Transportation Research Part D 119 (2023) 103769

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Delineating race-specific driving patterns for identifying racial segregation

Yirong Zhou [a], Ran Wei [b], Xiaoyue Cathy Liu [a,*], Danielle Wallace [c], Tony Grubesic [b]

[a] Department of Civil & Environmental Engineering, University of Utah, Salt Lake City, UT 84112, Unites States
[b] School of Public Policy, University of California, Riverside, Riverside, CA 92521, Unites States
[c] School of Criminology & Criminal Justice, Arizona State University, 411 N. Central Ave, Phoenix AZ 85004, Unites States

ARTICLE INFO

Keywords:
Intergroup exposure
Racial segregation
Social equity
Race-specific driving pattern

ABSTRACT

Transportation equity is a substantial concern for planners. Segregation and exposure analysis provide a lens from which community stakeholders can better decipher transportation equity challenges. This paper aims to expand racial segregation analysis beyond residential places to a more holistic activity space, including commuter populations. We filled existing research gaps on validity by calibrating Information Maximization (IM) model and a distance decay function to estimate race-specific driving patterns iteratively. A unique index of intergroup exposure and potential for contact between residents, workers, and commuters is proposed to understand the varying exposures different racial groups have with each other. We further identified the most racially-segregated road segments, residential and workplace areas, and how they become segregated based on the commuters' information. Given that exposure is a precursor to contact, understanding race-specific driving patterns is vital to understanding more extensive social mobility and segregation processes and their consequences for transport equity.

1. Introduction

Transportation planning goals have evolved throughout the late 20th and early 21st centuries. For example, social equity has become one of the major concerns for transportation researchers and policymakers (Manaugh et al., 2015, Zhou et al., 2020). Transportation directly impacts equity as mobility becomes a core part of people's daily life. Further, historically marginalized groups often face direct challenges to mobility. For instance, underprivileged groups often lack convenient access to public transportation or are forced to dedicate a larger share of household income to transportation. Language barriers, more exposure to air pollution, and restricted access to essential services also complicate equity issues for these populations (Lajunen, 2014; Zhou et al., 2021). One common way is to view the issue of transport equity through the lens of segregation. For example, racial segregation in residential spaces is extensively studied (Feitosa et al., 2007; Grady and McLafferty, 2007; Grubesic et al., 2018), and this lens often uses an urban setting. However, with rare exceptions (see Jang and Yao, 2014), little research includes commuters and their associated activity spaces. This research fills the gap by estimating commuters by race (or race-specific driving patterns) and proposing a novel exposure index based on the activity space of residents, workers, and commuters. To clarify, the term "race-specific driving patterns" refers to the racial distributions of commuters who use automobiles as their mode of transportation. This research focus raises a profound question: why should we care about automobile commuters?

* Corresponding author at: Department of Civil & Environmental Engineering, University of Utah, Salt Lake City, UT 84112, Unites States.
E-mail address: cathy.liu@utah.edu (X.C. Liu).

https://doi.org/10.1016/j.trd.2023.103769
Received 26 January 2023; Received in revised form 10 April 2023; Accepted 28 April 2023
Available online 11 May 2023
1361-9209/

First, examining the racial composition of car commuters on the road can offer practical benefits in several critical domains. For instance, recent studies on traffic-related air pollution indicate that individuals may experience racial segregation and prolonged exposure to air pollution beyond their immediate residential surroundings (Park and Kwan, 2020). Also, it is common for racial and ethnic groups in urban areas to work separately, often occupying different neighborhoods or parts of the city (Ellis et al., 2004). Therefore, accurately identifying the racial distributions of commuters is essential for establishing an accurate baseline that reflects the real-world geographic context of racial segregation and disproportionate exposure to air pollution. Second, the distribution of commuters is a strong benchmark for racial profiling. Racial profiling studies focus on the heightened risk of police contact for black or brown drivers (i.e., "driving while black or brown"), particularly in white areas (Lundman and Kaufman, 2003), and higher risks for more punitive stop outcomes, such as citations over warnings (Engel and Calnon, 2004; Hetey et al., 2016; Wallace et al., 2017; Wallace et al., 2018). One central question in evaluating police law enforcement on the road is establishing appropriate benchmarks. In this context, the racial distributions of commuters can provide valuable insights and serve such a purpose. Third, Latham and Pinto (2022) explored an alternative question, attempting to uncover the economic interconnections between commuters, employment centers, and bedroom communities, where the majority of residents commute elsewhere to work and come home to sleep. Analyzing commuting patterns enables researchers to examine the economic connections between different regions. These patterns reveal how labor markets extend across geographic areas and offer job prospects to residents in nearby jurisdictions.

While accurately estimating race-specific driving patterns is crucial across multiple domains, it may be unclear why one should incorporate commuters into traditional exposure analysis. For example, automobile commuters might initially appear to engage infrequently with locals, workers, and the broader community, yet substantial empirical evidence suggests otherwise.

For example, in criminological studies, it is essential to acknowledge that commuters cause shifts in the baseline populations that impact crime statistics (Mburu and Helbich, 2016). Specifically, commuting patterns significantly impact crime outcomes, with a notable correlation between increased inbound commuting and higher risks for random crimes such as theft and violence. Second, recent epidemiological research suggests that commuting is crucial to understanding health and environmental interactions. For example, Signorino et al. (2011) noted substantial differences in exposure to environmentally contaminated areas when comparing commuters to residents. Regardless of the substantive context, there is a dearth of work considering the interactions between commuters, residents, workers, and places for deepening our understanding of dynamic urban areas.

Finally, it is worth noting that, in addition to the explicit interactions discussed earlier, commuting plays a significant role in shaping commuters' perceptions and understandings of the spaces they choose to engage. For example, according to Wallace and Louton (2018) and Sampson (2012), commuters' experience with a neighborhood, even just by driving through, is critical to their attitudes toward interacting with the neighborhood and its residents. Additionally, Sampson and Raudenbush (2004) found evidence that when individuals see people of color in neighborhoods, they are more likely to report those neighborhoods as disorderly. Therefore, commuting (e.g., simply driving through and/or seeing people of color) could shape people's willingness to engage with the space. As a result, it is crucial to obtain precise estimates of race-specific driving patterns and integrate them into exposure-related research.

We justify our focus on car commuters in this research as follows. First, commuters who drive alone or carpool represent a significant portion of the commuting population in many areas. For example, in the United States, 76% of workers commuted to work by driving alone or carpooling in 2019 (US Census Bureau, 2019). Thus, using this group as a benchmark provides a representative sample of the overall commuting population for this research. Second, car commuters may have distinct travel patterns and ways of interacting with their surroundings compared to other modes of transportation. Therefore, including other modes of commuting in the study may introduce bias and require different methodological approaches.

This research is essential for four reasons. First, accurately estimating race-specific driving patterns is critical to understanding racial segregation on the road. Sharing space is a precursor for intergroup contact and ameliorating social issues like transportation justice, social segregation, and differential employment. Specifically, studying how space sharing occurs through mobility activity, such as a work commute, will help us understand urban processes surrounding racial segregation, differential mobility, and its underlying spatial dynamics. Second, this research attempts to reconstruct race-specific driving patterns and explain and describe the formation of such patterns by incorporating segregation and exposure analysis. By doing so, we can delineate drivers with different socioeconomic signatures and trip origins/destinations for an urban area. Third, using universally accessible data in this research makes the framework and results easily transferable (and replicable) to different regions in the United States and elsewhere. Fourth, accurately estimating race-specific driving patterns can contribute to many important research domains, from geography and transportation to epidemiology, sociology, urban planning, and criminology. Again, while census data provides a valid snapshot of residential populations and can account for commuter-adjusted population estimates, how these diverse groups intermix in time and space is critical for deepening our understanding of urban areas.

We organize the remainder of this paper as follows. Section 2 reviews racial segregation, social integration, and intergroup contact. We follow this with an outline of our data and its sources. Section 3 describes the data we used for this study, which is all publicly available in San Diego County. Section 4 details the methodological framework for constructing race-specific driving patterns and the analytical pipeline for identifying racial segregation, exposure, and potential intergroup contact between neighborhood residents and commuters. Finally, we present the results in Section 5 and provide a discussion and conclusion in Section 6.

2. A review of segregation and opportunities for intergroup contact

Urban segregation routinely entrenches negative socioeconomic consequences, particularly for disadvantaged communities in urban areas (Dixon et al., 2020). From concentrated poverty (Do et al., 2019) to inequitable access to healthcare (Scally et al., 2018) and educational resources (Fuller et al., 2019), segregation continues to shape and influence the fabric of metropolitan areas throughout the United States and elsewhere. As such, segregation becomes a lens for understanding differentiated mobility, activity spaces, intergroup contact, and urban dynamics, particularly along race/ethnic lines.

Classic segregation measures account for neighborhoods' demographic composition, geographic distributions, underlying spatial structures and scale, and the interplay of racial-ethnic and socioeconomic groups at the local level (Oka and Wong, 2019; Wong, 1993; Yao et al., 2019). However, this work is increasingly shifting toward better understanding segregation dynamics beyond residential spaces (Phillips et al., 2021). Specifically, efforts to map the activity spaces of individuals help researchers determine where individuals spend time, shop, recreate, and engage with urban spaces in their day-to-day lives (Phillips et al., 2021; Wong and Shaw, 2011) as well as the ambient population dynamics for a given city (Park and Kwan, 2018) and the potential for intergroup contact (Dixon et al., 2020).

In this context, both micro- and macro-level mobility processes are relevant. Macro-level mobility concerns community effects and structural connectedness. Specifically, Phillips et al. (2021) conceive structural connectedness as the extent to which neighborhoods in a city are tied to each other by residential travel. In this context, structural connectedness is a necessary precursor to macrosocial integration (Blau, 1977). At the micro-level, the *intergroup contact hypothesis* (Allport, 1954) is relevant. Without delving into the minutia, Allport (1954) suggested that positive effects of intergroup contact are possible within the bounds of four conditions: 1) equal status, 2) intergroup cooperation, 3) common goals, and 4) support from social and institutional authorities. Empirical work confirms the importance of these intergroup contacts in reducing prejudice, especially when friendship ties are present within a community (Pettigrew et al., 2011). Even in places where the formal mechanisms of segregation no longer operate, elements of preferential segregation (Dixon et al., 2020) persist: even when different groups physically overlap in an urban area, segregation continues to emerge in public schools, transport, recreational, and leisure spaces (Priest et al., 2014; Ramiah et al., 2014; Swyngedouw, 2013). Once again, structural connectedness is a precursor to opportunities for intergroup exposure and critical for facilitating the positive effects detailed by Allport (1954).

