IEEE *Access*
Multidisciplinary : Rapid Review : Open Access Journal

BikeWay: A Multi-Sensory Fuzzy-Based Quality Metric for Bike Paths and Tracks in Urban Areas

FRANKLIN OLIVEIRA[1], (Member, IEEE), DANIEL G. COSTA[2], (Senior Member, IEEE),
CRISTIAN DURAN-FAUNDEZ[3], (Member, IEEE), AND ANFRANSERAI DIAS[2], (Member, IEEE)

[1]UEFS-PGCC, State University of Feira de Santana, Feira de Santana 44036-900, Brazil
[2]UEFS-DTEC, Department of Technology, State University of Feira de Santana, Feira de Santana 44036-900, Brazil
[3]Department of Electrical and Electronic Engineering, University of the Bío-Bío, Concepción 4051381, Chile

Corresponding author: Daniel G. Costa (danielgcosta@uefs.br)

ABSTRACT Large cities are increasingly investing in efficient mobility and sustainable transportation as an alternative to expensive and pollutant traditional vehicles. In parallel, people are also seeking cleaner and healthier options for short and last-mile distances. In order to cope with this trend, which has boosted the adoption of bikes in urban areas, a major concern of the governments has been to build bike paths and tracks that allow cyclists to move safely and through shorter distances. However, such initiatives may result in bicycles infrastructure built alongside traditional vehicular roads or on inadequate regions. Therefore, there should be a flexible way to assess the quality of bike paths and tracks, combining variables that indicate adverse conditions for the health and safety of cyclists, such as statistical risk of accidents, air and noise pollution, excessive sunlight exposure, dangerous UV radiation, among others. This article then proposes a new comprehensive quality metric that combines sensed environmental data and historical reported incidents related to bike paths and tracks, which may be employed for traditional physical signaling or to support computer-assisted solutions for cycling monitoring and alerting. Such new metric exploits fuzzy logic to model a group of variables to ultimately provide a unified safety and health quality level, referred as BikeWay. Doing so, we expect to allow dynamic and historical perceptions of how healthy and safe the bike paths and tracks are for cyclists in modern cities.

INDEX TERMS Smart cycling, smart cities, Internet of Things, environmental monitoring, sustainability.

I. INTRODUCTION

The use of bikes for daily transportation is becoming increasingly common in large urban centers, driven by the mobility inefficiency of traditional transports and an urgent demand for healthy habits. Additionally, large cities have faced high levels of air and noise pollution, which also push governments to create initiatives to promote the use of bikes for transportation and leisure. In fact, there are dozens of mega cities worldwide and the urbanization process will remain accelerated in this century, putting more pressure on urban mobility issues [1]. Nevertheless, cycling has not been uniformly supported around the globe, with many cities having insufficient cycling infrastructure even in highly polluted zones [2], [3]. As a result, the construction of new and better

The associate editor coordinating the review of this manuscript and approving it for publication was Laxmisha Rai.

bike paths and tracks should be one priority when dealing with the urban mobility challenges of our era.

Actually, from the point of view of urban mobility, the contribution of continuous cycling is perceived by the reduction in traffic congestion due to the decreasing in the number of cars and motorcycles on roads. This promising scenario can be further enhanced when adopting shared bikes and scooters platforms [4], [5]. In fact, this reduction in the flow of motorized vehicles on urban roads directly reduces the emission of polluting gases produced by combustion engines, such as carbon dioxide (CO_2) [6]. Hence, the environmental agenda promoted by the United Nations and other organizations have fostered the creation of bike paths for transportation reasons, which may boost a highly necessary transformation of the urban landscape.

Although the promotion of urban cycling has an objective to create cleaner cities, the current reality is that cyclists may

be subject to high pollution levels, notably produced by vehicles. Daily cyclists are constantly exposed to different types of pollution, which may be prejudicial for them. Besides the inhalation of various pollutants emitted by the engines of vehicles, cyclists may also face high noise pollution levels and even dangerous heat exposition when bike tacks are built on inappropriate zones. As a consequence, cyclists are more likely to develop cardio respiratory diseases and others health conditions in large cities [7].

Besides environmental pollution, bike paths may also bring other types of risks when people are using bikes for transportation. The presence of poorly signaled bike tracks may increase the risk of accidents involving bikes and vehicles. In large cities, such kind of accident is mainly resulted from the dispute for space, a fact that could be minimized if cyclists are able to move safely on properly constructed paths [8]. Moreover, zones with high robbery and violence statistics also bring risks for cyclists, who might be alerted to avoid those bike paths or demand measures from the governments to face such problems. Overall, all those risk factors are relevant and cyclists should be clearly alerted about them.

Therefore, there are associated risk factors that should be properly known by cyclists when they plan their routes. In this sense, the processing of the aforementioned risks in a uniform and well-know quality metric can be valuable when creating smarter cities, allowing the classification of bike paths according to their expected perceived quality by cyclists, who acquire a practical way to decide the best routes to get. Additionally, governments can use such metric to improve the quality of already created paths and to plan new ones. Since all considered information can be processed in a dynamic way, the proposed metric can be updated continuously, which may be exploited in computer-assisted applications similarly to popular platforms as Waze and Google Maps used by drivers.

This article proposes the BikeWay, a quality metric that processes two different groups of information that directly or indirectly affect cyclists when they are riding on cities. The first group, BW-Environment, is related to environmental data that affects cyclists whatever is the nature of the used bike path. Usually, BW-Environment data will be retrieved from sensors attached to bikes or to fixed monitoring stations alongside bike paths or conventional roads. The second group, BW-Infrastructure, comprises data that affects cyclists according to the used bike path, as for example the historical risk of accidents on a particular area. For this second group, statistical data is expected to be considered when assessing a bike path, since real-time accounting of accidents or urban violence may be unfeasible in most cities. Then, combining both groups and their specific parameters, the BikeWay metric exploits fuzzy logic to present a quality indication within a group of possibilities: Very Good, Good, Moderate, Bad and Very Bad. To the best of our knowledge, such comprehensive fuzzy-based quality metric for bike paths and tracks in urban areas has not been proposed before.
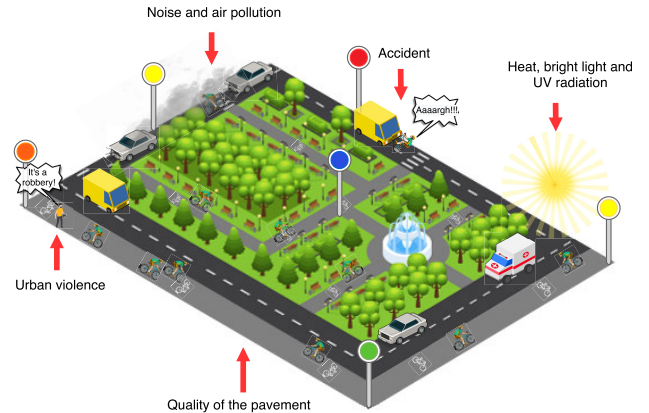

FIGURE 1. Cyclists on a city are subject to different risk factors.

Figure 1 depicts the general schema of the proposed metric, highlighting the different adverse conditions that may affect the health and safety of cyclists in a city.

The remainder of this article is organized as follows. Section II presents and discusses some related works that influenced this work. The current panorama of cycling in large cities is briefly discussed in Section III. Section IV brings the BikeWay metric, defining and modelling all parameters and procedures. Simulation results when computing the quality of some real bike paths and tracks are shown in Section V. Finally, conclusions and references are presented.

II. RELATED WORKS

The development of quality metrics is an important step for the maturation of most smart cities initiatives, since useful information can be provided to support better analyses of the achieved results in different contexts. In this scenario, the different characteristics of the cities and the employed technological solutions, each one with particular requirements and goals, have demanded the creation of different quality metrics. Moreover, since modern cities have been permeated by an increasing number of "smart solutions", with new approaches being constantly proposed, it is unreasonable to consider the existence of only a few unified all-purpose quality metrics. Actually, it is natural that different metrics may coexist, providing important information for the cities' inhabitants, as can be perceived when reviewing the literature in this area.

The definition of a quality metric for smart cities is not straightforward. A metric should provide meaningful information that gives a consistent perception of the modelled scenario. In such way, for example, a metric may process numeric data to compute an objective quality index within a range [9]. Differently, subjective computing may be also performed, computing for example the quality perceptions of the users about a particular system [10]. Typically, objective metrics are easier to map to some level of quality, allowing direct comparisons among different measures, but subjective metrics may provide a combined perception of different characteristics within a set of pre-defined significance levels [11].

In fact, both approaches have been considered in smart cities, with some promising results.

