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Reducing pedestrians' inhalation of traffic-related air pollution through route choices: Case study in California suburb

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ABSTRACT

Pedestrians often face risks of inhaling a high amount of traffic-related air pollution due to their proximity to the emission sources and increased breathing rates during walking. This paper presents an innovative way for pedestrians to mitigate such risks. Specifically, a method for incorporating the estimated inhaled mass of fine particles ($PM_{2.5}$) into walking route calculations was developed, and the calculated low air pollution inhalation route was compared against the traditional shortest duration route. For the case study of a suburban road network in Riverside, California, a low inhalation route could be found for 4% of the simulated walking trips in both morning and afternoon periods. In the morning period, the low inhalation routes would reduce a pedestrian's inhalation of traffic-related primary $PM_{2.5}$ by 48% while increasing the walking duration by only 2% on average. Similarly, in the afternoon period, the low inhalation routes would reduce the inhalation by 44% while increasing the walking duration by merely 1% on average. These results indicate that if people who choose to walk can accommodate a slight increase in walking duration in some of their walking trips, they can substantially reduce the inhalation of traffic-related primary $PM_{2.5}$ on those trips. The presented concept of low air pollution inhalation route can be enhanced by the integration of real-time traffic, weather, and even roadside air quality data to result in navigation applications for pedestrians. This may be particularly important for sensitive population groups such as school-aged children and seniors.

1. Introduction

Active transportation modes, such as walking and bicycling, are key elements of sustainable transportation systems. Walking is advocated as a way to reduce automobile dependency, foster community livability, and boost the local economy. From a health perspective, walking and bicycling help keep fitness and improve public health (Laverty et al., 2013; Schepers et al., 2015). However, with increasing motor vehicle traffic, pedestrians often find themselves walking by streets with heavy traffic and are exposed to various traffic emissions, such as nitrogen dioxide (NO_2) and fine particles ($PM_{2.5}$). Exposure to air pollutants has been shown to contribute to a range of health problems. Furthermore, roadside measurements have revealed that concentration of traffic-related air pollutants is elevated near roadways (Zhu et al., 2006; Hu et al., 2009). Among the various road users, pedestrians face risks of higher exposure of particle and gaseous emissions due to their increased breathing rate during walking (O'Donoghue et al., 2007; Quiros et al., 2013) as well as the longer time it takes to travel the same distance (for short trips within 3 miles), when compared with drivers and transit riders.

For the issue of travelers' exposure to air pollution, one area of research is measuring air pollutant concentration in the

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microenvironment of different transportation modes such as driving, walking, and bicycling (van Wijnen et al., 1995; Ragettli et al., 2013; Karanasiou et al., 2014). Some studies went a step further by quantifying the exposure of air pollutants for travelers based on measured or modeled air quality data (Ishaque and Noland, 2008; Gouge et al., 2010; Quiros et al., 2013; Shekarrizfard et al., 2016). For example, Quiros et al. (2013) used a portable instrument to measure ultrafine particle (UFP) concentration and calculated UFP inhalation of drivers, bicyclists, and pedestrians. The results indicated that respiratory UFP exposure (number of particles inhaled per trip) was 30 times higher when walking as compared to driving with windows closed. Dewulf et al. (2016) and Sun et al. (2017) utilized GPS data to assess the pollutant inhalation of active travelers at high temporal and spatial resolution. Another area of research attempts to explain and predict travelers' exposure to traffic-related air pollution (Hatzopoulou et al., 2013a; Bigazzi and Figliozzi, 2015). For example, Bigazzi and Figliozzi (2015) estimated the effects of roadway and travel variables on bicyclist exposure concentration, controlling for meteorology and background conditions. Bigazzi et al. (2016) analyzed exposure versus distance trade-offs among roadway facility types for bicyclists, and recommended that low-traffic routes should be provided in bicycle networks. Schepers et al. (2015) found that the introduction of bicycle paths and lanes, even along busy roads with mixed traffic, is likely to be associated with health benefits, primarily due to increased physical activity.

Building on the measurement and modeling studies, several researchers have attempted to develop mitigation strategies (Hertel et al., 2008; Hatzopoulou et al., 2013b; Pattinson et al., 2017), but only a few have proposed mitigation strategies that pedestrians can proactively use to protect themselves from excessive traffic emission exposure. For instance, individuals were encouraged to use less-busy street routes to reduce their exposure to vehicle emissions (McAuley and Pedroso, 2012). However, a less-busy street route may not necessarily have a lower level of air pollutant concentration, for example, if it is downwind of a major roadway with heavy traffic. Moreover, while information about air quality in U.S. cities is available (e.g., on http://www.airnow.gov/), it does not have adequate resolution to support pedestrians' route choice decisions.

In recent years, route planning and navigation tools that find travel routes between an origin and a destination are widely available. These tools are available on several platforms (e.g., web-based tool, smartphone app, etc.) and for many travel modes including auto, transit, and walking. As an example, Fig. 1 illustrates the web-based Google Map navigation tool for determining walking routes (https://www.google.com/maps). The suggested route options are usually the shortest in terms of walking distance or walking time. In the example in Fig. 1, the tool provides three different route options for a walking trip from home to school in Riverside, California, that have the same walking distance and walking time. However, these routes may not result in the same amount of traffic-related air pollution inhalation for the pedestrian. Based on the authors' knowledge of the area, Magnolia Ave is a major arterial with heavy traffic. Thus, the pedestrian would likely inhale a higher amount of air pollution if taking the blue dotted route. Also, parallel to Magnolia Ave to the south is State Route 91 (SR-91) that carries high volumes of traffic and is often congested. When the wind blows in the northwest direction, the blue dotted route would likely experience higher air pollutant concentration levels due to its close proximity to this major emission source. Therefore, for this particular trip, the pedestrian may inhale a lower amount of air pollution taking one of the two gray solid routes.

