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Consideration of exposure to traffic-related air pollution in bicycle route planning

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A B S T R A C T

Introduction: Active transportation modes such as bicycling are key elements of sustainable transportation. In order to promote bicycling as an alternative form of transportation, a holistic approach to improving the quality of the biking experience is needed. The planning of bicycle routes typically takes into consideration available right-of-way, existing roadway infrastructure, and safety concerns, among other factors. Exposure to traffic-related air pollution, on the other hand, is rarely considered despite bicyclists being vulnerable to the harmful air pollution due to their direct exposure to vehicular exhaust and increased breathing rate during biking.

Methods: This paper presents a method for incorporating exposure to traffic-related air pollution as another consideration in the bicycle route planning process. The method first applies a streamlined process for estimating the level of near-road air pollution concentration. Then a bicycle route planning tool is developed which allows planners and engineers to compare the exposure of bicyclists to traffic-related air pollution among different bicycle route options. Additionally, this paper demonstrates how to apply the method in two case studies in the City of Riverside, California.

Results: Through the case studies, it is shown that considering exposure to traffic-related air pollution can change the results of bicycle route planning.

Conclusions: The presented case studies illustrate how the consideration of exposure to traffic-related air pollution could impact the results of bicycle route planning. Planners may refer to the presented method or use the information in the analysis differently based on their needs in specific projects. Planners and stakeholders may jointly determine how important the different factors, including exposure to traffic-related air pollution, are in relation to one another and what tradeoff between different factors will be.

1. Introduction

Many local, regional, and state agencies in the United States are making efforts to increase bicycle infrastructure in order to promote sustainable and multi-modal transportation. Typically, the planning of bicycle routes considers multiple factors including available right-of-way, vehicle traffic volume, safety, and the built environment (Guide for the Deve, 2012). While bicyclists are most vulnerable to the harmful air pollution due to their direct exposure to vehicular exhaust and increased breathing rate during biking (Weichenthal et al., 2012; Thai et al., 2008), this factor is rarely considered in bicycle route planning.

Research studies have been conducted to investigate the issue of bicyclists' exposure to traffic-related air pollution. One area of research is measuring air pollutant concentrations in the microenvironment of different transportation modes such as driving, walking, and bicycling (van Wijnen et al., 1995; Karanasiou et al., 2014; Ragettli et al., 2013). Some studies went a step further by attempting to quantify the intake of air pollutants. For example, Quiros et al. used a portable instrument to measure ultrafine particle (UFP) concentration and calculated UFP inhalation of drivers, cyclists, and pedestrians. The results indicate that respiratory UFP exposure

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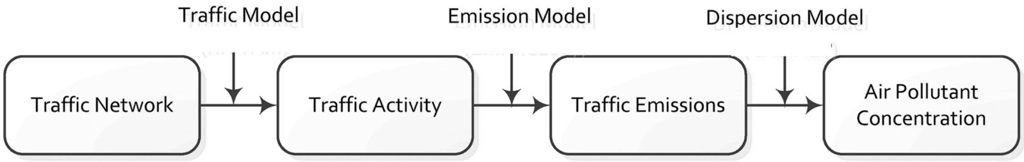

Fig. 1. Traffic-related air pollution modeling process.

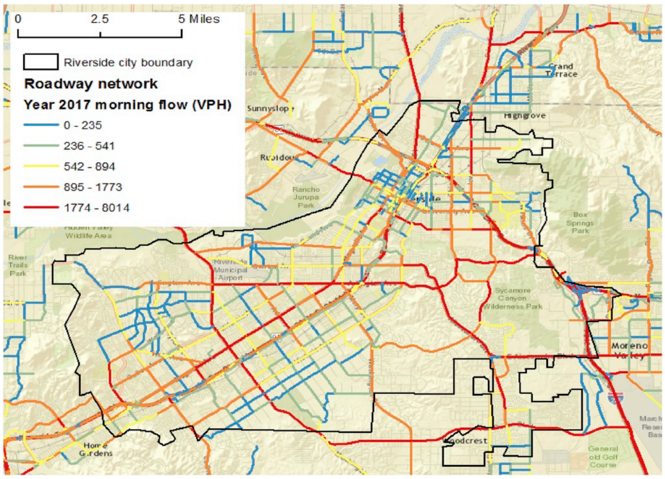

Fig. 2. Total flow (vehicles per hour) in the morning period.

