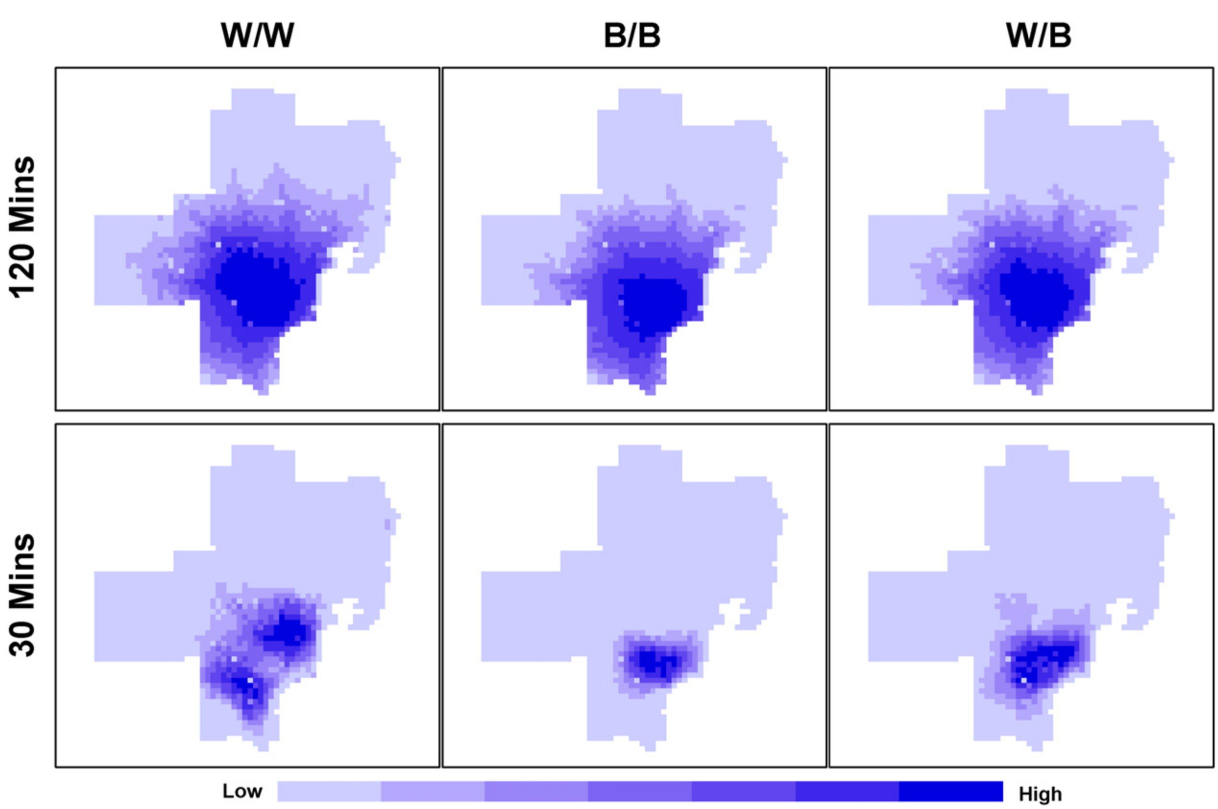

Fig. 9. Locations of social interaction potential, $SIPSEG_K$, for within-race and between-race interactions.