The main objective of this study is to determine whether and how much route choices, such as the one discussed earlier, can help reduce pedestrians' inhalation of traffic-related air pollution. In relation to that, another objective of this study is to evaluate the

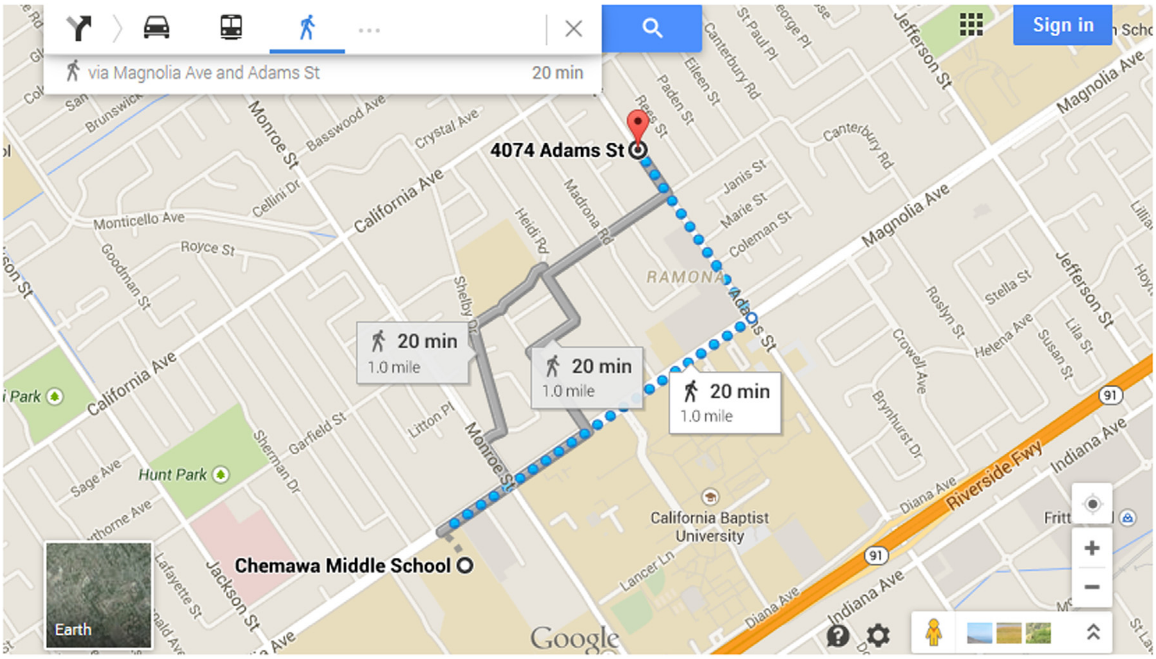

Fig. 1. Three walking route options for a home-to-school trip in Riverside, California (source: https://www.google.com/maps).

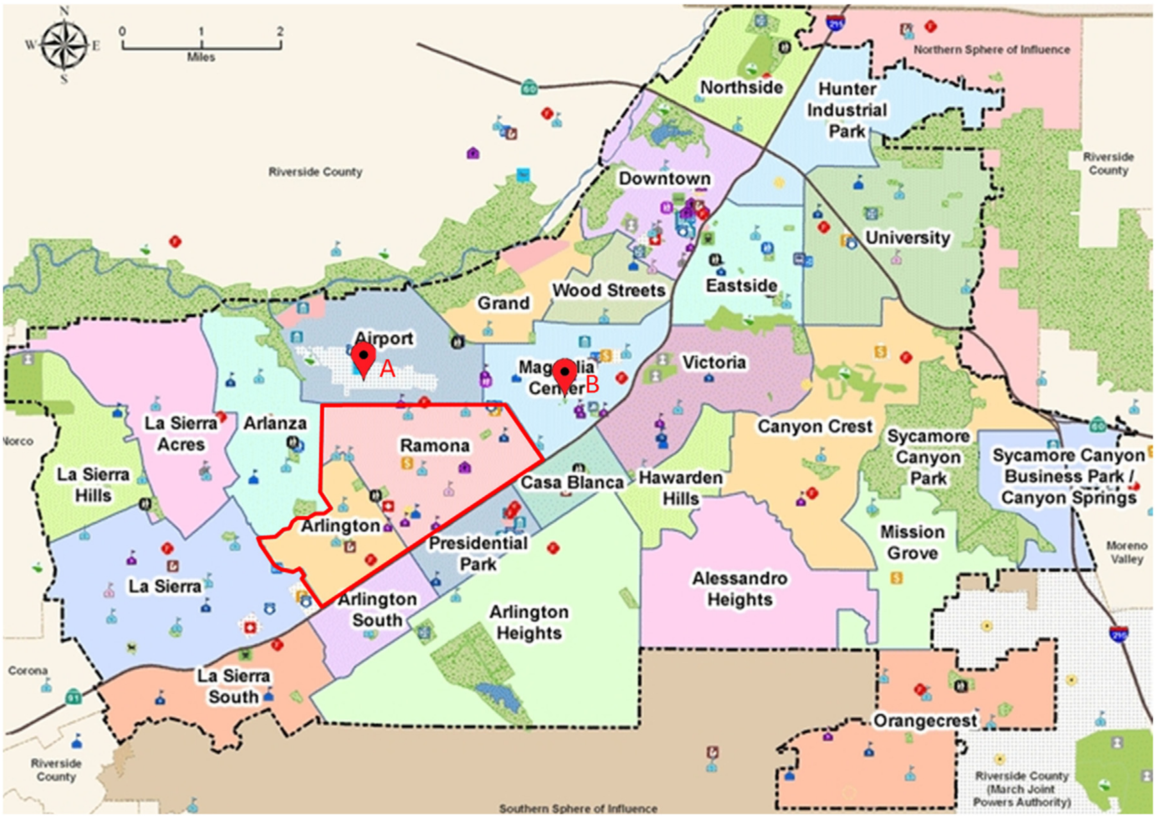

Fig. 2. Neighborhoods in Riverside, California (credit: City of Riverside). Point A and Point B mark the weather station and the air quality monitoring station used in this study, respectively.

travel time impact of taking a lower air pollution inhalation route as opposed to the traditional shortest distance or shortest duration routes. To meet these objectives, we opted for a modeling approach (instead of a measurement approach) so that the study could be conducted for a large number of walking trips. We chose the Ramona neighborhood and the adjacent Arlington neighborhood in the suburb of Riverside, California, as the study area. The city is generally automobile-centric and at the time of the study, the two neighborhoods were engaged in a walkability improvement project led by the city (Center for Sustainable Suburban Development, 2013). The neighborhoods have well-connected long street blocks with sidewalk and mature tree canopies present for most arterials (Riverside Neighborhood Walkability Recommendations, 2014). Fig. 2 maps the location of the neighborhoods and two nearby air quality monitor stations, which provide critical inputs for the air pollutant concentration modeling and validation.

