We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

6,900
Open access books available

186,000
International authors and editors

200M
Downloads

154
Countries delivered to

Our authors are among the
TOP 1%
most cited scientists

12.2%
Contributors from top 500 universities

BOOK CITATION INDEX
CLARIVATE ANALYTICS
INDEXED

WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com

Chapter 6

Urban Air Pollution Mapping and Traffic Intensity: Active Transport Application

Rasa Zalakeviciute, Adrian Buenaño,
David Sannino and Yves Rybarczyk

Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/intechopen.79570

Abstract

Air pollution represents one of the greatest risks to human health, with most of the world's cities exceeding World Health Organization's recommendations for air quality. In developing countries, a major share of air pollution comes from traffic, consequently, creating air pollution hot spots inside urban street networks. While the world needs to switch to more active and sustainable ways of commuting in order to reduce traffic emissions and help improve degrading cardiopulmonary health due to increasingly sedentary habits, studies point to the negative effects of physical activity near traffic emissions. Common approaches of urban cycling infrastructure planning rely on space availability and route needs, omitting the most vital aspect—air quality. This study, therefore, combines the worldwide need for active commute and health benefits of the cyclists. Our goal was to produce urban pollution map through the geoprocessing of Google Traffic data, validated through the correlation of street level $PM_{2.5}$ (particulate matter <2.5 μm) concentrations and traffic intensity in a selected district of Quito, Ecuador. The multidisciplinary approach presented in this study can be used by city planners all over the world to help identify the cycling network based on air quality conditions and, consequently, promoting active travel.

Keywords: air pollution, urban planning, active travel, mapping, health

1. Introduction

Rapid urbanization, motorization, and industrialization are causing millions of annual deaths by deteriorating air quality—the largest single environmental health risk [1]. In developing world, traffic is one of the major sources of health concerning $PM_{2.5}$ (particles with

IntechOpen

© 2018 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/3.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. cc BY

an aerodynamic diameter less than 2.5 μm) [2]. This demonstrates the widespread need to moderate the rate of motorization by introducing more sustainable ways of transportation. In addition, motorization and technological advances result in diminished physical activity among the world's population, with 23% of adults and 80% of adolescents being insufficiently physically active [3]. This also enhances the risks of cardiovascular diseases, cancer, and diabetes, summing up to one of the leading risk factors for death worldwide [4, 5]. Sadly, obesity levels caused by food and physical inactivity are expected to grow worldwide, and developing countries are projected to exceed the obesity levels of developed countries in the near future [6]. In accordance with the recommendations of World Health Organization (WHO), numerous countries are setting goals on reducing air pollution and insufficient physical activity [3]. It is suspected that both issues of deteriorating air quality and physical activity could be solved by promoting active modes of transportation. In comparison with motorized traffic, cycling alternative requires very little space, and in addition, it is economic, clean, and promotes health [4, 7, 8].

Transport infrastructure is influenced by historical, political, cultural, structural, and economic aspects of urban development [9]. In the era of motorization, the choice of active way of travel over motorized mode depends on a vast range of factors such as proximity, connectivity, convenience, safety, population density, costs, environmental quality, existence of infrastructure and land use mix [10]. Planning urban cycling network is, therefore, a complex task as the existing and potential uses have to be anticipated in order to assure the efficiency of the infrastructure. Simplifying, urban bicycle path planning approaches are based on space availability and route demand by using GIS, GPS, remote sensing and even artificial intelligence techniques [11, 12]. Any new infrastructure, previously unaccounted for in the city's traffic model, has to be incorporated in an existing urban design [8]. In developed countries, efficient regulations are prioritized (traffic calmed residential neighborhoods, car-free city centers, special bicycle streets, etc.) in order to assure the safety of cyclists [9, 13]. At the same time, the route demand requires analyzing the necessity for the bicycle paths. This is done by computational analysis of urban infrastructure and population (census) or user surveys, and recently by mobile phone user applications registering the cycling activity to study the prioritized pathways (e.g., Strava Metro, Kappo, Chaquiñan Urbano, etc.). These applications analyze mobility patterns through voluntary geo-information (crowdsourcing) [14, 15] and interact with the user through games, implemented levels, missions, and rewards to attract new users (Kappo, Capos SpA).