(number of particles inhaled per trip) was 15 times higher when cycling and 30 times higher when walking, as compared with driving with windows closed (Quiros et al., 2013).

Another focus is on assessing the health effects for travelers in various traffic microenvironment as well as measuring marker pollutants' concentration (McCreanor et al., 2007; Jarjour et al., 2013; Weichenthal et al., 2014). For instance, Weichenthal et al. conducted a cross-over study among 53 healthy non-smoking women who were exposed to traffic air pollutants for 2 hours on three separate occasions: cycling on high-traffic routes, low-traffic routes, and indoor. It was observed that indices of microvascular function and blood pressure were slightly negatively impacted with each interquartile increase of UFP exposure (Weichenthal et al., 2014).

The third research area not only involves the measurement but also considers explaining and predicting travelers' exposure to traffic-related air pollution (Hatzopoulou et al., 2013a; Bigazzi and Figliozzi, 2015). For example, Bigazzi et al. estimated the effects of roadway and travel variables on bicyclist exposure concentrations, controlling for meteorology and background conditions (Bigazzi and Figliozzi, 2015). Building on the measurement and prediction studies, several research groups have aimed to develop and characterize mitigation strategies (Hertel et al., 2008; Kendrick et al., 2014; Pattinson et al., 2017). For example, Hatzopoulou et al. (2013) developed a web-based route planning tool for individual bicyclists to reduce their exposure to ambient nitrogen dioxide (Hatzopoulou et al., 2013b).

Albeit a large body of literature in these research areas, to the best of our knowledge there has not been a research study that explicitly considers bicyclists' exposure to traffic-related air pollution in the planning of bicycle routes. We attempt to fill this gap by developing a method to incorporate reduced exposure to traffic-related air pollution as another consideration in the bicycle route planning process in order to improve the quality of the biking experience and promote active transportation. Specific objectives of this research include: 1) creating a streamlined process for estimating the level of near-road air pollution concentration; 2) developing a bicycle facility planning tool that allows planners and engineers to compare the exposure of bicyclists to traffic-related air pollution among different bicycle routes; and 3) demonstrating the method in two case studies.

2. Modeling street-level air pollutant concentration

Current air quality measurement data are not available at the spatial resolution necessary for the planning of bicycle facilities. In this research, high-resolution traffic-related air pollution concentrations are estimated through a streamlined modeling process. The air pollution concentration estimation process involves multiple steps, datasets, and modeling tools, as shown in Fig. 1. First, a digital map of roadway network was used as the input for a traffic model to estimate traffic activity, in terms of flow and 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 are input into a dispersion model to estimate air pollution concentration at receptor locations. This modeling chain has been applied by several research groups using a variety of model combinations (Amirjamshidi et al., 2013; Rowangould, 2015; Vallamsundar et al., 2016). The following sections describe the models and datasets applied in this study in detail.

2.1. Traffic activity and emissions modeling

Traffic activity data in year 2017 in Riverside City is based on the Regional Travel Demand Model (RTDM) (Regional Travel Dema, 2016). The data is available for four periods: morning (6–9 a.m.), midday (9 a.m.-3 p.m.), afternoon (3–7 p.m.), and nighttime (7 p. m.-6 a.m.). Traffic flow data includes separate values for four vehicle categories: 1) light duty automobile 2) light-heavy duty trucks; 3) medium-heavy duty trucks; and 4) heavy-heavy duty trucks. Total flow is the summation of the flow values and is shown in Fig. 2. Additionally, one traffic speed value represent the speed for all vehicle types on that link.

To estimate traffic emissions, emission factors were obtained from the California Air Resources Board's EMFAC model version 2014 for the fleet composition in Riverside County in calendar year 2017 (California Air Resource Board, 2014). EMFAC is the regulatory emission model for California. As an example, fine particle ($PM_{2.5}$) emission factors for speed from 5 mph to 70 mph were obtained for multiple vehicle categories in EMFAC 2014, which were then matched with vehicle types in RTDM. After that, the total $PM_{2.5}$ emission on each roadway link was calculated as:

$$E_i = \sum_j q_{i,j} \cdot e(v_i)_j \qquad \forall\, i = 1, \cdot 2, \cdot 3, \cdots, \&, 743 \tag{1}$$

where E_i is total emission on roadway link i (grams); $q_{i,j}$ is flow 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).