The smart cities scenario has seen a lot of useful quality metrics in recent years. In [12], a metric called ParkIndex was proposed to allow the evaluation of the potential use of parks in a given location. For this, a field research was carried out, interviewing people to know if some parks in Kansas City (USA) were used regularly. Exploiting this data, it was possible to make a quality analysis based on a set of variables, providing a ParkIndex value for some parks.

Considering roads and urban traffic, the work in [13] proposed a mechanism to assess the quality of roads based on the attainable speed of the vehicles, potentially supporting other systems. For that, a specialized sensing unit was created and attached to the target vehicles, exploiting data produced by an accelerometer. In a different way, in [14], fuel consumption information is retrieved from the electronic processing unit of the vehicles through a DB-II interface. Based on such information, the emission of the CO_2 gas can be estimated and associated to GPS coordinates. Doing so, roads can be classified according to their pollution levels.

In a different context, the authors in [15] considered different variables to define a general metric to assess the perceptual quality of a city for its inhabitants. For that, three major groups of data were considered as input: environmental data, location/mobility data and perceptual social data. Similarly, in [16], authors measured the quality of life in an urban environment, considering for that different variables. The proposed methodology was applied on the city of Cagliari (Italy), exploiting information from Census and geographical data. Another common scope for quality metrics is the assessment of urban transportation services, since they directly impact in the perceived quality of a city. In [17], different parameters are defined to assess the quality of the public bus service in different cities. The idea is to provide a reference for comparison of the provided services, taking as input some parameters such as the number of inhabitants, the available number of buses and the average number of daily passengers. For the authors in [18], the urban liveability of a city can be indirectly assessed exploiting the open database of the popular service Uber. Since it can be seen that the Estimated Time to Arrive (ETA) is related to the socio-economic indicators of a neighborhood, such data can be used as an indirect quality metric, potentially guiding governmental efforts to reduce inequalities.

Metrics can even evaluate the perceived quality of environmental conditions in a city scale. In [19], the authors evaluated a set of metrics to assess the ecological status of rivers according to its surrounding vegetation. They proposed the River Vegetation Quality Metric (RVQM), which applies an eco-hydromorphic approach to assess the integrity of the vegetation focused on lowland rivers. Actually, when rivers cross urban areas, such quality metrics can be valuable to prevent flooding and other emergencies. In a different work [20], a Markov chain model is used to compute a metric for the air pollution in a city. The idea is to integrate different sources of air pollution, supporting better analyses of how polluted cities are over time.

Although not directly related to this article, an important research trend when concerning smart cities has been the quality evaluation of the employed technological resources. Generally speaking, such quality assessment can be performed concerning the networking and sensing structure in different scenarios [21], evaluating the efficiency of the employed protocols and algorithms. Sensing accuracy has been also considered when assessing quality, with some interesting results when concerning more complex sensing units such as cameras [22]. Such metrics can give important indications of how a system will behave in a smart city scenario, indirectly impacting its perceived quality. For the proposed BikeWay metric, such technological assessment could be valuable in future works.

The discussed previous works are some recent examples that reinforce the need for quality assessment in the context of smart cities, influencing the development of the Bike-Way metric. Table 1 summarizes the reviewed works in this area.

As discussed in this section, many metrics may be proposed focusing on different aspects of modern urban areas. However, to the best of our knowledge, no metric has been proposed to assess the quality of bike paths when concerning the adverse conditions that may impact the health and safety of cyclists. The proposed BikeWay metric defines different input variables, as in [12], [15], also defining some reference quality levels, as in [16]. Additionally, the proposed metric may also exploit sensors to retrieve important data, as in [13]. Putting all these together, the proposed BikeWay metric can bring valuable contributions to the use of bikes in cities.

III. CYCLING IN URBAN AREAS

Nowadays, there is an increasing use of bicycles for transportation reasons in large cities, although motorized vehicles still remain the major form of locomotion [8]. The current panorama of urban centers is fulfilled by vehicles and heavy traffic configurations, producing a huge part of air and noise pollution that is perceived by people. Additionally, the massive use of vehicles also creates a scenario that is prone to the occurrence of deadly accidents involving pedestrians and bikes [8]. As a result, the particularities of large urban areas pose a constant threat to the health and safety of cyclists.

Since it is common for cyclists to ride close to vehicles, they can inhale the smoke produced by the combustion of fossil fuels. Such smoke contains CO and CO_2 gases, as well as a certain amount of harmful particles, which may potentially cause cardio-respiratory problems after long exposition periods (e.g. lung cancer, stroke and ischemic heart disease). In parallel, the daily high flow of motor vehicles on public roads has made these environments uncomfortable for people when concerning noise pollution, potentially making them unpleasant places to transit. In addition, exposure to noise levels above 53dB, as indicated by the World Health Organization (WHO), may increase the chances of people to develop

TABLE 1. Quality metrics in smart city scenarios.

Work	Year	Metric scope	Description
Kaczynski et al. [12]	2016	Public infrastructure	Data from interviews is combined relating to proximity, availability and infrastructure information of the parks, achieving a unified quality index
Prapulla et al. [13]	2017	Roads and vehicles	Accelerometer and a GPS device are used to associate the speed of a vehicle to its coordinates. The quality of a road (traffic and pavement conditions) can be measured according to the attainable speed
Oliveira et al. [14]	2017	Roads and vehicles	The ODB-II interface of vehicles is used to retrieve information about fuel and air flows in the combustion chamber. Such information is used to estimate air pollution emitted by the vehicles, which can be associated to the roads exploiting GPS coordinates
Griego et al. [15]	2017	Urban quality of life	Exploiting different types of sensors, the "quality" of a city is computed based on environmental data, location/mobility data and perceptual social data provided by the citizens
Garau and Pavan [16]	2018	Urban quality of life	A great number of variables are combined to compute a unified quality for an area of a city, ranging from Poor Quality to Excellent Quality
Carvalho et al. [17]	2015	Urban mobility	Transportation by public buses is assessed in different cities, highlighting that different cities in Brazil have pursued different goals concerning the perceived quality of the service. Quality indexes such as the Infrastructure Efficiency Indicator (IEI) and the Effectiveness Indicator (EI) are defined
Bezerra et al. [18]	2019	Urban mobility	The Estimated Time to Arrive (ETA) data retrieved from the Uber service can be used to indicate socio-economic inequalities of neighborhoods in a city, providing important information for urban planning
O'Briain et al. [19]	2018	Environment	Different factors in the ecosystem of rivers are evaluated to assess their quality, which may be valuable for smart city scenarios when such rivers cross urban areas
Gómez-Losada et al. [20]	2016	Environment	A metric based on Hidden Markov Models is defined to assess different pollutant gases emissions from different sources, supporting historical analyses in a city

some health problems, potentially affecting pedestrians and cyclists [23]–[26].

Besides adverse environmental conditions, cyclists should be aware of other threats to their health and safety. Actually, cyclists and pedestrians make the most fragile group in the vehicular traffic of big cities and the WHO claims these groups account for 26% of deaths due to traffic accidents around the world [27]. But some particularities have contributed to variations in this distribution, according to the observed region. In fact, adequate cycling infrastructure in urban centers and public initiatives of the governments have favored cyclists and pedestrians, reducing the number of accidents involving these groups [27].

In Brazil, for example, the group formed by cyclists and pedestrians is estimated at 25.8% of the population aged over 15 years. According to data from the Brazilian Unified Health System (SUS) these groups are responsible for 23.7% of hospitalizations for trauma due to traffic accidents in the country [28]. In order to better understand the main causes of these accidents, a study in Brazil concluded that the most impacting factor is the absence of adequate paths for cyclists and pedestrians, making them to compete for space with motor vehicles on roads and highways [8].

Still considering the case of Brazil, Figure 2 presents the lack of adequate infrastructure concerning bike paths in some large Brazilian cities. This data is retrieved from CyclOSM, an OpenStreetMap rendering logical layer aimed at showing useful information for cyclists [29].

The bike paths in Figure 2 are good examples of poor cycling infrastructure in some cities, a recurrent condition that can be found in a large number of cities around the world. In short, a bike path is defined as any path, track or road that cyclists can use to ride in a city, being generically referred as a "bike path". We define that a bike path p is represented by an undirected graph composed of a set of edges. Each edge connects a point p_i to a point p_j, with $0 \leq i < P$, $0 \leq j < P$ and $i \neq j$, for P vertices in the graph, and each point may be represented by GPS coordinates. For the BikeWay metric, any bike path p is treated as a single element and thus the computed metric is valid for the entire path as a unique element. In practical means, a considered bike path may be processed from an input file indicating the GPS coordinates of the points that compose each segment of that path.

