



Contents lists available at ScienceDirect

Journal of Transport & Health

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

Assessment for health equity of PM_{2.5} exposure in bikeshare systems: The case of Divvy in Chicago

Xiaodong Qian^a, Yizheng Wu^{b,*}^a Department of Civil Engineering, University of California at Davis, One Shields Avenue, Davis, CA, 95616, USA^b Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, Ministry of Transport, Beijing Jiaotong University, 3 Shangyuancun, Haidian District, Beijing, 100044, China

ARTICLE INFO

Keywords:

Equity assessment
Health impact
Bikeshare
Air quality

ABSTRACT

Introduction: Bikeshare is becoming more and more popular around the world. Many cities in the United States have implemented their own bikeshare systems or are considering having one. Among many other benefits by bikeshare, physical health improvement has been mentioned as one of them as a common sense. However, not enough attention has been paid to potential health impacts when using bikeshare. This is not even to mention how the health impact is distributed among different groups. To address this research gap, we conducted a preliminary study to analyze the uneven distribution of health impacts by making bikeshare trips.

Method: In our research, we chose the Divvy bikeshare system in Chicago since it is currently one of the biggest systems in the USA and its trip data are open. By incorporating emission and air dispersion modeling tools, we first estimated the high-resolution air pollution concentration level in the city. Then, we quantified the trip-based PM_{2.5} exposure by including every trip route and duration time. Finally, we conducted a spatial analysis for health exposure related to bikeshare trips in disadvantaged areas.

Results: In Chicago, most of routes with high PM_{2.5} exposure index are distributed in the southwest of Chicago, where there are more minority populations or low-income communities. From the station level, most of the stations in disadvantaged areas have a high level of PM_{2.5} exposure index on average.

Conclusions: Our research has clearly shown that users from disadvantaged areas are more likely to take a risk of absorbing more PM_{2.5}, especially when traveling to other areas with more job opportunities and other essential services by bikeshare. In summary, our research points out an ignored aspect in planning bikeshare. Bicycle infrastructure design and air pollution control should be integrated into the process of bikeshare promotion in disadvantaged areas.

1. Introduction

Bikeshare is becoming more and more popular around the world. Many cities in the United States have implemented their own bikeshare systems or are considering having one. As has been stated by many different researches, bikeshare systems bring many benefits, such as, reducing traffic congestion (Shaheen et al., 2010), being environmentally friendly (Wang and Zhou, 2017), and improving accessibility (Niemeier and Qian, 2018). Among all these, physical health benefit has been mentioned as a common sense (Qian and Niemeier, 2019).

* Corresponding author.

E-mail addresses: xdqian@ucdavis.edu (X. Qian), wuyizheng@bjtu.edu.cn (Y. Wu).<https://doi.org/10.1016/j.jth.2019.100596>

Received 28 January 2019; Received in revised form 9 July 2019; Accepted 17 July 2019

Available online 27 July 2019

2214-1405/ © 2019 Elsevier Ltd. All rights reserved.

Residents from low-income and disadvantage communities are continuously facing health issues, e.g., obesity (Lovasi et al., 2009). As an affordable and sustainable transportation mode, bikeshare has been believed as a promising way to relieve this situation. However, disadvantaged populations are still an unobvious proportion of bikeshare users (McNeil et al., 2017). Thus, many bikeshare programs are addressing this issue by promoting bikeshare in disadvantaged areas. For example, in July 2015, Chicago introduced the “Divvy for Everyone (D4E)” program, which provides affordable membership fees to qualifying residents (Motivate International, 2017).

Currently, as the fast development of bikeshare systems, more attention has shift from analysis of system operations and management to equity issues. However, most of the equity researches focused on addressing access barriers in order to attract more and more residents from low-income and disadvantage communities (Lovasi et al., 2009; Motivate International, 2017). However, the negative effects of air pollution are not trivial (Fishman et al., 2012), (Steinle et al., 2013). Cyclists may experience a certain level of health impact since they are exposed to air pollution directly. Additionally, the spatial distribution of air pollution is more serious along highways, where there are more disadvantaged communities (Karner et al., 2010), (Rowangould, 2013). Thus, we don't know, to what degree, if there exists an uneven distribution of air pollution exposure to bikeshare users in disadvantaged communities.

2. Literature reviews

2.1. Health benefits by bikeshare systems

There are a considerable amount of researches on health benefits brought by active transportation systems. Many researches have proved that active travel can significantly improve health, like decrease in mortality rate and relieve in cardiovascular load (Barnes, 2004)– (Tainio et al., 2016). Among all these methods quantifying the health effects, there are two main methods: Integrated Transport and Health Impact Modelling Tool (ITHIM), and Health Economic Assessment Tool (HEAT). ITHIM includes a lot of models and tools for health effect assessment developed by the Centre for Diet and Activity Research (CEDAR) (Integrated Transport and Health Impact Modelling Tool (ITHIM), 2019). The ITHIM models cover the changes in physical activity, traffic accident risk, and air pollution exposure. Similar to the function of ITHIM, the HEAT tool serves for users without expertise in health impact assessment, which can be used directly to estimates the economic value of specified amounts of walking or cycling (HEAT).

Besides these research for general cycling and walking, there are specific researches focusing on bikeshare. Woodcock et al. (2014) analyzed the health effects of a bikeshare system in London by comparing two scenarios (with and without bikeshare). Their health impact modelling includes the change in physical activity, exposure to air pollution, and reduction in traffic injuries. As pointed out in their conclusion that, overall health condition is positively improved by London's bikeshare, but all the potential benefits have not been proved to apply to all different groups. Fishman, Washington, and Haworth (2015) studied bikeshare's direct impact on active travel (e.g., walk and bike) and they concluded that, overall, bikeshare systems have positive influence on increasing active travel time. According to their researches, a large population of cyclists can generate a significant amount of reduction in health care costs. However, we have limited information of the potential uneven distribution of exposure to air pollution by active travelling (especially bikeshare) among different social groups.

2.2. Human exposure assessment

With increasing vehicle travel, air pollution emissions will continue to adversely affect human health. The negative effects of air pollution motivate policy makers and planners to evaluate transportation plans and policies in terms of their air quality and health impacts and to develop solutions aimed at improving air quality.

Current health impact assessment (HIA) tools can be used to forecast the health effects of transportation plans, however they generally output results at very coarse spatial scales (e.g. regional level or a single county) to quantify the average health benefits across the population (Ojaet al., 2011; Woodcock et al., 2013; Tainio et al., 2016). These aggregated results do not shed light on spatial variation in health outcomes that occur in communities or populations within a region. Additionally, given the spatial variability of air pollution concentrations, this coarse scale limits these tools' ability to accurately forecast the expected health effects of a transportation plan or policy.