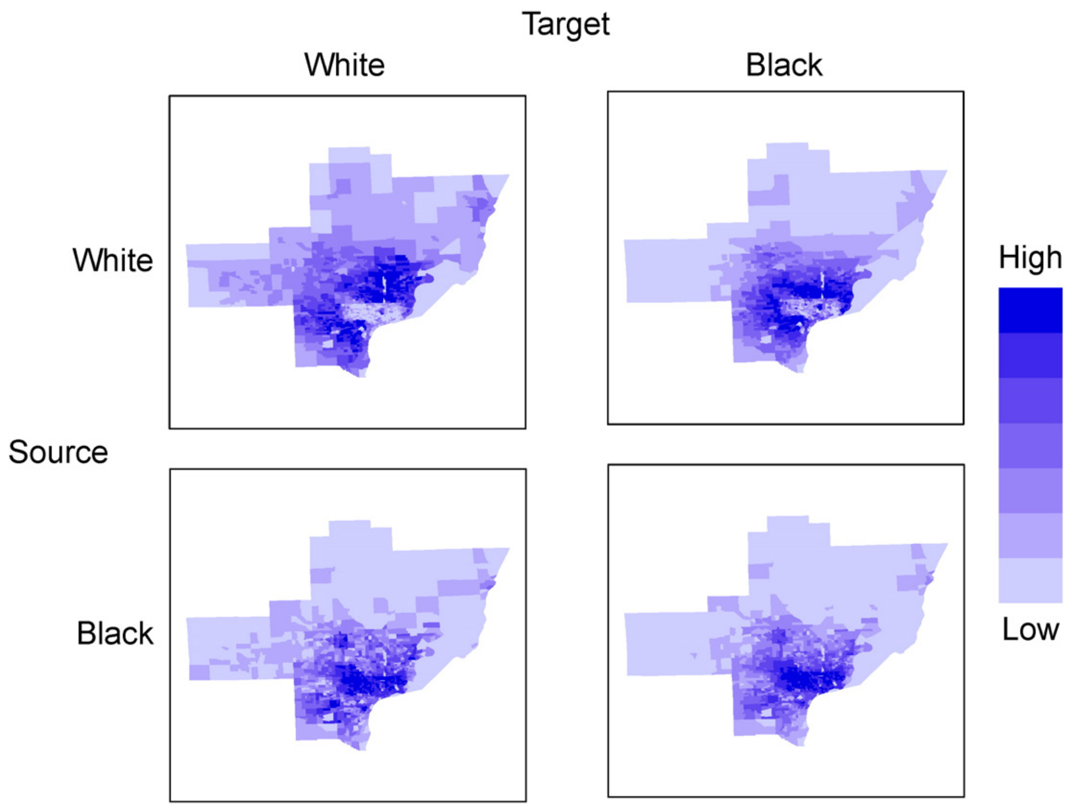

Fig. 10. Home-based SIPSEG opportunities for 30 min time budget.

reproducibility benefits associated with place-based approaches. From a UGCoP perspective, SIPSEG better established the ecological boundary of a person's daily life in comparison to zonal and neighbourhood approaches, and at the same time, attributes the individual's activity space using dynamic target populations. However, while sharing in the positive aspects of activity-based approaches, SIPSEG is clearly only