2.2. Air pollutant concentration modeling

R-LINE, a research-grade air dispersion model for near-roadway assessments developed by the U.S. Environmental Protection Agency (EPA), is used in this study (University of North Carolina at Chapel Hill, 2019; Snyder and David, 2013). The underlying relationship between air pollutant concentration and the line sources in R-LINE can be expressed as:

$$\boldsymbol{C}(\boldsymbol{x},\boldsymbol{y},z) = \boldsymbol{f}(\boldsymbol{Q},\ \textbf{\textit{source location}},\ \textbf{\textit{meterology}}\ ) \tag{2}$$

where $C(x,y,z)$ denotes emission concentration at a receptor location; and Q is average emission rate of on-road vehicles (grams/meter/second) obtained from traffic emission modeling in the previous step. For source location, each line segment's nodes coordinates are required. Typical meteorological data for R-LINE, such as air temperature, wind speed, surface friction velocity, Monin-Obukhov length, etc., are available from the South Coast Air Quality Management District (SCAQMD) website (South Coast Air Quality Management District, 2019).

In order to estimate high-resolution $PM_{2.5}$ concentration at the street level, receptors were set up as a 100 m × 100 m gridded network at the height of 1.5 m. This yielded 48,000 receptors in the modeling area, and more than 8000 roadway links. In an effort to keep the computation time reasonable while still capturing concentration distribution due to meteorological variation, we examined the meteorological variation across multiple years. The data of meteorological parameters are readily available from year 2008–2012 (South Coast Air Quality Management District, 2019). The analysis of these data for the five years revealed that the trends in weather patterns are comparable across the years. For example, our analysis showed that several critical parameters (e.g. sensible heat flux, temperature, surface friction velocity, etc.) for each time period and month from year 2009–2012 are similar across the years. Hence, we used the meteorological data of year 2012 to represent the weather condition in the model year, which is 2017. The meteorology station is managed by SCAQMD and is located near Mt. Rubidoux in Riverside (South Coast Air Quality Management District, 2019).

We considered a total of 36 hourly average meteorological conditions consisting of three time periods of day (morning, midday, and afternoon) for the 12 months in calendar year 2012. The 36 sets of estimated $PM_{2.5}$ concentration values were then weighted by the level of bicycle activities by time period of day and by month of year derived from the GPS dataset in the 2010-12 California Household Travel Survey. This resulted in a weighted average $PM_{2.5}$ concentration map for the city.

The reason for using the weighting method is that bicycle facilities, once planned and built, are not likely to be easily moved. For example, if more bicycle trips occur in the morning hours than during midday, a larger weight was given to the concentration values for the morning period than those for midday. Therefore, it is reasonable to weight the $PM_{2.5}$ concentration values for the different time scenarios based on the level of bicycle activities during each time scenario to result in one set of reference $PM_{2.5}$ concentration values for the purpose of planning future bicycle facilities.

2.3. Weighting air pollution concentration based on bicycling activities

To acquire bicycle activity data by hour of day and by month for the City of Riverside, we reviewed several travel surveys and datasets associated with bicycle use (National Household Travel, 2009; SCAG, 2010; National Renewable Energy Laboratory, 2010). We found that the GPS dataset from the California Household Travel Survey has a more balanced sample in terms of sociodemographic characteristics, and its data availability is more consistent. Data from the entire State of California were used because there are not enough bicycle trip counts within the boundary of the city. A survey of cyclists' activity in the local area should be included when implementing such projects. Fig. 3 maps hourly averaged bicycle trip counts by period of day and by month. It shows that the number

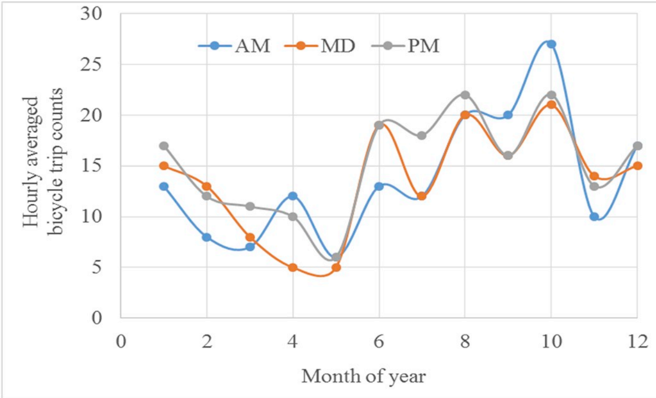

Fig. 3. Hourly averaged bicycle trip counts by period of day and by month for California State.

