



## Research article

## How to choose healthier urban biking routes: CO as a proxy of traffic pollution

L. Bertrand<sup>a</sup>, L. Dawkins<sup>b</sup>, R. Jayaratne<sup>c</sup>, L. Morawska<sup>c,\*</sup><sup>a</sup> Instituto de Investigaciones en Fisicoquímica de Córdoba, INFIQC–CONICET, Facultad de Ciencias Químicas, Universidad Nacional de Córdoba, Ciudad Universitaria, X5000HUA, Córdoba, Argentina<sup>b</sup> The Met Office, FitzRoy Road, Exeter, Devon, EX1 3PB, United Kingdom<sup>c</sup> International Laboratory for Air Quality & Health, School of Earth and Atmospheric Sciences, Queensland University of Technology, 2 George Street, Brisbane, Queensland, 4001, Australia

## ARTICLE INFO

## Keywords:

Atmospheric pollution  
 Active transport  
 Carbon monoxide  
 Inhaled dose  
 Physical activity  
 Atmospheric science  
 Environmental assessment  
 Environmental health  
 Environmental impact assessment  
 Environmental pollution  
 Environmental science

## ABSTRACT

According to the World Health Organization (WHO) air pollution in urban areas, mainly associated with inhalation of gaseous pollutants and particulate matter emitted from motor vehicles, is responsible for one million deaths per year. Carbon monoxide (CO) from the incomplete combustion of fuel is known to bind with hemoglobin, decreasing the blood oxygen-delivery and inducing tissues hypoxia; being more pronounced under conditions of stress like physical activity. The present study demonstrates the usefulness of a compact CO sensor (Alphasense CO-B4) mounted on a bicycle to evaluate atmospheric levels of CO associated with urban micro-environments within a growing Australian city (Brisbane). Urban bike pathways show pronounced and significant variations in air quality according to the surrounding microenvironment and the time of day. The inhaled dose in real time and the CO total dose over each trip were valuable for estimating the air quality of the route, and identified how the health benefits of riding a bicycle could be partially offset by poor air quality depending on where and when a cycle route is taken in the inner-city. Finally, environmental conditions, such as wind speed, were found to significantly affected atmospheric CO concentrations, at least during the study period. The present work provides information regarding commuters' exposure to atmospheric pollutants, necessary for modifying the population's (including cyclists) perception of pollution in the urban environment, providing people with the opportunity to choose a healthier route.

## 1. Introduction

A large number of studies describe particulate matter (PM<sub>1</sub>, PM<sub>2.5</sub>, PM<sub>10</sub>), gas pollutants including carbon monoxide (CO), nitrogen dioxide (NO<sub>2</sub>) and ozone (O<sub>3</sub>) and a range of complex organic compounds as the main atmospheric pollutants associated with fossil fuels combustions processes in urban areas (De Nazelle et al., 2017; Filonchyk and Yan, 2018). Recently, the World Health Organization (WHO) has identified the exposure to ambient (outdoor) air pollution in urban areas as the biggest environmental risk to health, associated with inhalation of pollutants, and responsible for more than 4 million deaths per year (WHO, 2016). Cerebrovascular disease, cardiovascular and respiratory affections, cancer, among others, are only a few examples of health effects associated with air pollution (Liu et al., 2018; Requia et al., 2017). The significant decline of air quality in major cities around the world,

especially in developed countries, has led to the establishment of expensive monitoring systems integrated into a fixed-station network, with the aim of measuring and regulating atmospheric pollutant emissions. In addition, considering risk exposure, air quality standards for the main pollutants have been defined, with the aim of reducing their effect on the health of the population (Queensland Government, 2019; U.S. EPA, 2014).

Moreover, motorized transport was identified as responsible for an increasingly sedentary lifestyle, being globally one of the major risk factors for mortality after illnesses (Laumbach et al., 2015). Consequently, in the last few decades, modern cities in developed countries have focused on developing networks of active transport paths, seeking to promote cycling and walking to the daily destinations. Active transport modes have been proposed by governments as a strategy, not only to reduce atmospheric emissions and transport costs, but to encourage a

\* Corresponding author.

E-mail address: [l.morawska@qut.edu.au](mailto:l.morawska@qut.edu.au) (L. Morawska).

healthier and more active lifestyle in their populations (Rojas-Rueda et al., 2011).

In urban environments, air quality associated with pollutants such as CO emitted at street level can be highly variable over short distances (tens of meters) and intervals of time due to several factors including topography, wind (speed and direction), vehicle congestion, fleet composition, vegetation density, among others (Forehead and Huynh, 2018; Pattinson et al., 2017; Schindler and Caruso, 2014). According to previous studies, data from fixed-site monitoring stations reflect poorly the pollutant levels associated with urban microenvironments, and the individual exposure risk could be easily underestimated (Huang et al., 2012; Minet et al., 2018). Moreover, the prohibitive cost of the measurements and analysis of a large number of compounds associated with car exhaust at a street level makes the use of proxies, such as NO<sub>2</sub> and CO (Wang et al., 2018; Weng et al., 2008), a much feasible option.

Over the past decade, new monitoring methodologies have been developed allowing for the measurement of not only atmospheric pollutants in urban microenvironments, but also the estimation of exposure levels associated with social behaviors such as the chosen mode of transport. Thereby, low-cost sensing technologies (<US\$100; Morawska et al., 2018) emerged with the aim to resolve monitoring costs and facilitate their use in mobile devices solving the “stationary” characteristic of standard quantification equipments. These sensors offer a huge opportunity for obtaining real-time air quality data (Morawska et al., 2018), useful for estimating population pollutants exposure and health risk associated with different urban travel microenvironments.

Previous reports describe significant variations in individuals’ pollutants exposure according to their daily habits, including commuting modes used (bus, car, bike, walking) (De Nazelle et al., 2017; Ramos et al., 2016). Consequently, travel microenvironments may result in the greatest exposure to air pollutants throughout daily activities for many people in cities. In this context, active transportation modes, like a bicycle ride, supposed to be full of benefits, could start to reveal some disadvantages if, for example, bike pathways pass through urban microenvironments with poor air quality. Moreover, cyclists are exposed to direct traffic emissions due to their proximity to on-road vehicles (Brand et al., 2019). This may mean that, at least in some conditions, the benefits associated with cycling, may be partially offset by the potential adverse health impacts as a result of exposure to traffic-related air pollution (Anowar et al., 2017). Given this background, it could be expected that not all bike pathways in a city are equally “good” considering their air quality and, the knowledge of urban microenvironments would represent a valuable tool for city design and management, as well as bicycle route selection through mobile applications. A recent study from Gössling et al. (2019) reported that the majority of cyclists underestimate individual air pollution exposure. According to the authors, except for unpleasant-smelling fumes and visible smoke, pollutants are hardly perceptible to humans, and instead the risk of injury has been identified as the main consideration when bike pathways are chosen. Even so, the authors found that cyclists would be willing to take a detour to reduce pollution exposure if specific bicycle route information was available, mainly related to the spatiotemporal distribution of atmospheric pollutants and exposure data associated with urban microenvironments (Gössling et al., 2019).