Integrated models of travel demand, emissions, and air dispersion have shown promise for allowing planners to evaluate the air quality and health impacts for different groups and in different regions. They have been used to estimate existing transportation pollution concentrations at fine spatial scales (Integrated Transport and Health Impact Modelling Tool (ITHIM), 2019; HEAT), as well as to forecast the air quality effects of transportation plans and policies at fine scales (Woodcock et al., 2014; Cavill and Davis, 2017). A handful of fine-grained integrated modeling studies go further by forecasting the health effects of transportation policies (Rowangould et al., 2018) and plans (Poorfakhraei et al., 2017). Rowangould et al. (2018) quantified the health effects of fine particulate matter (PM_{2.5}) due to the revision of a clean truck program at the Port of New York & New Jersey by integrating vehicle activity with the emissions, dispersion, and health models. Poorfakhraei et al. (2017) applied an integrated modeling framework to evaluate the health impacts due to the implementation of a long range transportation plan in Atlanta. However, both studies overlay US census block-level population estimates (which reflect static residential locations) with corresponding air pollution concentrations, essentially assuming a static population distribution in the exposure assessment. Assuming a static population is also common in epidemiological studies e.g. (Maizlish et al., 2013; Rojas-Rueda et al., 2011; Hatzopoulou and Miller, 2010). This type of approximation may be less problematic when comparing exposures in different regions (where a region's entire population is assumed to be exposed to an average regional concentration.) However, for finer scale analyses that compare population or community

exposures within a region, using residents' home locations to approximate their activity space fails to account for their exposure as they travel to work, school, etc., likely over- or under-estimating their risks when these destinations coincide with lower or greater concentrations than residents' homes, respectively.

Besides the human exposure assessment related to traffic activity, there is a large literature about residential segregation issue in PM_{2.5} exposure. There are two common conclusions across all these related researches. First, minority race is more likely to have higher exposures of PM_{2.5} than white population (Bell Michelle and Keita, 2012)– (Morello-Frosch et al., 2011). Second, in general, minority race (e.g., black) or low-income populations are more sensitive to unhealth outcomes (e.g., sinusitis) from exposure to PM_{2.5} (Nachman and Parker, 2012), (Adamkiewicz et al., 2011).

3. Methods

In our research, we chose Chicago and Divvy bikeshare as a case in the preliminary study. The modeling domain is the City of Chicago. It has a total area of 234 square miles, which consists of 29,860 census blocks. Several major traffic corridors pass through Chicago, including the Interstate Highway 90 (I90), the Interstate Highway 290 (I290), and the State Route 41. In this paper, air quality modeling framework is applied to evaluate the population exposure of PM_{2.5}. Emission modeling tool and air dispersion modeling tool are used to provide a high-resolution concentration map at census block level. After that, the authors estimated PM_{2.5} exposure by integrating trip route information for every bikeshare OD pair, and conducted equity analyses. Fig. 1 illustrates the process to conduct the whole analysis process.

It should be noted that although we only analyze the impacts of PM_{2.5} in this study, the method could apply to any primary, non-reactive vehicular pollutant.

3.1. Air quality modeling framework

The air quality modeling framework includes the emission model, and air dispersion model. In this study, the U.S. Environmental Protection Agency's MOVES (Motor Vehicle Emission Simulator, version 2014a) is applied as the emission model, and AERMOD (version 16216r) is applied as the air dispersion model. Both of them are regulatory models that reflect the state of art and practice.

By incorporating the traffic information¹ collected from local agency (Fig. 2), MOVES is run in the "Emission Inventory" scale to produce composite emission rates in terms of grams/hour (g/hour). After running the post-processing script for PM_{2.5} in terms of g/hour, the emission rates for each link are extracted from the MySQL database from MOVES and passed on to the air dispersion model to estimate concentrations at desired locations.

AERMOD is used to estimate the concentration of PM_{2.5} based on meteorological conditions, roadway locations and emission rates from MOVES outputs. Then, we estimated the level of PM_{2.5} concentration for census blocks (Fig. 3) based on geographic relation of census blocks and all receptors, i.e., the PM_{2.5} concentration level of a census block is the mean of all measurements by receptors in it or surround it if there is not any receptors in it.

3.2. Disadvantaged areas

The authors created a 400-m buffer around each bikesharing station, which is same with a research by Cohen (2016). In this research, disadvantaged communities refer to regions where low-income populations and people of color live. To define such communities for this study, the authors first identified those buffer areas with a median household income below \$50,000 (200% of the federal poverty line for a household with four people) (Jiang et al., 2016), (U. S. Department of Health and Human Services, 2016). Then, low, moderate and high thresholds for minority populations were set using the mean and standard deviation of the percentage of minority populations within each buffer. Finally, the process identified whether a bikeshare station buffer qualifies as a disadvantaged area or not based on income and percentage of minority population levels.

3.3. Bikeshare OD and routes

Divvy bikeshare in Chicago releases their database for all bikeshare trips recorded since July 2013. Every trip record covers trip origination and destination stations. Exploring this database, we can calculate the real OD matrix for the Divvy bikeshare system. This OD trips will be used to weight the health impact index for every station. Additionally, we only focus on the OD pairs with recorded trips since it will reflect the real bikeshare trip distribution situation.

To accurately calculate exposure to PM_{2.5} when finishing a bikeshare trip, we need to estimate trip routes for all bikeshare trips. There are a few researches analyzing bikeshare or general cycling route choices (Rowangould, 2015; Hao et al., 2010). According to their research, demographic information and route safety play important roles in deciding route choices. However, in our study, demographic information for every trip maker is not available and bike path information is limited. Considering all the limitations, we applied Google Direction API to estimate the most likely route choices for all OD pairs. For every route, the Google Direction API divides a whole route into several steps, indicating direction, step duration, and step distance. That information is useful when we accurately calculate air pollution exposure for bikeshare trips. The authors estimated the PM_{2.5} exposure based on every single step

¹ Traffic count data are from Illinois Department of Transportation (IDOT): <http://apps.dot.illinois.gov/gist/>.

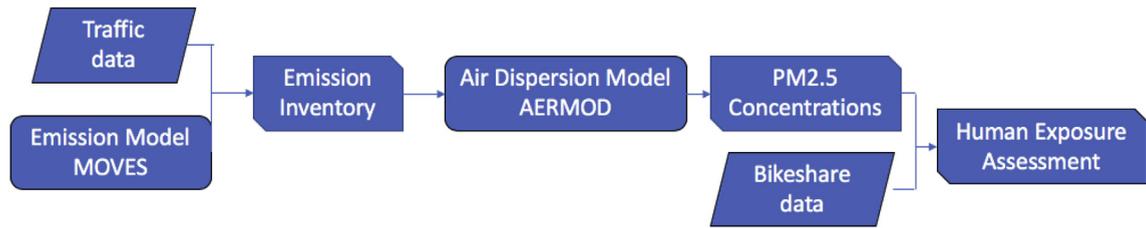


Fig. 1. Flow chart of methodology.