Note that in this study, we only considered primary $PM_{2.5}$ because even short-term exposure to this pollutant can trigger changes in several health indicators (Larsson et al., 2007; McCreanor et al., 2007; Weichenthal et al., 2014; Sinharay et al., 2017). We focused on primary $PM_{2.5}$ instead of secondary $PM_{2.5}$, because traffic is the principal source of spatial variation in the concentration of air pollutants in cities, especially where moderate or large point sources are located outside the area or are subject to strict emissions controls (Jerrett et al., 2005). We studied only the morning and afternoon peak periods (for calendar year 2014) as traffic and walking activities were relatively higher in these periods of the day.

2. Modeling street-level air pollutant concentration

The first part of the study was to model traffic-related air pollutant concentration in the study area at the street level so that pedestrians' inhalation of the air pollution could be estimated. The concentration prediction process involves multiple steps as shown in Fig. 3. First, a digital map of roadway network was used as input for a traffic model to estimate traffic activity, in terms of flow and

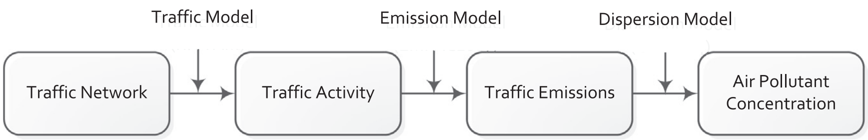

Fig. 3. Traffic-related air pollution modeling process.

speed, on each roadway link in the network. Then, the estimated traffic flow and speed were used in conjunction with an emission model to estimate the corresponding traffic emissions on each roadway link. Finally, these emission estimates were input into a dispersion model to estimate air pollution concentration at receptor locations.

2.1. Traffic activity and emissions modeling

Traffic activity data (in terms of traffic volume and speed in the calendar year 2014) on 743 roadway links which cover the study area were obtained directly from the Riverside County Transportation Analysis Model (RIVTAM) (Riverside County Transportation Department, 2008). The data were available for four periods: morning (AM; 6–9 a.m.), midday (MD; 9 a.m. to 3 p.m.), afternoon (PM; 3-7 p.m.), and nighttime (NT; 7 p.m. to 6 a.m.). Traffic volume data include separate values for six vehicle types: 1) DA - passenger car driving alone, 2) SR2 - passenger car shared ride with 2 persons, 3) SR3 - passenger car shared ride with 3 or more persons, 4) LHDT - light-heavy duty trucks, 5) MHDT - medium-heavy duty trucks, 6) HHDT - heavy-heavy duty trucks. Total volume was the summation of the volumes of all the six vehicle types (Fig. 4). On the other hand, traffic speed data only has one value that represents the speed of all vehicle types.

Next, emission factors were obtained from the California Air Resources Board's EMFAC model version 2011 (California Air Resources Board, 2016c) for the fleet composition in Riverside County in 2014. EMFAC is the regulatory emission model for California. $PM_{2.5}$ emission factors for speed from 5 mph to 70 mph were obtained for multiple vehicle categories in EMFAC, which were then matched with vehicle types in RIVTAM. After that, the total $PM_{2.5}$ emission on each roadway link was calculated using Eq. (1):

$$E_i = \sum_j q_{i,j} \bullet e(v_i)_j \;\forall\; i = 1, 2, 3, \ldots, 743 \tag{1}$$

where E_i is total emission on roadway link i (grams); $q_{i,j}$ is volume of vehicle type j on roadway link i (vehicles per hour); and $e(v_i)_j$ is emission factor of vehicle type j for the speed on roadway link i (grams per mile). The calculation was performed for all the roadway links not only in but also around the study area so that the effect of traffic-related air pollution carried into the study area by wind would be accounted for.

2.2. Air pollutant concentration modeling

CALINE4 (California Department of Transportation, 2016) was used to model $PM_{2.5}$ concentration in the study area. It is a line source dispersion model designed to estimate traffic-related air pollution near transportation facilities. CALINE4 is based on the Gaussian diffusion equation and employs a mixing zone concept to characterize pollutant dispersion over the roadways. It requires an array of model inputs related to roadway (e.g., type, coordinates, height, mixing zone width), receptor (e.g., coordinates, height), traffic (e.g., link flow, link emission factor), and meteorology (e.g., wind speed and direction, air temperature, stability class).

Meteorology inputs were obtained from the March Air Reserve Base weather station 300 m north of the study area, shown as Point A in Fig. 2 (California Air Resources Board, 2016b). As an example, Fig. 5 shows wind roses derived from the weather data for the entire year of 2012 (newer data were not available at the time of the study). On average, the weather data show that the air temperature peaked and the humidity reached the lowest point around 2:00 p.m. The wind speed increased significantly in the afternoon compared with that in the morning. This is a good representation of inland Southern California weather, where strong solar radiation during noon time drastically increases surface temperature, which induces more atmospheric turbulence.

To estimate high-resolution primary vehicular $PM_{2.5}$ concentration values at the street level, receptors were set up as a 50 m × 50 m gridded network at the height of 1.5 m. It yielded 18,300 receptors in the study area with 743 roadway links. For other modeling input parameters, roughness length (30 cm) was based on surface characteristics of the city of Riverside (South Coast Air Quality Management District, 2016). Molecular weight, setting velocity, deposition velocity values were all zero. One-hour average concentration was needed, so the average period was set as one. Altitude for all receptors were retrieved from a digital elevation map database (U.S. Geological Survey, 2016), and extracted using ArcMap raster process tools (ESRI, 2016a). All data were written into matrices and saved in comma-separated values (CSV) files.

Since CALINE4 allows only 20 roadway links and 20 receptors to be modeled at a time, several thousands of model runs were executed in batch mode using a MATLAB script (Mathworks, 2016). For each receptor, the modeled $PM_{2.5}$ concentration values from all the model runs were summed together to result in the total $PM_{2.5}$ concentration estimate.

Due to the limited resources for the study, it was not practical to conduct expansive measurements of $PM_{2.5}$ concentrations over the study area. To evaluate the reasonableness of the modeling results, we obtained historical $PM_{2.5}$ measurement data from the government's air quality monitoring station closest to the study area, i.e., Point B in Fig. 2 (California Air Resources Board, 2016a), which is about 600 m away from the SR-91 freeway. The median observed $PM_{2.5}$ concentration values by period of day are shown in Fig. 6 where the concentration is highest during the morning period and lowest during the afternoon period. Fig. 6 also shows the median values of estimated $PM_{2.5}$ concentration by period of day at the same location, which have the same trend as the observed values. The differences in the magnitude of concentration are partly because the observed concentration values are the total ambient concentration contributed by all the emission sources whereas the estimated values only account for traffic sources. Nevertheless, these values agree with findings in the literature that generally in urbanized areas in the United States, traffic contributes to about a quarter or less of the total ambient $PM_{2.5}$ concentration (e.g., Karagulian et al., 2015).