Finally, during the last few years, several reports have described the variability in pollutant exposure according to different commuting modes, however cyclist CO exposure measurements in urban environments have been less commonly reported on than other pollutants (De Nazelle et al., 2017; Kaur et al., 2007; Ramos et al., 2016). CO is considered to be one of the most common and ubiquitous atmospheric pollutants. It has been described as an indirect greenhouse gas because it is involved in producing methane (CH<sub>4</sub>), carbon dioxide (CO<sub>2</sub>) and ozone (O<sub>3</sub>) (WHO Regional Office for Europe, 2000). It is mainly emitted from incomplete burning of biomass, wastes and fuels which are significant air pollution sources in urban areas. Significant and positive correlations have been reported between CO, NO<sub>2</sub> and PM<sub>2.5</sub> concentrations, as well

as between other car exhaust pollutants, including a large variety of volatile organic compounds (Filonchik and Yan, 2018; Lodovici et al., 2003). Previous studies have attributed emissions to a large number of worldwide deaths annually and identified a significant association between short-term exposure to CO and cardiovascular disease mortality (Liu et al., 2018). The CO toxicity is primarily mediated through hypoxic pathways when CO molecules displace oxygen (O<sub>2</sub>), causing a decrease in the capacity of the blood to oxygenate tissues (WHO Regional Office for Europe, 2000). The toxicity mechanism, and associated risk, become more relevant if inhalation rates increase due to the physical effort during cycling.

Given this framework, the aim of our study was to use CO as a proxy of air quality during bicycle routes within the urban microenvironments of a modern Australian city that promotes to the use of bicycles. We employed a low-cost sensor, mounted on a bicycle, as a suitable methodology to determine street-level variability in an urban environment. Using the data obtained, we calculated the inhaled CO dose in real time and the total dose over each trip in order to estimate cyclist risk in different city microenvironments. Finally, relationships between CO concentrations and other variables, including meteorological and traffic parameters, were analyzed at different times, and in different zones of the city.

## 2. Methodology

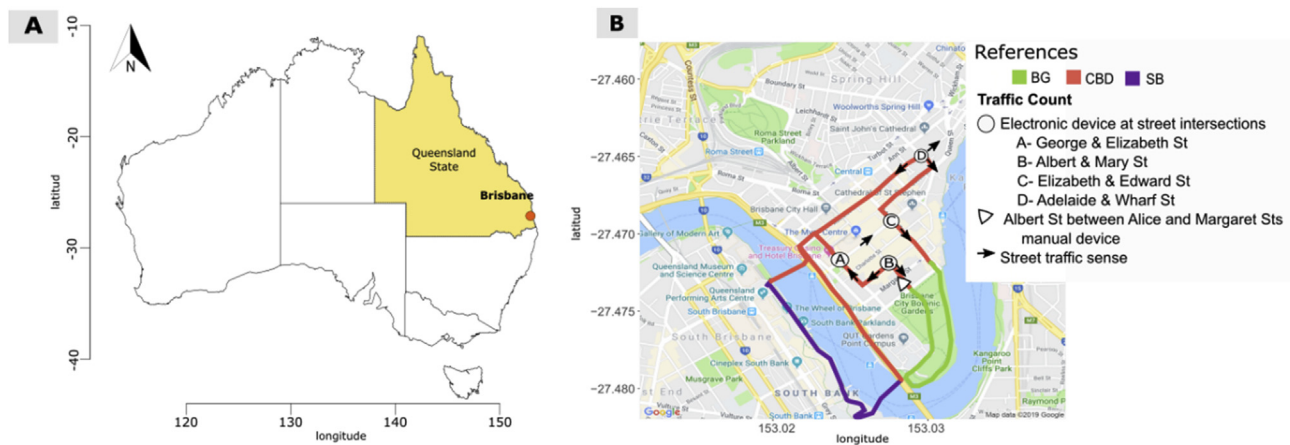
### 2.1. Sampling sites

Brisbane, the capital of the state of Queensland (Australia, Figure 1A), represents the third-largest urban area in the country with a population of 1.2 million inhabitants. The city and surroundings are characterized by a subtropical climate, with warm or hot weather during a high proportion of the year. Mean temperatures range between 11–21 °C and 21–30 °C during the dry winter and humid summer, respectively. Autumn weather presents a similar temperature range to spring (15–25 °C) and lower humidity than the summer season. In Brisbane, wind speeds are generally highest in the summer and spring. Brisbane city is located on the banks of the Brisbane River, with an extended residential area. It can be characterized as a fast-growing urban area, with a modern design that includes a high proportion of green space and infrastructure designed to promote active transport modes, such as cycling.

In the present study, the measurements were carried out during May 2018, including week days (10<sup>th</sup>, 15<sup>th</sup>, 17<sup>th</sup>, 22<sup>th</sup> and, 24<sup>th</sup>) and weekend days (13<sup>th</sup> and, 20<sup>th</sup>). Air monitoring was carried out along an 8.3 km route following urban bicycle pathways, selected according to those more frequently used by cyclists (<https://www.cyclingbrisbane.com.au>, Dawkins et al., 2019).

The selected route included three different zones, or urban microenvironments, with distinctly variable air quality levels (Figure 1B): \*Botanical garden (BG): bicycle pathways, located in the Brisbane Botanical Garden characterized as one of the main green spaces of the city and where motorized vehicles are banned or strictly limited; \*Central Business District (CBD): bicycle pathways going through Brisbane’s main roads, with high traffic density; \*South Bank (SB): bicycle pathway located along the river in the South Bank parkland. Low or middle-density traffic occurs along the road parallel to the South Bank parkland.

Air monitoring was conducted during weekdays during four-time slots (7:00–8:30; 8:30–10:00; 15:30–17:00; and 17:00–18:30) while two-time slots (10:00–11:30 and 11:30–13:00) were selected for weekend days. In all the cases, time slots were selected according to Brisbane cycle count data (Caldwell, 2017). Each time slot lasted 1.5 h and included two bicycle ride laps of the route. Simultaneously, for each lap, a traffic count was carried out manually at one site (Albert St., between Alice St and Margaret St, Figure 1B) located within the CBD zone using an electronic digital tally counter. In addition, traffic count data from four electronic intersections (George & Elizabeth St; Elizabeth & Edward St; Albert & Mary St; Adelaide & Wharf St) located in the CBD zone were



**Figure 1.** Map of monitored area: A- Brisbane city (orange dot) located in the Queensland State (Australia); B- Bicycle route and associated urban microenvironments: three different city zones were established, Botanical Garden (BG, green line), Central Business District (CBD, pink line) and South Bank (SB, violet line). Locations of electronic devices for traffic count from Brisbane City Council are shown (black circles) and as well as street traffic sensors (black arrows). In addition, traffic count data (using a manual device) from Albert St was registered at this study. Map source: Google Map through RStudio Software with authors' editions.

obtained from the Brisbane City Council and included in the present study (Figure 1B).