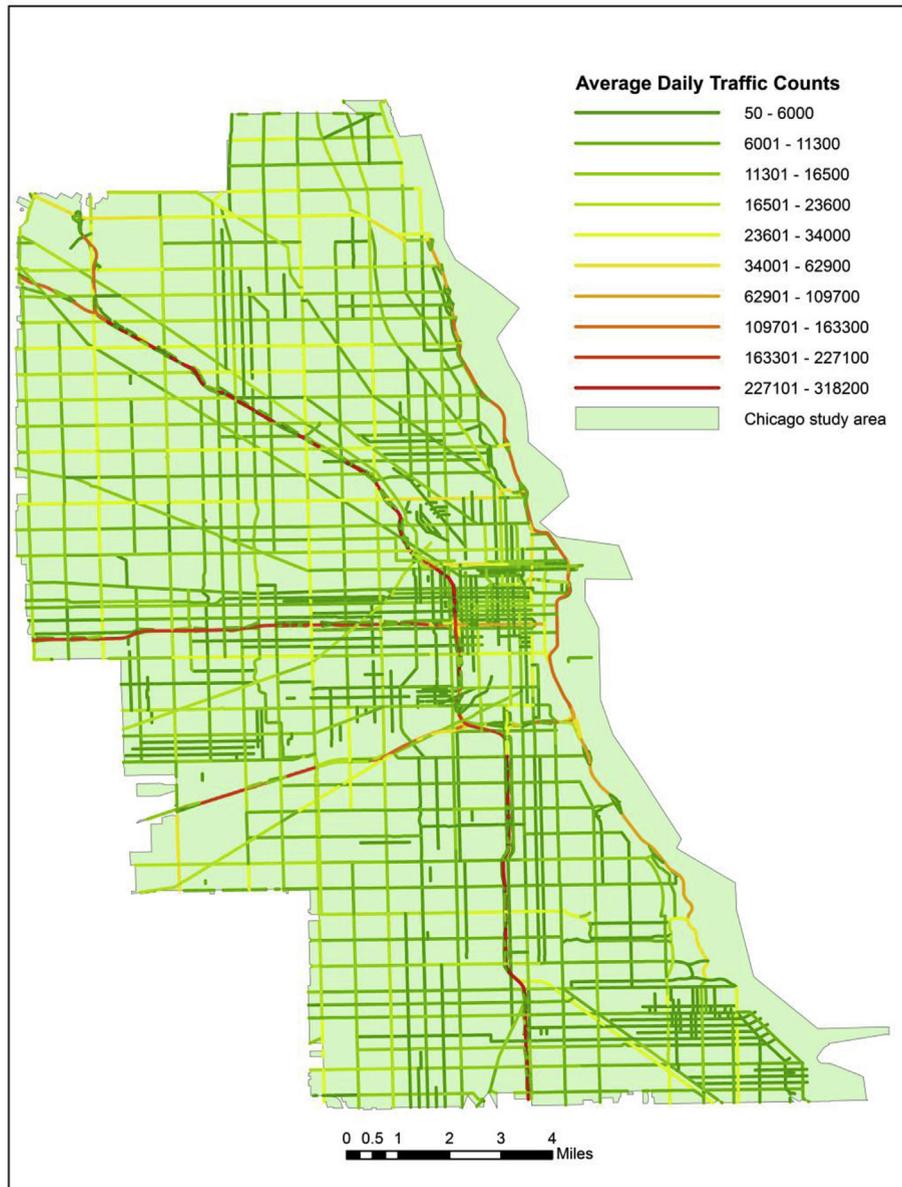


Fig. 2. Average daily traffic counts of main road in Chicago.

(step time times air pollution concentration level for this route step) in a trip route and summed them up to calculate a pollution exposure value for a whole trip route. Fig. 1 shows a geographic map of all routes for all OD pairs. As we can see in Fig. 4, most of the bikeshare stations are not located in disadvantaged areas. The majority of stations in disadvantaged areas are sited in south and west of Chicago, where there are a considerable amount of non-white populations and low-income households. These OD routes there have

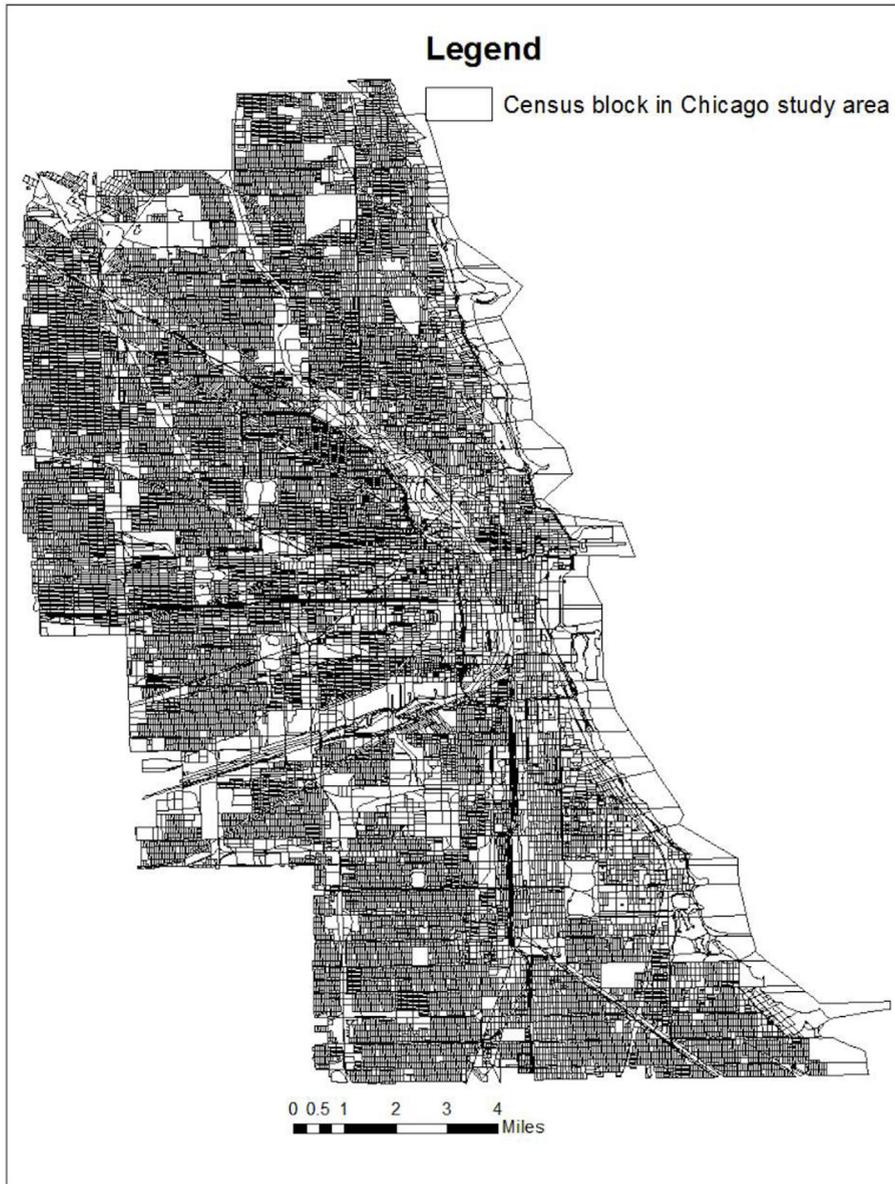


Fig. 3. Census block in Chicago.

a high-level overlap with main roads in Chicago (Fig. 2).