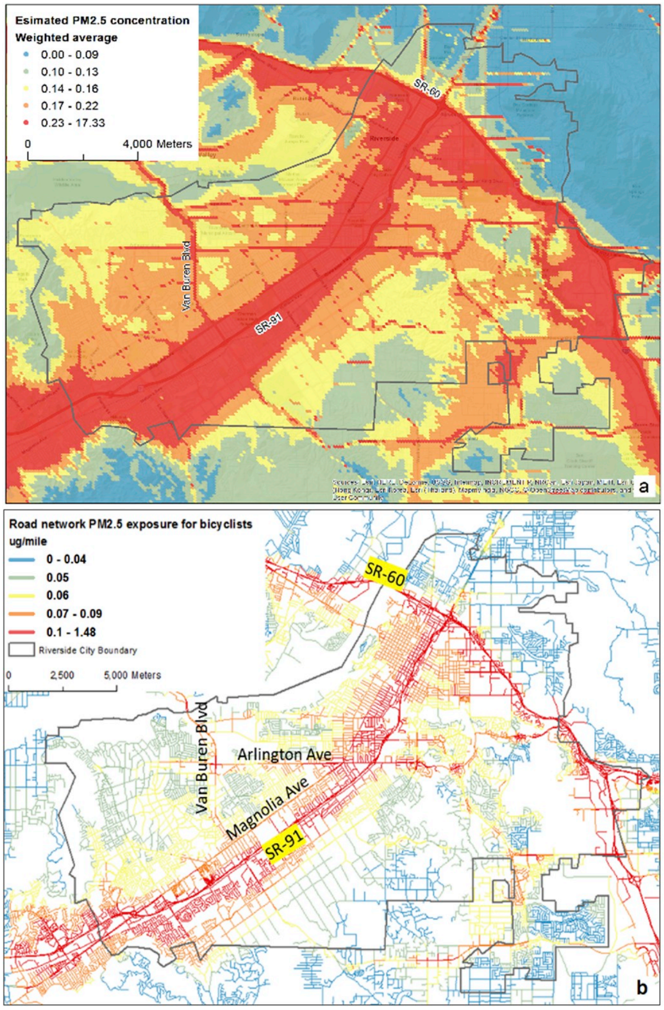

Fig. 4. a) Weighted $PM_{2.5}$ concentration based on bicycling activities in the State of California
b) Traffic-related primary $PM_{2.5}$ exposure per mile for bicyclists.

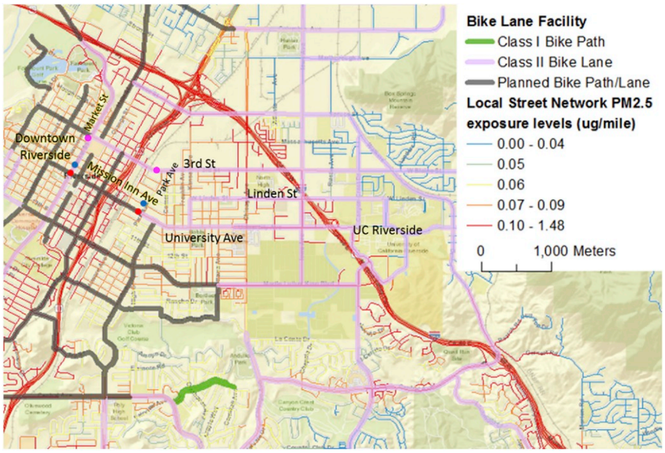

Fig. 5. Alternative bicycle routes between UC Riverside and Downtown Riverside.

of hourly averaged bicycle trips varies significantly by month rather than by time period.