Efforts to identify segregation often focus on residential areas within a city. Segregation measures often focus on gender, income, race, and ethnicity. Racial-ethnic segregation tends to attract the most attention, given that it is directly related to multiple aspects of social equity, such as transportation equity and justice (Galaskiewicz et al., 2021; Zhou et al., 2020), environmental equity (Downey and Hawkins, 2008; Grove et al., 2018), and educational disparities (Saporito and Sohoni, 2006). For example, Massey and Denton (1988) performed an extensive literature review to evaluate 20 exposure indices to deepen our understanding of segregation. These measures capture a given group's exposure to all other groups, including itself. Typically, these measures use census units (e.g., tracts) and the underlying populations of each. However, this largely ignores the dynamism of urban areas, failing to account for daily shifts in the population, including the movements of workers and commuters. This paper proposes a new exposure index that utilizes race-specific driving patterns to incorporate commuters and workers into the exposure measure. By doing so, we can delineate drivers with different socioeconomic signatures and trip origins/destinations, documenting *potential* opportunities for interaction outside their residential spaces – better capturing these urban dynamics.

Acknowledging the considerable effort made to estimate race-specific driving patterns or disaggregate trips by different features is essential. Several studies have attempted to use traffic accident data to identify where people drive by race (Alpert et al., 2004), but this approach has limitations. While accident data can pinpoint where accidents happen and the drivers' race, it is an incomplete representation of the commuter population, and it contains skewed data due to accident-prone locations, which may lead to an inaccurate estimate of the true driving population. Next, criminologists have attempted to determine driving patterns by race/ethnicity through observational studies, which have engaged a variety of forms of systematic social observation to gauge both driving behavior and the race/ethnicity of the driver. For example, the seminal study in this area used radar guns to determine driving speed while trained researchers in cars to determine the driver's race on the New Jersey turnpike (Lamberth, 1994). The benefit of observational studies is that in addition to determining the race/ethnicity of the driver, they can also capture law-abiding driving behavior or other constructs of interest. However, observational studies have many flaws; two are common and severe and, therefore, worth noting. First, observational studies in no way have the ability to accurately estimate underlying driving patterns within a city or on freeways (Ridgeway and Macdonald, 2010) due to time, capacity, and cost. Second, and vitally important, observational methods routinely disregard the complexity that driver skin tone introduces into observations (Alpert et al., 2004). In addition, transportation models have also been applied to disaggregate the trips on the road. O'Kelly and Lee (2005) developed a trip distribution model to disaggregate journey-to-work trips by occupation based on the Census Transportation Planning Products Program (CTPP) data. Similarly, Sang et al. (2011) modeled the commuting behavior of workers of different genders and occupations using (CTPP 2000) data for Rochester, MN. In another study, Ding and Bagchi-Sen (2019) explored the relationship between commuting distance sensitivity (decaying speed) and different groups of workers (e.g., income, age, type). While the studies mentioned above have developed models for commuting behavior, they do not address the need for estimating race-specific driving patterns.

However, in addition to delineating drivers by race on the road, we are also attempting to quantify the potential (i.e., opportunities) for intergroup contact through race-specific driving patterns at the Census block group level. A related and somewhat complementary corpus of research exists for detecting segregation between social groups based on their activity spaces (Kwan, 2000; Lee and Kwan, 2011; Wang et al., 2012). For example, Kwan (2000) developed a dynamic and interactive three-dimensional geovisualization tool to explore space–time travel patterns of different social groups – highlighting segregation in activity spaces for different ethnic groups and genders. Lee and Kwan (2011) developed four methods to effectively visualize different subgroups' activity patterns to understand better socio-spatial isolation based on an interviewing sample of Korean populations in Columbus, Ohio. Similarly, Wang et al. (2012) examine residents from different neighborhoods in Beijing, China, to discover the socio-spatial segregation of their activity space. Taking a meso-level perspective, Phillips and colleagues (2021) conceptualize segregation as the connectedness between city neighborhoods through visits to the neighborhood captured by geolocated tweets. Their results show that some neighborhoods have few ties to others and are deeply socially isolated. In a related study using the same data and measures, Wang et al. (2018) show that – compared to residents of white neighborhoods – residents of predominantly black and Hispanic neighborhoods are infrequently exposed to residents of nonpoor or white middle-class neighborhoods. In all instances, the authors found strong evidence of residential and time–space segregation.

However, all of these studies base their results on a smaller population sample since larger datasets of activity trajectories are often unavailable, though that is changing with the increase in geolocated mobility data. Further, many of these research endeavors focus on discovering and describing disparities in activity spaces rather than quantifying segregation. Nevertheless, work that helps identify intergroup contact and exposure within activity spaces also exists. Specifically, one can use behavioral data drawn from household travel surveys, global positioning systems (GPS), and mobile positioning data can highlight overlapping activity spaces (Ahas et al., 2007; Wong and Shaw, 2011). For example, Wong and Shaw (2011) provided an approach to measure the exposure of a referenced group to other groups encountered in the activity space by utilizing Census data and individual travel data in the tri-county area in southeast Florida. In addition, Ahas et al. (2007) used passive mobile phone positioning data to study ethnic segregation in non-employment activities. Here, the authors used linear and logistic regression models to analyze differences between two ethnic groups in San Diego via activity spaces. However, travel survey data often comes from a small percentage of households/individuals. Further, mobile positioning or GPS data is poorly semantical, meaning underlying socioeconomic information is rarely available. To fill the gap, we use transportation models to associate commuters' activity space with residential socioeconomics to measure potential intergroup contact within commuting flows at the block group level.

3. Data

This study uses San Diego County, California, to demonstrate our methodological framework. San Diego County provides an excellent natural laboratory for this work. With a population of 3.2 million, it is the second-most populous county in California and exhibits a variable mix of dense urban and suburban (commuter) communities. Further, San Diego County is diverse, with approximately 48% of the population identifying as White, 34% identifying as Hispanic or Latino, 12% Asian, 4% Black, and 5% multi-racial (US Census Bureau, 2022).

There are three major categories of data used in the study:

- Employer-Household Information (LODES Data)
- Network Data (Shapefiles and ArcGIS Streetmap Data)
- Population Distribution (Census data)

The employer-household information contains the distribution of residents and workers and helps determine their distributions at the census block group level. The network information consists of vehicle routing data and network shapefiles. This data is crucial for estimating parameters such as the distance between census blocks and the routing of trips. Finally, the population distribution provides input for the exposure index, which includes the number of residents, workers, and commuters by race in a given area. We detail all of the datasets and their categories below.

The primary data source of this study is LEHD (Longitudinal Employer-Household Dynamics) Origin-Destination Employment Statistics (LODES) (US Census Bureau, 2022). LEHD data is a series of products from a partnership between the Census Bureau, and US states to provide high-quality information on the local labor market. LODES data, specifically, contain information on where workers live and work. Version 7 of LODES used in this study was enumerated by 2010 Census Blocks and organized into three types: Origin-Destination (OD), Residence Area Characteristics (RAC), and Workplace Area Characteristics (WAC) (US Census Bureau, 2022). Data is available for most states from 2002 through 2018, including California. The *OD dataset* describes the total number of jobs associated with a home Census block and a work Census block (Table 1). In addition, we know the number of jobs whose home address is within a specific Census block from the RAC dataset.

Furthermore, the racial split is available in the *RAC dataset*. The *WAC dataset* contains information on the total number of jobs associated with a work Census block, including the racial split. Note that the OD dataset does not have race information available. Furthermore, for WAC and RAC, Race is classified as 1) White (alone), 2) Black (alone), 3) American Indian or Alaska Native (alone), 4) Asian (alone), 5) Native Hawaiian or Other Pacific Islander (alone), and (6) two or more race groups (i.e., multi-racial). For this research, we compare white residents to all other races (non-white) combined to demonstrate the analytics pipeline, but other

Table 1
Description of datasets used in this study.

Dataset Name	Description
LODES Origin-Destination (OD)	Number of jobs associated with a home Census Block and a work Census block
LODES Residence Area Characteristics (RAC)	Number of jobs associated with a home Census block
LODES Workplace Area Characteristics (WAC)	Number of jobs associated with a work Census block
San Diego TIGER/Line Shapefiles	Polygons representing 2020 US Census Bureau block groups for San Diego County
ArcGIS Streetmap Premium North America	Data for supporting map display, geocoding, and routing
2016–2020 American Community Survey 5-year estimates	Population by race at the Census block group level

combinations are possible.

Other datasets used in this study include the San Diego TIGER/Line Shapefiles. The shapefile of San Diego contains polygons representing the 2010 US Census Bureau Block Groups for San Diego County (US Census Bureau, 2014). In addition, the National Household Travel Survey (NHTS) is used to validate the assumption that the distance decay parameter is consistent across different racial groups. Furthermore, we obtain the historical traffic information and San Diego County street network from ArcGIS StreetMap Premium data. Finally, we extract population distributions, by race, from the 2016–2020 American Community Survey 5-year estimates at the block group level.