## 2.2. Carbon monoxide monitoring and environmental data

The carbon monoxide concentrations were monitored using an Alphasense CO-B4 manufactured by Alphasense Ltd, United Kingdom ([www.alphasense.com](http://www.alphasense.com)). The technical details specify a detection range of 0–1000 ppm with an accuracy of 4 ppb. The operating life of the sensor is given as 3 years with a specified zero drift of  $\pm 100$  ppb yr<sup>-1</sup>. The sensor was calibrated immediately before the experiments were conducted (Supplementary Material, Figure SM1). Subsidiary experiments showed that the drift in the readings of the Alphasense CO-B4 sensor was of the order of 100 ppb per year (Liu et al., 2020). Because the data used in the present study derived from the two-week monitoring campaign, no significant error associated with drift are expected. For CO measurements, the sensor was installed within a compact battery-powered monitor, including a secure digital card for data storage. The monitor was attached to the front of a bicycle, close to the rider. Geolocation of CO concentrations along the selected route was obtained through a Global Positioning System tracker (GPS, 'LocaToWeb' app: <https://locatoweb.com/>) carried on the bicycle. The sensor and GPS were synchronized to provide CO atmospheric concentrations and geolocation data every five seconds along the route.

Data corresponding to a total of 48 laps of the route over five weekdays and two weekend days were recorded.

Meteorological data for the monitoring period were obtained from the Queensland Department of Environment and Science (DES) web page (<https://environment.des.qld.gov.au>). For the present study, available data of wind speed (m s<sup>-1</sup>), wind direction (degree, 1 h average), temperature (°C) and relative humidity (%) were obtained from the South Brisbane DES air quality monitoring station.

## 2.3. Data analysis

The CO concentrations obtained in the present study were corrected following the sensor calibration described by Castell et al. (2017).

$$CO = CO_{\text{sensor}} + CO_{\text{cte}}$$

where CO is the actual concentration of carbon monoxide, CO<sub>sensor</sub> is the concentration of the CO (ppb) measured by the sensor and CO<sub>cte</sub> is a constant value (166 ppb) established during the calibration of CO-B4

Carbon Monoxide Sensor for urban studies (dense traffic periods) (Castell et al., 2017). Subsequently, CO concentrations were expressed in mg m<sup>-3</sup> using the mean air temperature of the period (25 °C) and a pressure of 1 atm.

The data obtained from each bicycle lap was classified into city zones (BG, SB and CBD).

The CO Inhaled Dose in real time (ID, mg km<sup>-1</sup>) was calculated, for each lap of the route discriminating city zones, according to the following formula described by Ramos et al. (2016):

$$\text{Inhaled Dose} = \frac{C_{ix} * VE * t_x}{km_x}$$

where:

$C_{ix}$  is the average concentration (mg m<sup>-3</sup>) of the pollutant measured for a certain city zone along one bicycle ride lap.

$VE$  is the minute ventilation according to EPA (2011). Average values for males (age range: 21 – < 61 years old, unadjusted for body weight) were considered being  $1.39 \times 10^{-2}$  m<sup>3</sup> min<sup>-1</sup> for light-intensity activities and  $5.59 \times 10^{-2}$  m<sup>3</sup> min<sup>-1</sup> for high-intensity activities. Considering Brisbane's topography and according to Ramos et al. (2016), the VE rate for high-intensity activities has been considered for the present study.

$km_x$  is the distance of the route through a certain city zone along one bicycle ride lap, being 1.7 km, 1.7 km and 4.9 km for BG, SB and CBD, respectively.

$t_x$  is the time spent within a certain city zone along one bicycle ride lap.

The carbon monoxide total dose over each trip (COD, mg) for a cyclist was calculated as the cumulated sum of inhaled CO by minute along each lap of the route, for all studied time periods during week and weekend days, according to the following equation:

$$COD = \sum_{i=1}^n \bar{C}_i * VE$$

where  $\bar{C}_i$  is the average concentration of CO (mg m<sup>-3</sup>) by minute of each bicycle lap, VE is the minute ventilation (m<sup>3</sup> min<sup>-1</sup>) and,  $n$  is the total duration (min) of each cycled lap. Data is expressed as the average  $\pm$  standard deviation (SD). For statistical analysis, normality and variance homogeneity were tested using Infostat Software (Version, 2013). A posteriori testing was used to prove significant differences between studied city zones and time slots ( $p < 0.05$ ). Plots and maps were obtained using R Studio Software (Version 1.0.153).

### 3. Results and discussion

#### 3.1. Atmospheric concentrations of carbon monoxide

Significant spatiotemporal differences in atmospheric CO concentrations along the selected bicycle route (Figure 2) were observed, demonstrating the presence of varying urban microenvironments. As expected, due to the absence of traffic, the lowest values occurred in the BG during the week ( $0.20 \pm 0.03 \text{ mg m}^{-3}$  for 15:30–17:00 time-slot) and weekend days ( $0.12 \pm 0.04 \text{ mg m}^{-3}$  for 11:30–13:00 time-slot). Conversely, the highest CO concentrations were observed in the CBD zone, reaching  $0.80 \pm 0.22 \text{ mg m}^{-3}$  during weekdays (17:00–18:30 time-slot) and levels falling by half during weekend days ( $0.36 \pm 0.06 \text{ mg m}^{-3}$ , 10:00–11:30 time-slot). The average CO concentration measured in Brisbane during the present study period was  $0.42 \pm 0.46 \text{ mg m}^{-3}$ . While the maximum hourly average determined was  $0.87 \pm 1.04 \text{ mg m}^{-3}$ . These values are relatively low when compared to many large cities in the world. CO concentrations are generally reported as 8-hour rolling averages because WHO and national air quality guidelines specify a maximum CO level of  $10 \text{ mg m}^{-3}$  over 8 h (WHO Regional Office for Europe, 2000). Previous studies in Brisbane have also shown that average CO concentration is generally of the order of  $0.46 \text{ mg m}^{-3}$  (one year data), in good agreement with the present measurements (Morawska et al., 2002a).