3.4. PM_{2.5} exposure assessment

In this study, PM_{2.5} exposure levels are computed based on bicyclists' route, duration information, and pollutant concentration from AERMOD. The trip based PM_{2.5} exposure quantification is proposed by using the product of duration time in each spatial unit and the concentration for that unit, which is showed in Equation (1). Similar approaches are observed in other human exposure studies (Tayarani et al., 2016; Rowangould et al., 2018).

$$HP_{PM_{2.5}} = \sum_i C(PM_{2.5})_i \times T_i \quad (1)$$

where $C(PM_{2.5})_i$ is the PM_{2.5} concentration level (ug/m³) of a census block i , T_i is the duration time of a bike trip in this block i , and $HP_{PM_{2.5}}$ is the health impact index (s*ug/m³) for this bikeshare trip.

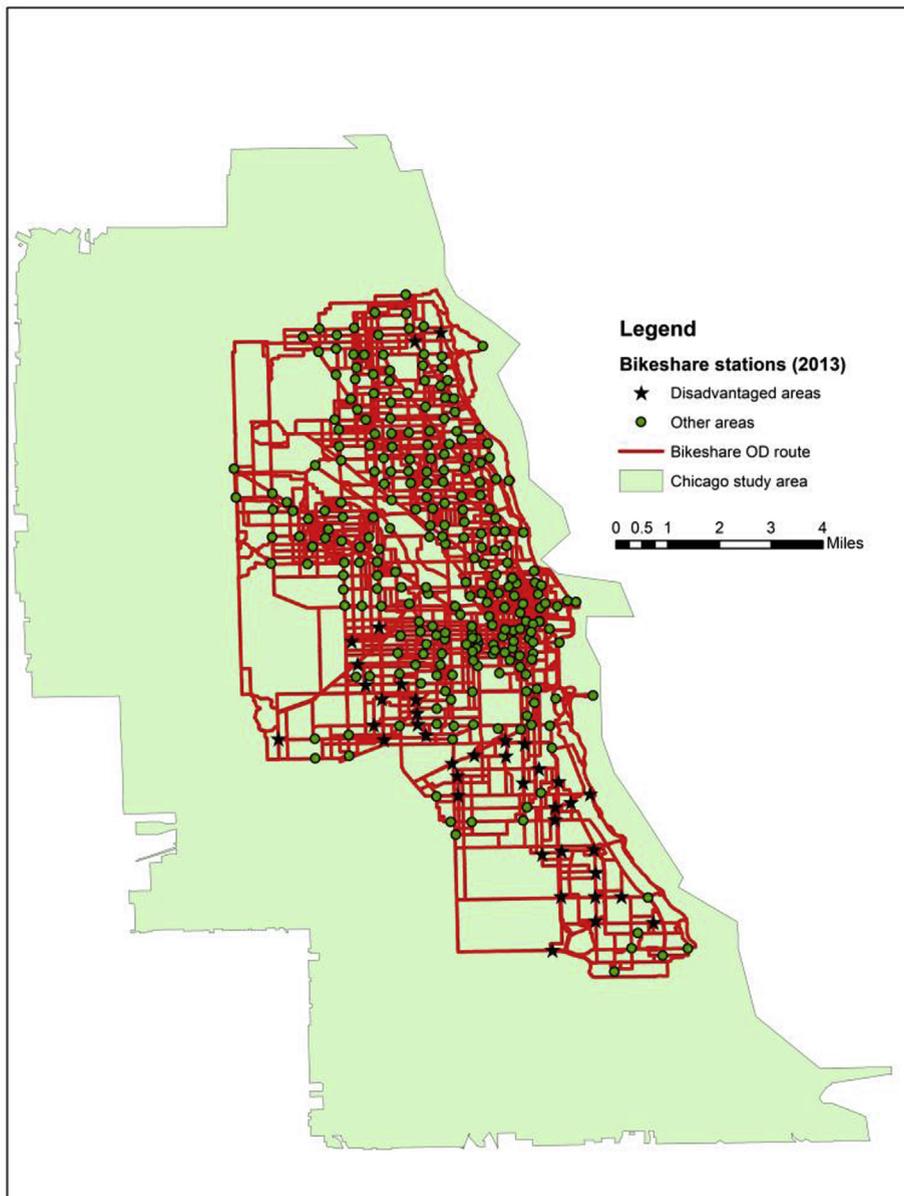


Fig. 4. Station distribution and OD routes.

4. Results

4.1. Air pollution in Chicago

MOVES is used to estimate the emission rates for each link. Meteorological files from the surface station at Chicago O'Hare International Airport, which is the closest station to the modeling domain. This meteorological data is used to determine the temperature and humidity required to calculate emissions.

In MOVES, PM_{2.5} emissions are estimated for vehicle exhaust, crankcase running exhaust, brake wear, and tire wear. The result is the composite emission rates (g/hour) for each roadway links. Those links are then considered as emission sources in the AERMOD model.

The Chicago O'Hare International Airport meteorological data are also used to estimate pollution dispersion. The processed hourly meteorological data (including temperature, humidity, wind, etc.) and roadway information for each link (including emission rates, longitude/latitude, angle, width, and length) are incorporated into AERMOD in the form of external files. Emissions from each link are traced to user-specific point virtual receptor locations in AERMOD. The dispersion of emissions from each link to each receptor is