4. Methodology

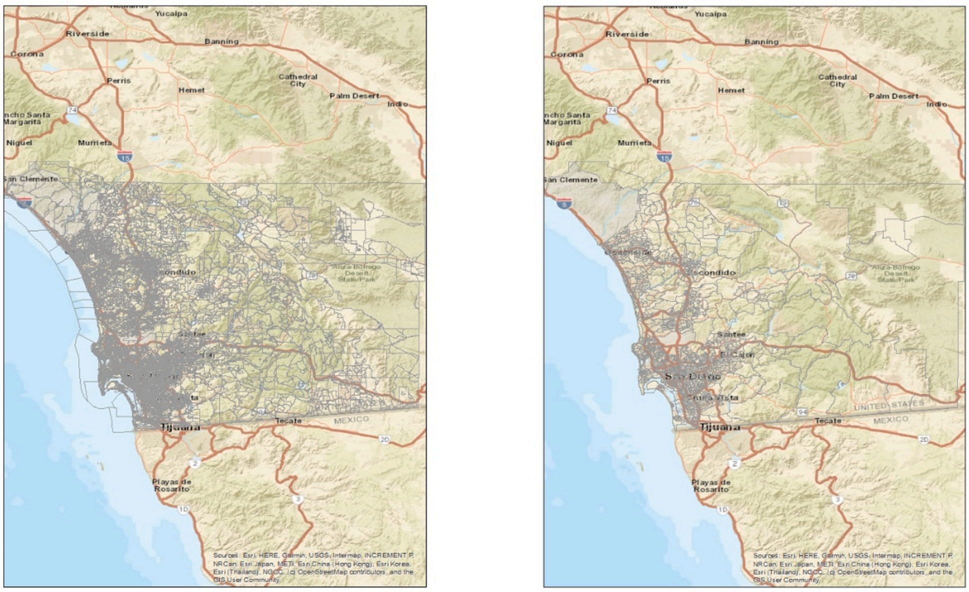
Several pieces of information are needed to perform segregation analysis and to evaluate potential intergroup contact and commuting flow in San Diego County. This information includes commuter routes, the number of commuters for each route, and the racial split of commuters for each road segment.

San Diego County has 39,930 Census blocks, 28,418 of which have residents. 17,942 Census blocks have workers, and 1,023,915 pairs exist between different census blocks (after removing the pairs with no data). This count makes routing calculation and traffic assignment computationally implausible. Thus, we further aggregated the LODES data into Census block groups which reduced the total geographical units to 1,794 and the total number of interacting pairs to 427,526, with 1,794 block groups with residents and 1,792 block groups with workers. Fig. 1 shows the visual comparison between the choice of Census blocks and Census block Groups. Of the 1,794 block groups, we exclude Camp Pendleton – one of the largest and most diverse military bases in the United States. In short, it exhibits a relatively high population, but there are insufficient commuting trips to justify its inclusion in our model.

Next, we identify the centroid (geographical center of the polygon) for every block group in San Diego County and treat them as the origins and destinations for trips that start/end within those block groups. Again, 1,794 applicable points serve as either the origin or destination of all commuting trips in San Diego County. Then, we calculate the optimal routings between those 1,794 centroids using ArcGIS Network Analyst and ArcGIS StreetMap Premium data based on the average speed of historic traffic in the past two years. ArcGIS StreetMap Premium data includes detailed base maps, locators for geocoding, and a network dataset for routing. Predictive and live traffic is available, as well as historical traffic, speed limits, limited street coverage, and minimal street coverage. Using StreetMap Premium data helps us avoid the system error introduced by estimating or simulating traffic based on shortest path distance, system optimal traffic assignment, user equilibrium traffic assignment, or other methods. Also, one can infer the race split for each block group from the *RAC* and *WAC datasets*. Next, we estimate the commuting flows between pairs of block groups using an IM model.

4.1. IM model

O'Kelly and Lee (2005) developed the IM model to disaggregate commuting trips by occupation. The method has been used in several socioeconomic studies on commuting (Kim et al., 2012; Sang et al., 2011; Jang and Yao, 2014; Farber et al., 2015) and has



(a) (b)

Fig. 1. (a) Census Blocks; and (b) Census Block Groups.

undergone substantial validation testing using the LEHD dataset, with results indicating a high level of accuracy in reproducing known disaggregated OD flows (Niedzielski et al., 2015). The IM model works well under most circumstances, but there are unique cases where the model might not be robust. For example, when using the LEHD dataset to create disaggregated flows, the OD flows are almost always unbalanced, which could hurt the performance of the IM model. Taking San Diego County, for instance, we can categorize commuters into three categories:

1. Live and work in San Diego County;
2. Live in but work outside San Diego County; and
3. Live outside but work in San Diego County.

If we utilize these three categories of commuters without additional processing, the OD flows will be imbalanced. Our solution is to focus only on category (1), who live and work in San Diego County, since it accounts for most of the population.

The IM model setting is as follows:

$$T_{ij}^k = A_i^k O_i^k B_j^k D_j^k exp\left(-\beta^k c_{ij}\right) \tag{1}$$

where,

$$A_i^k = \left[\sum_j B_j^k D_j^k exp\left(-\beta^k c_{ij}\right)\right]^{-1} \tag{2}$$

$$B_j^k = \left[\sum_i A_i^k O_i^k exp\left(-\beta^k c_{ij}\right)\right]^{-1} \tag{3}$$

Subject to

$$\sum_j T_{ij}^k = O_i^k \forall i \tag{4}$$

$$\sum_i T_{ij}^k = D_j^k \forall j \tag{5}$$

Here, k is the index of racial groups. T_{ij}^k is the commuting flow between spatial units i and j for group k. O_i^k and D_{ij}^k represent the number of workers in spatial units i and j for group k. β^k represents the distance decay parameter for group k and c_{ij} is the travel distance between spatial units i and j. The objective of the IM model is to estimate T_{ij}^k for all k groups successfully. In this research, the spatial units are the block groups in San Diego County, and k refers to different race groups, as detailed in Section 3.1. To estimate T_{ij}^k for specific race groups k, we need to iteratively calculate Eqs. (2) and (3) until Eqs. (4) and (5) are satisfied with a tolerable error. However, two parameters remain unknown in the IM model: β^k and c_{ij}.

4.1.1. *Estimating travel distance* – c_{ij}

To estimate β^k, we need to determine c_{ij}. c_{ij} is the distance between block groups i and j. We use the shortest path distance between two block group centroids for c_{ij}. This shortest path is calculated by overlaying 1,794 centroids onto the network in San Diego County and snapping centroids to their nearest roads. However, this method will always give a zero distance for intrazonal trips. There are many ways of estimating intrazonal distances, most of which utilize Euclidean distances only and assume a circular zone shape. For example, Batty (1976) suggested calculating the intrazonal distances as follows:

$$C_{ii} = \frac{r_i}{\sqrt{2}} \tag{6}$$

Here, r_i refers to the radius of the zone in terms of trip length. Fotheringham (1988) suggested that intrazonal distance can be estimated using the formula C_{ii} =0.846 * r_i, based on analyzing the potential minimum and maximum travel in a zone. O'Kelly and Lee (2005) and Jang and Yao (2014) propose calculating intrazonal distance as the zone's radius. In our study, we define the radius as:

$$R = \frac{\sqrt{S}}{\pi} \tag{7}$$

This study quantifies the relationship between the shortest path and Euclidean distances via a regression model. We represent the centroid-to-centroid distance as follows:

$$C_{ij}\ \beta_1 * \sqrt{S_i} + \beta_2 * \sqrt{S_j} + \beta_3 * D_{ij} \tag{8}$$

where C_{ij} is the shortest path distance between block groups i and j, S_i and S_j are the areas of block groups i and j, respectively, and D_{ij} is the Euclidean distance between centroids of block groups i and j.

To estimate the intrazonal distance, we made two assumptions.

1. The block groups are roughly circular.
2. The network distance between a point and the centroid of its block group is proportional to the Euclidean distance between them.

The expected value of the distance between a random point X and the centroid on a circular disk of radius *r* can be calculated based on the PDF:

$$F_X(x) = \frac{\pi x^2}{\pi r^2} |x| \leq r \tag{9}$$

We calculate the expected value as follows:

$$\frac{1}{r^2}\int_0^r 2x^2 dx = \frac{2r}{3} \tag{10}$$

The next step is to estimate r_i for block group *i* based on the regression result.

In the above regression settings, the terms $\beta_1 * \sqrt{S_i}$ and $\beta_2 * \sqrt{S_j}$ accounts for the distance from centroids of block groups *i* and *j* to their border separately, while $\beta_3 * D_{ij}$ accounts for the travel distance between block groups. To estimate r_i, we let $D_{ii} = 0$, which represents two overlapping block groups that share the same centroid. In this case, there is no outside-block group travel. i.e., C_{ii} represents the distance from centroid to border and back to the same centroid. Thus, r_i is estimated as $\frac{C_{ii}}{2}$, and we calculate the intrazonal distance as:

$$Intrazonal_i = \frac{2r_i}{3} = \frac{C_{ii}}{2} * \frac{2}{3} = \frac{c_{ii}}{3}$$

4.1.2. Estimating distance decay parameter $-\beta^k$

Fotheringham and O'Kelly (1989) proposed a negative exponential relationship between commuting flows and distances, which features a similar distance decay parameter:

$$T_i = e^{-\beta \overline{D_i}} \tag{12}$$

where T_i is the commuting flow in commuting interval *i*. Here, the commuting interval is equal-length distance range starting from 0 (e.g. [0, 150 m), [150 m, 300 m), …). $\overline{D_i}$ is the average commuting distance within interval *i*. For example, for interval [150 m, 300 m), $\overline{D_i}$ can be any value between 150 m and 300 m, given different distributions of commuting distances that fall into this interval. The calculation of $\overline{D_i}$ involves c_{ij}. Since we assume that trips from/to any block group start/end at the centroid, trips between two specific block groups may have the same commuting distance. T_i is estimated from the LODES dataset, which contains information on residents and workers in different block groups, including data on race.