The estimated $PM_{2.5}$ concentration values at the receptors were used to create concentration contour maps (Fig. 7) using the Kriging tool in ArcMap software (ESRI, 2016b). Although the traffic flows in both periods were similar, $PM_{2.5}$ were generally lower in

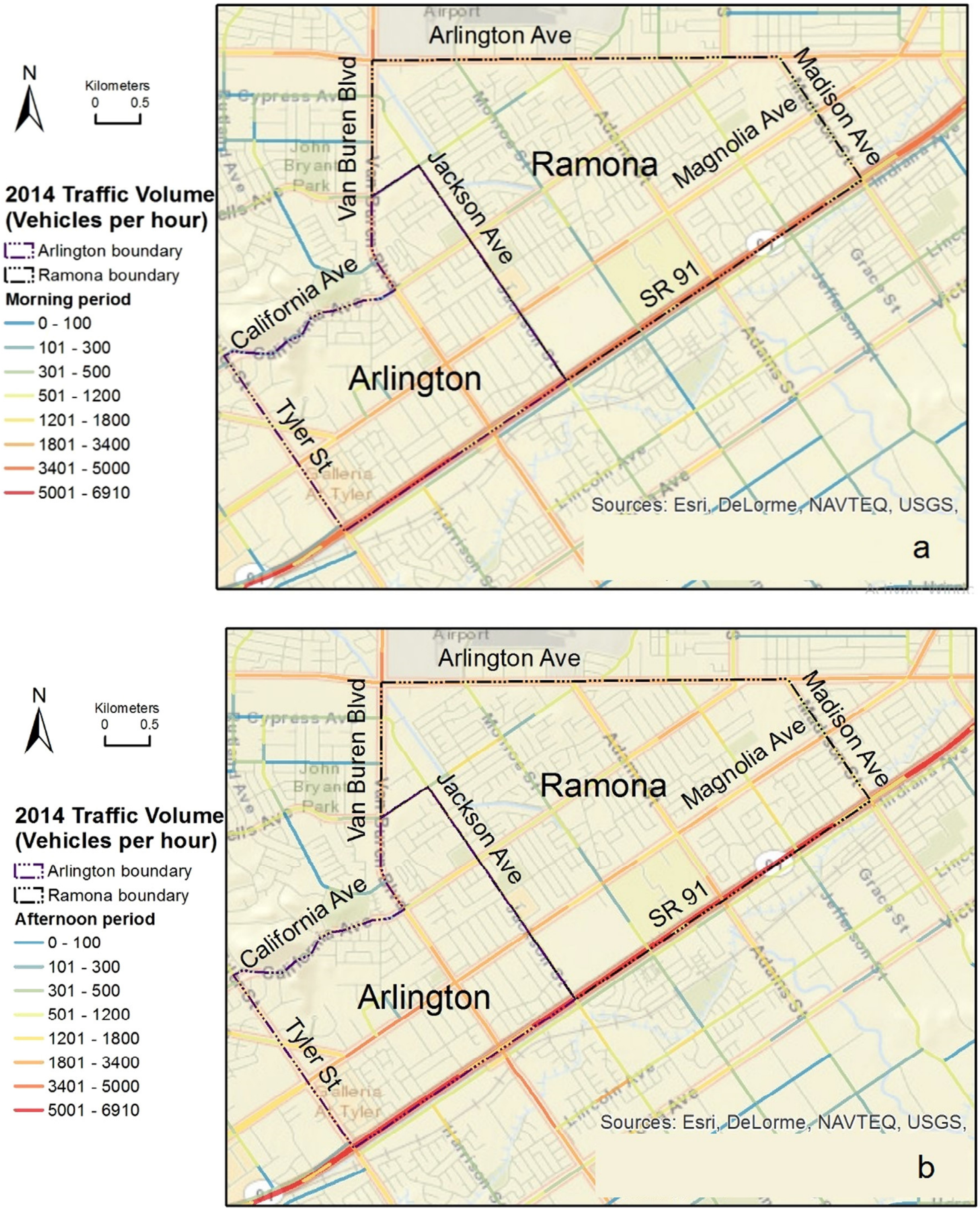

Fig. 4. Total volume (vehicles per hour) for morning (a) and afternoon (b) periods.

the afternoon than in the morning. In the morning the high concentration plume from the SR-91 freeway was approximately one kilometer wide, while in the afternoon the plume only spread a couple of hundred meters from the freeway. The contour maps were used to calculate $PM_{2.5}$ concentration on each roadway link by averaging the values at the starting, mid, and ending points of the link.

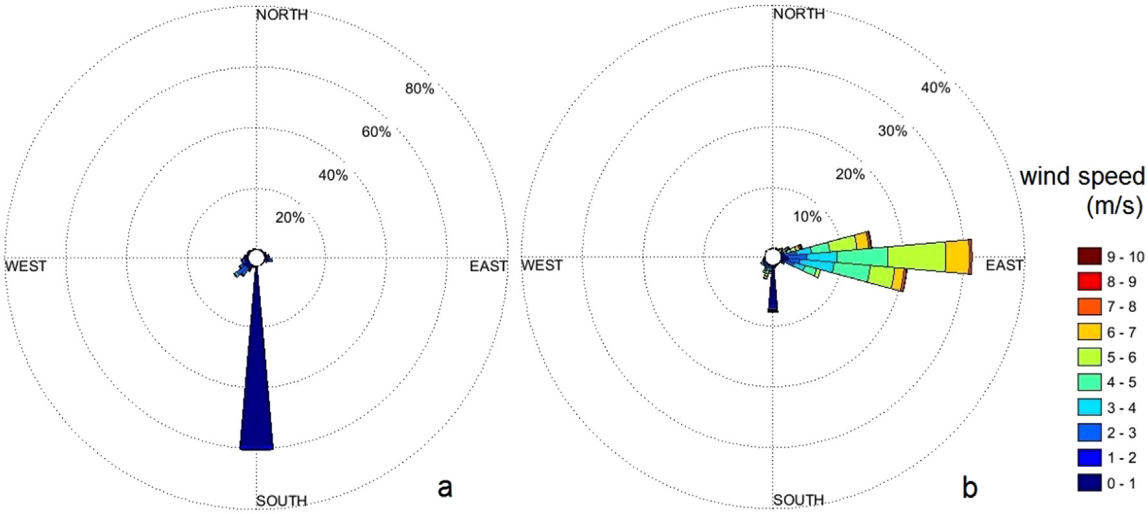

Fig. 5. Wind directions during the morning (a) and afternoon (b) periods for year 2012.