Common approaches, however, often locate the bicycle lanes, tracks, and paths on the roads or in close proximity to motorized traffic. To improve travel safety and accident prevention on the road, a pioneer strategy applies a clear priority rules limited to two types of transport (e.g., bicycle and bus, or bicycle and cars, etc.) [8]. While it helps to reduce the cases of transit accidents, it does little in terms of cardiopulmonary health, especially in developing countries. While earlier studies on cycling focused on engineering, safety, and promoting cycling [7, 16], a number of recent studies discuss health benefits of cycling. For example, research indicates that if using the roads, the personal exposure of cyclists to combustion gas and particle pollution is significantly increased due to the higher concentrations adjacent to traffic and respiratory intensity of cycling [4, 17–22], which is even further increased in high altitude urban areas [23]. In addition, there are no cardiopulmonary health benefits to physical activity on traffic-polluted roads [24]. This study, therefore, proposes a health-centered novel approach to bicycle infrastructure planning based on air quality and traffic intensity. While most of the related research is reported from significantly less traffic-polluted developed countries, this proposal is supported by a study performed in a rapidly growing city of the developing world. Quito is a high elevation (2850 m.a.s.l.), midsize (pop. 2.2 million) city with a decade long $PM_{2.5}$ pollution problem, not only violating WHO recommendations for air quality but even significantly higher limits of national standards [25–27]. Due to older engine technologies (Euro 0–3), high sulfur content fuels (300–650 ppm), terrain inclination and driving style, engine combustion emissions are contributing to over 62% of total $PM_{2.5}$ [28].

This chapter consists of studying the fine particulate pollution at the street level in the central district of Quito, correlating $PM_{2.5}$ concentrations with traffic counts, and comparing the $PM_{2.5}$ pollution map with typical traffic activity, in order to suggest an economic way to plan a healthier active transport infrastructure. Section 2 describes the used methodology. Section 3 is a presentation and a discussion of the results. And Section 4 draws conclusions on the current issues in urban cycling path planning and proposals to improve it.

2. Methods

The historical Mariscal (area 1.5 km^2) district of Quito, Ecuador, was chosen for this study due to the existing network of bicycle lanes and a low variation in traffic intensity. A motorized traffic count was performed to determine the influence of traffic load on the concentration of $PM_{2.5}$. It was evaluated by manual observations [29] based on a week's (February 20–26, 2017) traffic counts, performed in a number of one- and two-way streets of the district. In case of two-way streets, the vehicle count was performed both ways. All heavy (trucks, buses, minibuses) and light (light vehicles and taxis) vehicles were counted from 7 to 8 pm.

At the same time of the experiment, $PM_{2.5}$ pollution scans were performed. To account for different vertical pollution mixing conditions, a multiple coverage of the main streets was performed. Street level $PM_{2.5}$ concentrations were measured using a portable real-time CEL-712 Microdust Pro™ monitor [30] coupled with a GPS [31]. The Microdust Pro was calibrated before the experiment using zero-air and a known concentration filter (164 mg/m^3). The performance of the Microdust Pro sensor based on near-forward angle light scattering technique was validated collocating it with Thermo Scientific 5014i Beta Continuous Ambient Particulate Monitor (R^2 = 0.74). The particle sensor and the GPS were both functioning at a synchronized step of 10 s (particle sensor at 10 s average), held at the height of 1.5 m facing the particle inlet forward while walking at an approximate speed of 2 km/h on the side of the street or an existing bicycle path. The gathered data were then combined with the GPS data to elaborate a pollution map in Qgis. All the collected points were used for the data processing, but atypical data were eliminated. This was done to reduce the impact of these values, which may be the result of some equipment failure [32]. The running average of 1 min was used to represent the points on the map. Geostatistical interpolation of $PM_{2.5}$ concentrations for the district was performed in Qgis using ordinary kriging method. Ordinary kriging is used in pollution dispersion models to estimate an unmeasured region, assuming a constant linear mean over space [33].

Particulate matter $PM_{2.5}$ is mainly produced by the vehicular traffic, especially by diesel vehicles. Thus, in order to assess the correlation between traffic and contamination, pollution maps are compared with traffic maps provided by Google Maps Traffic. Google Maps sets four levels going from fast to slow represented by colors green, orange, red, and brown, respectively. For our analysis, slow traffic representing red and brown were combined together. In the case of $PM_{2.5}$ concentrations, the maximum permissible limits of 24-h international and Ecuadorian regulations were used, three ranges were established: <25, 25–50, and > 50 μg/m^3). These ranges of pollution were also assigned by the same colors: green, orange, and, red respectively; in this case, brown is also combined with red. Once the ranges were defined in the GIS software, in this case Qgis, we proceeded to establish the format of the points for the pixel analysis. It was defined that each spatial point has a size of 6 pixels. In addition, the primary colors of green, blue (accounting for yellow), and red were used for the different levels, because it improved the subsequent computation of the spatial representation of the pollution. To create the traffic layers, the $PM_{2.5}$ pollution map was taken as a basis, and depending on the usual traffic, the color was modified point by point to add the traffic information to each cell. This process was done with the usual traffic of labor days at hours 09h00, 11h00, and 13h00 to cover the hours of the sampling for every studies. A complete street sampling took over 6 h (8h00–14h00) per day.