However, Fotheringham and O'Kelly (1989) assumed a constant β for all workers. Therefore, the first question to ask is whether it is reasonable to assume that all racial groups share the same distance decay parameter, β^k. LODES provides information on race and workers' residential and work locations, but it does not indicate how many workers live and work in each location simultaneously. For example, LODES does not provide information on the number of white workers who live in block group A and work in block group B. Therefore, as mentioned in Section 3, we introduced the NHTS, which contains detailed trip descriptions and the demographics of drivers. These data allow us to estimate T_i and $\overline{D_i}$ for all races included in the survey. Later, we applied the logarithm to both sides of Eq. (12).

$$logT_i = -\beta \overline{D_i} \tag{13}$$

Eq. (13) establishes a linear relationship between $\log T_i$ and average commuting distance $\overline{D_i}$. It is worth mentioning that the NHTS dataset contains far fewer records than the LODES data. The linear relationship in Eq. (13) is modeled on 2,055 commuting trips in San Diego County for both non-white and white drivers separately. The estimates of β are 0.0486 (white) and 0.0468 (non-white), whi are quite similar. Despite the small sample size from the NHTS dataset, it appears to be a safe assumption that distance decay works equally across different racial groups in San Diego County. Thus, we transform Eqs. (1), (2), and (3) into the following:

$$T_{ij}^k = A_i^k O_i^k B_j^k D_j^k exp(-\beta c_{ij}) \tag{14}$$

$$A_i^k = \left[\sum_j B_j^k D_j^k exp(-\beta c_{ij})\right]^{-1} \tag{15}$$

$$B_j^k = \left[\sum_i A_i^k O_i^k exp(-\beta c_{ij})\right]^{-1} \tag{16}$$

The next step is to estimate the distance decay parameter β based on LODES dataset.

4.2. Potential intergroup exposure

The results from IM model tell us the exact racial split of commuters between any pair of block groups. This information is essential because routing specifics are needed to deepen our understanding of the racial split in the road network (i.e., along each road segment). Our network data contains information on real-time routing between block groups provided by StreetMap Premium data. Thus, by combining routing information with results from IM model, the detailed commuter split can be found for each trajectory point recorded in the network data. For the case of San Diego County, it contains 102,375 trajectory points. However, these trajectory points congregate in certain regions (e.g., downtown San Diego), making it challenging to observe distinct commuting corridors. Therefore, we further aggregate all trajectory points by block group to identify the unique paths traversing the block groups. By doing so, we can retrieve the information of all commuters that pass through each block group.

Then, to understand the possible intergroup contact between commuting populations, working populations, and residents, we formulate an exposure index as follows:

$$E_{i,ra\times cb} = \frac{r_i^a}{R^a}\frac{wt_{ic}^b c_i^b}{wt_{ir}^a r_i^a + wt_{ir}^b r_i^b + wt_{ic}^a c_i^a + wt_{ic}^b c_i^b + wt_{iw}^a w_i^a + wt_{iw}^b w_i^b} \tag{17}$$

$$E_{i,ra\times ca} = \frac{r_i^a}{R^a}\frac{wt_{ic}^b c_i^a}{wt_{ir}^a r_i^a + wt_{ir}^b r_i^b + wt_{ic}^a c_i^a + wt_{ic}^b c_i^b + wt_{iw}^a w_i^a + wt_{iw}^b w_i^b}\# \tag{18}$$

$$E_{i,ra\times rb} = \frac{r_i^a}{R^a}\frac{wt_{ir}^b r_i^b}{wt_{ir}^a r_i^a + wt_{ir}^b r_i^b + wt_{ic}^a c_i^a + wt_{ic}^b c_i^b + wt_{iw}^a w_i^a + wt_{iw}^b w_i^b} \tag{19}$$

$$I_{i,ra\times ra} = \frac{r_i^a}{R^a}\frac{wt_{ir}^a r_i^a}{wt_{ir}^a r_i^a + wt_{ir}^b r_i^b + wt_{ic}^a c_i^a + wt_{ic}^b c_i^b + wt_{iw}^a w_i^a + wt_{iw}^b w_i^b} \tag{20}$$

$$E_{i,ra\times wb} = \frac{r_i^a}{R^a}\frac{wt_{iw}^b w_i^b}{wt_{ir}^a r_i^a + wt_{ir}^b r_i^b + wt_{ic}^a c_i^a + wt_{ic}^b c_i^b + wt_{iw}^a w_i^a + wt_{iw}^b w_i^b}\# \tag{21}$$

$$E_{i,ra\times wa} = \frac{r_i^a}{R^a}\frac{wt_{iw}^a w_i^a}{wt_{ir}^a r_i^a + wt_{ir}^b r_i^b + wt_{ic}^a c_i^a + wt_{ic}^b c_i^b + wt_{iw}^a w_i^a + wt_{iw}^b w_i^b} \tag{22}$$

where,

$$r_i^a = thenumberofgroupAresidentsatblockgroupi$$

$$r_i^b = thenumberofgroupBresidentsatblockgroupi$$

$$c_i^a = thenumberofgroupAcommutersatblockgroupi$$

$$c_i^b = thenumberofgroupBcommutersatblockgroupi$$

$$w_i^a = thenumberofgroupAworkersatblockgroupi$$

$$w_i^b = thenumberofgroupBworkersatblockgroupi$$

$$R^a = thetotalnumberofgroupAresidentsintheregion$$

$$R^b = thetotalnumberofgroupBresidentsintheregion$$

$$C^a = thetotalnumberofgroupAcommutersintheregion$$

$$C^b = thetotalnumberofgroupBcommutersintheregion$$

$$wt_{ir}^a = weightassociatedwithgroupAresidentsatblockgroupi$$

$$wt_{ir}^b = weightassociatedwithgroupBresidentsatblockgroupi$$

$$wt_{iw}^a = weightassociatedwithgroupAworkersatblockgroupi$$

$$wt_{iw}^b = weightassociatedwithgroupBworkersatblockgroupi$$

$$wt_{ic}^{a} = weightassociatedwithgroupAcommutersatblockgroupi$$

$$wt_{ic}^{b} = weightassociatedwithgroupBcommutersatblockgroupi$$

The weight aims to adjust the contribution of residents, workers, and commuters of different racial groups in different areas. For example, residents may spend more time at home, while workers may spend more time in the workplace or commuting. Therefore, applying different weights to residents and workers can reflect their varying exposure patterns and better estimate their potential exposure. The same holds for commuters. Commuters may pass a specific region quickly without interaction, especially when commuting via highways. Thus, the weights allow us to customize their individual contribution according to network conditions, land-use information, racial splits, criminal rates, etc.

In addition, the exposure indices of white residents to non-white (1) workers and commuters and (2) residents, workers, and commuters are defined as follows:

$$E_{i,ra\times(rb\&wb)} = \frac{r_i^a}{R^a}\frac{wt_{ir}^{b}r_i^b + wt_{iw}^{b}w_i^b}{wt_{ir}^{a}r_i^a + wt_{ir}^{b}r_i^b + wt_{ic}^{a}c_i^a + wt_{ic}^{b}c_i^b + wt_{iw}^{a}w_i^a + wt_{iw}^{b}w_i^b} \tag{23}$$

$$E_{i,ra\times(rb,wb\&cb)} = \frac{r_i^a}{R^a}\frac{wt_{ir}^{b}r_i^b + wt_{iw}^{b}w_i^b + wt_{ic}^{b}c_i^b}{wt_{ir}^{a}r_i^a + wt_{ir}^{b}r_i^b + wt_{ic}^{a}c_i^a + wt_{ic}^{b}c_i^b + wt_{iw}^{a}w_i^a + wt_{iw}^{b}w_i^b}\#(24)$$

5. Results and analysis

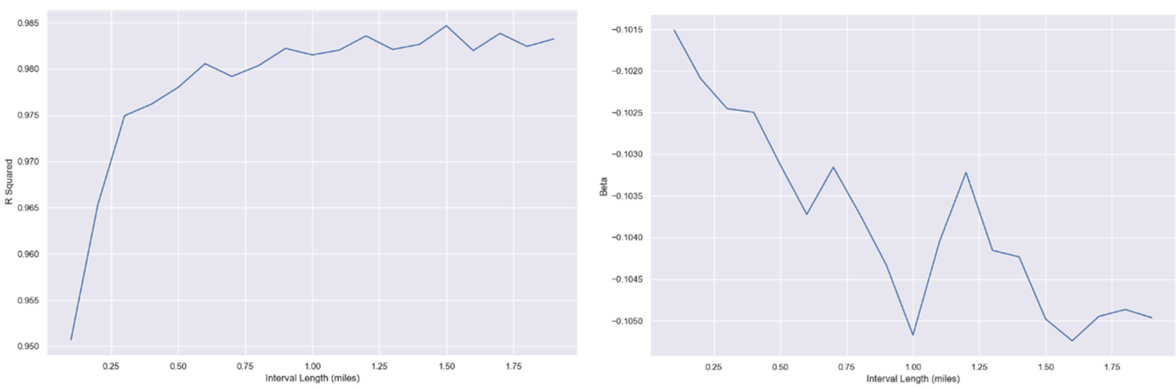
5.1. Calibrating the IM model

As discussed in Section 4, there are 1,793 block groups in total and two types of distance, 1) shortest-path distance (between block groups) and 2) intrazonal distance (within block groups). The distances between the two block groups range from 0.039 to 122.706 miles, while intrazonal distances range from 0.075 to 14.641 miles. Following the discussion in Section 4.1.1, the intrazonal distances were estimated using a regression model between the shortest path distance and Euclidean distances and the areas of origin and destination block groups. The model is regressed based on the data collected in San Diego County. $\sqrt{S_i}$ and $\sqrt{S_j}$ are retrieved directly from the shapefiles of San Diego County. C_{ij} and D_{ij} are calculated as shortest-path distance and Euclidean distance between centroids of block groups in San Diego County. By applying 10-fold cross-validation, the mean R^2 is 0.9741. Next, Fig. 2 plots R^2 and β against different choices of interval lengths from 0.1 to 2 miles. From Fig. 2, we know that an interval length of 1.5 miles gives us the best R^2, and the corresponding β is 0.105.

We present the corresponding distribution of commuting distances with an interval length of 1.5 miles in Fig. 3. Hence, T_{ij}^{k} is now the only unknown variable in Eqs. (7) through (9). As a result, we can calculate T_{ij}^{k} for any racial group k.

5.2. Potential intergroup contact and exposure

This section highlights the distribution of white and non-white populations, segregation by road segment, and the potential intergroup contact (i.e., exposure) between white residents and non-white commuters.



(a) (b)

Fig. 2. (a) R^2 versus Interval Length (b) β versus Interval Length.