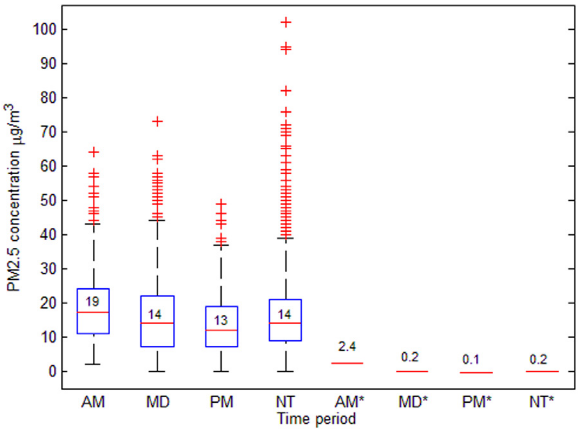

Fig. 6. Comparison of variation in median $PM_{2.5}$ concentration by period of day between observed values (AM, MD, PM, NT) and estimated values (AM*, MD*, PM*, NT*) for year 2014.

3. Evaluating impact of route choices on pedestrians' air pollution inhalation

3.1. Estimating pedestrians' inhalation of traffic-related air pollution

Studies of human exposure to traffic-related air pollution mostly focus on inhalation intake in specific microenvironments (Ott et al., 2006, Quiros et al., 2013). Several exposure models have been developed and used by researchers and practitioners. For example, the Hazardous Air Pollutant Exposure Model (HAPEM), developed by the U.S. Environmental Protection Agency, is designed to simulate long-term and large-scale exposure to air toxics (U.S. Environmental Protection Agency, 2016). Since the exposure scenario in this study is a pedestrian's direct exposure to out-of-tailpipe $PM_{2.5}$ in a near-road outdoor microenvironment, we used inhaled mass as a metric to quantify the level of exposure. It is a function of $PM_{2.5}$ concentration during the trip, duration of the trip, and breathing rate of the pedestrian. In this study, $PM_{2.5}$ concentration was estimated for each roadway link. Therefore, inhaled mass of $PM_{2.5}$ for pedestrian k walking on roadway link i can be expressed as in Eq. (2), assuming that the breathing rate of the pedestrian remains the same throughout the roadway link.

$$IM_{i,k} = c_i \bullet t_{i,k} \bullet BR_{i,k} \quad (2)$$

where IM is inhaled mass of $PM_{2.5}$ (μg); c is $PM_{2.5}$ concentration (μg/m^3); t is walking duration (minutes); BR is breathing rate of the pedestrian (m^3/minute). The walking duration on a roadway link was calculated based on the link length (*meters*) and the assumed walking speed of an average pedestrian–1.2 m/s (Knoblauch et al., 1996; Lam and Cheung, 2000; Fitzpatrick et al. 2006). The breathing rate of an average pedestrian is assumed to be 0.02 m^3/min based on health studies (Adams, 1993).

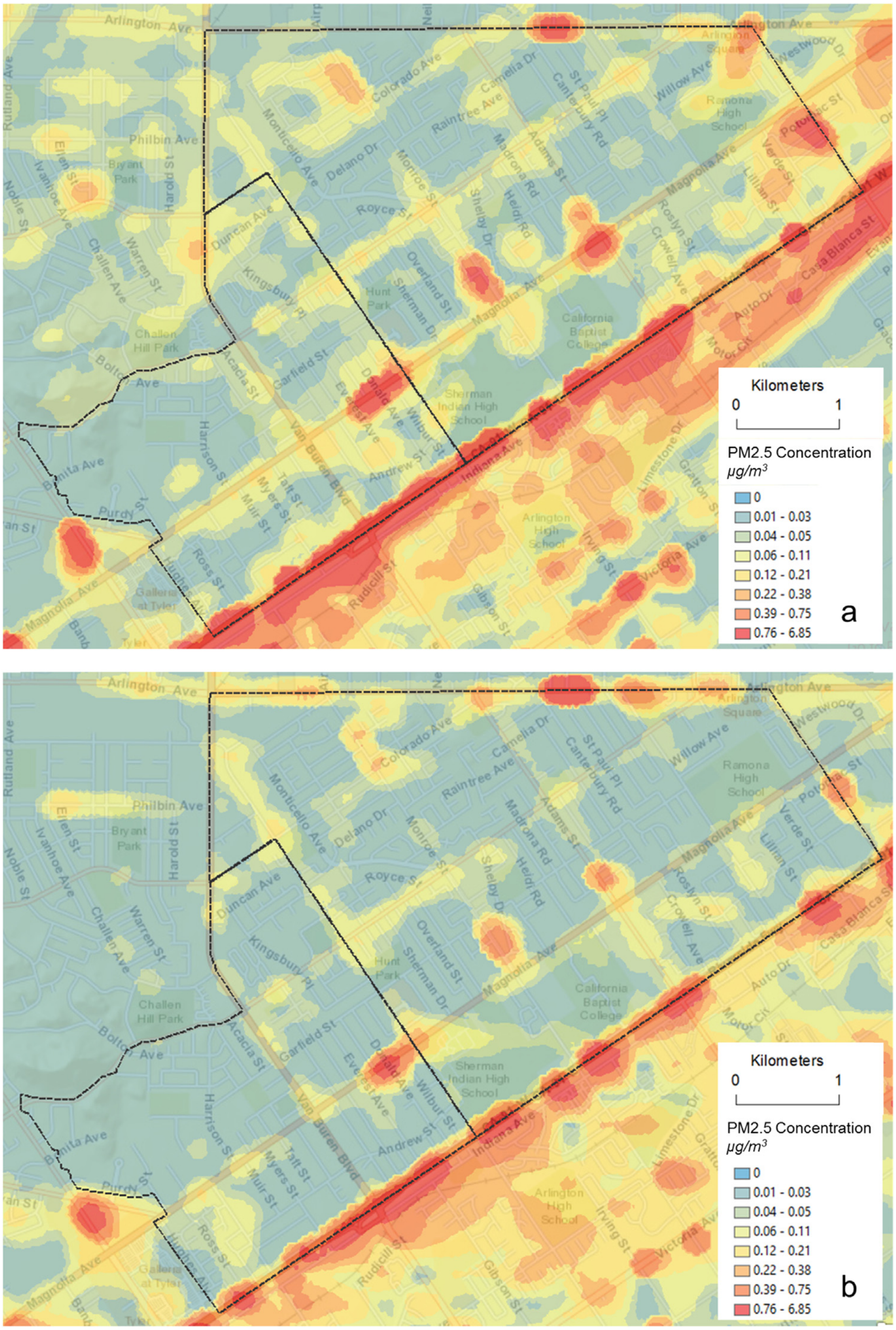

Fig. 7. Estimated $PM_{2.5}$ concentration contour maps for morning (a) and afternoon (b).