Based on Fig. 3, we used the hourly averaged bicycle trip counts (36 data points) as weight factors for the 36 p.m.$_{2.5}$ concentration maps generated earlier. The concentration vector for each time period of each month can be expressed as:

$$C_{ijk} = \begin{bmatrix} c_{1jk} \\ c_{2jk} \\ \vdots \\ c_{48000,j,k} \end{bmatrix} \tag{3}$$

where i is index for receptor (from 1 to 48,000); j is index for month (from 1 to 12); and k is index for time period (from 1 to 3, representing morning, midday and afternoon, respectively). The final concentration vector, C, can be calculated by Equation (4):

$$C = \frac{\sum_{jk}(C_{ijk} \cdot count_{jk})}{\sum_{jk} count_{jk}} \tag{4}$$

where $count_{jk}$ denotes bicycle trip counts in month j and time period k as in Fig. 3. After weighting based on the level of bicycle activities, the final concentration map was generated as shown in Fig. 4a.

3. Generating air pollution exposure map for bicycle facility planning

Using the final $PM_{2.5}$ concentration map (Fig. 4a), a bicyclist's exposure to traffic-related air pollution on each roadway link in the City of Riverside can be estimated. The exposure scenario in this study is a bicyclist's direct exposure to vehicular $PM_{2.5}$ in a near-road outdoor microenvironment. We use *inhaled mass* as a metric for quantifying the level of exposure. It is a function of air pollutant concentration that the bicyclist is exposed to, duration of the exposure, and breathing rate of the bicyclist during the time of exposure. In this study, $PM_{2.5}$ concentration was estimated for each roadway link. Therefore, inhaled mass of $PM_{2.5}$ for bicyclist k traveling on roadway link i can be expressed as in Equation (5), assuming that the breathing rate of the bicyclist remains the same throughout the roadway link.

$$IM_{i,k} = c_i \cdot t_{i,k} \cdot BR_{i,k} \tag{5}$$

where IM is inhaled mass of $PM_{2.5}$ (μg); c is $PM_{2.5}$ concentration ($\mu g/m^3$) along the roadway link; t is travel duration (*minutes*); and BR is breathing rate of the bicyclist ($m^3/minute$). c is calculated by first extracting the locations of vertices on each link and then determining the $PM_{2.5}$ concentration at each location from the concentration map. Each link has at least 3 vertices (i.e., start point, midpoint, and end point), and c is calculated as the average of the concentration values at all the vertices. The bicycling duration on a roadway link was calculated based on the link length (meters), and the assumed speed of an average bicyclist of 9 miles per hour (National Renewable Energy Laboratory, 2010). The breathing rate of an average bicyclist is assumed to be 0.04 $m^3/minute$ based on health studies (Chapter 6 and Exposure Facto, 2011; Bigazzi and Figliozzi, 2014).

Fig. 4b shows the level of exposure to $PM_{2.5}$ for an average bicyclist on a link-by-link basis, where the inhaled mass values are normalized by link length. The color map is categorized by five quantiles based on the normalized exposure values and the number of links. As expected, the map shows that most of the links in the top 20% bracket (red color) are in close proximity to the two major freeways passing through the city - State Route 91 (SR-91) and State Route 60 (SR-60). The exposure information can be used in conjunction with other information pertinent to safety, connectivity, accessibility, and other metrics in the planning of new bicycle paths and lanes.

Table 1
Attributes, weight of importance (w_i) and ranks of alternative bicycle route segments between UC riverside and downtown riverside.

Attributes	w_i	Third St		Mission Inn Ave		University Ave	
		Value	Rank	Value	Rank	Value	Rank
Connection to land uses	10	Mix of residential and industry, few people on street	3	Mix of residential and businesses, many people on street	1	Mostly businesses, moderate number of people on street	2
Posted speed limit (mph)	9	30	2	25	1	35	3
Total number of lanes	8	3	2	2	3	4	1
Road shoulder width (ft)	7	5	2	5	2	5	2
Estimated average daily traffic volume in year 2017 (vehicles/ln/day)	6	5577	1.5	9455	3	5628	1.5
Terrain and road grade	5	Generally level	1.5	Generally level	1.5	Uphill and downhill around SR-91 bridge	3
Roadside parking allowed?	4	Most sections do not allow parking	1.5	Most sections allow parking	3	Most sections do not allow parking	1.5
Barriers	3	Train tracks	2.5	Train tracks	2.5	None	1
Number of intersections along the segment	2	8	2.5	8	2.5	6	1
Total $PM_{2.5}$ exposure (μg)	1	0.09	1	0.11	2	0.14	3
Simple average rank		*1.95*		*2.15*		*1.90*	
Weighted average rank		*2.07*		*1.98*		*1.95*	

Fig. 6. a) Simple average rank and b) weighted average rank of the alternative route segments between UCR and downtown Riverside.