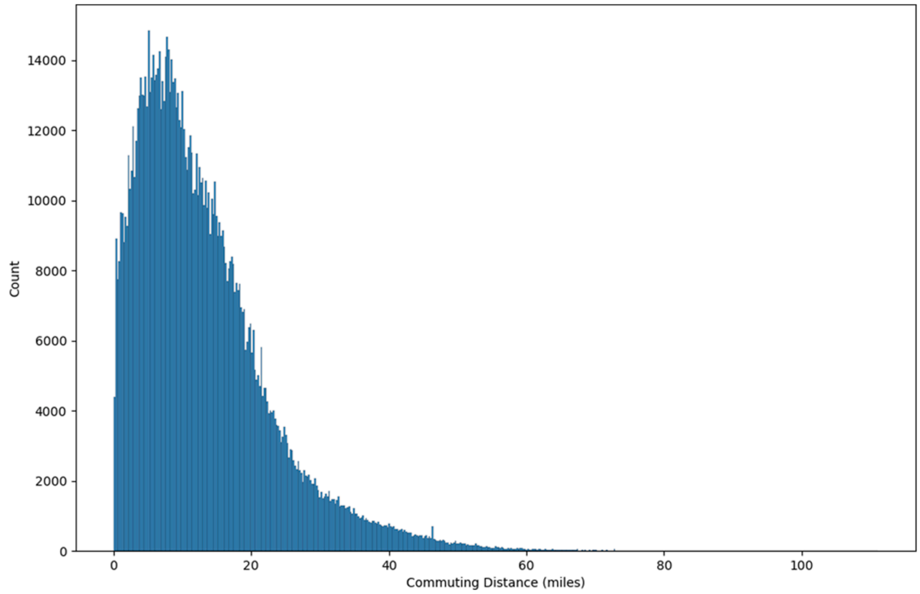


Fig. 3. Histogram of Commuting Distances.

5.2.1. *Residents*

Using 2016–2020 American Community Survey 5-year estimates, we highlight the distributions of white and non-white populations in Fig. 4. Specifically, we calculate the percentage of white/non-white population by using the total population (i.e., white population plus non-white population) as the denominator. Judging from Fig. 4, most of the block groups in San Diego County are highly segregated. In this instance, white or non-white populations dominate their respective block groups. Moreover, there are two clusters of non-white dominated Census Block Groups located around San Diego Downtown and Mira Mesa, both of which are heavily populated regions in the City of San Diego (more than 37,000 residents in San Diego Downtown and more than 80,000 residents in Mira Mesa).

5.2.2. *Commuters*

The number of commuters traversing a Census Block Group is another key factor contributing to residents' potential intergroup contact and exposure to commuters. Fig. 5. demonstrates the percentages of white/non-white commuters in all block groups, which we calculate as the white/non-white commuters with a denominator of total commuters in the block group. Based on Fig. 4 and Fig. 5, it is not surprising that block groups with the highest percentage of white / non-white populations experience the highest percentage of white / non-white commuters since the workers are usually proportional to the total population.

However, an interesting result emerges if we consider employment and commuting corridors. Fig. 6 demonstrates the number of

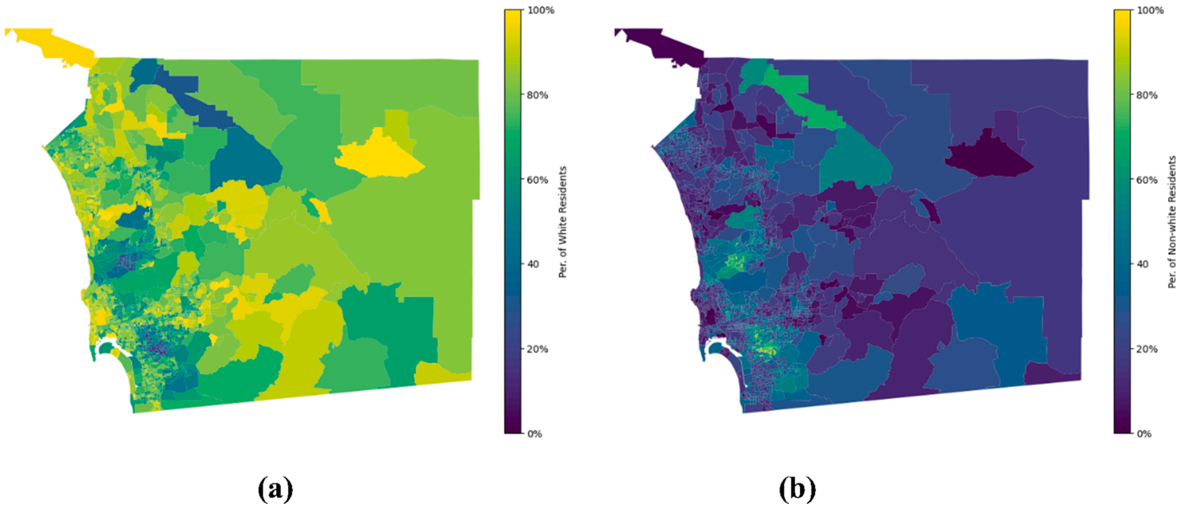


Fig. 4. (a) Percentage of White Population; and (b) Percentage of Non-white Population.

white/non-white commuters passing through each Census Block Group divided by the total number of white/non-white commuters in San Diego County. We synchronize the color schemes for Fig. 6(a) and Fig. 6(b) for comparative purposes. Fig. 6 suggests that white and non-white commuters share the same commuting corridors in San Diego. Both types of commuters travel from outlying zones to the central area. Further, the commuting corridors correspond to major arterials, including interstate highways such as I-15 and I-805.

5.2.3. Potential intergroup contact and exposure

In this section, we performed a sensitivity analysis considering two scenarios. We first apply the same weight to different races and block groups in the segregation analysis, based on the assumption that each race and block group bear the same importance in determining the level of segregation in the area. Treating all races and block groups equally when calculating the exposure index ensures that each group's contribution to the overall level of segregation is weighted the same. Applying different weights based on race or block group could introduce bias and potentially lead to inaccurate results. However, we acknowledge that this is a simplified assumption. Future research may explore alternative weighting schemes that account for potential differences in the level of segregation based on race or block group, if supported by evidence or when additional data is available. Consequently, in the following sensitivity analysis, we assume that: $wt_{ir}^{b} = wt_{ir}^{a} \mathit{foralli}$ (25)

$$wt_{iw}^{b} = wt_{iw}^{a} \mathit{foralli} \tag{26}$$

$$wt_{ic}^{b} = wt_{ic}^{a} \mathit{foralli} \tag{27}$$

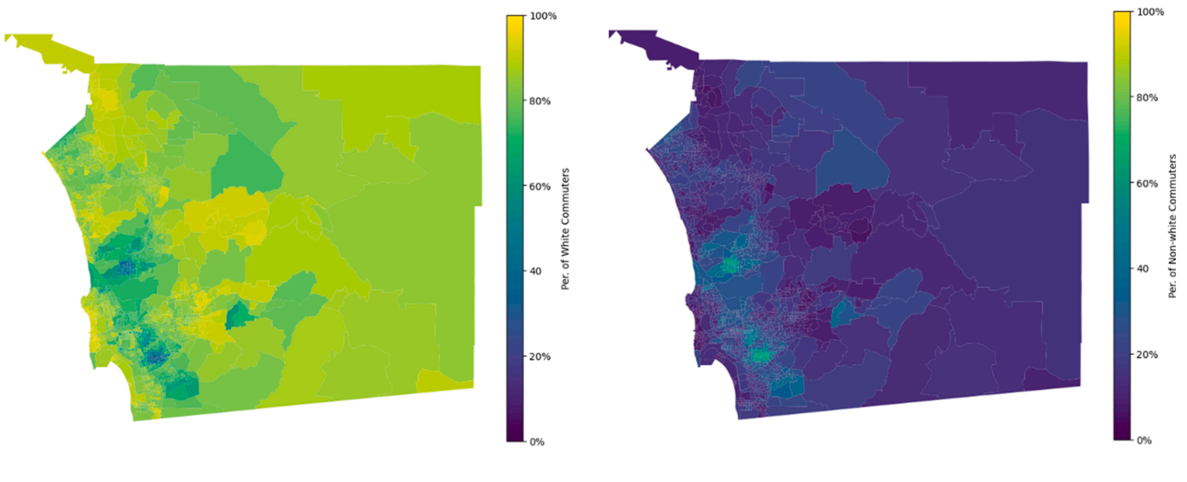
We define the two potential scenarios:

Consider the exposure of white residents to non-white commuters. i.e., $wt_{ir}^{b} = wt_{ir}^{a} = wt_{iw}^{b} = wt_{iw}^{a} = 1$ and $wt_{ic}^{b} = wt_{ic}^{a} = 0.25, 0.5, 0.75, 1$.

Consider the exposure of non-white residents to white commuters. i.e., $wt_{ir}^{b} = wt_{ir}^{a} = wt_{iw}^{b} = wt_{iw}^{a} = 1$ and $wt_{ic}^{b} = wt_{ic}^{a} = 0.25, 0.5, 0.75, 1$.

In Scenario 1, our analysis focuses on white residents' exposure to non-white commuters, but the weights of commuters have four different variations, 0.25, 0.5, 0.75, and 1. Fig. 7 displays the potential intergroup contact (i.e., exposure) of white residents with non-white commuters of different weights. There are several key observations. To begin with, despite the variation of weights applied to commuters, block groups with the highest percentage of white populations, such as suburbs and the coast (Fig. 4(a)), exhibit low exposure to non-white commuters. This outcome suggests two things. First, very few non-white commuters pass through those areas. Second, the overwhelming wealth of these coastal block groups may reflect elements of preferential segregation (Dixon et al., 2020) within San Diego County. In addition, the region with the highest levels of potential intergroup contact is found in the county's southern reaches, where total populations are relatively large, and there is a proportional balance between white and non-white populations. Lastly, regions functioning as employment hubs, such as Kearny Mesa, experience high levels of potential intergroup contact because of the large number of non-white workers commuting to the region. Moreover, by comparing the results across the four weights, we noticed that the absolute values of local exposures are increasing in certain areas as the weights increase. However, in most regions, the exposure stays low because of either a low white population or low non-white commuters. In addition, the region with the highest levels of potential intergroup contact remains the county's southern reaches. The comparison shows that the proposed exposure indices demonstrate varying patterns when the weights of commuters are adjusted.