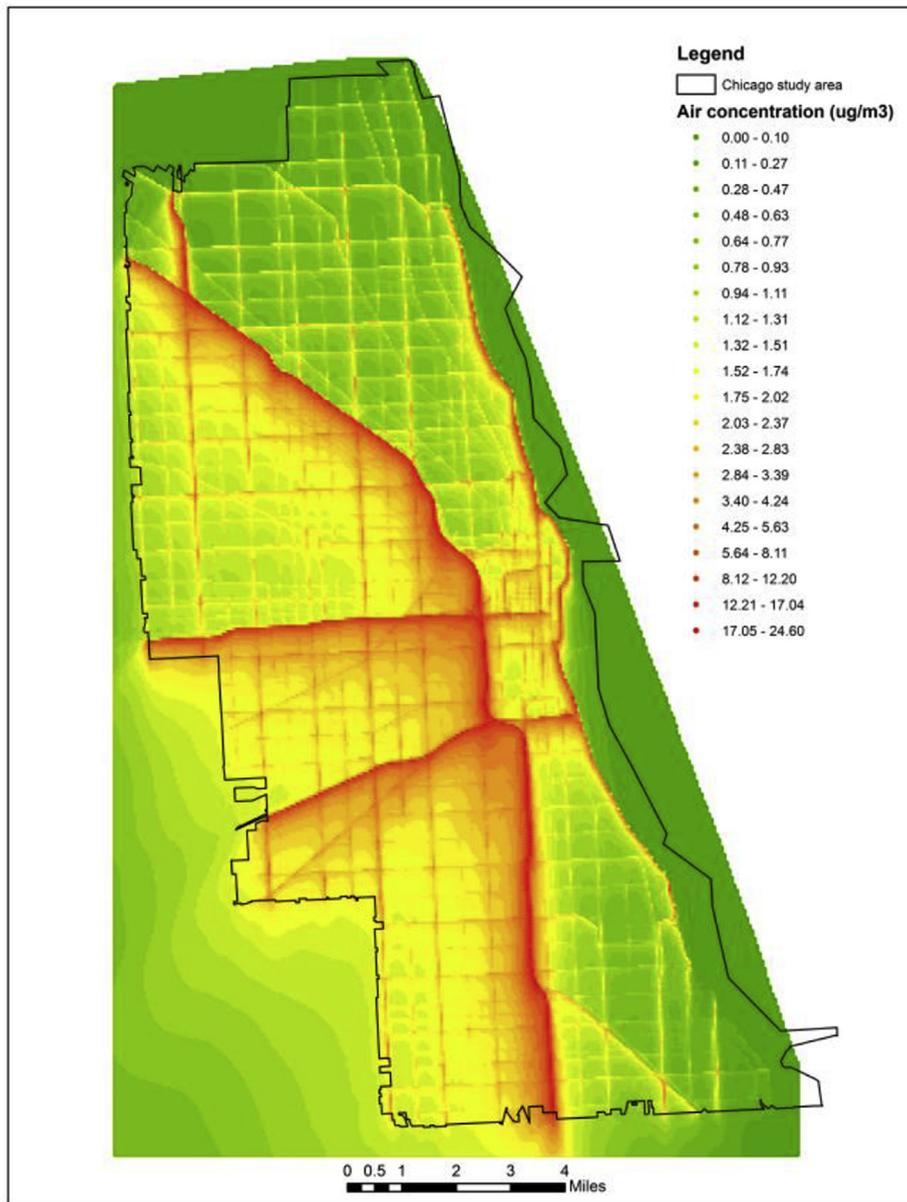


Fig. 5. Air concentration in Chicago.

modeled independently by AERMOD. Receptors are placed at an average human inhalation height of 1.8 m. Since the pollutant concentration varies along roadways to capture this heterogeneity receptors spaced at distances of 75 m within the case study domain (resulting in a total of 121,501 receptors). The results are the annual average PM_{2.5} concentration ($\mu\text{g}/\text{m}^3$) for each receptor and then aggregated to census block by averaging the receptors in each block. The results estimated by air quality modeling framework is showed in Fig. 5.

4.2. Trip-based PM_{2.5} exposure analysis

As mentioned in Section 3.3, we firstly divided every OD pair into several links by the boundaries of census blocks. A PM_{2.5} exposure index for every link is calculated using duration of trip in a census block and air concentration in this block (Equation (1)). After that, a sum of PM_{2.5} exposure index is assigned to every OD route as in the left panel in Fig. 6. Links with higher PM_{2.5} exposure index (the right panel in Fig. 6) have a significantly spatial overlap with high air pollution highway areas (Fig. 5). However, the PM_{2.5} exposure index for OD route is kind of different from that of links since a route may not include all links within high air pollution areas. Most of routes with high PM_{2.5} exposure index are distributed in the southwest of Chicago, where there are more

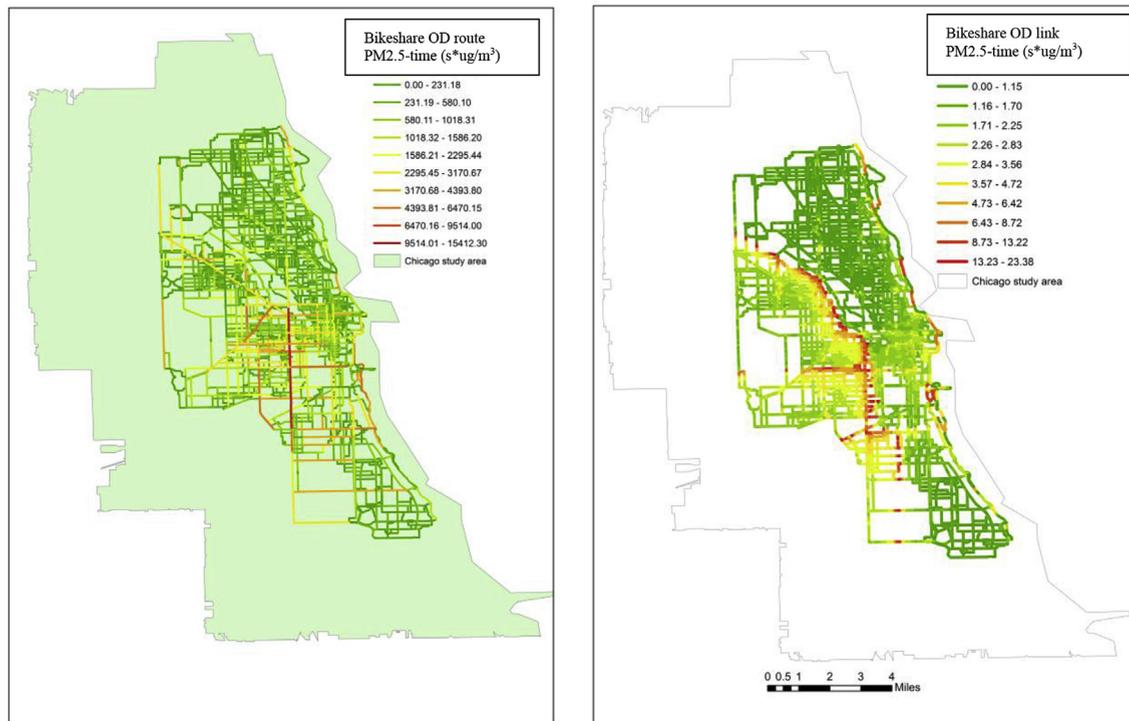


Fig. 6. PM2.5 exposure index for bikeshare OD links and routes in Chicago.

minority population or low-income communities.