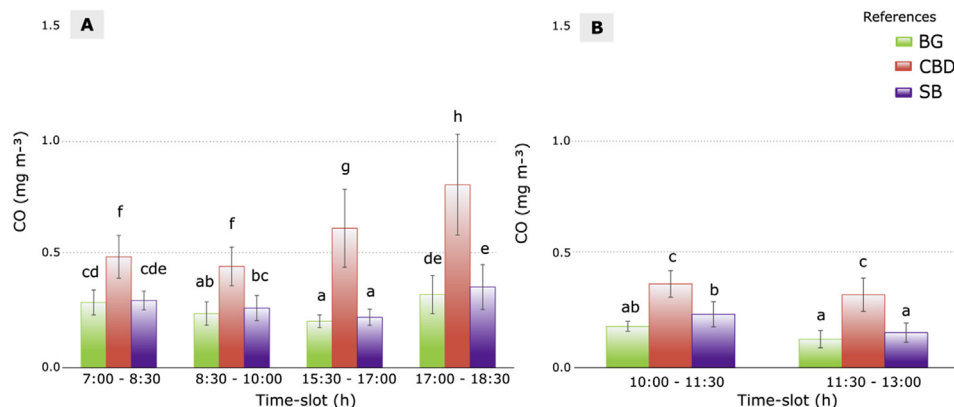
Considering only the weekdays (Figure 2A), CO levels in the CBD remained constant during the morning until around midday, increasing significantly over the afternoon hours into the evening. A slightly different pattern has been observed for BG and SB zones, where the highest concentrations were observed during the earliest time-slot in the morning and after 17:00 h. On the other hand, during the weekend days CO levels remained constant in the CBD and BG zones along the studied time-slots while, a significant decrease was observed in SB at midday (11:30–13:00 h) compared with the earlier time-slot (Figure 2B).

Carbon monoxide concentrations at the fixed monitoring site (South Brisbane station) showed a different pattern of variation (Supplementary Material, Table SM1) compared to data from the monitor on the bike. Even though during the weekdays' CO levels from the fixed monitoring site remained in the same range as those obtained in the present study, it showed the highest concentration during the 9:00–11:00 h time period ( $0.90 \pm 0.07 \text{ mg m}^{-3}$ ). Conversely, for weekend days, data from the fixed station overestimated exposure concentrations ( $0.82 \pm 0.05 \text{ mg m}^{-3}$ ) compared with our results (Figure 2). Therefore, as it was previously reported for other cities (Huang et al., 2012; Kaur et al., 2005), pollutant concentrations from fixed-station monitoring may not always be appropriate and representative of personal concentration exposure in urban microenvironments.

During weekdays, the average traffic flow in the CBD zone remained constant until the afternoon and increased significantly during the 17:00–18:30 h time slot, reaching a value of  $32.1 \pm 2.9$  vehicles per minute (Supplementary Material, Table SM2A). No significant daily variation was observed during weekends. In addition, the traffic count was significantly different according to the street intersections considered during week and weekend days (Supplementary Material, Table SM2B). The pattern of traffic volume at the four streets intersections suggested a difference in the use of city streets according to the period of the day (Supplementary Material, Figure SM2). The George & Elizabeth St showed a significantly higher traffic volume early in the morning until 10:00, decreasing after midday. The lowest traffic volumes were observed at Albert & Mary St intersection during the morning, increasing progressively after midday and reaching a maximum during the evening (17:00–18:30 time slot). George St and Albert St are one-way streets, that are used in the morning by motorists coming into the CBD zone. On the contrary, motorists chose Albert St during the evening for the return route, as reflected by the higher traffic counts manually registered at this location during the present study (Supplementary Material, Figure SM2, dashed line). The Elizabeth & Edward St and Adelaide & Wharf St. intersections did not show significant variations in their traffic volumes over the course of the day ( $p > 0.05$ ). The linear regression analyses between the measured CO levels for CBD zone and the traffic count data, showed a significant and positive relationship, with the traffic flow able to explain slightly more than 40% of CO concentration variability ( $R^2 = 0.41$ ,  $p < 0.05$ , Supplementary Material, Figure SM3). This result shows that motor vehicles are the main source of CO, which is to be expected in urban microenvironments. According to previous reports, vehicles' exhaust have been shown to be the main source of CO emission (up to 95%) in cities (U.S. EPA, 2014), including Brisbane (Morawska et al., 2002b). In our study, during weekdays, the peak of the CO levels occurring during the 17:00–18:30 time-slot was in agreement with the observed evening traffic rush hour in most of the street sites considered. However, traffic flow occurring early in the morning was not reflected in higher CO concentrations at street-level.

#### 3.2. Pollutant maps

Pollutant maps depict measured concentrations of compounds coupled with the GPS position as a result of the data collected along the studied route. Previous reports indicate that pollutant maps are very suitable to detect hotspots of high pollutant concentrations (Berghmans et al., 2008). In our study, as expected, CO pollutant maps (Figure 3 and Supplementary Material, Figure SM4) reveal a marked decrease in the pollutant concentration as bicycle pathways move away from source emissions. The lowest concentrations of CO were observed along the



**Figure 2.** Atmospheric carbon monoxide (CO) concentrations ( $\text{mg m}^{-3}$ ) during week ( $n = 10$ ) (A) and weekend ( $n = 4$ ) (B) days. Mean and standard deviation (SD) are given for Botanical Garden (BG), Central Business District (CBD) and South Bank (SB) city zones for each studied time-slot. Different letters indicate statistically significant differences among time-slots for each plot ( $p < 0.05$ ).



cycle paths that cross the green city zone (BG) and places further away from the traffic (SB). Likewise, it is possible to observe CO hotspots mainly on bike pathways located in streets belonging to the CBD zone reaching values close to  $9 \text{ mg m}^{-3}$  in some instances. Most of these events, coincided with street junction traffic lights where vehicles, including bicycles, slow down or stop.