In Fig. 8, Scenario 2, we demonstrate the exposure of non-white residents to white commuters under four different weights. We



(a) **(b)**

Fig. 5. (a) Percentage of White Commuters (b) Percentage of Non-white Commuters.

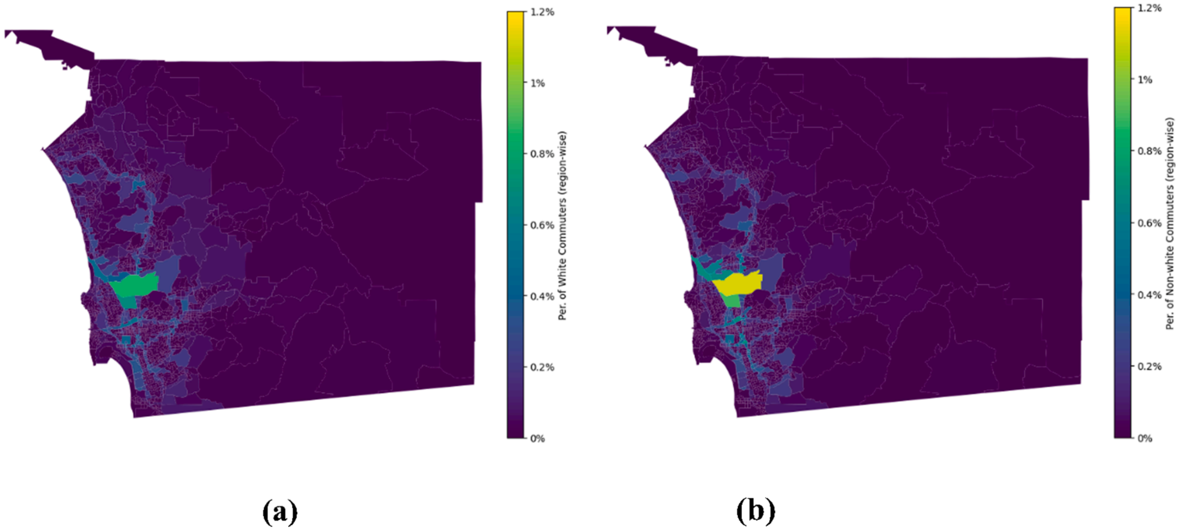


Fig. 6. (a) White Commuting Corridors; and (b) Non-white Commuting Corridors.

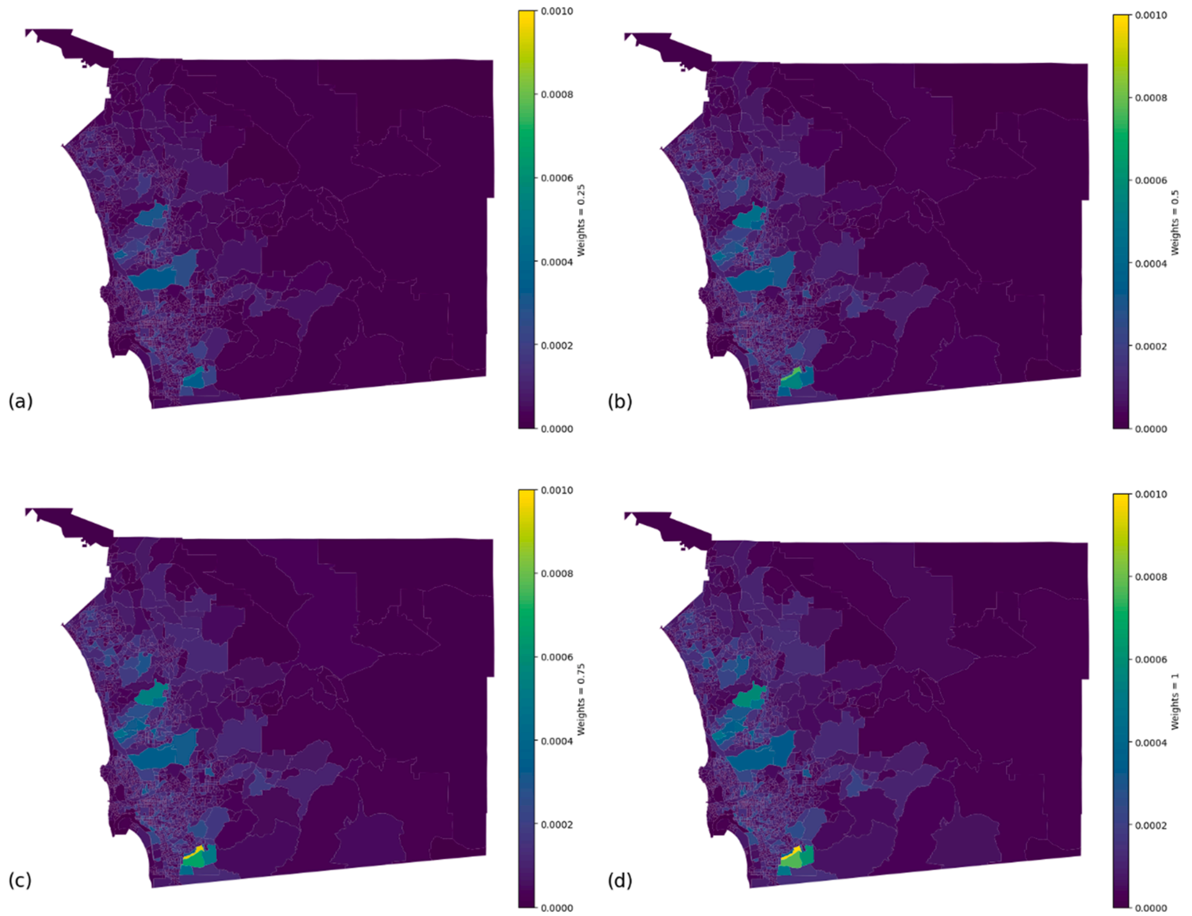


Fig. 7. Exposure of white residents to non-white commuters (a) $wt_{ic}^{b} = wt_{ic}^{a} = 0.25$ (b) $wt_{ic}^{b} = wt_{ic}^{a} = 0.5$ (c) $wt_{ic}^{b} = wt_{ic}^{a} = 0.75$ (d).$wt_{ic}^{b} = wt_{ic}^{a} = 1$

observe similar results; however, areas with high percentages of non-white populations tend to have higher levels of exposure (see Fig. 8(b)). This outcome is mainly due to the imbalanced distribution of non-white populations. As demonstrated in our analysis, changes in the weights assigned to commuters can significantly impact exposure levels. When weights are small, only areas with the highest percentage of non-white populations exhibit a notable exposure level. However, as weights assigned to commuters gradually increase, more regions are identified as having elevated exposure levels. These findings suggest that many white commuters are present in the southern regions of the county. When the weights assigned to commuters are small, exposure levels are lower due to the low percentage of non-white populations. However, as weights increase, the contributions of commuters grow, and exposure levels rise accordingly. This outcome highlights the significance of adjusting the weights assigned to different contributors in the exposure index, providing flexibility to tailor the index based on various scenarios.

6. Discussion and conclusions

In this paper, we identified the gap in current segregation analysis and justified the importance of incorporating commuters into the activity space of urban areas. Then, we derived race-specific driving patterns on community roadways based on universally accessible data, making the framework transferable to locations with similar data source availability. Furthermore, we extended exposure measures from residents and workers by including commuters based on the race-specific driving patterns we delineated. The novel measure of intergroup exposure and potential for contact incorporated information on residents, workers, and commuters and their race-specific driving patterns to understand how different racial groups are exposed to each other within San Diego block groups. We applied this index to roadways and underlying sociodemographic characteristics and found that elements of driving-related segregation exist within San Diego County. There is very little chance of intergroup exposure in the block groups near the coastal areas throughout the region. These locations are overwhelmingly white (Fig. 4) and affluent. In short, San Diego roadways are segregated, showing that differential commuting patterns likely shape opportunities for intergroup exposure and contact (or lack of it).

Intergroup exposure and contact are critical for many social processes. At the most basic, intergroup exposure shapes how individuals view others outside their own racial groups. For example, studies in psychology have long shown that intergroup exposure and contact is a powerful tool in shaping and reducing between-racial group conflict and prejudice in a wide variety of settings (Dovidio et al., 2003; Pettigrew et al., 2011), including within the workplace (Darling-Hammond et al., 2021; Herda, 2018), between physicians and patients (Onyeador et al., 2020), among college students (Bowman and Denson, 2012), and within space (i.e., spatial proximity (Wessel, 2009). Further, these mechanisms shape the tolerance of individuals of different races than one's own by simple exposure (Wessel, 2009); contact does not need to occur. Finally, indirect exposure to other groups reduces prejudice (Pettigrew et al., 2011). In areas where driving is the dominant mode of transportation, our intergroup exposure index helps determine locales where intergroup exposure is possible; our results show large swaths of coastal and suburban areas in San Diego where driving patterns create few if any, opportunities for intergroup contact/exposure. With driving-related exposure and opportunities for contact between races relatively low in San Diego, social issues such as between-racial group conflict and prejudice will likely remain.

The practical application of this research is significant for transportation researchers and policymakers. Accurately estimating race-specific driving patterns is critical for understanding racial segregation on the road and improving transportation equity. The proposed exposure index can help identify areas with high levels of exposure to different racial groups and inform policies to address the transportation needs of historically marginalized groups. Using universally available data makes the framework and results transferable and replicable to different regions in the United States and beyond. Additionally, one can extend the proposed framework to other modes of transportation, such as public transit or biking, with adjustments made to the estimation of trip patterns based on the specific mode of transportation.