Since we have two types of bikeshare stations (disadvantaged and other), there are four types of OD pairs: 1) disadvantaged areas to disadvantaged areas; 2) disadvantaged areas to other areas; 3) other areas to disadvantaged areas; 4) other areas to other areas. First, we show the health exposure of PM2.5 for every OD pair of different categories (Fig. 7). Trips both originating from and terminating in disadvantaged areas (Type 1) have the same level of health exposure with trips within other areas. However, if a user wants to travel between disadvantaged areas and other areas (Type 2 and 3), they will suffer from more serious air pollution exposure. This results from the geographic feature of the case study city, Chicago. Most of the stations in disadvantaged areas are located in the west and south of Chicago (Fig. 4). If users from disadvantaged areas want to bike to other areas, there is a high possibility that they need to cross the highway area, where the air pollution is more severe. In order to remove the influence of trip

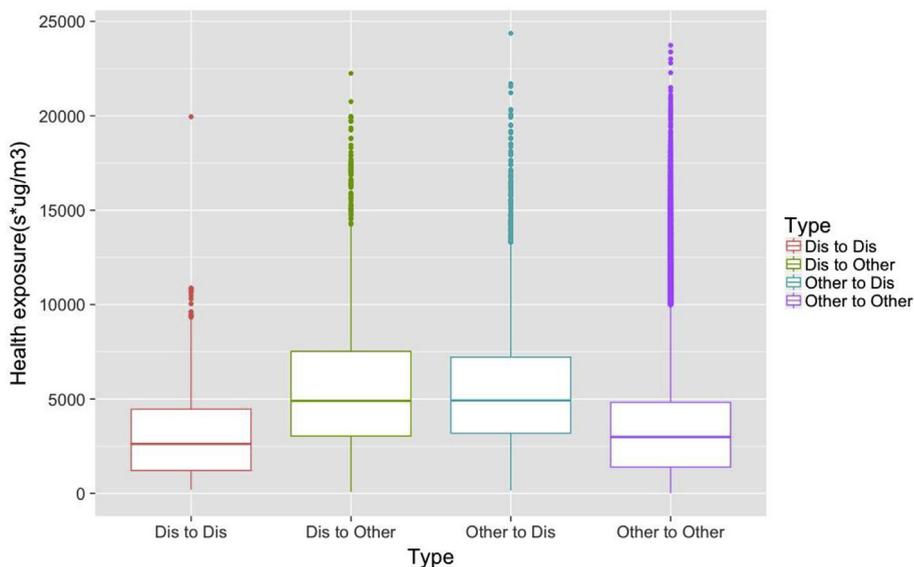


Fig. 7. Boxplot of route health exposure index by OD types (“Dis” stands for “Disadvantaged”).

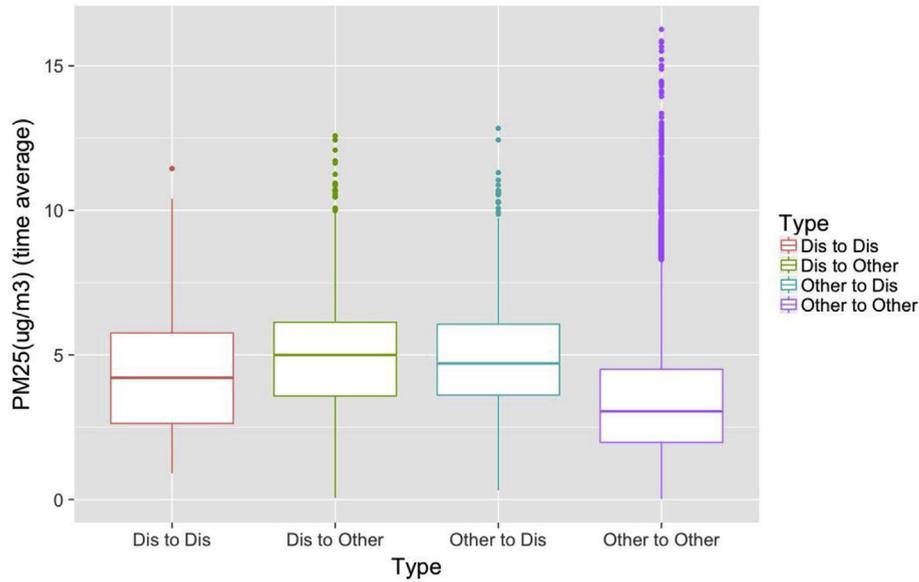


Fig. 8. Boxplot of route time-average health exposure index by OD types (“Dis” stands for “Disadvantaged”).

time on health impact assessment of bikeshare trips, we also calculated the time-average health exposure index for every OD pair (Fig. 8). The trips within disadvantaged areas have obvious higher time-average health impact than trips within other areas. The reason is that trip within disadvantaged areas are short trips and near high air pollution areas.

Thus, users will have to bear a risk of exposure to more air pollution if they plan to commute to other areas where there may be more job opportunities, more grocery stores, and better school, among many others. Unfortunately, they have no idea of the health risk when they are making a bike trip.

We calculated the average health impact weighted by trip for every bikeshare station (Fig. 9). As we can see, most of the stations in disadvantaged areas have a high level of health impact index on average. In terms of histogram (Fig. 10), the difference is more obvious. There may be a couple of reasons to explain for the difference in experiencing pollution exposure between disadvantaged areas and other areas. One obvious reason is that disadvantaged areas tend to be overlapped with areas with higher air pollution since the house price or living cost is lower there. Another reason is that insufficient exclusive bike paths in disadvantaged areas. Additionally, according to the Google Direction API estimation, most of the bikeshare trip routes in disadvantaged areas are closely along local vehicle roads. Users there will easily be exposed to pollution generated by on-road vehicles when riding a bike on vehicle roads.

5. Discussion

Since this research does not have true trip routes, readers may argue that the true bikeshare routes are not exactly the same with the those estimated by Google API. However, there is no information about the true trip routes. Even though there are travel time estimation errors by Google Direction API, existing research provides limited improvement of the estimation accuracy (Wu and Frias-Martinez, 2015). Under current situation, the Google Direction API can provide an acceptable estimation of bikeshare trip routes.

This study has shown that bikeshare trips originated from disadvantaged areas tend to have higher time-average PM2.5 exposure. There is one obvious reason that most of most of the bikeshare trip routes in disadvantaged areas estimated by Google Direction API overlap with state highways. As informed by the developer guide for Google Direction API, this API will return a shortest bicycling route via bicycle paths and preferred streets (where available). Because there is insufficient well-designed or exclusive bike paths in those disadvantaged areas, users there tend to cycle on vehicle roads, where there is high level of air concentration caused by on-road traffic. Currently, many researchers are concerned about access barriers for users from disadvantaged areas to enjoy bikeshare (Qian and Niemeier, 2019), (Buck, 2013), (Howland et al., 2017). However, without enough bicycle facility infrastructure, users there will have the risk of absorbing more PM2.5 when using bikeshare. Besides the health concern, there are also safety worry caused by unprotected bike paths (McNeil et al., 2017), which is beyond the scope of this paper. Thus, a promotion of bikeshare in disadvantaged areas should be after or at least in accompany with that bicycle infrastructure is well developed there.