3.2. Incorporating pedestrians' pollution inhalation into route calculation

In general, routing algorithms find a route in the road network that has the lowest travel costs defined by a cost function. In the case of traditional routing, travel distance or duration is often used as the single cost in route calculation. Because walking speed is typically assumed to be a constant, the shortest distance and shortest duration routes for pedestrians are essentially the same. In this study, pedestrians' air pollution inhalation was incorporated into the route calculation by including estimated inhaled mass of $PM_{2.5}$, in addition to walking duration, in the cost function:

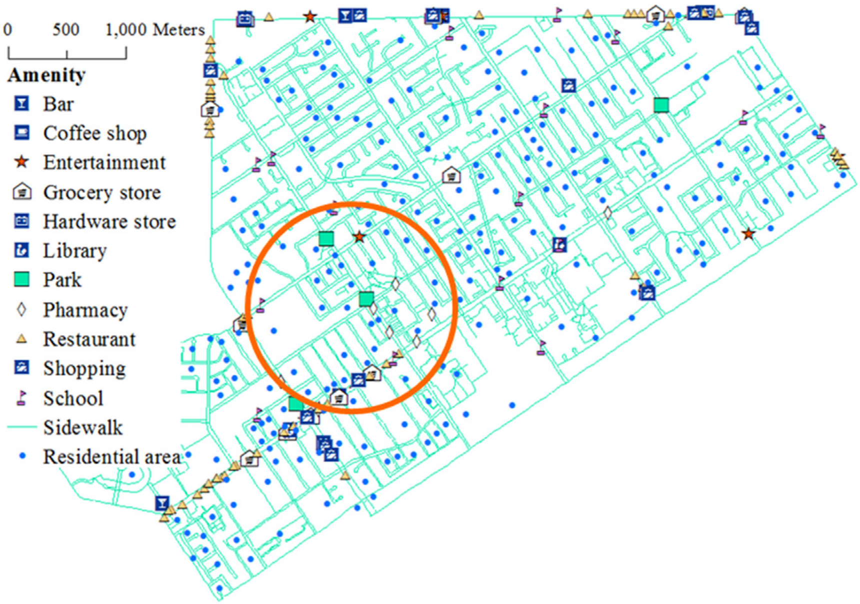

Fig. 8. Location of homes and amenities used in routing experiment.

$$Cost_i = w \bullet IM_i' + (1-w) \bullet t_i' \tag{3}$$

$$IM_i' = \frac{IM_i}{IM_{max}} \tag{4}$$

$$t_i' = \frac{t_i}{t_{max}} \tag{5}$$

where $Cost_i$ is the travel cost of roadway link i; w is weighting factor; IM_{max} is the maximum value of the estimated inhaled mass of $PM_{2.5}$ among all the roadway links (μg); and t_{max} is the maximum walking duration among all the roadway links (minutes). If w is set as 0, then the route calculation will yield the traditional shortest duration route. If it is set as 1, then the calculated route will be the least air pollution inhalation route. For many trips, the least pollution inhalation route may not be practical because it could be a detour that increases the walking duration significantly. In the next section, we discuss the setup of the routing experiment, a sensitivity analysis of the w value, and the tradeoff between walking duration increase and air pollution inhalation reduction.

3.3. Routing experiment

To evaluate walking route choices, we used multiple origin-destination pairs in the study area to represent home-to-amenity trips. Specifically, the centroids of 242 residential blocks selected from U.S. Census 2010 were used as the origins, and 139 addresses of a variety of amenities obtained from Google Maps were used as the destinations (see Fig. 8).

Amenities within 1 mile of each origin were used as potential destinations, resulting in more than 9,000 home-to-amenity walking

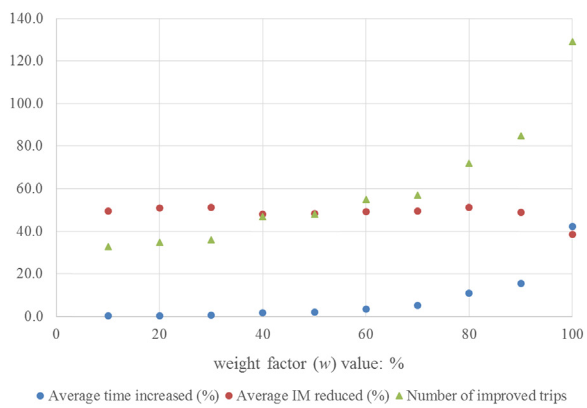

Fig. 9. Sensitivity analysis results of weighting factor for morning period.

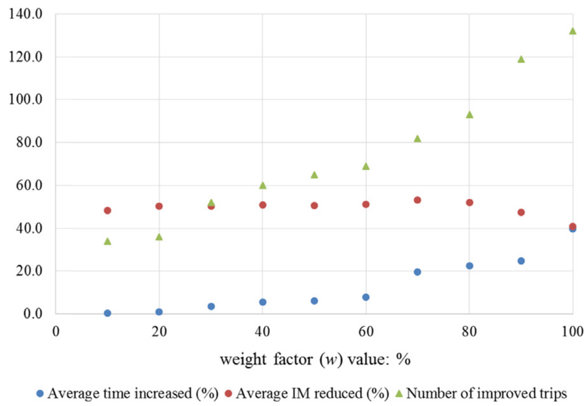

Fig. 10. Sensitivity analysis results of weighting factor for afternoon period.

trips (Carr et al., 2010). Among different countries and areas, the daily walking time and distance vary significantly. For instance, the analysis of commute pattern reveals that the average walking distance per trip is 0.53 km (km) in London, 1.21 km in San Diego, and 0.94 km (approximately 14-16 min) in Los Angeles (Moovit Insights, 2018). Considering the long street blocks in the study area and with the attempt to capture a wide range of walking trips, we chose 30 min as the maximum threshold for one-way trips in this study, which resulted in 1,142 unique trips. Among the 1,142 trips, there are 180 trips (16%) within 10 min, 417 trips (36%) between 10 to 20 min, and 545 trips (48%) between 20 and 30 min. We conducted a sensitivity analysis by varying the weighting factor w from 0.1 to 1.0 and plotted the tradeoff between walking duration increase and air pollution inhalation reduction, for both morning and afternoon periods.