However, there are some limitations to the proposed approach. First, the accuracy of the exposure index relies on the assumptions made regarding the weightings of different groups and their respective activity spaces. The weights present the intensity of explicit or implicit interaction between different groups. When determining the weights of commuters across different block groups, it is essential to consider their actual travel routes. For example, if most commuters pass through census block A by highway, while another census block group, B, primarily by local roads, then commuters passing through census block group B should be given greater weight. This contingency represents the likelihood of interaction between commuters, residents, and workers in block group B - which can substantially impact exposure patterns and other outcomes. In summary, creating an accurate estimate of the weights of different races, locations, and groups (residents, workers, and commuters) is challenging yet critical. Additionally, the framework only considers race-specific driving patterns and exposure. Other important factors such as income, education, and network characteristics (speed limit, point of interest, land use, etc.) may also affect the interaction between different groups in urban areas. Also, it is essential to acknowledge that the results from San Diego County may not broadly represent other locations in California or the United States. For example, while white and non-white commuters share the same commuting corridors in this region, such results may diverge in places such as Los Angeles, Portland, Chicago, or elsewhere. Regardless, the underlying framework for estimating these driving patterns is transferrable to other locales and can provide a functional denominator for establishing the presence of racially biased policing in other metropolitan areas or law enforcement jurisdictions.

Finally, using census block groups as proxies for activity spaces may lead to some measurement errors. Given the size of San Diego County, the bulk of our empirical work needed to focus on the block group level. However, Wong (2003) notes that empirical analyses of segregation, and their results, can vary by scale (e.g., between block groups, tracts, etc.). Moving forward, this is an essential consideration for evaluating racially biased traffic stops, and analysts must account for these empirical uncertainties using sensitivity analysis or scale-agnostic estimation approaches.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to

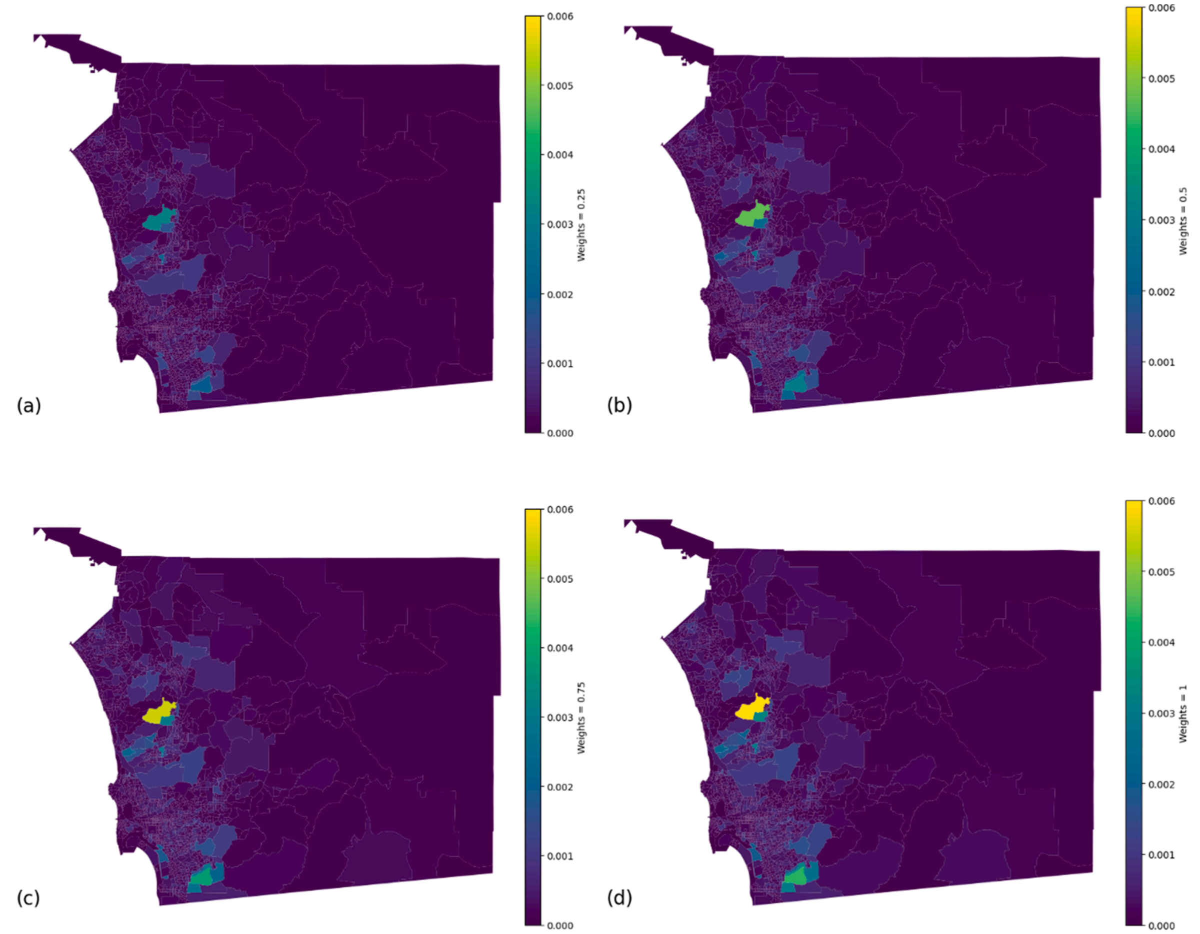


Fig. 8. Exposure of Non-white Residents to White Commuters (a) $wt_{ic}^{b} = wt_{ic}^{a} = 0.25$ (b) $wt_{ic}^{b} = wt_{ic}^{a} = 0.5$ (c) $wt_{ic}^{b} = wt_{ic}^{a} = 0.75$ (d).$wt_{ic}^{b} = wt_{ic}^{a} = 1$

influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgment

This article is based upon work partially supported by the National Science Foundation, United States, under Grant No. 2051226 and partially supported by the National Institute for Transportation and Communities (NITC, grant number 1519), a U.S. DOT University Transportation Center. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the author(s).

References

Ahas, R., Aasa, A., Silm, S., Aunap, R., Kalle, H., Mark, Ü., 2007. Mobile positioning in space–time behaviour studies: social positioning method experiments in Estonia. Cartogr. Geogr. Inf. Sci. 34 (4), 259–273.

Allport, G.W., 1954. The Nature of Prejudice. Addison-Wesley, Cambridge, MA.

Alpert, G.P., Smith, M.R., Dunham, R.G., 2004. Toward a better benchmark: Assessing the utility of not-at-fault traffic crash data in racial profiling research. Justice Res. Policy 6 (1), 43–69.

Batty, M., 1976. Urban Modeling: Algorithms, Calibrations, Predictions. Cambridge University Press, London.

Blau, P.M., 1977. Inequality and Heterogeneity: A Primitive Theory of Social Structure. Free Press, New York, vol. 7, pp. 677–683.

Bowman, N.A., Denson, N., 2012. What's past is prologue: How precollege exposure to racial diversity shapes the impact of college interracial interactions. Res. High. Educ. 53 (4), 406–425.

Darling-Hammond, S., Lee, R.T., Mendoza-Denton, R., 2021. Interracial contact at work: Does workplace diversity reduce bias? Group Process. Intergroup Relat. 24 (7), 1114–1131.

Ding, N., Bagchi-Sen, S., 2019. An analysis of commuting distance and job accessibility for residents in a US legacy city. Ann. Am. Assoc. Geogr. 109 (5), 1560–1582.