The original maps produced with Qgis are processed with a program written in Java (**Figure 1**). The first step consists of formatting the maps as a grid. Thus, it is possible to compare the color (level of pollution/traffic) between a cell of the traffic grid and its corresponding cell in the pollution grid. In the second step, the coordinates and the value (1 for green, 2 for yellow, and 3 for red) of each colored cell are recorded in a table, in which the correlation analysis is performed. Two methods are used to carry out the correlation. The first method is based on a strict matching between the colors of the peer cells. Thus, the assessment is Boolean. If the color of both cells is the same, the matching is evaluated as 1, otherwise the value is 0. Then, the value of the correlation (*r*) is calculated by Eq. (1).

$$r = \frac{\sum_{i=1}^{n}(m_i)}{N} \tag{1}$$

where m_i stands for a true matching and N is the total number of pairs of cells.

The second method is based on a weighted correlation. A weight is calculated according to the amplitude of the difference between the peer cells. For instance, if one cell is red (high) and the other is green (low), the value will be 2. But, if one cell is red and the other is yellow (medium), the value will be 1, only. And if there is no difference between the cells, the score will be 0. For this method, the calculation of the correlation (*r*) is provided by Eq. (2).

$$r = \frac{2N - \sum_{i=1}^{n} | t_i - p_i |}{2N} \qquad (2)$$

where t_i stands for the color value of the traffic, p_i stands for the color value of the pollution, and N is the total number of pairs of cells.