IV. PROPOSED METRIC

Currently, in large urban areas, bike paths and tracks are daily used by cyclists even under unsatisfactory conditions. As discussed before, there are many adverse conditions that can negatively impact the health of cyclists when riding on such paths, while accidents and urban violence can jeopardize their safety. Therefore, a new quality metric to combine the negative impacts of all these risks is highly welcome, supporting the evaluation of bike paths.

The following subsections present the definitions and procedures to compute the proposed BikeWay metric. Such procedures are required to compute the final BikeWay level
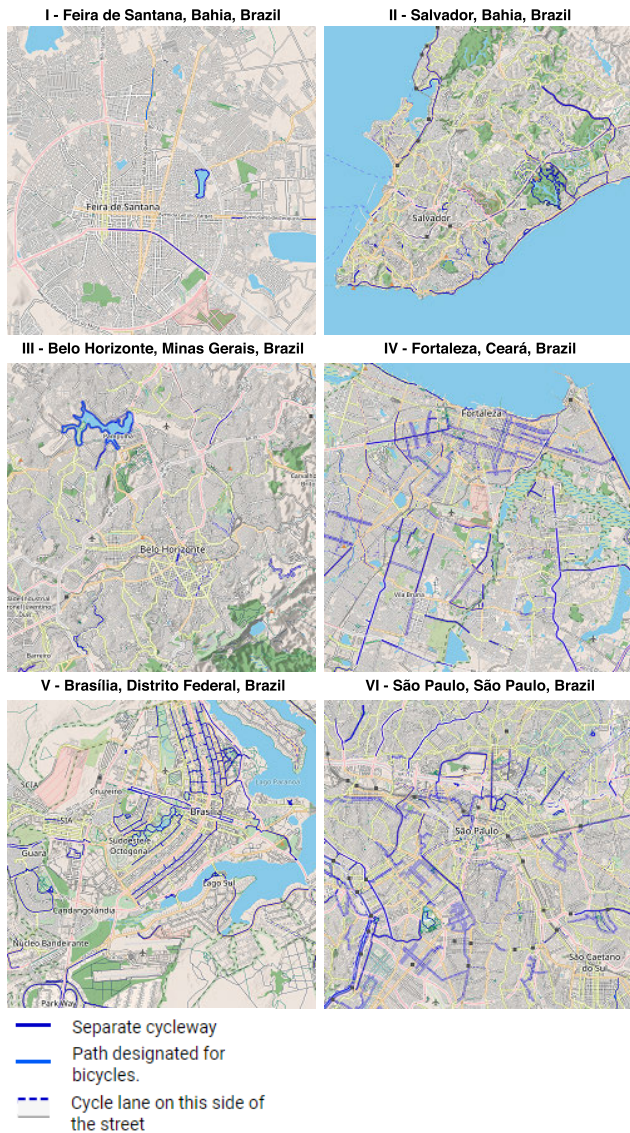
FIGURE 2. Some bike paths in Brazil - source: CyclOSM [29].

for each considered bike path, as depicted by the flowchart in Figure 3.

A. THE QUALITY VARIABLES

The risks associated to a bike path are modelled as quality variables. The proposed metric is processed based on such variables, which are organized into two different groups: BW-Environment (M1), composed of data associated to environmental conditions and that can be provided by any sensors-based solution [30]; and BW-Infrastructure (M2), which consists of a set of data referring to the safety and infrastructure of cycle paths provided by different agencies and databases. Both groups are detailed in Table 2.

The variables shown in Table 2 were chosen based on their impact on the cyclist's health and safety, as well as according to the possibility of measurement through low-cost
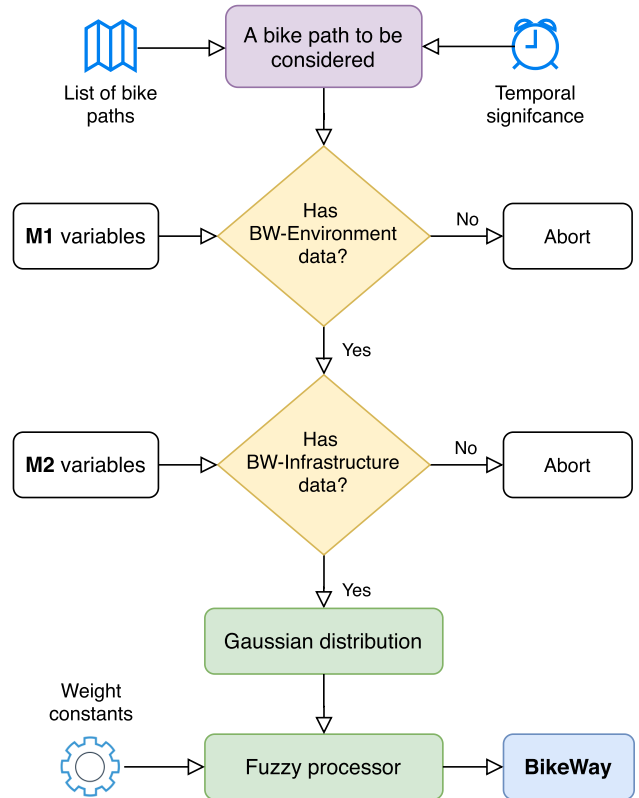

FIGURE 3. Flowchart describing the computing of the BikeWay metric.

TABLE 2. Defined quality variables.

M1: BW-Environment (sensing variables)	
Variable	Description
M1.1: Air pollution	CO_2 concentration in $\mu g/m^3$
M1.2: Noise pollution	Sound intensity in dB
M1.3: UV radiation	UV index level
M1.4: Heat index	Thermal sensation based on temperature and humidity measures
M1.5: Luminosity	Light intensity in lux
M2: BW-Infrastructure (statistical variables)	
Variable	Description
M2.1: Accident data	Number of accidents per month
M2.2: Security data	Number of robberies/homicides per month
M2.3: Bike path type	It informs whether a path is a) absent, b) shared with a road or c) isolated (exclusive)

sensors or even "simple" computational techniques. For the BW-Environmental group, the impact on cyclists' health in the short/medium term can be highlighted: constant inhalation of polluted air may cause cardio-respiratory diseases; exposure to high intensity noise and low/high heat index may be very unpleasant; and high UV radiation may favor the appearance of skin cancer. Additionally, low luminosity and high noise may be dangerous when cycling. On the other hand, for the chosen BW-Infrastructure variables, their impacts are related to events that can instantly harm the

TABLE 3. Defined variable ranges for normalization. The chosen values are directly or indirectly provided by previous works.

Variable	Work	L_v	H_v
M1.1	[31]	$0\mu g/m^3$	$70\mu g/m^3$
M1.2	[23]	$0dB$	$65dB$
M1.3	[32]	0	11
M1.4	[33]	$-10°$; $10°$	$10°$; $52°$
M1.5	[34]	$0lux$	$32000lux$
M2.1	[35]	0	20 accidents
M2.2	[36]	0	8 incidents
M2.3	[29]	"Isolated"	"None"

TABLE 4. Gaussian parameters for each variable.

Variable	σ	μ
M1.1	40	70
M1.2	6	65
M1.3	4	11
M1.4		
-10 to 10 ℃	7	-10
10 to 52 ℃	12	52
M1.5	15000	32000
M2.1	6	20
M2.2	3	8

cyclist. At the moment he/she rides on a non-exclusive cycle path or with high historical records of accidents, it is assumed that the probability for a traffic accident is much higher than on a cycle path with a low accident rate. And the same principle applies for the urban violence factor.

Once the quality variables are defined, it is necessary to specify the range of values to be considered and their impacts on the final BikeWay level. In first place, a realistic range of possible values was defined for each variable, assuming then only values within such ranges. This is a very reasonable decision, especially considering the real possibilities for the climatic conditions in modern cities. Therefore, for each variable v, we defined a "relevance range" from L_v to H_v, considering for those limits some reference values that were indicated by the WHO or by some works in the literature.

Actually, although the variables may virtually assume any value, they may have almost the same significance outside the defined relevance range and this is why the limits are required. For example, two different very high temperature levels of $50°$ and $55°$ will have almost the same impact on cyclists, which is both "too severe" for them. Therefore, the definition of a numeric range for each variable facilitates the adoption of the metric in practical applications, focusing on more common values in the cities. Hence, if $d_v < L_v$, $d_v = L_v$, while $d_v = H_v$ when $d_v > H_v$, for $L_v < H_v$.

Table 3 presents the defined ranges for each variable when computing the BikeWay metric, considering range limits according to empirical definitions in previous works and also following recommendations by the World Health Organization.