Table 2
Attributes, weight of importance (w_i) and ranks of alternative bicycle route segments around MLK high school.

Attributes	w_i	Van Buren Blvd		Krameria Ave	
		Value	Rank	Value	Rank
Connection to land uses	10	Mostly businesses	1.5	Mostly residential	1.5
Posted speed limit (mph)	9	50	2	25	1
Total number of lanes	8	4	1	1–2	2
Road shoulder width (ft)	7	3–5	1.5	2–5	1.5
Estimated average daily traffic volume in year 2017 (vehicles/lane/day)	6	7689	2	1578	1
Terrain and road grade	5	Moderate road grade	1.5	Moderate road grade	1.5
Roadside parking allowed?	4	Mostly no	1	Parking is allowed on some of the residential sections	2
Barriers	3	None	1.5	None	1.5
Number of intersections along the segment	2	11	1	12	2
Total $PM_{2.5}$ exposure (μg)	1	0.2	2	0.07	1
Simple average rank		*1.50*		*1.50*	
Weighted average rank		*1.52*		*1.48*	

To develop an online tool for future bicycle facility planning, we have integrated several useful map layers and published them online at http://arcg.is/29CESgp. Users can select roadway links whose attributes match specified criteria to facilitate decision-making process.

4. Case studies of considering traffic-related air pollution exposure in bicycle ROUTE planning

4.1. University of California (UC) riverside to Downtown Riverside corridor

This corridor connects the two major trip origins/destinations in the city with potential for high bicycle mode share. Fig. 5 shows the map of the corridor. Since there are already bicycle facilities along this corridor, notably on part of University Ave, Linden Street, and Third St, we conducted a comparison of a short segment on each route, illustrated by the three pairs of dots in Fig. 5.

Table 1 lists key attributes that should be considered when planning bicycle routes (Guide for the Deve, 2012) and their weight of importance in this case study based on local input. The weight is from 1 to 10 with a higher weight representing a higher level of importance. The attribute values of each route segment were collected through a combination of the regional transportation model, street images, and site visits. Based on the attributes, the rank values were determined. While it is desirable that the attributes considered are quantitative, it is not always possible. Some of the attributes considered in this case study are qualitative. Therefore, when comparing the attribute values among the three alternatives, it is appropriate to use an ordinal scale or rank order (1st, 2nd, 3rd, …). The ordinal scale can be easily understood therefore making it straightforward to communicate with the general public about the process. In '***Rank***' column of Table 1, value '1' means highest rank (i.e., the most preferred alternative). In some cases, two or more alternatives have the same rank meaning that they are equally preferred. As an example, for the posted speed limit, Mission Inn Ave is ranked 1 as it has the lowest posted speed limit (25 mph) while University Ave is ranked 3 as it has the highest posted speed limit (35 mph). As another example, in the case of terrain and road grade, both 3rd St and Mission Inn Ave are both level in general whereas University Ave has uphill and downhill around the SR-91 overpass. In this case, University Ave is ranked 3 and the other two routes share the rank of 1.5, which is the average of 1 and 2.

We calculated two types of average rank: 1) simple average rank, and 2) weighted average rank as:

$$\text{Simple average rank} = \frac{1}{N}\sum_{i=1}^{N} r_i \tag{6}$$

$$\text{Weighted average rank} = \frac{\sum_{i=1}^{N}(r_i \cdot w_i)}{\sum_{i=1}^{N} w_i} \tag{7}$$

where r_i is rank of attribute i; w_i is weight of attribute i; and N is number of attributes.

Fig. 6a shows the simple average rank values of the three alternative route segments with and without the total $PM_{2.5}$ exposure attribute. Based on this figure, University Ave would be the best alternative regardless of whether the exposure to $PM_{2.5}$ is taken into account or not.