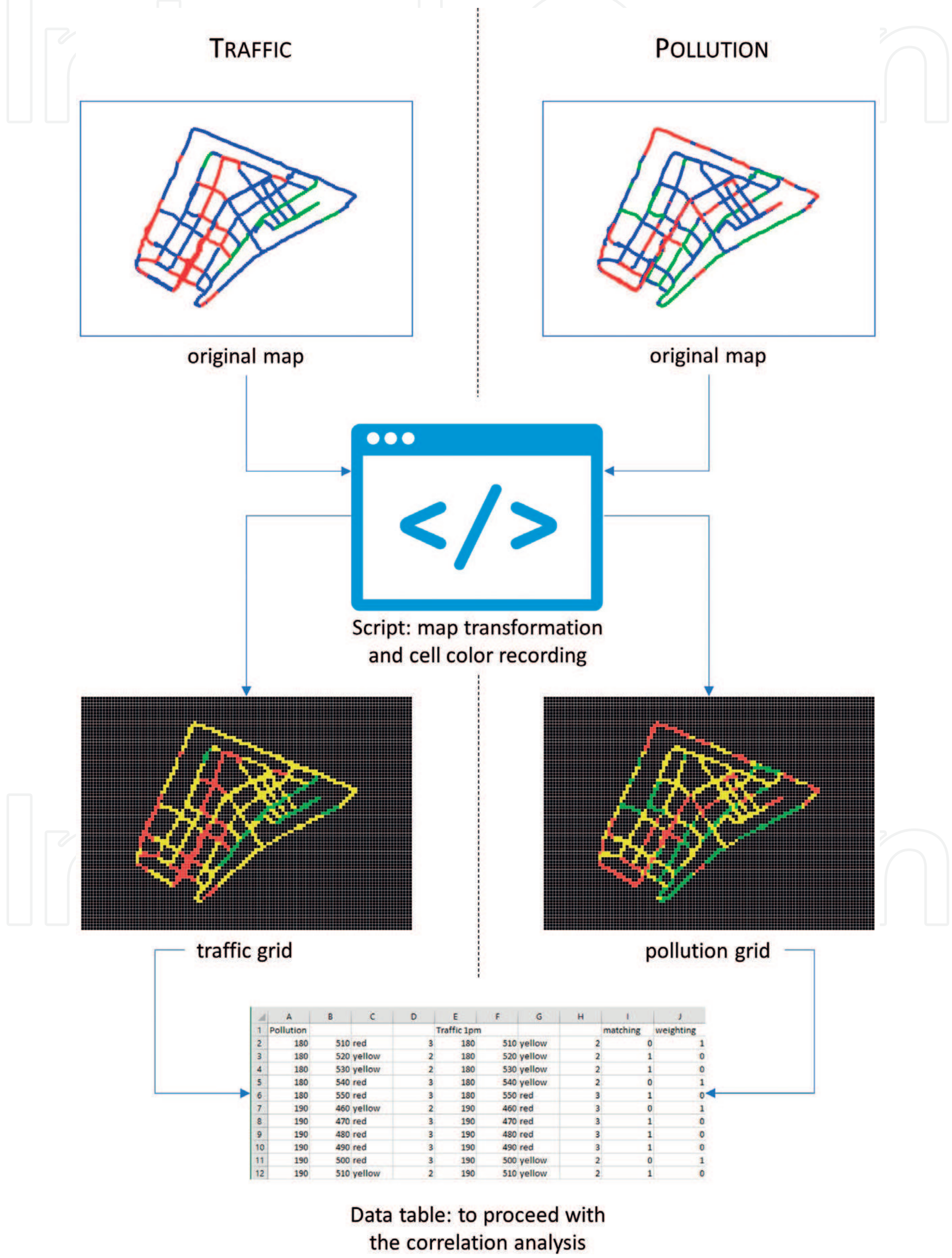

Figure 1. Flowchart to process traffic and pollution data from maps, and compare the values between each matching cell.

3. Results and discussion

During the study, temperature and relative humidity averaged 20°C and 53%, respectively. It is known that higher wind speed helps ventilate the pollution from the street canyons and lower personal exposure [34]. Thus, the low winds registered during the experiment (< 2.5 m/s) offered optimal conditions to measure trapped urban pollution. Higher winds are more common during dry season months of June-August, while current conditions represent Quito weather the rest of the year. This suggests that the results of this study represent usual conditions in the city.

The sampling route (approximately 6 h of sampling and 20 km long) covered a complete urban street infrastructure of the district, which also included sections of four existing bicycle lanes (indicated by broken lines in **Figure 2**). $PM_{2.5}$ concentrations averaged per street and spatial interpolation (ordinary kriging) are represented by the same scale in **Figure 2**. The $PM_{2.5}$ concentrations varied from 27 to 93 μg/m³. These levels exceed the WHO recommended levels for 24-h exposure (25 μg/m³). Meanwhile, punctual $PM_{2.5}$ concentrations (10 s averages) varied from 0 to 624 μg/m³. The sampling peaks nearly exclusively originated from the accelerating diesel buses and minibuses, often at traffic-light-controlled intersections (**Figure 2**).