After defining the ranges, the quality variables have to be considered following a normalization process, converting their values (d_v) to a number within a scale from "0.0" (best) to "1.0" (worst), for each variable v. Doing so, it is defined a uniform relevance for all variables, equally impacting on the computed metric. Among the possibilities, a Gaussian distribution has been commonly used to perform such task, even with some lack of precision [37], [38]. For the BikeWay metric, since it provides a general perspective combining different variables, we believe that a Gaussian distribution will provide a consistent perspective of the variables, with low computational cost, when the Gaussian functions are properly configured.

Therefore, a general Gaussian equation was defined to model the variables, just changing the configuration parameters as expressed in Table 4. Equation (1) computes a value from "0.0" to "1.0" for each variable.

$$f(d_v, \sigma, \mu) = e^{-(d_v-\mu)^2/2\sigma^2} \tag{1}$$

In the defined Gaussian equation, the values of σ and μ vary according to the considered variable v. The chosen σ and μ parameters are presented in Table 4, which are retrieved from definitions and experiments performed by previous works [23], [31]–[34].

Following these definitions, all variables are processed for the same interval, which indicates the best condition when they are closer to 0.0. Doing so, the variables assume the same scope of significance when computing the BikeWay metric. Once again, since the relevance ranges and the Gaussian parameters were obtained from previous works in the literature, we expect that the achieved results are very realistic for cycling in urban areas.

The complete normalization process for each Gaussian function is depicted in Figure 4 (note the limits in Table 3). For the M2.3 variable, we established a value of "0.0" for isolated paths, "0.5" for a bike path that is "shared" with a traditional road and "1.0" for an absent path.

B. PROCESSING THE VARIABLES GROUPS
After normalizing all variables of both M1 and M2 groups, the next step is to compute an average value for them. In such processing, the resulting average values will be also within the interval from 0.0 to 1.0. The weighted results for each group are computed as expressed in Equation 2 and Equation 3.

$$M1_{level} = \sum_{i=1}^{5} M1.i(w1_i) \tag{2}$$

$$M2_{level} = \sum_{i=1}^{3} M2.i(w2_i) \tag{3}$$

For the defined equations, wg_p represents the weight of the variable p at the group g, and by default it has the same value for all variables in the same group. However, alternative
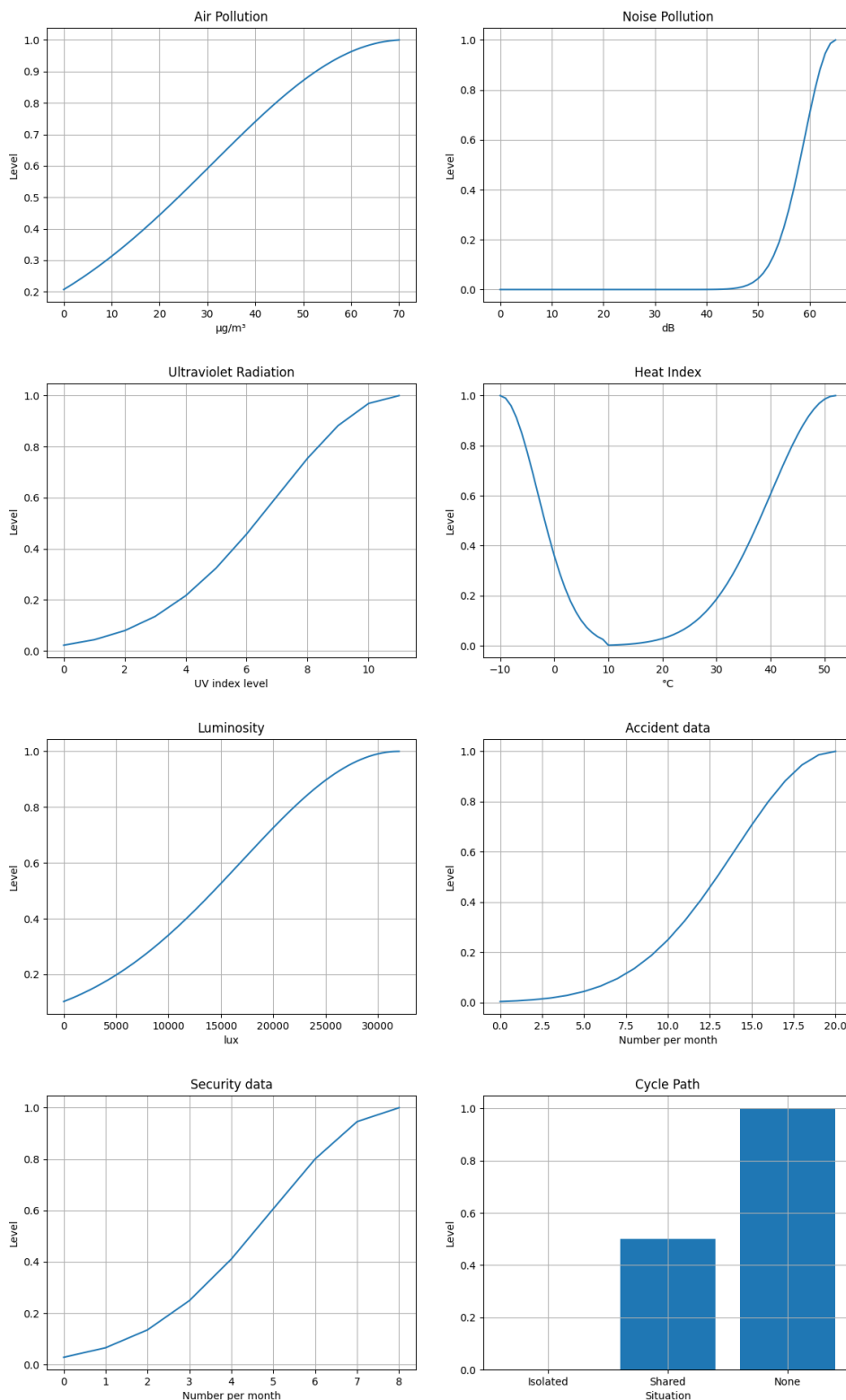
FIGURE 4. The Gaussian-based normalization of the defined quality variables. The exception is the M2.3 variable.

implementations of the metric might define different weights for the variables. Whatever the case, it is required that $w1_1 + w1_2 + w1_3 + w1_4 + w1_5 = 1.0$ and $w2_1 + w2_2 + w2_3 = 1.0$.

Hence, after applying the weight coefficients, the final values of $M1_{level}$ and $M2_{level}$ will be both within the interval from 0.0 to 1.0.

C. DEFINING THE WEIGHT OF THE VARIABLES

The task of defining a comprehensive and highly configurable quality metric is not straightforward, with a lot of complexities and scopes of influence affecting the overall perception of the idea of "quality". When coming to the urban context, the dynamics of modern cities provide a large amount of data, which may be processed to extracting useful information in different ways. Such complex environment poses inherent challenges when assessing the quality of bike paths, ultimately affecting the way the BikeWay metric is computed.

A total of 8 variables were selected to compose the proposed metric, divided into two different groups. Actually, the effective impact of each variable in the final computed BikeWay level is not easy to evaluate, since it depends on many factors. In this sense, the defined wg_p constants are expected to calibrate the impact of the variables, making the BikeWay metric adaptable for the particularities of different cities. But the question remains: what is the best choice for the wg_p constants?

Among the possibilities to answer this question, variables that more severely impact the health and safety of cyclists could employ higher weight constant, although this may vary according to the considered city. For example, in cities with higher incidences of skin cancer, we could expect that genetic factors of the population or even the low latitude of a city could bring inherent risks that should be considered. In this case, it would be natural to expect that the value of $w1_3$ would be higher than the other weight constants, since higher exposition to UV radiation should be avoided in this hypothetical scenario. Following this same principle, high levels of air pollution may not only increase the potential of developing respiratory diseases after extensive exposition, but also compromise cardio-respiratory efficiency of cyclists due to the adverse effects of CO and CO_2 gases in red blood cells. In this case, when a bike path is used for competitive reasons, the value of $w1_1$ could be increased to reinforce its negative impact on the expected performance of the cyclists.

Finally, the chosen quality variables are divided into two groups according to their "nature", which are related either to Environmental data or Infrastructure data. But the impact of each variable from the same group may be different, since the BikeWay metric primarily combines health and safety perspectives. However, the BikeWay metric also captures the perception of how pleasant is a bike path for the cyclist: while we can associate the heat index to the degradation of a cyclist's health along the time, an inadequate heat index is also very unpleasant for them. Fatigue due to excessive effort, dehydration, earaches, among others, are also adverse effects that also impact the immediate quality of a bike path, although not necessarily putting lives in risk. Such considerations reinforce the idea that the weight constants should be freely defined according to the characteristics of the considered cities.