When looking at the weighted average rank shown in Table 1, University Ave would again be the best alternative as it has the lowest rank value. This weighted average ranking is based on the weight of importance listed in the table where the total $PM_{2.5}$ exposure attribute is given the least importance ($w_i = 1$). Fig. 6b examines the impact of changing the weight of the $PM_{2.5}$ exposure attribute. Based on this figure, Mission Inn Ave would become the best alternative if the weight of the total $PM_{2.5}$ exposure attribute is between 2 and 9. If the weight of the total $PM_{2.5}$ exposure attribute is 10, then Third St would become the best alternative. Note that there are already bike lanes on some segments of Third St, which is included in this case study for comparison purposes only. On the other hand,

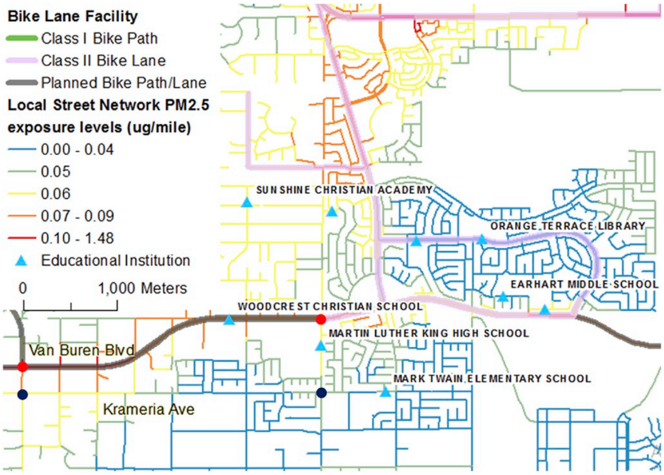

Fig. 7. Alternative bicycle routes along Van Buren corridor around MLK High School.

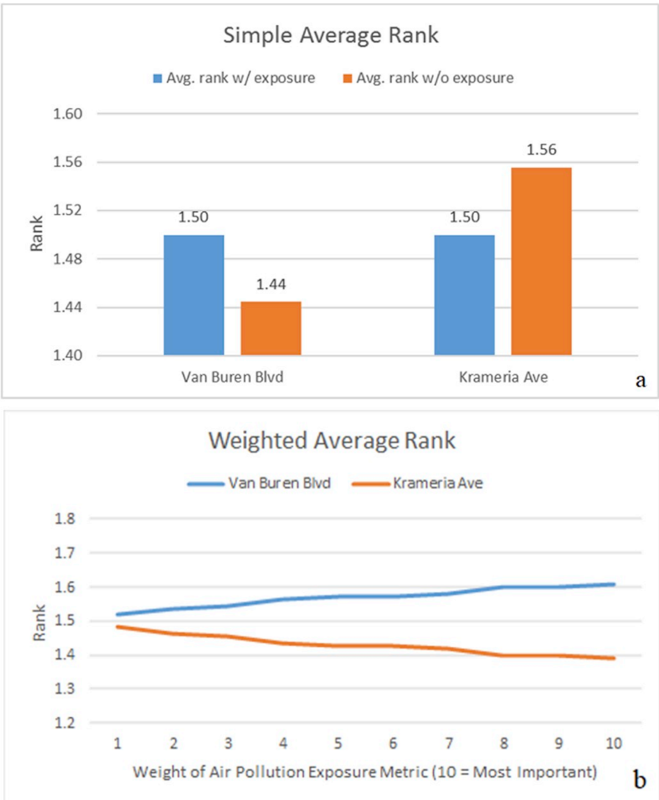

Fig. 8. a) Simple average rank and b) weighted average rank of the alternative route segments on Van Buren Blvd corridor near MLK High School.

there are no existing bike lanes on either University Ave or Mission Inn Ave, and the two streets are a block away from each other. Both streets connect to the major area of the city, and either of them would be a suitable candidate for adding bike lanes. The results in Fig. 6b indicate that the choice between the two streets could depends on whether exposure to traffic-related air pollution is taken into consideration and how important this factor is relative to other factors.

4.2. Van Buren Blvd corridor

In this case study, we chose a segment of Van Buren Blvd around Martin Luther King (MLK) High School. There are many schools and residential communities located near the segment. Also, this area has steep road grade, and high roadway intersection density, making it a representative case study.