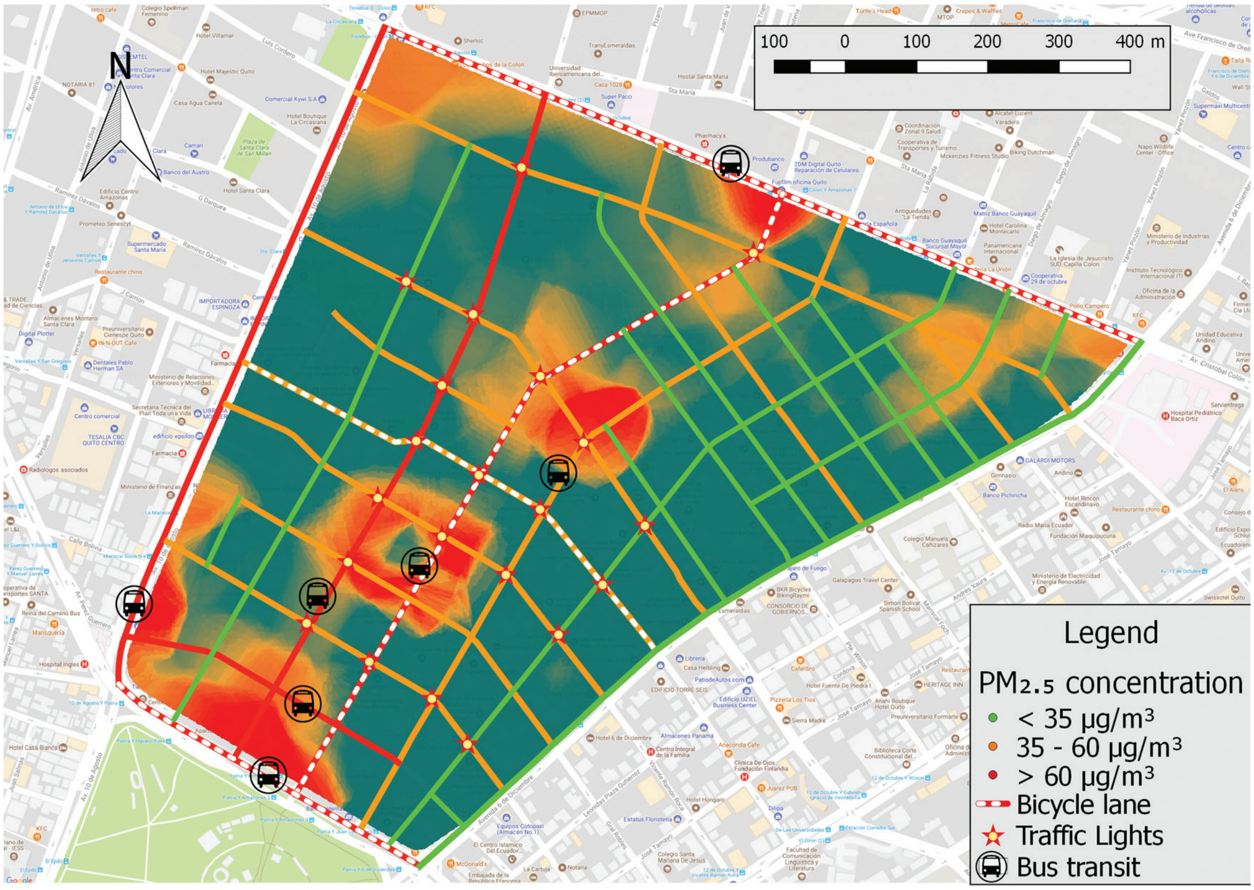

Figure 2. $PM_{2.5}$ concentrations in the urban street network of Quito district Mariscal averaged per street and spatial interpolation (ordinary kriging).

http://dx.doi.org/10.5772/intechopen.79570

This suggests very high levels of short time exposure to traffic-related $PM_{2.5}$ pollution, which is of a great concern to people near traffic sources.

It can be noted that the concentrations of $PM_{2.5}$ are higher at the streets containing bicycle lanes (**Figure 2**). Statistical analysis of street level concentrations indicated that the average concentration at the streets with cycling lanes is 1.58 times higher than the rest of the streets in the district. This suggests that the personal cyclist exposure to traffic pollution is significantly higher if using existing bicycle lane infrastructure than less densely transited parallel streets, especially streets not permitting city buses (see **Figure 2**). Often, current bicycle paths are located in the most direct and widest streets, thus commonly used by city transport (diesel engines). This places cyclists in the worst air quality conditions suggesting that the users are exposed to the highest level of contamination, and may not be reaping the expected health benefits of active commuting [4, 17–22]. In a few similar studies, the route choices were evaluated in terms of personal exposure to traffic pollution [35, 36], indicating that the choices of "greener" routes significantly reduced personal exposure to direct combustion emissions, but not city background pollution. However, in the case of many cities of the developing world, there are no "greener" options, and the traffic emission levels are significantly higher [37]. Previous studies conclude the importance of the selected travel route, ventilation rate, travel speed for the personal exposure of the person to the traffic pollution, etc. [4, 17]. We confirm the importance of relocating urban bike lanes to the calmer streets, especially in the cities with poor-quality fuels and technologies [17, 20].

For the traffic and $PM_{2.5}$ pollution correlation analysis, the vehicle counts and $PM_{2.5}$ concentration data were averaged per street during all the study period. Correlation analysis is summarized in **Figure 3**. It confirms that there is a strong positive correlation ($R^2 = 0.73$) between the presence of heavy vehicles and the concentrations of $PM_{2.5}$. The number of light personal vehicles and taxis also positively correlated ($R^2 = 0.67$) with the $PM_{2.5}$ concentrations (**Figure 3**). These findings are consistent with other studies [36].

$PM_{2.5}$ concentrations at the street level were also compared with the nearest air quality monitoring station (1.5 km away) representing air quality conditions for central Quito. During the study, the street level pollution was 2.5 times higher than at the monitoring site (elevated at about 10 m above the street infrastructure). The average $PM_{2.5}$ concentrations at the monitoring site were 23.3 ± 8 μg/m^3, while at the street level, the concentrations highly varied at 58.5 ± 91 μg/m^3.There was a positive correlation ($R^2 = 0.42$) between the two measurements, suggesting some relationship between the two traffic-busy areas. However, the significant difference questions current estimates of population exposure to air pollution based on monitoring network data. This especially underestimates the exposure of people that spend a considerable time outside in the street canyons (couriers, police, street vendors, etc.). This inconsistency was suggested by the previous study, where low correlation ($r = 0.31$ all day, $r = 0.49$ morning rush hours) was found between the $PM_{2.5}$ pollution at a monitoring station (elevated above street level) and the surrounding traffic activity [38].