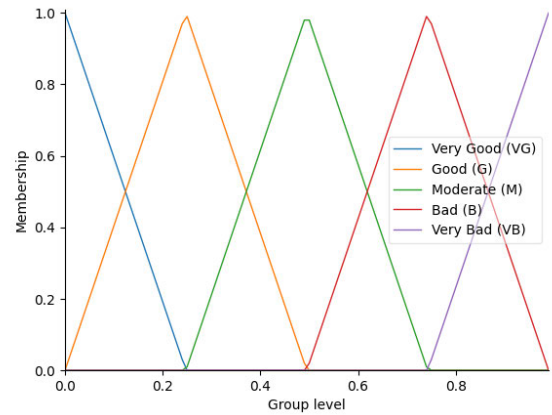| Conf	$w1_1$	$w1_2$	$w1_3$	$w1_4$	$w1_5$	$w2_1$	$w2_2$	$w2_3$
1	0.20	0.20	0.20	0.20	0.20	1/3	1/3	1/3
2	0.40	0.15	0.15	0.15	0.15	0.30	0.40	0.30
3	0.20	0.10	0.40	0.20	0.10	0.20	0.20	0.60

FIGURE 5. Defined diffuse fuzzy logic groups.

Table 5 presents three different examples to be used as reference when employing the BikeWay metric. The "Conf 1" is the standard configuration, which defines the same relevance for all variables within the same group. The "Conf 2" presents a city that has been more severely affected by air pollution ($w1_1$), probably due to inefficiencies in its public healthcare system, while also presenting a slightly higher occurrence or urban violence. At last, "Conf 3" features a tropical city, which has high UV indexes and temperatures that can be uncomfortable to ride, with insignificant historical occurrences of accidents ($w2.1$) and urban violence ($w2.2$).

D. CLASSIFICATION BY FUZZY LOGIC

The use of fuzzy logic creates a set of decision rules capable of computing the antecedents $M1_{level}$ and $M2_{level}$. For that, their numeric values are mapped to one of five different fuzzy groups, allowing a direct combination. Actually, since the BikeWay metric combines different variables, a final numeric value could not indicate a meaningful perception of the quality of the bike paths. In a different way, the use of subjective fuzzy groups give a good perception of the overall quality, with easy visualization by the users of the metric.

Initially, a diffuse set of five values was defined, ranging from the worst case (Very Bad) to the best case (Very Good), as expressed in Figure 5.

Following these definitions, Table 6 relates the values of the "antecedents" (input) to the ideal result stored in the "consequent" (output), resulting in a final logic set.

From this table, the equations that define the five decision rules of the implemented fuzzy logic were extracted, defined in detail as follows:

TABLE 6. Defined fuzzy logic rules.

M1 level (M1)	M2 level (M2)	BikeWay (BW)
Very Bad (VB)	Very Bad (VB)	Very Bad (VB)
Very Bad (VB)	Bad (B)	Very Bad (VB)
Very Bad (VB)	Moderate (M)	Very Bad (VB)
Very Bad (VB)	Good (G)	Very Bad (VB)
Very Bad (VB)	Very Good (VG)	Very Bad (VB)
Bad (B)	Very Bad (VB)	Very Bad (VB)
Bad (B)	Bad (B)	Bad (B)
Bad (B)	Moderate (M)	Bad (B)
Bad (B)	Good (G)	Moderate (M)
Bad (B)	Very Good (VG)	Moderate (M)
Moderate (M)	Very Bad (VB)	Very Bad (VB)
Moderate (M)	Bad (B)	Bad (B)
Moderate (M)	Moderate (M)	Moderate (M)
Moderate (M)	Good (G)	Good (G)
Moderate (M)	Very Good (VG)	Good (G)
Good (G)	Very Bad (VB)	Very Bad (VB)
Good (G)	Bad (B)	Moderate (M)
Good (G)	Moderate (M)	Good (G)
Good (G)	Good (G)	Good (G)
Good (G)	Very Good (VG)	Very Good (VG)
Very Good (VG)	Very Bad (VB)	Very Bad (VB)
Very Good (VG)	Bad (B)	Moderate (M)
Very Good (VG)	Moderate (M)	Good (G)
Very Good (VG)	Good (G)	Very Good (VG)
Very Good (VG)	Very Good (VG)	Very Good (VG)

TABLE 7. A useful mapping from BikeWay to a color indication.

BikeWay (BW)	Color	
Very Bad (VB)	Red	
Bad (B)	Orange	
Moderate (M)	Yellow	
Good (G)	Green	
Very Good (VG)	Blue	

1) BW[VB] = M1[VB] or M2[VB];
2) BW[B] = (M1[B] and M2[B or M]) or (M1[M] and M2[B]);
3) BW[M] = (M1[B] and (M2[G or VG]) or (M1[M] and M2[M]) or (M1[G or VG] and M2[B]);
4) BW[G] = (M1[M] and M2[G or VG]) or (M1[G] and M2[M or G]) or (M1[VG] and M2[M]);
5) BW[VG] = M1[G or VG] and M2[G or VG];

The final result of this process is the BikeWay (BW) metric, which characterizes the quality of any bike path. In fact, the value of the BikeWay can be displayed in different ways, but we believe that an easy and practical way is employing colors for better visualization and understanding. Table 7 presents an useful mapping between the computed BikeWay and a color indication.
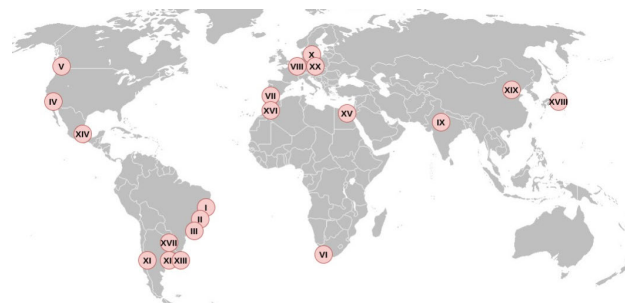

FIGURE 6. Considered cities for the tests.

Then, after computing the BikeWay metric, users are expected to be able to easily see its value (e.g. color) through traditional signs or even in computer-assisted applications.

As a final remark, the computation of the BikeWay metric will combine quality variables that will have different time significance, since they can be detected in a real-time basis or according to statistical perceptions. Whatever the case, a unique time scope is defined for the BikeWay metric, which requires the processing of some quality variables according to their average values. Although the time significance of the metric can be adjusted by the users, the standard procedure is to compute the metric for each month, considering average results during that period. In other words, the proposed metric is intended to assess the past perceived quality of the paths, which is reasonable and cost-effective for urban monitoring.

V. SIMULATION RESULTS

The proposed metric is an important contribution to the usage, development and maintenance of bike paths and tracks in urban areas. Actually, when properly implemented, the Bike-Way metric may support the creation of important services to improve the quality of life in cities, in a similar way of popular services as Waze and Google Maps. However, since it is an innovative metric that has not been proposed before, to the best of our knowledge, the evaluation of the BikeWay metric was focused on practical examples of how it could be exploited in real cities, since comparisons among different approaches could not be performed in a meaningful way.

The evaluation of the BikeWay metric was performed considering real data retrieved from different databases, giving a more realist perception of how this metric can be exploited in cities. For that, we created a simple simulation tool to process a set of data (quality variables) from different locations, presenting as result the computed BikeWay metric. This simulation tool was implemented in the Python programming language and it is freely and openly available at https://github.com/lablara/bikeway.git. The variables are defined in the "input.csv" file and the output is stored in the "output.csv" file. This output file presents data in rows, following this structure: $M1_{level}, M2_{level}, BikeWay\text{-}Level, Color$.