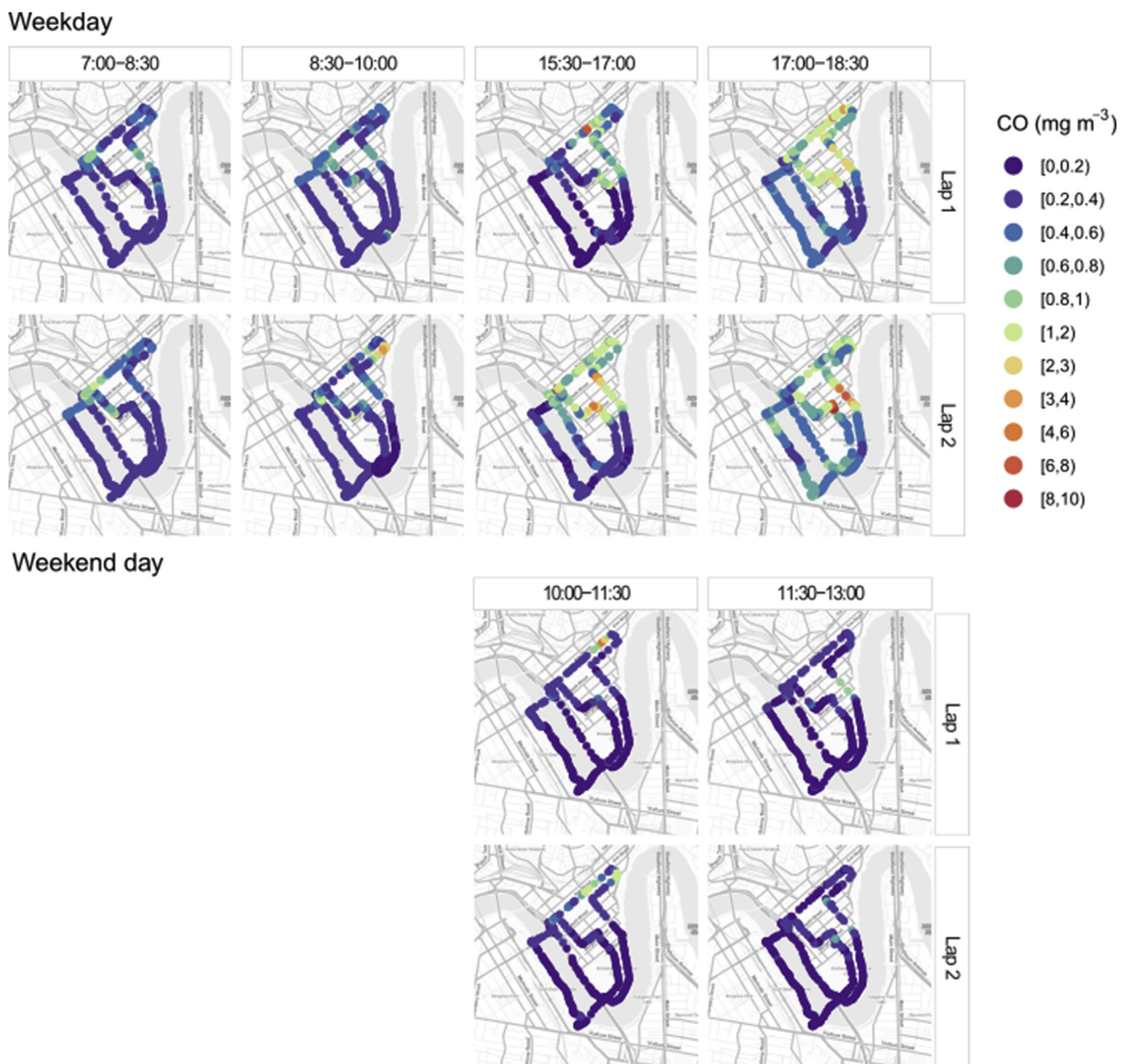
### 3.3. Inhaled CO dose in real time

According to previous studies, concentrations of air pollutants represent only part of the exposure assessment. In addition, it is suitable to take into consideration physiological properties and exposure time in order to more comprehensively describe the commuter's exposure.

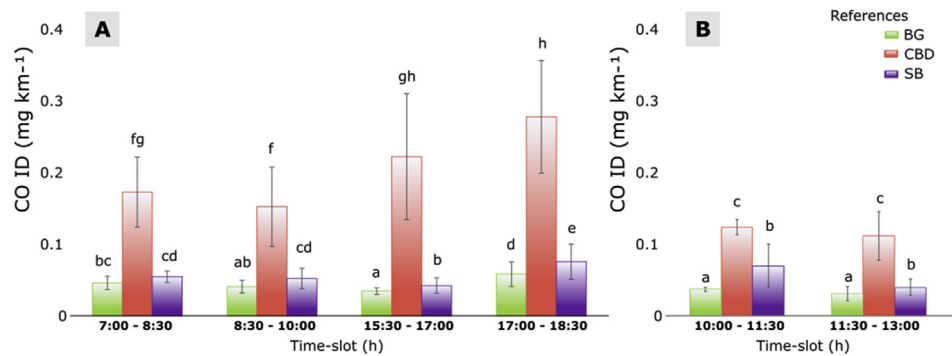
In our study, during weekdays (Figure 4A), the inhaled CO dose in real time (ID) decreased in the following order:  $\text{CBD} > \text{SB} \geq \text{BG}$ . In the CBD zone, the ID was significantly higher after midday, reaching values of  $0.28 \pm 0.08 \text{ mg per km}$  for the later monitored time-slot (17:00–18:30h). Conversely, in those zones with lower traffic density,

the ID was slightly higher in the SB (range:  $0.06\text{--}0.08 \text{ mg km}^{-1}$ ) compared with BG (range:  $0.03\text{--}0.04 \text{ mg km}^{-1}$ ) especially during the evening but, in both cases, significantly lower than calculated for CBD. On the other hand, during weekend days (Figure 4B), ID was not significantly different between the studied time-slots. Instead, significant differences occurred among city zones, displaying the same pattern as previously described for weekdays. Described variability in pollutant exposure, according to the bike pathway zone chosen and the period of the day considered, is in agreement with the recent Brand et al. (2019) study where the cyclist exposure to black carbon particles was related to the mentioned variables.

Comparing ID for Brisbane city with previous studies, Ramos et al. (2016) reported Lisbon (Portugal) weekday ID values from  $0.06 \text{ mg km}^{-1}$  during the morning (from 8:00–11:00) to  $0.08 \text{ mg km}^{-1}$  in the afternoon (17:30 h), considering cyclists going through a popular route of the city. On the other hand, Huang et al. (2012) reported average CO concentrations during light and heavy traffic times for cyclists in Beijing (China). The Huang et al. data showed ID values of  $0.19 \pm 0.04 \text{ mg km}^{-1}$



**Figure 3.** Carbon Monoxide (CO) maps: Atmospheric CO concentrations ( $\text{mg m}^{-3}$ ) measured along the monitored lap for botanical garden (BG), Central Business District (CBD) and South Bank (SB) city zones for each studied time zone. Reddish spots point out those urban microenvironments with pollution hotspots. Data from weekday (22<sup>th</sup> May) and weekend day (13<sup>th</sup> May) are represented. The “[” and “)” means closed and open concentration intervals, represented with a colour scale.



**Figure 4.** Carbon monoxide inhaled dose in real time (CO ID,  $\text{mg km}^{-1}$ ) for high-intensity activities during weekdays (A) and weekend days (B). Mean and standard deviation (SD) are informed for botanical garden (BG), Central Business District (CBD) and South Bank (SB) city zones. Different letters indicate statistically significant differences ( $p < 0.05$ ).

(light-traffic hours) and  $0.31 \pm 0.04 \text{ mg km}^{-1}$  (high-traffic hours) for a cyclist traveling during winter times in Beijing (China). Reported levels of ID are close to those described for the CBD zone in Brisbane which is surprising considering that Beijing is characterized by a high-density population (reaching more than 20 million), heavy traffic jams and intensive human activities, including industrial, causing serious air pollution events (Yu et al., 2019). Probably, the lower VE value ( $0.026 \text{ m}^3 \text{ min}^{-1}$ ) reported could explain, at least in part, a probable underestimation of the ID values for pollutants. Even so, a strong influence of city design and climatic variables on air quality and associated population exposure cannot be discarded, beyond the local atmospheric emissions.