6. Conclusions and future work

In this study, the health impacts of vehicular air pollution are at a fine-grained spatial scale (i.e. census block level), accounting for bikeshare user's route. The distribution of health impacts among bikeshare trips generated from/terminated at different demographic areas is evaluated by using proposed model framework and PM2.5 exposure assessment at the City of Chicago. Results show

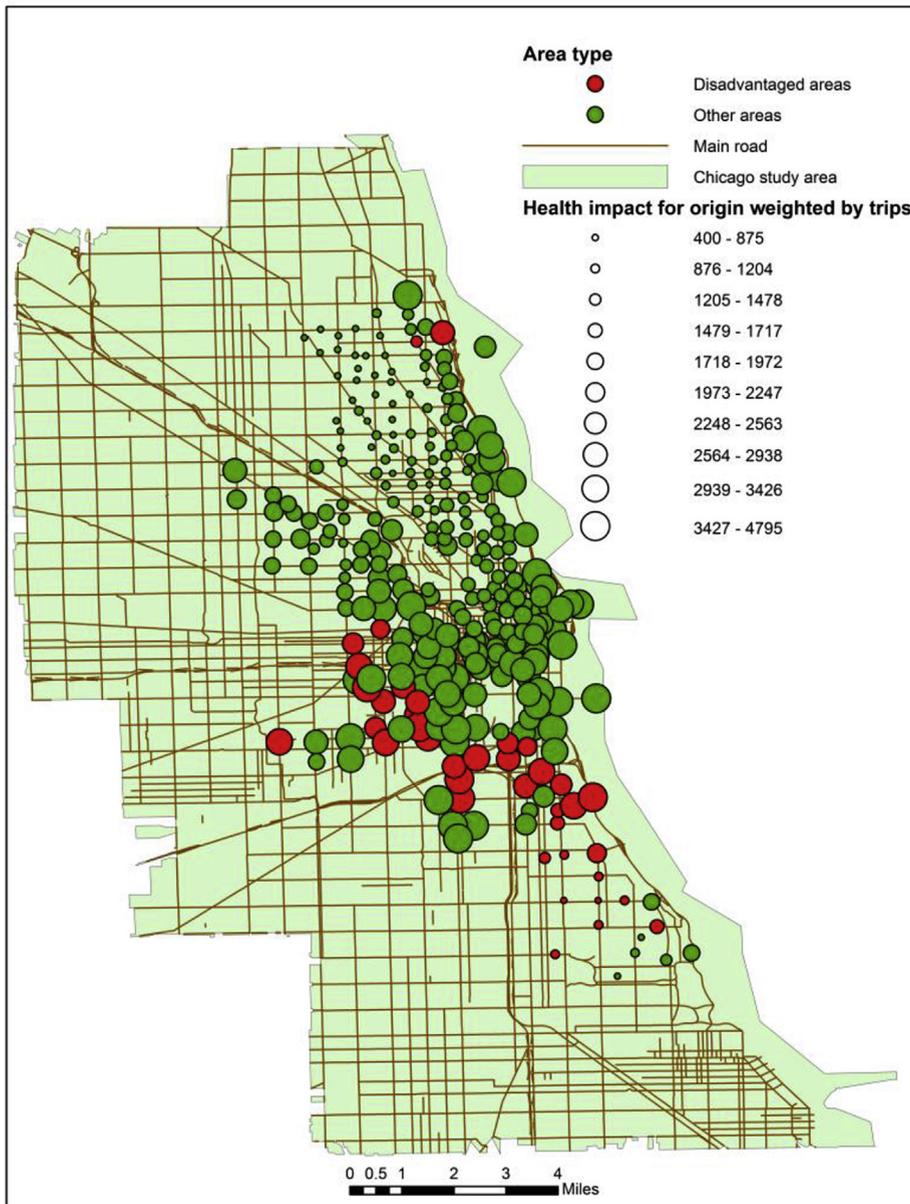


Fig. 9. Health impact at station level.

that the air pollution concentration have a greater value near the major corridor. In addition, we applied Google API to estimate the most potential routes for every OD pair. As we can see (Fig. 4), most of the bike routes are assigned along local vehicle routes and are away from the main interstate highways, which are the major air pollution sources. However, the bikeshare users still cannot avoid exposure to serious air pollution. We calculated human exposure by overlapping bikeshare trip route with PM_{2.5} concentration in census blocks. Overall, bikeshare trip near main highways have a higher human exposure to air pollution (i.e., PM_{2.5} in our case). Though, this trip-level PM_{2.5} exposure varies by where you start or end a bikeshare trip. It means that if a trip is originated from or terminated at a station in disadvantaged areas, the bikeshare user will be exposed to more serious air pollution, no matter in terms of whole-trip or time-average health exposure (Figs. 7 and 8). However, for residents in disadvantaged areas, travelling to other areas may mean access to more job opportunities or other essential services. Thus, disadvantaged population will, more likely, take a risk of a potential health impact if they use bikeshare frequently to commute to other areas. Our study does not mean that bikeshare is not suitable for disadvantaged areas. On the contrary, we want to remind our planners that promoting bikeshare in disadvantaged areas should be combined with air pollution control and infrastructure design. A well-planned exclusive bike paths to avoid air pollution areas and restricting serious air pollution sources there should be combined to address this equity issue raised by our study.

There are two main limitations in this research. First, this study is an empirical study on quantifying health impact of bikeshare

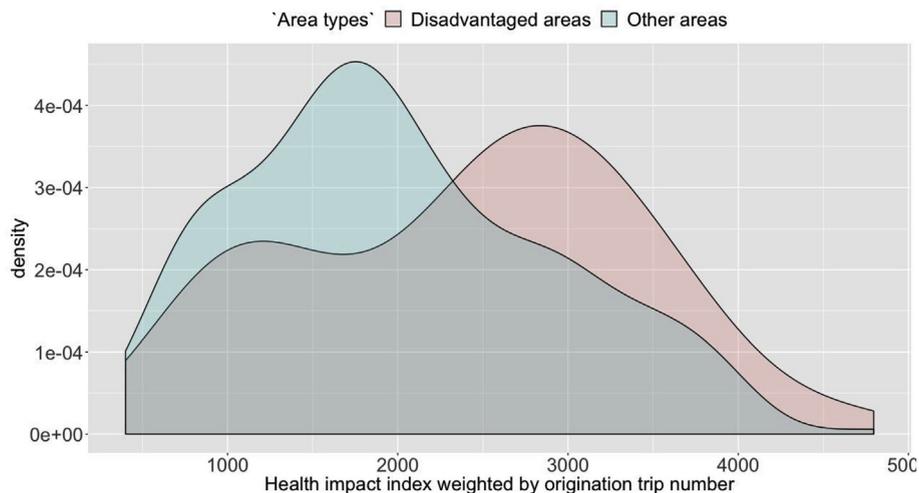


Fig. 10. Histogram of health impact weigh by origination trips.

trips. If time were allowed, a more comprehensive study with more case study cities and including all other pollution particulates could be carried on. Thus, the conclusions in this paper could be applied to other cities around the world. Secondly, there is a limitation in bikeshare data. Since the trajectory data for bikeshare trips are no available, we applied Google API to estimate the potential route for every OD pair. If we could get access to the true trip route information, we could conduct a more accurate analysis for health impact on bikeshare trips.

Author contributions

The authors confirm contribution to the paper as follows: conceptualization, X. Qian and Y. Wu; methodology, X. Qian and Y. Wu; formal analysis, X. Qian; data curation, X. Qian; writing—original draft preparation, X. Qian and Y. Wu; writing—review and editing, X. Qian and Y. Wu; visualization, X. Qian; supervision, X. Qian and Y. Wu; funding acquisition, Y. Wu.

Funding

This research was funded by the Fundamental Research Funds for the Central Universities #2019RC010.

Conflicts of interest

The authors declare no conflict of interest.