Initially, in order to test the practical usage of the metric, average values for the variables of both groups M1 and M2 were considered, assuming the month of July 2020
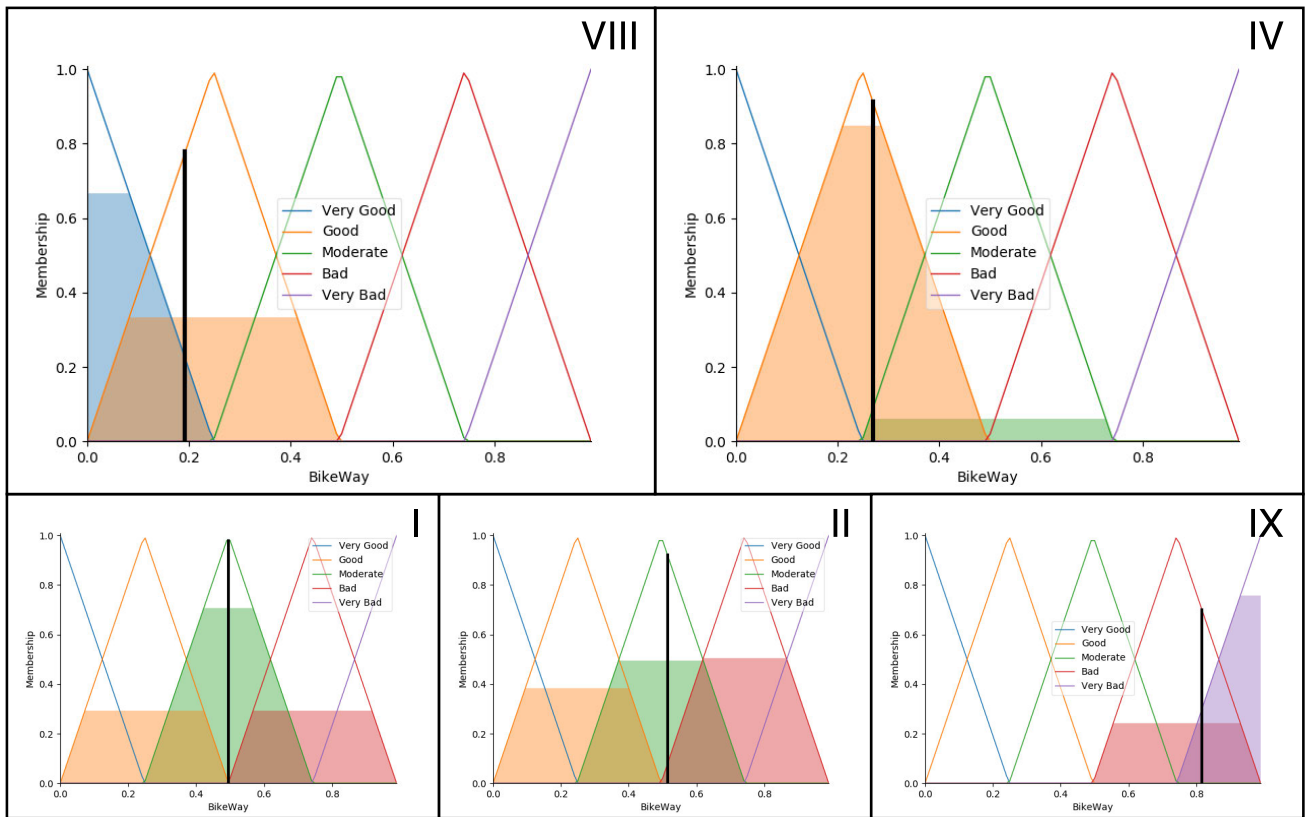
FIGURE 7. Some cities with the five possible levels of the BikeWay metric (Fuzzy Logic Membership Chart).

as reference. This data was obtained considering different sources (Accuweather, CycloOSM and local news in web pages), allowing a more realistic perception of the BikeWay metric. Actually, although the M1 quality variables are usually expected to be provided by sensors, using multi-sensory approaches such as the one presented in [30], we considered historical data for them in each of the selected city. Nevertheless, when active sensors-based monitoring is performed, more detailed data for each bike path in the same city might be retrieved.

A total of 20 different cities were considered for evaluation. The chosen cities are all large cities but with different characteristics concerning their infrastructure for safe cycling. For each of those cities, a single bike path was chosen, considering as reference the most common occurrence of a bike path according to variable M2.3 ("absent", "shared with a road" or "isolated"). Figure 6 presents the considered cities for this evaluation phase, highlighting the different regions of the globe for the tests.

Table 8 shows the variable values resulted from the performed data collection. Based on those variables, the Bike-Way metric was computed for each of the selected bike paths.

Once the variables in Table 8 were processed, it was possible to generate the membership chart for each city. Figure 7 shows the graphs for some of the considered cities, showing all the quality levels for the selected bike paths.

Finally, through the output file generated by the simulation scripts, it was possible to compute the BikeWay for one bike

TABLE 8. Simulation input data.

City	M1					M2		
	1	2	3	4	5	1	2	3
I	5.8	57	8	27	1k	13	4	None
II	43.5	65	10	21	10k	8	2	None
III	16	68	7	18	1.1k	21	1	Shared
IV	31.6	63	8	21	5.3k	4	4	Isolated
V	78.6	71	9	25	5.3k	2	4	Isolated
VI	3.3	55	6	9	10k	1	5	None
VII	6.4	53	7	22	5.3k	10	10	Shared
VIII	22.2	46	8	23	10.5k	0	0	Isolated
IX	70.8	75	5	27	0.1k	17	17	None
X	22.5	65	8	13	0.1k	0	0	Isolated
XI	17	66	6	25	10k	5	4	Isolated
XII	3.3	58	6	24	10k	3	3	Isolated
XIII	2.7	55	6	13	10.5k	2	0	Shared
XIV	19.1	69	12	27	5.3k	9	13	Shared
XV	21.1	65	6	31	10k	0	1	None
XVI	8.1	68	7	23	5.3k	0	0	None
XVII	40.2	54	9	29	10.5k	7	15	None
XVIII	3.7	65	6	17	10.5k	3	0	Shared
XIX	63.9	70	5	16	1k	4	6	None
XX	3.7	50	2	18	1k	0	2	Isolated

path in all considered cities, as presented in Table 9. In this computation, the weight constants were defined according to "Conf 1" in Table 5.
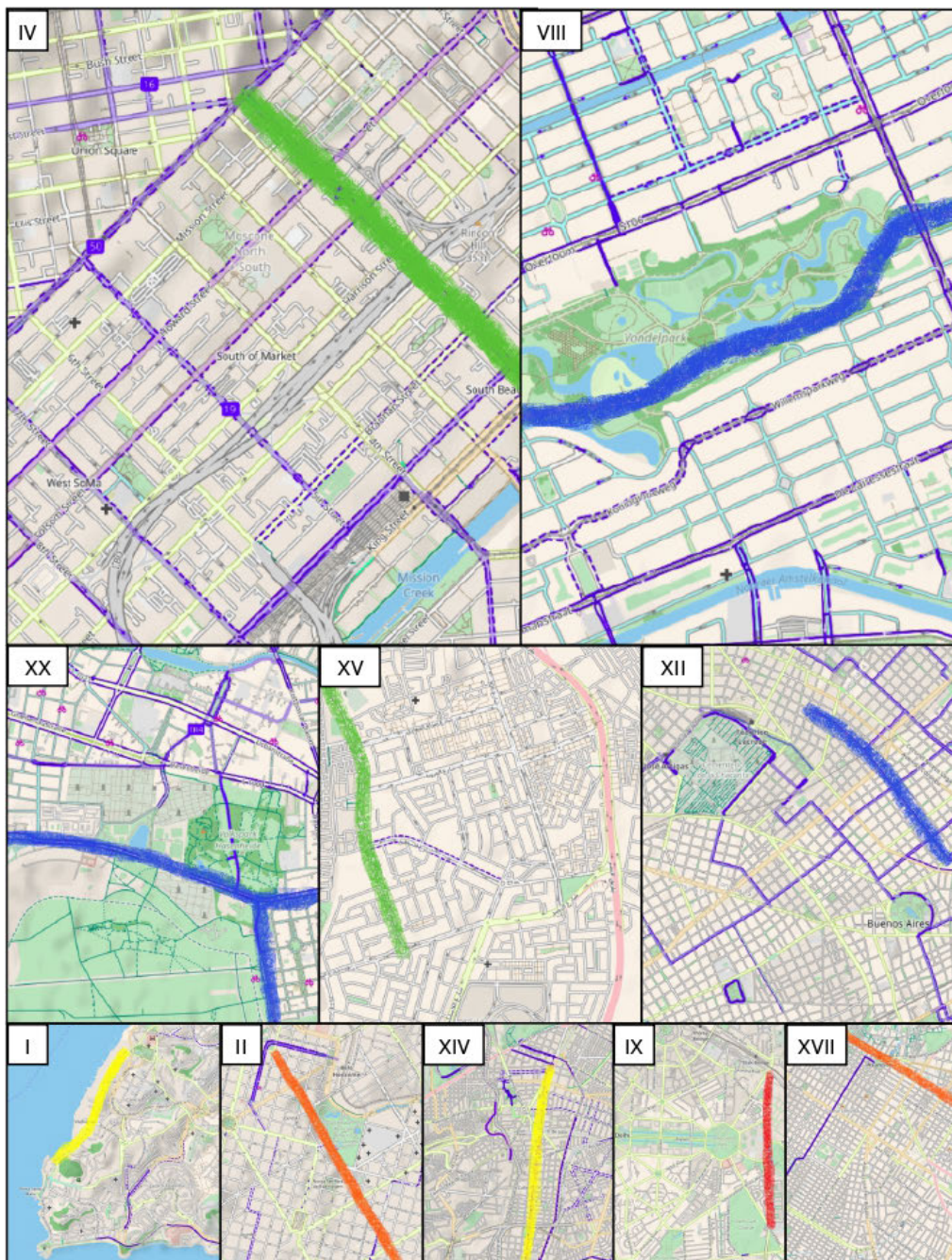
FIGURE 8. Bike paths with the computed BikeWay metric for July 2020.