Next, we calculated the ratios of the ID between each of the more polluted city zones (CBD and SB) and that determined in the cleanest CO sector (the BG green area) (Figure 5).

During the weekdays (Figure 5A), the ratio was almost four times higher in the CBD before midday, reaching just over six times higher during the afternoon. On the other hand, the ratio in SB remained close to one (ratios range: 1.19–1.30) during all studied time-slots, indicating a CO exposure comparable with that reported for the green area. During the weekend, ratios in the CBD were similar to those described for morning time during the week, which implied an inhaled dose close to four times higher than those occurring in the BG (Figure 5B). Finally, SB showed similar ratio values to those described during the week, being slightly higher during the 10:00–11:30 time-slot (ratio 1.90). Previous reports have considered the ratio calculated among different travel modes (bicycle, car, bus, among others) (Ramos et al., 2016) or routes (Huang et al., 2012) but, to our knowledge, no previous studies have compared CO inhaled doses in urban microenvironments associated with bicycle pathways.

According to Filonchyk and Yan (2018) a positive and significant correlation occurs among CO,  $\text{NO}_2$ ,  $\text{SO}_2$  and  $\text{PM}_{2.5}$  levels in the urban

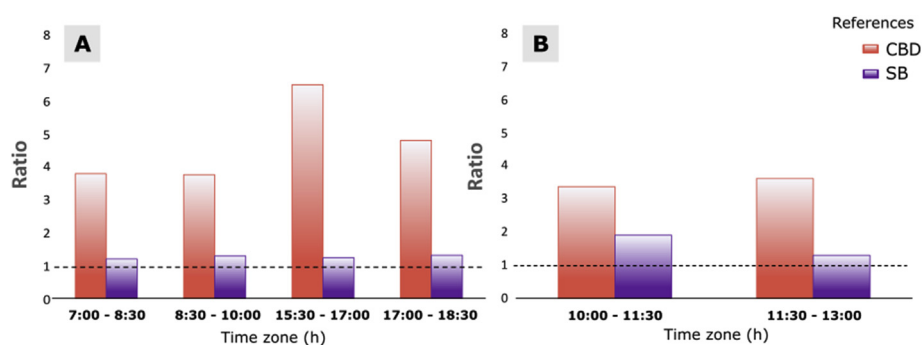
environment, reflecting a shared emission source of the pollutants. In this context, the proposed proxy (CO) would be indicative of simultaneous exposures to the aforementioned pollutants, and therefore the risks associated with this. Future studies evaluating the simultaneous ID of different atmospheric pollutants in urban microenvironments would contribute to the understanding of cyclists' exposure in Brisbane city.

### 3.4. Carbon monoxide total dose over each trip

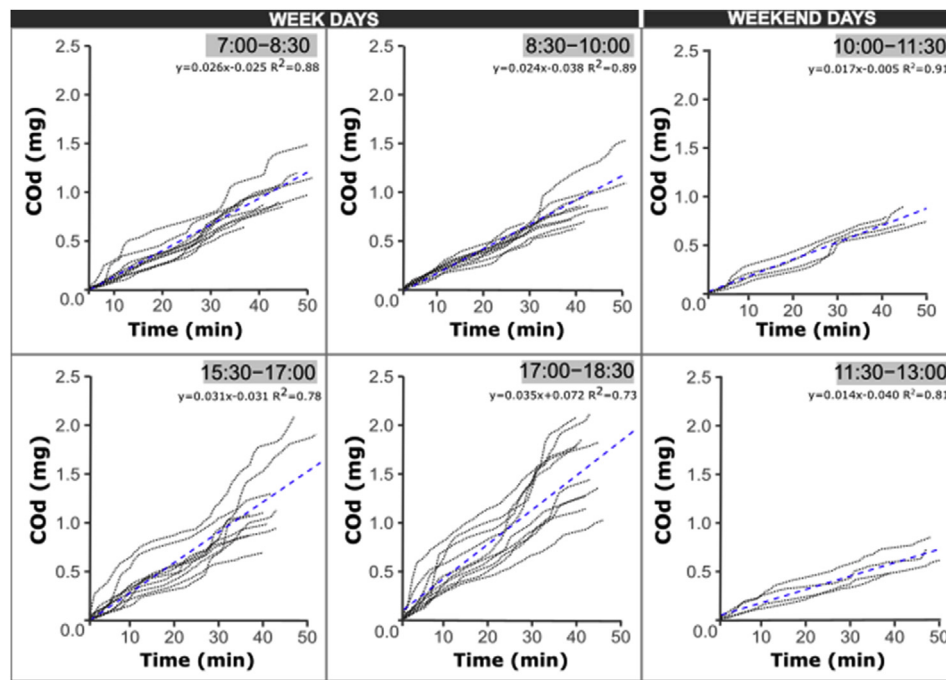
Considering the CO atmospheric concentration, VE and trip duration, the carbon monoxide total dose over each trip (COD, mg) was calculated for each time-slot (Figure 6). For a trip duration of around 45 min, COD values remained below 1.5 mg before midday, reaching 2.0 mg during the evening (17:00–18:30 time-slot) for weekdays, while not exceeding 1.0 mg for weekend days. Similar values have been reported by Huang et al. (2012) for a bike commuter traveling in Beijing City during traffic-light times ( $1.31 \pm 0.32 \text{ mg}$  of CO) and traffic-heavy times ( $2.11 \pm 0.35 \text{ mg}$  of CO) through a bike trip around 10 min shorter ( $\sim 35 \text{ min}$ ). Considering the expected increase of lung diffusion capacity (up to a factor of 3) during physical exercises (Bigazzi and Figliozzi, 2014), cyclists would likely absorb a greater proportion of the COD than, for example, a person with a similar COD choosing a non-active transport mode.

### 3.5. Environmental variables influencing CO levels

To quantify the contribution of those environmental variables, known to have a significant association with atmospheric CO levels, we ran a multivariate regression analysis. To fit with the averaging time slots of the meteorological data used, here we modeled full 2 h' time-slots (e.g. 7:00–9:00, 9:00–11:00, etc.). The obtained model for Brisbane city



**Figure 5.** Ratios between inhaled dose in the Botanical Garden (BG) and all the others studied city zones (CBD and SB) during the week (A) and weekend (B) days. The dotted line indicates a ratio equal to one, meaning same inhaled rates than those measured in the BG.