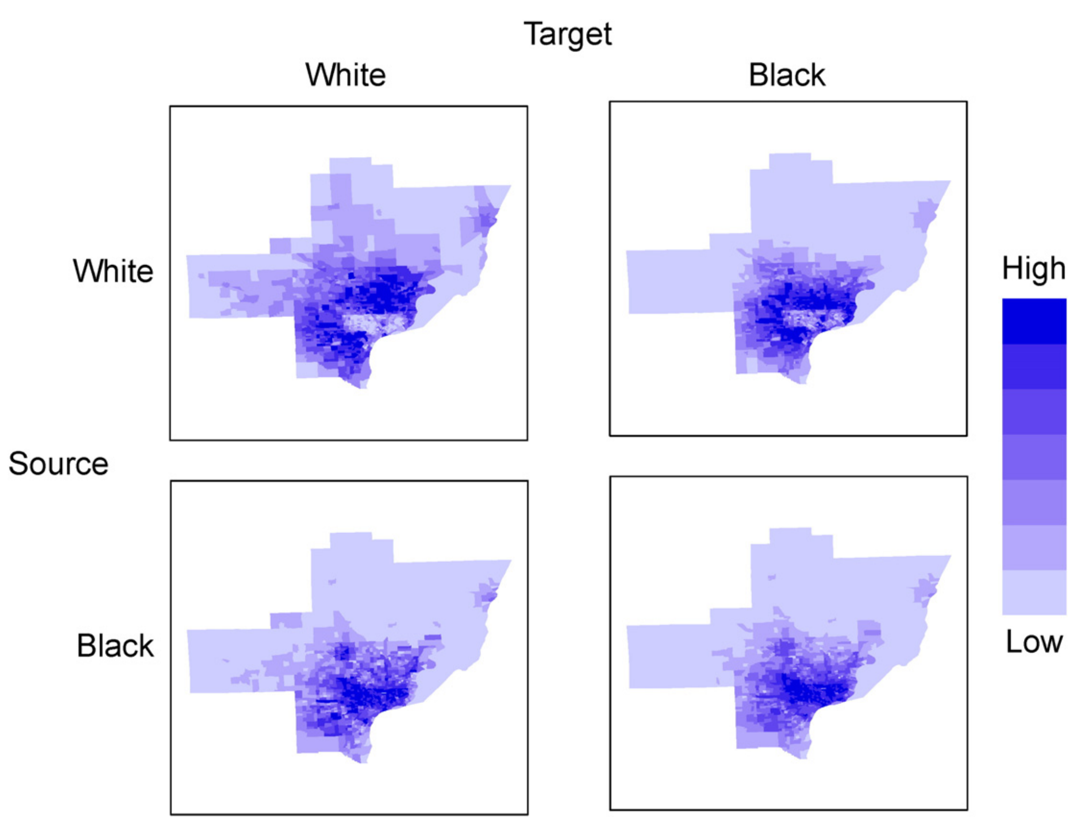

Fig. 11. Work-based SIPSEG opportunities for 30 min time budget.

taking advantage of a modest portion of the detailed time-use and activity patterns typically considered in activity modelling. In particular, we are not utilizing anything more than an individual's home and work locations and free-flow automobile travel speeds to formulate our knowledge of their space–time constraints. This is a far cry from the sophisticated small-sample time-geographical analyses of individual level characteristics, attitudes, and activity patterns used in modern travel demand modelling. This may be unsatisfying to some, but our approach is not intended to help us better understand how policies will impact activity behaviour, as is the case for activity modelling, but rather to help identify differences in social interaction opportunities and the causes of those differences. As transportation and land use planners, it is often the opportunities for interaction that we can produce or remove with our policies, and previous work on SIP has established that social interaction activities are more likely to occur when levels of SIP are higher (Farber et al., 2014).

Another potential criticism of the SIP approach is that it does not directly deal with the materiality of space. The measurement of interaction potential is based solely on the concept of joint accessibility, which can be understood as the minimum threshold to face-to-face interaction potential. Layered on top of this are subjective interactions between space and the individual (e.g. whether there are appropriate facilities available to engage in social activities and whether there are social constructions of space that are conducive to interactions) that modify whether space–time opportunity will translate into heightened likelihood of interaction. Clearly, there is room for future research in both of these directions. Through an attraction parameter for activity locations, the SIP framework is poised to incorporate new measures of materiality such as Silver's (2011) *scenescapes*. This kind of extension is in line with the quantitative, aggregate qualities of SIP, and seems far more feasible than trying to account for subjective and individual-based attitudes towards space. More detailed qualitative approaches are clearly more suited to the latter.

The broader directions for further research are largely empirical. We would like to compute SIP-based measures of segregation for the largest cities across the United States, and compare these to traditional place-based measures. We anticipate that our metric, because it relies on the basic spatial structure of activity patterns, will portray a more nuanced story of experienced segregation in cities across the US, while aggregate enough to easily compute scores for a large set of places. By computing SIPSEG measures for many cities, we should be able to identify particular trends in spatial structure, such as compactness or urban sprawl, that lead to higher or lower levels of social integration. And, similarly, we would like to see whether higher and lower levels of segregation are related to social characteristics of regions, such as social cohesion or political polarization.

Although SIPSEG has been framed in terms of a social segregation measure, it is feasible to think of other economic interpretations by computing SIPSEG for workers in the various industrial sectors in a region. Higher levels of within-sector interaction potential should theoretically be associated with higher levels of productivity, which may be captured by measures of gross regional product (GRP) or wages. Similarly, from social equity perspectives, we could try to better understand the disparities in SIP among people with different mobility capabilities (i.e. car drivers versus transit users), or among those with different time-budget constraints (i.e. workers versus non-workers or workers with and without children). All of these investigations should be possible given the current levels of data availability in the CTPP and our updated tools for synthesizing socially disaggregated OD matrices. Moreover, the interplay between spatial structure and time availability and its effect on SIPSEG will be an important avenue to explore in any future empirical work.

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