As can be seen in Table 9, from the assessment made by the BikeWay metric in 20 cities, for one month, different bike paths may have different qualities in terms of adverse conditions for the health and safety of cyclists. Actually, such results might be displayed in different ways, for example using some visualization tool, potentially enhancing the adoption of the proposed metric. Figure 8 depicts the selected bike path in 10 of the chosen cities, highlighting them with the color of the computed BikeWay.

Actually, the value of the BikeWay metric may vary considerably along a year, even for the same bike path, since the values of the variables may vary due to different reasons such as the Seasons and Holidays calendar. Nevertheless, we are particularly concerned in demonstrating how the metric can be computed and exploited in practical applications, and thus the actual values of the variables for different months would bring different results but with the same final significance.

TABLE 9. Simulation output data for July 2020.

City	M1	M2	BW	Color
I-Salvador	Good	Bad	Moderate	
II-Belo Horizonte	Bad	Moderate	Bad	
III-São Paulo	Moderate	Moderate	Moderate	
IV-San Francisco	Moderate	Good	Good	
V-Vancouver	Bad	Good	Moderate	
VI-Cape Town	Good	Moderate	Good	
VII-Lisbon	Good	Good	Good	
VIII-Amsterdam	Good	Very Good	Very Good	
IX-New Delhi	Moderate	Very Bad	Very Bad	
X-Copenhagen	Moderate	Very Good	Good	
XI-Santiago	Moderate	Good	Good	
XII-Buenos Aires	Good	Very Good	Very Good	
XIII-Montevideo	Good	Good	Good	
XIV-Mexico City	Moderate	Moderate	Moderate	
XV-Cairo	Moderate	Good	Good	
XVI-Casablanca	Moderate	Good	Good	
XVII-Asuncion	Moderate	Bad	Bad	
XVIII-Tokyo	Good	Good	Good	
XIX-Beijing	Moderate	Moderate	Moderate	
XX-Berlin	Very Good	Very Good	Very Good	

Finally, after the performed computations, we concluded that the proposed metric is meaningful and valuable for practical quality evaluation of bike paths in terms of adverse conditions for the health and safety of cyclists. In first place, the metric can be used to evaluate individual bike paths in a more precise way, providing a comprehensive perception of the cycling infrastructure of any city. Secondly, since the most common occurrence of a bike path in a city may be selected, according to the definition of variable M2.3, the computed BikeWay metric can roughly give an approximated perception of a city as a whole, giving some clues of how a city is managing its cycling infrastructure.

VI. CONCLUSION

The way of living in large cities, with high levels of pollution and inefficient urban mobility, has demanded new solutions to address such well-known challenges. Among promising solutions to relieve heavy traffic and reduce excessive noise and air pollution, the use of bikes has been advocated as a feasible and affordable alternative for short distances, improving the overall quality of life in cities while stimulating the adoption of healthier habits. However, the current infrastructure for cycling may be unsatisfactory for the health and safety of cyclists. Therefore, mechanisms to assess the quality of bike paths and tracks are highly welcome.

While it can be said that many cities in underdeveloped countries lack an efficient cycle path system, many cities around the world suffer from similar problems. As expected, such lack of adequate infrastructure directly impacts the quality of life of cyclists, making them more susceptible to traffic accidents, exposure to polluting gases and noise

emitted by vehicles. Actually, as a first step to minimize all these problems, governments should implement bike paths that cover a good part of the cities, ensuring that cyclists do not need to travel in the midst of motor vehicles. But where exactly should they be created? And how good are the existing bike paths? The proposed metric is an important resource to support the answering of such questions.

This article proposed a multi-sensory fuzzy-based quality metric to assess current bike paths and tracks in urban areas, providing a practical way to perceive their quality along the time. Exploiting different data sources, the proposed Bike-Way metric may be used as an important tool for cyclists and governments: while cyclists may better choose the routes to follow, governments can execute projects to enhance the quality of bike paths with lower BikeWay level. Actually, since it considers a diverse set of input variables, the proposed metric can give a realistic perception of the quality of bike paths in any city, as could be seen in the performed simulations.

The quality of the bike paths may vary considerably and such differences may be even more evident for developing countries, as could be seen when employing the BikeWay metric. In this sense, some countries are creating initiatives to improve the quality of their bike paths. In Brazil, for example, in September 2018 the Federal Senate approved the Bicycle Brazil Program, which provides resources for the construction of bike paths in Brazilian cities [39]. In such cases, the use of the proposed metric can give important clues about the better zones to create new paths and the areas that should be avoided.

The considered data sources when computing the BikeWay metric have different significance when achieving a unified perception of the paths quality. Such significance depends on the way such data is obtained, with different complexities. Although the experiments were performed using historical data retrieved from the news and official reports, a more practical way to obtain the BW-Environment variables is actively sensing the environment using sensors-based monitoring approaches. Actually, we still expect to attach sensing units to a group of bikes to obtain a set of variables (at least in the group from M1.1 to M1.5), as defined in our previous work [30], providing then a more automatic behavior for the computation of the metric.

Finally, the performed experiments presented how the BikeWay metric can be used in real cities for quality assessment of bike paths. As future works, we will apply the metric to evaluate a greater number of bike paths, providing important information. Additionally, we will create a searching tool to easily display information about the BikeWay metric of any registered bike path, incorporating it to the growing supportive tool landscape that is being created around the smart cities concept.

REFERENCES

[1] D. Pojani and D. Stead, "Sustainable urban transport in the developing world: Beyond megacities," *Sustainability*, vol. 7, no. 6, pp. 7784–7805, Jun. 2015.

[2] J. Pucher, R. Buehler, D. R. Bassett, and A. L. Dannenberg, "Walking and cycling to health: A comparative analysis of city, state, and international data," *Amer. J. Public Health*, vol. 100, no. 10, pp. 1986–1992, Oct. 2010.

[3] S. D. S. Fraser and K. Lock, "Cycling for transport and public health: A systematic review of the effect of the environment on cycling," *Eur. J. Public Health*, vol. 21, no. 6, pp. 738–743, Dec. 2011.

[4] A. A. Campbell, C. R. Cherry, M. S. Ryerson, and X. Yang, "Factors influencing the choice of shared bicycles and shared electric bikes in Beijing," *Transp. Res. C, Emerg. Technol.*, vol. 67, pp. 399–414, Jun. 2016.

[5] J. Bao, X. Shi, and H. Zhang, "Spatial analysis of bikeshare ridership with smart card and POI data using geographically weighted regression method," *IEEE Access*, vol. 6, pp. 76049–76059, 2018.

[6] Y. Zhang and Z. Mi, "Environmental benefits of bike sharing: A big data-based analysis," *Appl. Energy*, vol. 220, pp. 296–301, Jun. 2018.

[7] X. Zhang, P. Wargocki, Z. Lian, and C. Thyregod, "Effects of exposure to carbon dioxide and bioeffluents on perceived air quality, self-assessed acute health symptoms, and cognitive performance," *Indoor Air*, vol. 27, no. 1, pp. 47–64, Jan. 2017.

[8] L. A. Brasileiro and L. C. Comar, "Análise da segurança de pedestres e ciclistas em rodovias urbanas," *Revista Nacional de Gerenciamento de Cidades*, vol. 3, no. 19, pp. 89–97, Sep. 2015.

[9] H. P. McKenna, "Innovating metrics for smarter, responsive cities," *Data*, vol. 4, no. 1, p. 25, Feb. 2019. [Online]. Available: https://www.mdpi.com/2306-5729/4/1/25

[10] P. Brooks and B. Hestnes, "User measures of quality of experience: Why being objective and quantitative is important," *IEEE Netw.*, vol. 24, no. 2, pp. 8–13, Mar. 2010.

[11] D. G. Costa, L. A. Guedes, F. Vasques, and P. Portugal, "QoV: Assessing the monitoring quality in visual sensor networks," in *Proc. IEEE 8th Int. Conf. Wireless Mobile Comput., Netw. Commun. (WiMob)*, Oct. 2012, pp. 667–674.

[12] A. T. Kaczynski, J. Schipperijn, J. A. Hipp, G. M. Besenyi, S. A. W. Stanis, S. M. Hughey, and S. Wilcox, "ParkIndex: Development of a standardized metric of park access for research and planning," *Preventive Med.*, vol. 87, pp. 110–114, Jun. 2016.