Dixon, J., Tredoux, C., Davies, G., Huck, J., Hocking, B., Sturgeon, B., Whyatt, D., Jarman, N., Bryan, D., 2020. Parallel lives: Intergroup contact, threat and the segregation of everyday activity spaces. J. Pers. Soc. Psychol. 118 (3), 457–480.
Do, D.P., Locklar, L.R., Florsheim, P., 2019. Triple jeopardy: the joint impact of racial segregation and neighborhood poverty on the mental health of black Americans. Soc. Psychiatry Psychiatr. Epidemiol. 54 (5), 533–541.
Dovidio, J.F., Gaertner, S.L., Kawakami, K., 2003. Intergroup contact: the past, present, and the future. Group Process. Intergroup Relat. 6 (1), 5–21.
Downey, L., Hawkins, B., 2008. Race, income, and environmental inequality in the United States. Sociol. Perspect. 51 (4), 759–781.
Ellis, M., Wright, R., Parks, V., 2004. Work together, live apart? Geographies of racial and ethnic segregation at home and at work. Ann. Assoc. Am. Geogr. 94, 620–637.
Engel, R.S., Calnon, J.M., 2004. Examining the influence of drivers' characteristics during traffic stops with police: results from a national survey. Justice Q. 21 (1), 49–90.
Farber, S., O'Kelly, M., Miller, H.J., Neutens, T., 2015. Measuring segregation using patterns of daily travel behavior: a social interaction based model of exposure. J. Transp. Geogr. 49, 26–38.
Feitosa, F.F., Camara, G., Monteiro, A.M.V., Koschitzki, T., Silva, M.P.S., 2007. Global and local spatial indices of urban segregation. Int. J. Geogr. Inf. Sci. 21, 299–323.
Fotheringham, S., O'Kelly, M.E., 1989. Spatial Interaction Models: Formulations and Applications. Kluwer Academic Publishers.
Fotheringham, A.S. 1988. Market share analysis techniques:a review and illustration of current U.S. practice. In N. Wrigley, editor, Store Choice, Store Location and Market Analysis, pages 120–159. Routledge, London.
Fuller, B., Kim, Y., Galindo, C., Bathia, S., Bridges, M., Duncan, G.J., García Valdivia, I., 2019. Worsening school segregation for latino children? Educ. Res. 48 (7), 407–420.
Galaskiewicz, J., Anderson, K.F., Thompson-Dyck, K., 2021. Minority-White income inequality across metropolitan areas: The role of racial/ethnic residential segregation and transportation networks. J. Urban Aff. 43 (1), 16–39.
Grady, S.C., McLafferty, S., 2007. Segregation, nativity, and health: reproductive health inequalities for immigrant and native-born black women in New York City. Urban Geogr. 28 (4), 377–397.
Grove, M., Ogden, L., Pickett, S., Boone, C., Buckley, G., Locke, D.H., Lord, C., Hall, B., 2018. The legacy effect: understanding how segregation and environmental injustice unfold over time in Baltimore. Ann. Am. Assoc. Geogr. 108 (2), 524–537. https://doi.org/10.1080/24694452.2017.1365585.
Grubesic, T.H., Wallace, D., Chamberlain, A.W., Nelson, J.R., 2018. Using unmanned aerial systems (UAS) for remotely sensing physical disorder in neighborhoods. Landsc. Urban Plan. 169, 148–159.
Herda, D., 2018. "To Hell with Them All!": perceived discrimination, interracial contact, and racial attitudes. Sociol. Focus 51 (2), 111–129.
Hetey, R.C., Monin, B., Maitreyi, A., Eberhardt, J.L., 2016. Data for Change: A Statistical Analysis of Police Stops, Searches, Handcuffings, and Arrests in Oakland, Calif., 2013-2014. Stanford SPARQ.
Jang, W., Yao, X., 2014. Tracking ethnically divided commuting patterns over time: a case study of Atlanta. Prof. Geogr. 66, 274–283.
Kim, C., Sang, S., Chun, Y., Lee, W., 2012. Exploring urban commuting imbalance by jobs and gender. Appl. Geogr. 32, 532–545.
Kwan, M.P., 2000. Interactive geovisualization of activity-travel patterns using three-dimensional geographical information systems: a methodological exploration with a large data set. Transport. Res. Part C: Emerg. Technol. 8 (1–6), 185–203.
Lajunen, A., 2014. Energy consumption and cost-benefit analysis of hybrid and electric city buses. Transp. Res. Part C 38, 1–15.
Lamberth, J., 1994. Revised Statistical Analysis of the Incidence of Police Stops and Arrests of Black Drivers/Travelers on the New Jersey Turnpike Between Exits or Interchanges 1 and 3 from the Years 1988 through 1991. Lamberth Consulting.
Latham, S., Pinto, S. 2022, Commuting Patterns and Economic Connectivity in the Fifth District. Federal Reserve Bank of Richmond Economic Brief, No. 22-47.
Lee, J.Y., Kwan, M.P., 2011. Visualisation of socio-spatial isolation based on human activity patterns and social networks in space-time. Tijdchr. Econ. Soc. Geogr. 102 (4), 468–485.
Lundman, R.J., Kaufman, R.L., 2003. Driving while black: Effects of race, ethnicity, and gender on citizen self-reports of traffic stops and police actions. Criminology 41 (1), 195–220.
Manaugh, K., Badami, M.G., El-Geneidy, A.M., 2015. Integrating social equity into urban transportation planning: a critical evaluation of equity objectives and measures in transportation plans in North America. Transp. Policy 37, 167–176.
Massey, D.S., Denton, N.A., 1988. The Dimensions of Residential Segregation. Soc. Forces 67 (2), 281–315. https://doi.org/10.1093/sf/67.2.281.
Mburu, L.W., Helbich, M., 2016. Crime risk estimation with a commuter-harmonized ambient population. Ann. Am. Assoc. Geogr. 106(4), 804–818. http://www.jstor.org/stable/45387643.
Niedzielski, M.A., O'Kelly, M.E., Boschmann, E.E., 2015. Synthesizing spatial interaction data for social science research: validation and an investigation of spatial mismatch in Wichita. Kansas. Comput. Environ. Urban. Syst. 54, 204–218.
Oka, M., Wong, D.W., 2019. Segregation: A Multi-Contextual and Multi-faceted Phenomenon in Stratified Societies. In Handbook of Urban Geography. Edward Elgar Publishing.
O'Kelly, M.E., Lee, W., 2005. Disaggregate journey-to-work data: implications for excess commuting and jobs–housing balance. Environ. Plan. A 37 (12), 2233–2252.
Onyeador, I.N., Wittlin, N.M., Burke, S.E., Dovidio, J.F., Perry, S.P., Hardeman, R.R., Dyrbye, L.N., Herrin, J., Phelan, S.M., Ryn, M.V., 2020. The value of interracial contact for reducing anti-black bias among non-black physicians: a cognitive habits and growth evaluation (CHANGE) study report. Psychol. Sci. 31 (1), 18–30.
Park, Y.M., Kwan, M.P., 2018. Beyond residential segregation: a spatiotemporal approach to examining multi-contextual segregation. Comput. Environ. Urban Syst. 71, 98–108.
Park, Y.M., Kwan, M.P., 2020. Understanding racial disparities in exposure to traffic-related air pollution: considering the spatiotemporal dynamics of population distribution. Int. J. Environ. Res. Public Health 17 (3), 908.
Pettigrew, T.F., Tropp, L.R., Wagner, U., Christ, O., 2011. Recent advances in intergroup contact theory. Int. J. Intercult. Relat. 35 (3), 271–280.
Phillips, N.E., Levy, B.L., Sampson, R.J., Small, M.L., Wang, R.Q., 2021. The social integration of American cities: network measures of connectedness based on everyday mobility across neighborhoods. Sociol. Methods Res. 50 (3), 1110–1149.
Priest, N., Paradies, Y., Ferdinand, A., Rouhani, L., Kelaher, M., 2014. Patterns of intergroup contact in public spaces: micro-ecology of segregation in Australian communities. Societies 4 (1), 30–44.
Ramiah, A.A., Schmid, K., Hewstone, M., Floe, C., 2014. Why are all the White (Asian) kids sitting together in the cafeteria? Re-segregation and the role of intergroup attributions and norms. Brit. J. Social Psychol. 54(1), 100–124.
Ridgeway, G., MacDonald, J., 2010. Methods for assessing racially biased policing. Race, Ethnicity, Policing: New Essential Readings 180–204.
Sampson, R.J., Raudenbush, S.W., 2004. Seeing disorder: neighborhood stigma and the social construction of "broken windows". Soc. Psychol. Q. 67 (4), 319–342.
Sampson, R.J., 2012. Great American city: Chicago and the Enduring Neighborhood Effect. University of Chicago Press.
Sang, S., O'Kelly, M.E., Kwan, M.P., 2011. Examining commuting patterns: results from a journey-to-work model disaggregated by gender and occupation. Urban Stud. 48, 891–909.
Saporito, S., Sohoni, D., 2006. Coloring outside the lines: Racial segregation in public schools and their attendance boundaries. Sociol. Educ. 79 (2), 81–105.
Scally, B.J., Krieger, N., Chen, J.T., 2018. Racialized economic segregation and stage at diagnosis of colorectal cancer in the United States. Cancer Causes Control 29 (6), 527–537.
Signorino, G., Pasetto, R., Gatto, E., et al., 2011. Gravity models to classify commuting vs. resident workers. An application to the analysis of residential risk in a contaminated area. Int. J. Health Geogr 10, 11. https://doi.org/10.1186/1476-072X-10-11.
Swyngedouw, E., 2013. The segregation of social interactions in the Red Line L-Train in Chicago. Symbolic Interact. 36(3), 293–313. 10.1002/symb.64.
Transportation Planning Products Program (CTPP). http://ctpp.beyond2020.com/ctpp2000/Browse/browsetables.aspx.
US Census Bureau, 2014. 2010 US Census Block Groups for the County of San Diego. US Census Bureau, Washington, DC.
US Census Bureau. 2019. Commuting in the United States: 2017. https://www.census.gov/content/dam/Census/library/publications/2019/acs/ACS-36.pdf.

US Census Bureau, 2022. LEHD Origin-Destination Employment Statistics Data (2002-2019). Washington, DC: US Census Bureau, Longitudinal-Employer Household Dynamics Program, accessed on 01/02/2022 at https://lehd.ces.census.gov/data/#lodes. LODES 7.5.

Wallace, D., Louton, B., Nelson, J., Gricius, M., Tyler, D. H., Coble, S., Kramer, K., 2017. Yearly Report for the Maricopa County Sheriff's Office: Years 2015-16. Phoenix, AZ.

Wallace, D., Tyler, D.H., Kramer, K., Kempany, K.G., Louton, B., Sweeten, G., … Gricius, M., 2018. Annual Report for the Maricopa County Sheriff's Office : Years 2016 to 2017. Phoenix, AZ.

Wallace, D., Louton, B., 2018. The disorder perceptions of nonresidents: a textual analysis of open-ended survey responses to photographic stimuli. City Community 17 (1), 21–43.

Wang, D., Li, F., Chai, Y., 2012. Activity spaces and sociospatial segregation in Beijing. Urban Geogr. 33 (2), 256–277.

Wang, Q., Phillips, N.E., Small, M.L., Sampson, R.J., 2018. Urban mobility and neighborhood isolation in America's 50 largest cities. Proc. Natl. Acad. Sci. 115 (30), 7735–7740.

Wessel, T., 2009. Does diversity in urban space enhance intergroup contact and tolerance? Geografiska Ann.: Ser. B, Human Geogr. 91 (1), 5–17.

Wong, D.W., 1993. Spatial indices of segregation. Urban Stud. 30 (3), 559–572.

Wong, D.W., 2003. Spatial decomposition of segregation indices: a framework toward measuring segregation at multiple levels. Geogr. Anal. 35 (3), 179–194.

Wong, D.W., Shaw, S.L., 2011. Measuring segregation: an activity space approach. J. Geogr. Syst. 13 (2), 127–145.

Yao, J., Wong, D.W., Bailey, N., Minton, J., 2019. Spatial segregation measures: a methodological review. Tijdchr. Econ. Soc. Geogr. 110 (3), 235–250.

Zhou, Y., Liu, X.C., Wei, R., Golub, A., 2020. Bi-objective optimization for battery electric bus deployment considering cost and environmental equity. IEEE Trans. Intell. Transp. Syst. 22 (4), 2487–2497.

Zhou, Y., Liu, X.C., Grubesic, T., 2021. Unravel the impact of COVID-19 on the spatio-temporal mobility patterns of microtransit, Journal of Transport Geography, Volume 97,103226. ISSN 0966–6923. https://doi.org/10.1016/j.jtrangeo.2021.103226.