References

- Adamkiewicz, G., et al., Nov. 2011. Moving environmental justice indoors: understanding structural influences on residential exposure patterns in low-income communities. *Am. J. Public Health* 101 (S1), S238–S245.
- Barnes, G., 2004. The Benefits of Bicycling in Minnesota.
- Bell Michelle, L., Keita, Ebisu, Dec. 2012. Environmental inequality in exposures to airborne particulate matter components in the United States. *Environ. Health Perspect.* 120 (12), 1699–1704.
- Buck, D., 2013. Encouraging equitable access to public bikesharing systems. *Institute Transp. Eng. ITE J.* 83 (3), 24.
- Cavill, N.A., Davis, A., 2017. Cycling and Health; What's the Evidence? *Cycling England*.
- Cohen, A., 2016. Equity in Motion. Department of Urban Planning at the University of California, Los Angeles.
- Fishman, E., Washington, S., Haworth, N., 2012. Barriers and facilitators to public bicycle scheme use: a qualitative approach. *Transp. Res. F Traffic Psychol. Behav.* 15 (6), 686–698.
- Hao, J., Hatzopoulou, M., Miller, E., Nov. 2010. Integrating an activity-based travel demand model with dynamic traffic assignment and emission models. *Transp. Res. Rec.: J. Transp. Res. Board* 2176, 1–13.
- Hatzopoulou, M., Miller, E.J., Aug. 2010. "Linking an activity-based travel demand model with traffic emission and dispersion models: Transport's contribution to air pollution in Toronto. *Transp. Res. D Transp. Environ.* 15 (6), 315–325.
- HEAT Welcome to the health economic assessment tool (HEAT) for walking and cycling by WHO/europe. Available: <https://www.heatwalkingcycling.org/#homepage>.
- Howland, S., McNeil, N., Broach, J.P., Rankins, K., MacArthur, J., Dill, J., 2017. Breaking Barriers to Bike Share: Insights on Equity from a Survey of Bike Share System Owners and Operators.
- Integrated Transport and Health Impact Modelling Tool (ITHIM) The Centre for Diet and activity research. Available: <https://www.cedar.iph.cam.ac.uk/research/modelling/ithim/>, Accessed date: 8 July 2019.
- Jiang, Y., Ekono, M., Skinner, C., 2016. Basic facts about low-income children. In: National Center for Children in Poverty. Columbia University, New York.
- Karner, A., Eisinger, D., Niemeier, D., Jul. 2010. Near-roadway air quality: synthesizing the findings from real-world data. *Environ. Sci. Technol.* 44 (14), 5334–5344.
- Lovasi, G.S., Hutson, M.A., Guerra, M., Kathryn, N., 2009. Built environments and obesity in disadvantaged populations. *Epidemiol. Rev.* 31 (1), 7–20.
- Maizlish, N., Woodcock, J., Co, S., Ostro, B., Fanai, A., Fairley, D., 2013. Health cobenefits and transportation-related reductions in greenhouse gas emissions in the San

- Francisco Bay area. *Am. J. Public Health* 103 (4), 703–709.
- McNeil, N., Dill, J., MacArthur, J., Broach, J., 2017. Breaking Barriers to Bike Share: Insights from Bike Share Users.
- Morello-Frosch, R., Zuk, M., Jerrett, M., Shamasunder, B., Kyle, A.D., May 2011. Understanding the cumulative impacts of inequalities in environmental health: implications for policy. *Health Aff.* 30 (5), 879–887.
- Motivate International, 2017. Divvy for Everyone (D4E).
- Nachman, K.E., Parker, J.D., Apr. 2012. Exposures to fine particulate air pollution and respiratory outcomes in adults using two national datasets: a cross-sectional study. *Environ. Health* 11 (1), 25.
- Niemeier, D., Qian, X., 2018. High Impact Prioritization of Bikeshare Program Investment to Improve Underserved Communities' Access to Jobs and Essential Services.
- Oja, P., et al., 2011. Health benefits of cycling: a systematic review. *Scand. J. Med. Sci. Sport.* 21 (4), 496–509.
- Poorfakhraei, A., Tayarani, M., Rowangould, G., Sep. 2017. Evaluating health outcomes from vehicle emissions exposure in the long range regional transportation planning process. *J. Transp. Health* 6, 501–515.
- Qian, X., Niemeier, D., Apr. 2019. “High impact prioritization of bikeshare program investment to improve disadvantaged communities' access to jobs and essential services. *J. Transp. Geogr.* 76, 52–70.
- Rojas-Rueda, D., de Nazelle, A., Tainio, M., Nieuwenhuijsen, M.J., Aug. 2011. The health risks and benefits of cycling in urban environments compared with car use: health impact assessment study. *BMJ* 343, d4521.
- Rowangould, G.M., 2013. A census of the US near-roadway population: public health and environmental justice considerations. *Transp. Res. D Transp. Environ.* 25, 59–67.
- Rowangould, G.M., Jan. 2015. A new approach for evaluating regional exposure to particulate matter emissions from motor vehicles. *Transp. Res. D Transp. Environ.* 34, 307–317.
- Rowangould, D., Rowangould, G., Niemeier, D., 2018. Evaluation of the health impacts of rolling back a Port clean trucks program. In: Presented at the Transportation Research Board 97th Annual Meeting/Transportation Research Board.
- Shaheen, S., Guzman, S., Zhang, H., 2010. Bikesharing in europe, the americas, and asia: past, present, and future. *Transp. Res. Rec.: J. Transp. Res. Board* 2143, 159–167.
- Steinle, S., Reis, S., Sabel, C.E., Jan. 2013. “Quantifying human exposure to air pollution—moving from static monitoring to spatio-temporally resolved personal exposure assessment. *Sci. Total Environ.* 443, 184–193.
- Tainio, M., et al., 2016. Can air pollution negate the health benefits of cycling and walking? *Prev. Med.* 87, 233–236.
- Tayarani, M., Poorfakhraei, A., Nadafianshahamabadi, R., Rowangould, G.M., Dec. 2016. Evaluating unintended outcomes of regional smart-growth strategies: environmental justice and public health concerns. *Transp. Res. D Transp. Environ.* 49, 280–290.
- U. S. Department of Health and Human Services, 2016. Computations for the 2016 Poverty Guidelines.
- Wang, M., Zhou, X., 2017. Bike-sharing systems and congestion: evidence from US cities. *J. Transp. Geogr.* 65, 147–154.
- Woodcock, J., Givoni, M., Morgan, A.S., Jan. 2013. Health impact modelling of active travel visions for england and wales using an integrated Transport and health impact modelling tool (ITHIM). *PLoS One* 8 (1), e51462.
- Woodcock, J., Tainio, M., Cheshire, J., O'Brien, O., Goodman, A., Feb. 2014. Health effects of the London bicycle sharing system: health impact modelling study. *BMJ* 348, g425.
- Wu, M., Frias-Martinez, V., 2015. Crowdsourcing biking times. In: Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers, pp. 1123–1131 New York, NY, USA.