[13] S. B. Prapulla, S. N. Rao, and V. A. Herur, "Road quality analysis and mapping for faster and safer travel," in *Proc. Int. Conf. Energy, Commun., Data Analytics Soft Comput. (ICECDS)*, Aug. 2017, pp. 2487–2490.

[14] J. Oliveira, J. Lemos, E. Vieira, I. Silva, J. Abrantes, D. Barros, and D. G. Costa, "CO_2 catcher: A platform for monitoring of vehicular pollution in smart cities," in *Proc. IEEE 1st Summer School Smart Cities (S C)*, Aug. 2017, pp. 37–42.

[15] D. Griego, V. Buff, E. Hayoz, I. Moise, and E. Pournaras, "Sensing and mining urban qualities in smart cities," in *Proc. IEEE 31st Int. Conf. Adv. Inf. Netw. Appl. (AINA)*, Mar. 2017, pp. 1004–1011.

[16] C. Garau and V. Pavan, "Evaluating urban quality: Indicators and assessment tools for smart sustainable cities," *Sustainability*, vol. 10, no. 3, p. 575, Feb. 2018.

[17] M. Carvalho, T. Syguiy, and D. N. E. Silva, "Efficiency and effectiveness analysis of public transport of Brazilian cities," *J. Transp. Literature*, vol. 9, no. 3, pp. 40–44, Sep. 2015.

[18] A. Bezerra, G. Alves, I. Silva, P. Rosati, P. T. Endo, and T. Lynn, "A preliminary exploration of uber data as an indicator of urban liveability," in *Proc. Int. Conf. Cyber Situational Awareness, Data Analytics Assessment (Cyber SA)*, Jun. 2019, pp. 1–8.

[19] R. O'Briain, S. Shephard, and B. Coghlan, "A river vegetation quality metric in the eco-hydromorphology philosophy," *River Res. Appl.*, vol. 34, no. 3, pp. 207–217, Mar. 2018.

[20] Á. Gómez-Losada, J. C. M. Pires, and R. Pino-Mejías, "Characterization of background air pollution exposure in urban environments using a metric based on hidden Markov models," *Atmos. Environ.*, vol. 127, pp. 255–261, Feb. 2016.

[21] M. Kuzlu, M. Pipattanasomporn, and S. Rahman, "Assessment of communication technologies supporting smart streetlighting applications," in *Proc. IEEE Int. Smart Cities Conf. (ISC)*, Sep. 2018, pp. 1–7.

[22] T. C. Jesus, D. G. Costa, P. Portugal, and F. Vasques, "FoV-based quality assessment and optimization for area coverage in wireless visual sensor networks," *IEEE Access*, vol. 8, pp. 109568–109580, 2020.

[23] *Burden of Disease From Environmental Noise: Quantification of Healthy Life Years Lost in Europe*, Regional Office Eur., World Health Org., Geneva, Switzerland, 2011.

[24] K. M. Paiva, M. R. A. Cardoso, and P. H. T. Zannin, "Exposure to road traffic noise: Annoyance, perception and associated factors among Brazil's adult population," *Sci. Total Environ.*, vol. 650, pp. 978–986, Feb. 2019.

[25] P. Apparicio, M. Carrier, J. Gelb, A.-M. Séguin, and S. Kingham, "Cyclists' exposure to air pollution and road traffic noise in central city neighbourhoods of montreal," *J. Transp. Geography*, vol. 57, pp. 63–69, Dec. 2016.

[26] J. Díaz and C. L. Gil, "Traffic noise and adverse birth outcomes in Madrid: A time-series analysis," *Epidemiology*, vol. 27, no. 1, pp. e2–e3, Jan. 2016.

[27] World Health Organization, "Global status report on road safety 2018: Summary," World Health Org., Geneva, Switzerland, Tech. Rep. WHO/NMH/NVI/18.20, 2018.

[28] DATASUS. (2020). *Mortalidade–1996 A 2018, PELA CID-10*. Accessed: Aug. 11, 2020. [Online]. Available: https://datasus.saude.gov.br/mortalidade-1996-a-2017-pela-cid-10-2/

[29] CyclOSM. (2020). *Cycloosm: Openstreetmap-Based Bicycle Map*. Accessed: Aug. 11, 2020. [Online]. Available: https://www.cyclosm.org/

[30] F. Oliveira, D. G. Costa, and A. Dias, "A multi-tier sensors-based environmental monitoring approach to assess the quality of bike paths in urban areas," in *Proc. IEEE Int. Smart Cities Conf. (ISC)*, Sep. 2020, pp. 1–4.

[31] *Ambient Air Pollution: A Global Assessment of Exposure and Burden of Disease*, World Health Org., Geneva, Switzerland, 2016.

[32] *Global Solar UV Index: A Practical Guide*, World Health Organization, Geneva, Switzerland, 2002.

[33] National Oceanic and Atmospheric Administration. (2020). *NOAA Heat Index*. Accessed: Aug. 18, 2020. [Online]. Available: https://www.weather.gov/safety/heat-index

[34] A. Joseph, *The Impact of Light on Outcomes in Healthcare Settings*. Center for Health Design, Sep. 2006, pp. 1–12.

[35] C. A. M. D. Sousa, C. A. Bahia, and P. Constantino, "Analysis of factors associated with traffic accidents of cyclists attended in Brazilian state capitals," *Ciencia Saude Coletiva*, vol. 21, no. 12, pp. 3683–3690, 2016.

[36] A. Golub, M. L. Hoffmann, A. E. Lugo, and G. F. Sandoval, *Bicycle Justice and Urban Transformation: Biking for All*. Evanston, IL, USA: Routledge, 2016.

[37] C. Tebaldi and B. Sansó, "Joint projections of temperature and precipitation change from multiple climate models: A hierarchical Bayesian approach," *J. Roy. Stat. Soc. A, Statist. Soc.*, vol. 172, no. 1, pp. 83–106, 2009.

[38] J. Zhou, H. H. Chang, and M. Fuentes, "Estimating the health impact of climate change with calibrated climate model output," *J. Agricult., Biol., Environ. Statist.*, vol. 17, no. 3, pp. 377–394, 2012.

[39] S. Federal. (2019). *Programa Bicicleta Brasil*. Accessed: Jul. 2020. [Online]. Available: https://www12.senado.leg.br/noticias/infomaterias/2019/09/programa-bicicleta-brasil-agora-vai

FRANKLIN OLIVEIRA (Member, IEEE) received the B.Sc. degree in computer engineering from the State University of Feira de Santana, Brazil, in 2019, with an exchange period at the University of Porto, Portugal, from 2018 to 2019. He is currently pursuing the M.Sc. degree in computer science with the State University of Feira de Santana. He is also a Researcher with the Advanced Applications and Networks Laboratory (LARA) and contributes to the development of embedded systems and applications focused on Internet of Things for smart cities.

DANIEL G. COSTA (Senior Member, IEEE) received the B.Sc. degree in computer engineering, and the M.Sc. and D.Sc. degrees in electrical engineering from the Federal University of Rio Grande do Norte, Brazil, in 2005, 2006, and 2013, respectively.

He did research internship at the University of Porto, Portugal. He is currently an Associate Professor with the Department of Technology, State University of Feira de Santana, Brazil. He also coordinates the Advanced Networks and Applications Laboratory (LARA), State University of Feira de Santana. He has served several number of committees of distinguished international conferences. He is author or coauthor of more than 100 articles in the areas of computer networks, industrial communication systems, the Internet of Things, smart cities, and sensor networks. He acted as a Reviewer for high-quality journals.

CRISTIAN DURAN-FAUNDEZ (Member, IEEE) received the Ph.D. degree in automation, signal processing and computer engineering from Henri Poincaré University, Nancy 1, France. Since 2005, he has been an Informatics Engineer with the University of the Bío-Bío, Concepción, Chile, where he has also been a Professor with the Department of Electrical and Electronic Engineering, since 2005. He was working with the Centre for Automatic Control of Nancy, France, in 2009. His research interests include wireless sensor networks with an emphasis on image communication, localization methods, and applications for advanced manufacturing and the Internet of Things.

ANFRANSERAI DIAS (Member, IEEE) received the D.Sc. degree in electrical engineering from the Federal University of Rio Grande do Norte, in 2007. He is currently an Assistant Professor with the State University of Feira de Santana. He also coordinates the Digital Electronics and Systems Laboratory (LEDS). He develops scientific research and technology projects in the following lines, such as robotics, embedded systems, design of circuits based on FPGA's, and education, with emphasis on the Problem-based Learning (PBL) methodology and its application in engineering.

● ● ●