There are already bike lanes on Van Buren Blvd east of MLK High School. There is a plan to extend these bike lanes westward to the intersection with Washington St, as represented by the two red dots. An alternative is a parallel segment on Krameria Ave south of Van Buren Blvd, as marked by the pair of black dots. The black dot on the east end is about 2000 ft south of the red dot on the east, while the black dot on the west end is about 1000 ft south of the red dot on the west end. As in the previous case study, the attribute values of each route segment were gathered from the regional transportation model, street images, and site visits. They are summarized in Table 2.

Next, the *simple averaged rank* and *weighted average rank* were calculated based on Equation (6) and (7), respectively. Fig. 8a shows that without considering the exposure to $PM_{2.5}$, Van Buren Blvd would be a better alternative. But when taking such exposure into account, both route segments would be equally appropriate. This is not surprising because the total $PM_{2.5}$ exposure on Van Buren Blvd is higher than that on Krameria Ave.

According to the weighted average rank in Table 2, Krameria Ave would be a better alternative by a slight margin when the total $PM_{2.5}$ exposure attribute is the least important factor (weight = 1). According to Fig. 8b, Krameria Ave would be the better alternative no matter how much weight is given to the $PM_{2.5}$ exposure attribute, as long as it is taken into consideration. The higher the weight is, the bigger the margin between Krameria Ave and Van Buren Blvd because Krameria Ave has a lower exposure value than Van Buren Blvd.

Note that when looking at the two alternative route segments in Fig. 7 from the bicycle facility network perspective, they do not directly compete with each other. Van Buren Blvd would be a good option for expanding the bicycle facility network in the city as it is a major arterial with many businesses along the road. Bicyclists who want to access the amenities on Van Buren Blvd or want to travel to destinations west of the end of the existing bike lanes could benefit from extended bike lanes on this route. On the other hand, there are many schools south of Van Buren Blvd. For children attending these schools, Krameria Ave would be a safer and lower air-pollution-exposure route for them to bike to school. Adding bike lanes on this route could potentially encourage residents, especially school-aged children and their parents, to ride bicycles more (Dill and Carr, 2003). Thus, in this case study, adding bike lanes on both routes would be ideal where the bike lanes on each route would serve different types of users making different types of trips.

5. Conclusions and future directions

The planning of bicycle routes typically takes many factors into account, including available right-of-way, existing roadway infrastructure, vehicular traffic volume, safety concerns, and built environment, among others. Exposure to traffic-related air pollution, on the other hand, is rarely considered despite bicyclists being vulnerable to the harmful air pollution due to their direct exposure to vehicular exhaust and increased breathing rate during biking. This paper presents a method for incorporating exposure to traffic-related air pollution as another consideration in the bicycle route planning process. In addition, it demonstrates how to apply the method through two case studies.

The presented case studies illustrate how the consideration of exposure to traffic-related air pollution could impact the results of bicycle route planning. Planners may refer to the presented method or use it differently based on their needs in specific projects. For example, model parameters related to bicyclist characteristics (e.g., average biking speed, breathing rate, and receptor height) can be adjusted towards children-specific values when planning bicycle routes that will be used by many children, such as near schools and in residential neighborhoods. This is important because children are especially susceptible to traffic-related air pollution in terms of physical health and cognitive development (Bayer-Oglesby et al., 2005; Jerrett et al., 2014; Sunyer et al., 2015). As another example, both the order and the weight of importance for the different factors can be adjusted, which may affect the ranking results. Planners and stakeholders may jointly determine how important the different factors, including exposure to traffic-related air pollution, are in relation to one another and what tradeoff between different factors will be. It should be noted that the examples in the two case studies do not necessarily include all factors that may be considered. In other areas or cities, there may be additional factors that should also be taken into consideration in the planning of bicycle routes.

Several aspects of this research can be improved and expanded in the future. For instance, traffic activity data could be enhanced with more spatial and temporal details such as wait time at crossings and intersections. Air pollutant concentration modeling could consider the in-plume/near-plume effects near tailpipes, and include other major sources of air pollutant emissions such as industrial sources. In the future, if air quality measurement data become available at the necessary spatial resolution, they can be used to validate the modeling results used in the bicycle facility planning process directly in lieu of the estimated values. Additionally, other weighting methods can be used in the ranking of bicycle routes to take advantage of the quantitative attributes that are included in the consideration.

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