For each trip, both the shortest duration route ($w = 0$ in Eq. (3)) and the low inhalation route ($w = 0.1, 0.2, 0.3\ldots 1.0$ in Eq. (3)) were determined. For both routes, the total *IM* of $PM_{2.5}$ and the total walking duration for the trip were calculated.

Fig. 9 shows that in the morning period, as the w value increases, the average walking duration and the number of low inhalation routes increase as well. However, the average *IM* reduction of the low inhalation routes does not increase significantly, and even decreases in some cases. This is because higher w values result in longer walking duration, which excludes a number of trips as a result of the time increase limit. A similar trend is also observed for the afternoon period, as shown in Fig. 10.

To balance between the *IM* reduction and the undesired walking time increase, we chose the value of w to be 0.8 and 0.6 for the morning and afternoon periods, respectively.

3.4. Results and discussion

In this study, a low inhalation route is designated as an “improved trip” if the walking duration of the route does not increase by more than a time increase limit, as compared to the shortest duration route. We set the time increase limit to be 10%, but this value can be changed based on a pedestrian's preference. Additionally, the three cases of time increase limit, i.e., 10% (improved trips), 20%, and 30%, are compared in Table 1. Pedestrians can select the limit based on their preferences. For example, if a pedestrian is willing to walk for a longer time to reduce a higher amount of air pollution inhalation, then he or she could choose a higher time increase limit.

As shown in Table 1, when the time increase limit is 10%, improved trips could be found for about 4% of the walking trips, both in the morning and in the afternoon. On average, the improved trips would reduce the inhaled mass of $PM_{2.5}$ in the morning by 48% while increasing the walking duration by only 2%. In the afternoon, the improved trips would reduce the inhaled mass of $PM_{2.5}$ by 44% while increasing the walking duration by merely 1% on average. As the time increase limit becomes higher, more low inhalation routes can be found. Note that, as seen in Fig. 7, the study area is upwind of the SR-91 freeway. Therefore, the overall level of traffic-related air pollution is relatively low as compared to that of the neighborhoods downwind of the freeway. It is expected that more

Table 1
Statistics of low inhalation routes.

Max trip travel time increase	Analysis period	Trips under 30 min	Low inhalation route		$PM_{2.5}$ IM reduction (%)		Walking duration increase (%)	
			Trips	%	Max	Mean	Max	Mean
10%	Morning	1,142	50	4.4	86.1	48.1	9.5	1.5
	Afternoon	1,142	49	4.3	86.8	43.9	9.5	1.2
20%	Morning	1,142	57	5.0	86.1	50.0	19.6	3.2
	Afternoon	1,142	57	5.0	86.8	46.9	19.6	3.1
30%	Morning	1,142	63	5.5	86.1	50.9	26.2	5.0
	Afternoon	1,142	63	5.5	86.8	50.2	26.2	4.9

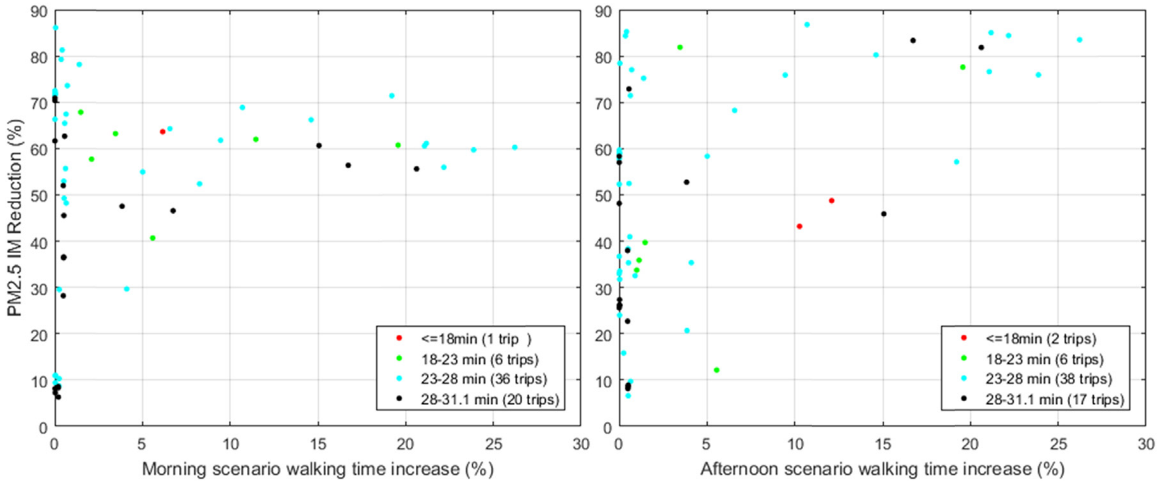

Fig. 11. Reduction in $PM_{2.5}$ inhalation versus increase in walking duration.

improved trips would be found in those neighborhoods where the pollutant plumes from the freeway extend into.

Fig. 11 shows the scatter plots of the reduction in inhaled mass of $PM_{2.5}$ versus the increase in walking duration with the time increase limit of 30% (also includes 10% and 20%). The data points in both plots are mostly clustered on the left side of the plots, indicating that for the majority of the trips, the pedestrians could considerably reduce the amount of $PM_{2.5}$ inhaled if they accept a slight increase in walking duration.