Therefore, a deeper traffic intensity and $PM_{2.5}$ pollution study were performed. We compared the typical traffic at urban street infrastructure with street level $PM_{2.5}$ levels. The results of the

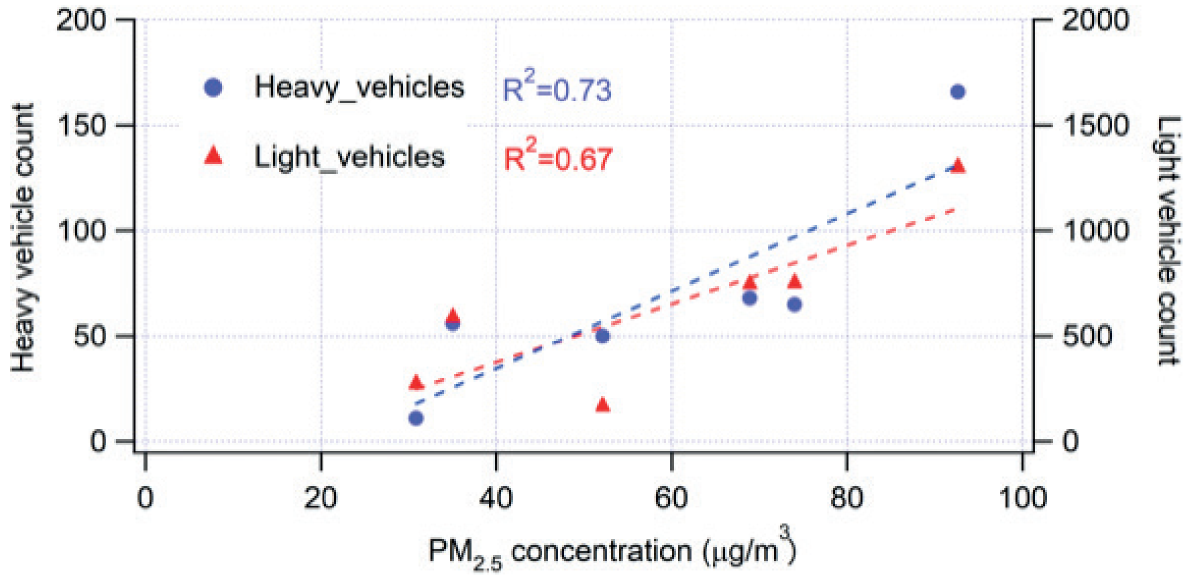

Figure 3. $PM_{2.5}$ concentrations plotted versus the counts of heavy and light vehicles in a few selected main streets, 4/6 of these streets contain bicycle paths (the highest concentrations).

Time	Strict correlation	Weighted correlation
9 am	0.5	0.73
1 pm	0.43	0.69

Table 1. Values of the coefficients r according to the method and the time.

comparison are presented in **Table 1**. The coefficients r obtained from the strict correlation analysis (method 1) are 0.5 and 0.43 at 9 am and 1 pm, respectively. Since the baseline is 0.33 (three possible levels), we can conclude that the correlation is largely above the chance level and, consequently, a significant part of the air pollution is directly explained by the urban traffic. The slight decreases of the correlation in the afternoon can be explained by an augmentation of the dilution of the pollutants in the atmosphere that occurs at this time of day [38]. These results are confirmed by the weighted correlation analysis. This second method provides us with coefficients of 0.73 and 0.69 at 9 am and 1 pm, respectively. Although the baseline of this method is higher (r = 0.5) than in the first analysis, the obtained values cannot be the effect of the hazard. As expected, the correlation between traffic and $PM_{2.5}$ is superior when the concentrations are recorded at the street level than at the monitoring station level. Taken together with the results presented in **Figure 3**, these findings support the hypothesis of considering traffic density in the planning of urban cycling paths.

While there is a serious traffic and physical inactivity problem in the world, one of the seemingly best solutions—cycling—might not be widely adopted due to multiple issues such as missing infrastructure, crime/safety, and environmental pollution [39]. The results of this study encourage city planners to locate cycling paths on less trafficked, light vehicle streets rather than on major streets, especially in developing countries using high sulfur content fuels that cause more particulate pollution. Not many cities can afford greenways (undeveloped land in or near urban area) for cycling; thus for the best solution, some lighter traffic density parallel street options can be used to redirect bicycle traffic to reduce the exposure to high concentrations of primary pollutants. Following the example of Amsterdam, Netherlands, the bicycle paths could be located on the streets of exclusively light vehicle traffic, not only reducing the risks of safety but also air pollution. This could further encourage new conversions toward more active commuting.