**Figure 6.** Carbon monoxide total dose over each trip (COd, mg) for studied time-slot (grey box) during week and weekend days. Linear regression (blue line) including the equation and R-squared (R<sup>2</sup>) are shown.

explained 72% of the variability of CO concentrations (R<sup>2</sup> = 0.72, p < 0.05; Supplementary material, Table SM3). According to our results, the considered city zone (CZ) was the parameter that most affected pollutant concentrations, followed by the time-slot (TS); giving positive β coefficients in both cases (Table 1). Finally, the wind speed (WS) showed a negative β coefficient, pointing to the dispersion of atmospheric pollutants during more windy time periods. If WS is considered, average values during the [9:00–11:00) and [15:00–17:00) time-slots remained close to 1.70 m s<sup>-1</sup>, falling significantly during the [17:00–19:00) time interval (0.98 ± 0.50 m s<sup>-1</sup>; p < 0.05). The WS during the [7:00–9:00) time-slot (1.47 ± 0.56 m s<sup>-1</sup>) did not show any significant difference from all the time periods previously mentioned. According to these results, the decay of wind speed seems to be responsible, at least in part, for the highest CO concentrations after 17:00 h, mainly in the CBD zone, during weekdays. Other variables including relative humidity, temperature and wind direction have not shown significant effects on CO levels in Brisbane city. Our study is in agreement with previous studies, where wind speed has been identified as a variable with a significant effect on atmospheric pollutant concentrations, including carbon monoxide (De Nazelle et al., 2012; Kaur et al., 2007).

#### 4. Conclusions

In the present study, the monitoring of CO at street levels was proposed as a low-cost proxy of exposure to a large number of car exhaust pollutants. The mobile platform and instrument used were able to provide information on the spatiotemporal variation of CO concentrations in urban microenvironments. The results demonstrated that the exposure to CO varied widely between different bicycle microenvironments. In this context, the benefits of riding a bicycle would be partially offset depending on where and when people are cycling in the inner-city. Weekdays after 17 h were signaled as the worst time to ride a bicycle through the streets of the CBD zone. City zones with heavy traffic flow showed pollutant inhaled dose values that were up to six times higher than those measured in green areas, being in some cases comparable with those described for large mega-cities. The description of sites with pollution hotspots shows the usefulness of such studies for future urban planning and design, as well as for local decision-makers on environment and health policies. Results point out to how city design, transit flows and climatic variables, such as wind speed, can contribute significantly to pollutant exposure beyond emissions rates.

**Table 1.** Multivariate analysis for environmental variables influencing CO levels in Brisbane city during week and weekend days: the model considered wind speed (WS), % of humidity (%H), temperature (T), wind direction (WD) including northwest (NW) and northeast (NE), city zones (CZ) including Central Business District (CBD) and South Bank (SB), and time-slot (TS). Only statistically significant coefficients are shown (p < 0.05).

Model	Intercept	β for WS	β for % H	β for T	Wind Direction <sup>a</sup>			City Zone <sup>b</sup>		Time-Slot <sup>c</sup>			
					β for NE	β for SE	β for SW	β for CBD	β for SB	β for [7:00–9:00)	β for [9:00–11:00)	β for [15:00–17:00)	β for [17:00–19:00)
Log CO ~ WS + %H + T + WD + CZ + TS	2.09	-0.07	-	-	-	-	-	0.32	-	0.24	0.14	0.16	0.31

Considered variables: Wind Speed (WS); % of Humidity (%H), Temperature (T), Wind Direction (WD), City Zone (CZ) and, Time-Slot (TS).

Note: The “[” and “)” mean closed and open time intervals, respectively.

<sup>a</sup> NW was considered as reference for Wind Direction.

<sup>b</sup> BG was considered as reference for City Zone.

<sup>c</sup> [11:00–13:00) period from weekend days was considered as reference for Time-Slot.



Finally, the present work contributes to information about commuters' exposure to atmospheric pollutants, necessary for modifying the population's, including cyclist's, perception of pollution in the urban environment, giving people the opportunity to choose a healthier route. In this context, knowledge of the air quality associated with urban microenvironments is significantly valuable for the development of mobile applications, where the "best active transport pathway" can be selected according to, not only the distance and travel time, but also considering the healthiest option. Finally, as co-exposure to atmospheric pollutants coming from vehicle exhausts is expected, future studies focusing on other atmospheric pollutants at street levels would be useful for a better understanding of potential uptake doses and health effects associated with active transport modes in urban environments.

## Declarations

### Author contribution statement

Lidwina Bertrand: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Laura Dawkins: Conceived and designed the experiments; Performed the experiments.

Rohan Jayaratne: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Lidia Morawska: Conceived and designed the experiments; Wrote the paper.

### Funding statement

This work was supported by Australian Research Council Linkage Grant LP16010051. L. Bertrand was supported by the "Endeavour Research Fellowship from Australian Government" as well as through fellowship from the CONICET (Argentina).

### Competing interest statement

The authors declare no conflict of interest.

### Additional information

Supplementary content related to this article has been published online at <https://doi.org/10.1016/j.heliyon.2020.e04195>.

## Acknowledgements

This work was supported by Australian Research Council Linkage Grant LP16010051. L. Bertrand was supported by the "Endeavour Leadership Program - an Australian Government initiative" as well as through fellowship from the CONICET (Argentina).

## References

Anowar, S., Eluru, N., Hatzopoulou, M., 2017. Quantifying the value of a clean ride: how far would you bicycle to avoid exposure to traffic-related air pollution? *Transp. Res. Part A Policy Pract.* 105, 66–78.

Berghmans, P., Bleux, N., Panis, L.L., Mishra, V.K., Torfs, R., Poppel, M. Van, 2008. Exposure assessment of a cyclist to PM 10 and ultrafine particles. *Sci. Total Environ.* 407, 1286–1298.

Bigazzi, A.Y., Figliozzi, M.A., 2014. A transnational review of urban bicyclists' intake and uptake of traffic-related air pollution. *Transp. Rev. A Transnatl. Transdiscipl. J.* 37–41.

Brand, V.S., Kumar, P., Santos Damacena, A., Pritchard, J.P., Geurs, K.T., Andrade, M. de F., 2019. Impact of route choice and period of the day on cyclists' exposure to black carbon in London, Rotterdam and São Paulo. *J. Transp. Geogr.* 76, 153–165.

Caldwell, B.F., 2017. Brisbane Cycling Data Reveals when and where People Hop on Their Bikes. *Brisbane Times*.

Castell, N., Dauge, F.R., Schneider, P., Vogt, M., Lerner, U., Fishbain, B., Broday, D., Bartonova, A., 2017. Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? *Environ. Int.* 99, 293–302.

Dawkins, L.C., Williamson, D.B., Mengersen, K.L., Morawska, L., 2019. Where is the clean Air? A Bayesian decision framework for personalised cyclist route selection using R-INLA. *Bayesian Anal.* 1–31.

De Nazelle, A., Bode, O., Orjuela, J.P., 2017. Comparison of air pollution exposures in active vs. passive travel modes in European cities: a quantitative review. *Environ. Int.* 99, 151–160.