We also analyzed the impact of waiting time at roadway intersections on the amount of air pollution inhaled. On average, the roadway links in the study area have a length of 314 m, which will take 4.4 min to traverse at a walking speed of 1.2 m/second. The average inhaled mass on each link, based on Eq. (2), is 0.049 μg in the morning and 0.026 μg in the afternoon. If we assume that the average waiting time of pedestrians at an intersection varies from 1 to 10 seconds (Huang and Cynecki, 2001; Shirazi and Morris, 2016), then the air pollution inhalation while waiting at the intersection will range from 8.7×10^{-5} µg to 8.7×10^{-4} µg in the morning, and 4.7×10^{-5} µg to 4.7×10^{-4} µg in the afternoon. Therefore, waiting at intersections will add an extra 0.2% to 1.8% to the overall inhaled mass. This range will vary by trip length, specific traffic condition at intersections, and individual pedestrians'

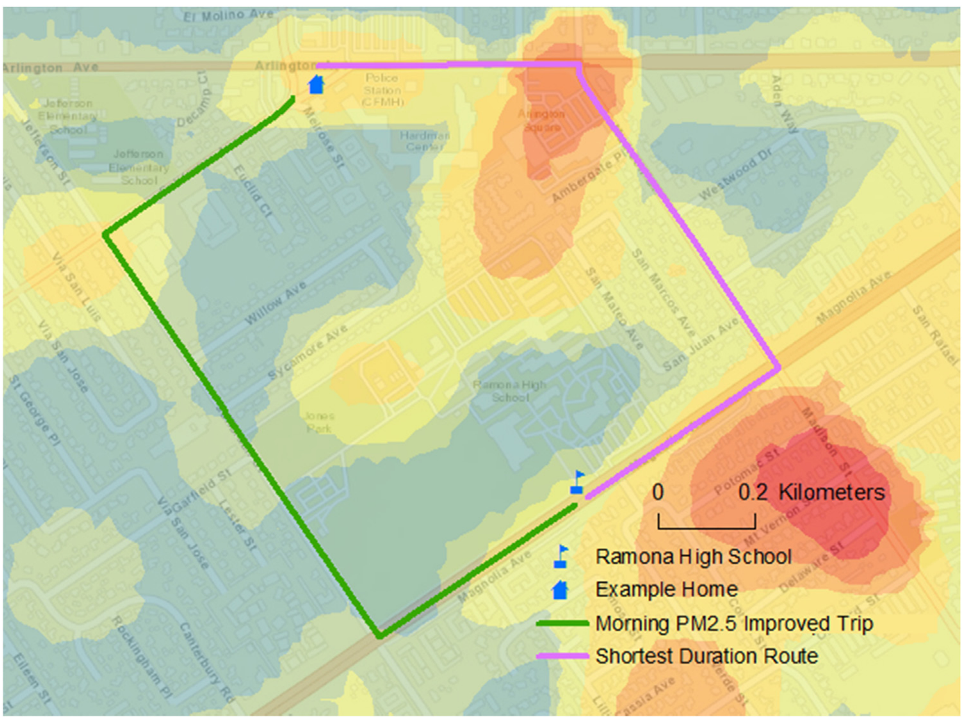

Fig. 12. Example of an improved trip in the study area.

physical condition.

Fig. 12 illustrates an example of improved trips. It is a trip between a house and a school in the study area. The shortest duration route is shown in pink while the improved trip is shown in green. The shortest duration route is the same both in the morning and in the afternoon. The same is true for the improved trip. When overlaid on the $PM_{2.5}$ concentration maps as in Fig. 12, it can be clearly seen that the improved trip traverses roadway links with relatively lower $PM_{2.5}$ concentration. In the morning, the improved trip would reduce inhaled mass of $PM_{2.5}$ by 68% with a mere 2% increase in walking duration as compared to the shortest duration route. In the afternoon, the improved trip would result in a 40% reduction in inhaled mass of $PM_{2.5}$ with a 2% increase in walking duration. For this particular example, the slight increase in walking duration coupled with the significant reduction in the inhaled mass of $PM_{2.5}$ could make the improved trip appealing for students and parents who are aware of the health effects of traffic emissions. Similarly, other residents in the study area could apply such information in making route choice decisions for their walking trips (e.g., seniors walk from home to restaurant, pharmacy, etc.).

4. Conclusions and future directions

Pedestrians often face risks of inhaling a high amount of traffic-related air pollution due to their proximity to the emission sources and increased breathing rates during walking. Many studies have investigated the relationships between walking and exposure to traffic-related air pollution. However, very few have sought mitigation measures that pedestrians can proactively use to protect themselves from excessive exposure and reduce the amount of air pollution inhalation. This study examines route choices as one such measure and evaluates its potential through modeling and simulation. Specifically, a method for incorporating the estimated inhaled mass of $PM_{2.5}$ into walking route calculation was developed, and the calculated low inhalation route was compared against the traditional shortest duration route. For the case study of a suburban road network in Riverside, California, it was found that among the samples of 1142 walking trips under 30 min:

- A low inhalation route could be found for about 4% of the walking trips in both morning and afternoon periods.
- On average, the low inhalation routes would reduce the inhaled mass of traffic-related primary $PM_{2.5}$ in the morning period by 48% while increasing the walking duration by only 2%.
- In the afternoon period, the low inhalation routes would reduce the inhaled mass of traffic-related primary $PM_{2.5}$ by 44% while increasing the walking duration by merely 1% on average.

These results indicate that if pedestrians can accommodate a slight increase in walking duration in some of their walking trips, they can substantially reduce their inhalation of traffic-related primary $PM_{2.5}$ on those trips. This may be particularly important for sensitive population groups such as children, seniors, and people with respiratory health problems. Note that the results presented in this paper are for the specific road network topology, traffic conditions, and weather patterns in the study area. The impacts of route choices may be different in other areas.

The public should be encouraged to harness the health benefits of walking, and the low air pollution inhalation routing concept presented in this paper can be applied in several ways. For example, in the short term it can be used to assist Safe Routes to School programs (McAuley and Pedroso, 2012) to select walking routes that address both safety and air quality concerns for children in heavy-traffic areas. In the long term, the concept can be applied in conjunction with other efforts by cities, such as promoting clean vehicles and expanding sidewalk network, in order to improve accessibility, safety, and air quality for travelers in a holistic manner.

In terms of future research directions, this study has established a framework for determining low air pollution inhalation routes for pedestrians. Several aspects can be improved and expanded in the future, for instance:

- Accounting for other sources of emissions and background concentration,
- Refining walking speed and breathing rate assumptions by using values specific to demographic groups such as school-aged children,
- Evaluating the benefits of low inhalation route choices in other settings (e.g., urban road network with more complex terrain), and
- Integrating with real-time traffic, weather, and even roadside air quality data to result in navigation applications for pedestrians.

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Conflict of interest

The authors report that they have no conflicts of interest.

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