4. Conclusions

To the best of our knowledge, this is the only study proposing to base urban cycling path planning on the benefits of cardiopulmonary health and offering an economic solution applicable for any country. During the study, the street level pollution in a central district of Quito was 58.5 ± 91 $\mu g/m^3$, significantly exceeding the WHO recommended levels for air quality. This large variation suggests an extremely high level of short time exposure to traffic-related $PM_{2.5}$ pollution, which is of a great concern to people near traffic sources. The results of this study show that there is a strong positive correlation between the amount of heavy diesel vehicles (especially city busses) on the road and the concentrations of $PM_{2.5}$. We also demonstrate that most of the bicycle paths in the central Quito are located on the most polluted streets. This indicates the importance of an appropriate selection of routes with low vehicular traffic load to reduce cyclists' exposure to fine particulate matter. We also conclude a high correlation between the motorized traffic intensity (Google Traffic Maps service) and $PM_{2.5}$ pollution. Traffic maps offer a reliable and economic method for healthier cycling infrastructure planning in any city of the world. Therefore, this study serves as a reference for implementing control measures for public transport and for the planning of strategic routes, as well as the implementation of adequate infrastructure to support active transportation by reducing vehicular pollution exposure and promoting human health.

Acknowledgements

We want to thank the Secretariat of the Environment of the Municipality of the Metropolitan District of Quito in Quito, Ecuador, especially Maria Valeria Diaz Suarez for the infinite collaboration.

Conflict of interest

The authors declare no conflicts of interest.

Author details

Rasa Zalakeviciute[1]*, Adrian Buenaño[1,2], David Sannino[3] and Yves Rybarczyk[1,4]

*Address all correspondence to: rasa.zalake@gmail.com

1 Universidad de Las Americas, FICA, Intelligent & Interactive Systems Lab (SI² Lab), Quito, Ecuador

2 Department of Environmental Quality, Ministry of Environment, Porto Viejo, Ecuador

3 Department of Microbiology, Cornell University, Ithaca, NY, USA

4 Universidade Nova de Lisboa, DEE/UNINOVA/CTS, Monte de Caparica, Portugal

References

[1] WHO. WHO | 7 Million Premature Deaths Annually Linked to Air Pollution Page 1 of 2 WHO | 7 Million Premature Deaths Annually Linked to Air Pollution Page 2 of 2. Media Cent; 2014. pp. 6-7

[2] Karagulian F et al. Contributions to cities' ambient particulate matter (PM): A systematic review of local source contributions at global level. Atmospheric Environment. 2015;**120**:475-483

[3] WHO. WHO | Physical Activity. WHO; 2018. Retrieved from: http://www.who.int/en/news-room/fact-sheets/detail/physical-activity

[4] de Hartog JJ, Boogaard H, Nijland H, Hoek G. Do the health benefits of cycling outweigh the risks? Environmental Health Perspectives. 2010;**118**(8):1109-1116

[5] Bauman AE. Updating the evidence that physical activity is good for health: An epidemiological review 2000-2003. Journal of Science and Medicine in Sport. 2004;**7**(1):6-19

[6] Bhurosy T, Jeewon R. Overweight and obesity epidemic in developing countries: A problem with diet, physical activity, or socioeconomic status? Scientific World Journal. 2014. 7 p. Article ID: 964236. http://dx.doi.org/10.1155/2014/964236

[7] Handy S, van Wee B, Kroesen M. Promoting cycling for transport: Research needs and challenges. Transport Reviews. 2014;**34**(1):4-24

[8] van der Horst I. Cycling Culture in Amsterdam. 2014

[9] Koglin T. Velomobility and the Politics of Transport Planning. 2014

[10] Saelens BE, Frank LD, Med AB. Environmental correlates of walking and cycling: Findings from the transportation, urban design, and planning literatures. Society of Behavioral Medicine, no. c. 2003:80-91

[11] Guerreiro T d CM, Kirner Providelo J, Pitombo CS, Antonio Rodrigues Ramos R, Rodrigues da Silva AN. Data-mining, GIS and multicriteria analysis in a comprehensive

method for bicycle network planning and design. International Journal of Sustainable Transportation. 2018;**12**(3):179-191

[12] Forsyth A, Krizek K. Urban design: Is there a distinctive view from the bicycle? Journal of Urban Design. 2011;**16**(4):531-549

[13] Pucher J, Buehler R. Making cycling irresistible: Lessons from the Netherlands, Denmark and Germany. Transport Reviews. 2008;**28**(4):495-528

[14] Orellana D, Hermida C, Osorio Guerrero P. Comprendiendo los patrones de movilidad de ciclistas y peatones. Una síntesis de literatura. Revista Transporte y Territorio. 2017;**16**:167-183

[15] Strava. Data-Driven Bicycle and Pedestrian Planning. Published at Hubspot; 2016. pp. 1-4. Retrieved from: http://cdn2.hubspot.net/hubfs/1979139/Strava_Metro___Data-Driven_Planning.pdf