De Nazelle, A., Fruin, S., Westerdahl, D., Martinez, D., Ripoll, A., Kubesch, N., Nieuwenhuijsen, M., 2012. A travel mode comparison of commuters' exposures to air pollutants in Barcelona. *Atmos. Environ.* 59, 151–159.

EPA, 2011. Exposure Factors Handbook: 2011 Edition, EPA/600/R. National Center for Environmental Assessment, Washington, DC. USA.

Filonchik, M., Yan, H., 2018. The characteristics of air pollutants during different seasons in the urban area of Lanzhou, Northwest China. *Environ. Earth Sci.* 77, 763.

Forehead, H., Huynh, N., 2018. Review of modelling air pollution from traffic at street-level - the state of the science. *Environ. Pollut.* 241, 775–786.

Gössling, S., Humpel, A., Litman, T., Metzler, D., 2019. Effects of perceived traffic risks, noise, and exhaust smells on bicyclist behaviour: an economic evaluation. *Sustainability* 11, 1–15.

Huang, J., Deng, F., Wu, S., Guo, X., 2012. Environment Comparisons of personal exposure to PM 2.5 and CO by different commuting modes in Beijing, China. *Sci. Total Environ.* 425, 52–59.

Kaur, S., Nieuwenhuijsen, M.J., Colville, R.N., 2007. Fine particulate matter and carbon monoxide exposure concentrations in urban street transport microenvironments. *Atmos. Environ.* 41, 4781–4810.

Kaur, S.A., Nieuwenhuijsen, M., Colville, R., 2005. Personal Exposure of Street canyon Intersection Users to PM 2.5, Ultrafine Particle Counts and Carbon Monoxide in Central London, UK, 39, 3629–3641.

Laumbach, R., Meng, Q., Kipen, H., 2015. What can individuals do to reduce personal health risks from air pollution? *J. Thorac. Dis.* 7, 96–107.

Liu, C., Yin, P., Chen, R., Meng, X., Wang, L., Niu, Y., Lin, Z., Liu, Y., Liu, J., Qi, J., You, J., Kan, H., 2018. Ambient carbon monoxide and cardiovascular mortality: a nationwide time-series analysis in 272 cities in China. *Lancet Planet. Heal.* 2, e12–e18.

Liu, X., Jayaratne, R., Thai, P., Kuhn, T., Zing, I., Christensen, B., Lamont, R., Dunbabin, M., Zhu, S., Gao, J., Wainwright, D., Neale, D., Kan, R., Kirkwood, J., Morawska, L., 2020. Low-cost sensors as an alternative for long-term air quality monitoring. *Environ. Res.* 185, 109438.

Lodovici, M., Venturini, M., Marini, E., Grechi, D., Dolara, P., 2003. Polycyclic aromatic hydrocarbons air levels in Florence, Italy, and their correlation with other air pollutants. *Chemosphere* 50, 377–382.

Minet, L., Stokes, J., Scott, J., Xu, J., Weichenthal, S., Hatzopoulou, M., 2018. Should traffic-related air pollution and noise be considered when designing urban bicycle networks? *Transp. Res. Part D* 65, 736–749.

Morawska, L., Jayaratne, E.R., Mengersen, K., Jamriska, M., Thomas, S., 2002a. Differences in airborne particle and gaseous concentrations in urban air between weekdays and weekends. *Atmos. Environ.* 36, 4375–4383.

Morawska, L., Thai, P.K., Liu, X., Asumadu-Sakyi, A., Ayoko, G., Bartonova, A., Bedini, A., Chai, F., Christensen, B., Dunbabin, M., Gao, J., Hagler, G.S.W., Jayaratne, R., Kumar, P., Lau, A.K.H., Louie, P.K.K., Mazaheri, M., Ning, Z., Motta, N., Mullins, B., Rahman, M.M., Ristovski, Z., Shafiei, M., Tjondronegoro, D., Westerdahl, D., Williams, R., 2018. Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: how far have they gone? *Environ. Int.* 116, 286–299.

Morawska, L., Vishvakarman, D., Mengersen, K., Thomas, S., 2002b. Spatial variation of airborne pollutant concentrations in Brisbane, Australia and its potential impact on population exposure assessment. *Atmos. Environ.* 36, 3545–3555.

Pattinson, W., Kingham, S., Longley, I., Salmund, J., 2017. Potential pollution exposure reductions from small-distance bicycle lane separations. *J. Transp. Heal.* 4, 40–52.

Queensland Government, 2019. Air Quality index [WWW Document]. URL: <https://www.qld.gov.au/environment/pollution/monitoring/air/air-monitoring/air-quality-index>.

Ramos, C.A., Wolterbeek, H.T., Almeida, S.M., 2016. Air pollutant exposure and inhaled dose during urban commuting: a comparison between cycling and motorized modes. *Air Qual. Atmos. Heal.* 9, 867–879.

Requia, W.J., Adams, M.D., Arain, A., Papatheodorou, S., Koutrakis, P., Mahmoud, M., 2017. Global association of air pollution and cardiorespiratory diseases: a systematic review, meta-analysis, and investigation of modifier variables. *Am. J. Publ. Health* e1–e8.

Rojas-Rueda, D., De Nazelle, A., Tainio, M., 2011. The health risks and benefits of cycling in urban environments compared with car use: health impact assessment study. *BMJ* 1–8.

Schindler, M., Caruso, G., 2014. Computers, Environment and Urban Systems Urban compactness and the trade-off between air pollution emission and exposure: lessons from a spatially explicit theoretical model. *Comput. Environ. Urban Syst.* 45, 13–23.

U.S. EPA, 2014. A Guide to Air Quality and Your Health.

Wang, J.Y.T., Dirks, K.N., Ehrgott, M., Pearce, J., Cheung, A.K.L., 2018. Supporting healthy route choice for commuter cyclists: the trade-off between travel time and pollutant dose. *Oper. Res. Heal. Care* 19, 156–164.



Weng, H.-H., Tsai, S.-S., Chen, C.-C., Chiu, H.-F., Wu, T.-N., Yang, C.-Y., 2008. Childhood leukemia development and correlation with traffic air pollution in taiwan using nitrogen dioxide as an air pollutant marker. *J. Toxicol. Environ. Heal. Part A Curr. Issues* 37–41.

WHO, 2016. *Ambient Air Pollution: A Global Assessment of Exposure and burden of Disease*. World Health Organization, Geneva, Switzerland.

WHO Regional Office for Europe, 2000. *Air Quality Guidelines for Europe*, second ed. Copenhagen.

Yu, S., Liu, Weijian, Xu, Y., Yi, K., Zhou, M., Tao, S., Liu, Wenxin, 2019. Characteristics and oxidative potential of atmospheric PM<sub>2.5</sub> in Beijing : source apportionment and seasonal variation. *Sci. Total Environ.* 650, 277–287.