[16] Pucher J, Dill J, Handy S. Infrastructure, programs, and policies to increase bicycling: An international review. Preventive Medicine (Baltimore). 2010;**50**:S106-S125

[17] Apparicio P, Carrier M, Gelb J, Séguin AM, Kingham S. Cyclists' exposure to air pollution and road traffic noise in central city neighbourhoods of Montreal. Journal of Transport Geography. 2016;**57**:63-69

[18] Hankey S, Marshall JD. On-bicycle exposure to particulate air pollution: Particle number, black carbon, PM2.5, and particle size. Atmospheric Environment. 2015;**122**:65-73

[19] Int Panis L et al. Exposure to particulate matter in traffic: A comparison of cyclists and car passengers. Atmospheric Environment. 2010;**44**(19):2263-2270

[20] MacNaughton P, Melly S, Vallarino J, Adamkiewicz G, Spengler JD. Impact of bicycle route type on exposure to traffic-related air pollution. The Science of the Total Environment. 2014;**490**:37-43

[21] Quiros DC, Lee ES, Wang R, Zhu Y. Ultrafine particle exposures while walking, cycling, and driving along an urban residential roadway. Atmospheric Environment. 2013;**73**:185-194

[22] Wu DL et al. Influences of commuting mode, air conditioning mode and meteorological parameters on fine particle (PM2.5) exposure levels in traffic microenvironments. Aerosol and Air Quality Research. 2013;**13**(2):709-720

[23] Bravo Alvarez H, Sosa Echeverria R, Sanchez Alvarez P, Krupa S. Air quality standards for particulate matter (PM) at high altitude cities. Environmental Pollution. 2013;**173**:255-256

[24] Sinharay R et al. Respiratory and cardiovascular responses to walking down a traffic-polluted road compared with walking in a traffic-free area in participants aged 60 years and older with chronic lung or heart disease and age-matched healthy controls: A randomised, crosso. Lancet. 2018;**391**(10118):339-349

[25] Kleine Deters J, Zalakeviciute R, Gonzalez M, Rybarczyk Y. Modeling PM2.5 urban pollution using machine learning and selected meteorological parameters. Journal of Electrical

and Computer Engineering. 2017. 14 p. Article ID: 5106045. https://doi.org/10.1155/2017/5106045

[26] Zalakeviciute R, Rybarczyk Y, López-Villada J, Diaz Suarez MV. Quantifying decade-long effects of fuel and traffic regulations on urban ambient PM2.5 pollution in a mid-size south American city. Atmospheric Pollution Research. 2017;**9**(1):66-75

[27] Rybarczyk Y, Zalakeviciute R. Machine learning approach to forecasting urban pollution. In: 2016 IEEE Ecuador Technical Chapters Meeting; ETCM; 2016

[28] Secretaría de Ambiente. Secretaria de Ambiente: Informe Final Inventario de Emisiones de Contaminantes Criterio, DMQ 2011. 2014. p. 53

[29] Skszek S. Report on Non-Traditional Traffic Counting Methods. Vol. 85748. Tanque Verde Loop Rd. Tucson, AZ: 2001. p. 505

[30] Casella. Microdust Pro Real-Time Dust Monitor. No. 800. pp. 1-62

[31] Garmin. eTrex Owner's Manual. 2011. p. 60

[32] Rohde RA, Muller RA. Air pollution in China: Mapping of concentrations and sources. PLoS One. 2015;**10**(8):e0135749

[33] Kim S-Y et al. Ordinary kriging approach to predicting long-term particulate matter concentrations in seven major Korean cities. Environmental Health and Toxicology. 2014;**29**:e2014012

[34] Kingham S, Meaton J, Sheard A, Lawrenson O. Assessment of exposure to traffic-related fumes during the journey to work. Transportation Research Part D: Transport and Environment. 1998;**3**(4):271-274

[35] Hertel O, Hvidberg M, Ketzel M, Storm L, Stausgaard L. A proper choice of route significantly reduces air pollution exposure—A study on bicycle and bus trips in urban streets. The Science of the Total Environment. 2008;**389**(1):58-70

[36] Jarjour S et al. Cyclist route choice, traffic-related air pollution, and lung function: A scripted exposure study. Environmental Health. 2013;**12**(1):14

[37] WHO | Air pollution levels rising in many of the world's poorest cities. WHO: 2017

[38] Rybarczyk Y, Zalakeviciute R. Regression models to predict air pollution from affordable data collections. In: Machine Learning—Advanced Techniques and Emerging Applications. 2018

[39] Majumdar BB, Mitra S. Development of level of service criteria for pedestrians. Journal of Urban Planning and Development. 2018;**144**(2)