Calculating Walkability and Bikeability of Cities with a Multimodal and Multiscale Approach

Juan Pablo Duque[1], Maria Brovelli[1]

[1] Department of Civil and Environmental Engineering (DICA), Politecnico di Milano – juanpablo.duque@polimi.it; maria.brovelli@polimi.it

Keywords: urban sustainability, street networks, crowdsourced datasets, walkability, bikeability

Abstract

In the framework of sustainable development, the study of urban mobility networks is fundamental, in particular, the role of active mobility and street networks. Active mobility is known to positively impact several Sustainable Development Goals (SDGs), which makes its analysis fundamental to achieve sustainable transportation. Using a generalised and globally applicable methodology that leverages the use of open and crowd-sourced data, we characterised walkability and bikeability of the urban areas of 16 medium and large cities around the world, spread in 8 geographical areas. The methodology employs a graph-based multimodal and multiscale approach over driving, pedestrian, and biking street networks to calculate 20 indices and metrics (e.g., intersection density, steepness, circuity, orientation entropy, etc.) that characterise walkability and bikeability. This study presents the results and interpretation of the calculation of multiple walkability and bikeability metrics for the selected cities, as well as a discussion on the limitations of using global and crowd-sourced data for the calculation of active mobility indices.

1. Introduction

Every city has its personality. Some cities have narrow and picturesque alleys that tell countless stories, some are gigantic metropolises where millions of souls interact in a daily basis moving through intricate networks of every type of traffic. Some cities are gargantuan car-centric urban areas with immense highways that every day mobilise millions of people, while others require having a bicycle as an immediate necessity. What makes every city unique is its people and their movements, dictated by the spatial arrangement of their mobility networks and the means of transportation that traverse them.

In urban contexts, mobility refers to the movement or transportation that occurs within urban areas. In the framework of sustainable development, the study and optimization of urban mobility networks is fundamental. Within sustainable mobility, the role of active transportation, which comprises human-powered mobility such as biking or walking, is of major importance. It has been studied that encouraging active transportation options and providing infrastructure for alternative types of mobility is beneficial for cities, contributing towards multiple Sustainable Development Goals (SDGs). Active mobility positively impacts, health –SDG 3: Good health and wellbeing–, citizen participation and social capital –SDG 16: Peace, justice and strong institutions–, and sustainable transportation –SDG 11: Sustainable cities and communities–.

This study focuses on the usage of multimodal and multiscale street networks to calculate the level and quality of active mobility of urban areas through the calculation of quantitative metrics and indicators that characterise walkability and bikeability. Using the crowd-sourced dataset OpenStreetMap (OSM) as our data source, we intend to provide a methodology that can be applied to any urban area in the world.

This paper is organized as follows: section 2 presents the concepts and theoretical basis of the study as a contextualisation, section 3 describes the proposed methodology, and section 4 presents the results of applying our methodology to 16 cities around the world with a discussion on some of the results and its limitations.

2. Theoretical Framework

2.1 Street Networks and OpenStreetMap

A street network is the system that models the roads of an area as a set of interconnected points and lines. It is the basis for network analysis and is widely used in urban planning. Mobility flows through street networks, and a street network can represent one or more means of transportation, such as cars, pedestrians, public transportation, or bikes.

OpenStreetMap is a collaborative, free, and open-source mapping project. It provides the street networks for most places of the world with, overall, high quality (Boeing, 2017), making it ideal for both local and global analyses. One particularly useful tool for street network analysis with OSM is the library OSMnx (Boeing, 2017), which is a python open-source library based on Networkx to download and manage street networks from OSM as graphs. This library has been extensively used for street network analysis studies (Ma et al., 2024, Wu et al., 2024).

When a street network contains spatial properties (i.e., the geometries of intersections and street segments), it is called a spatial network (Rodrigue, 2024). Spatial networks are easily visualised in GIS software by storing nodes as points and the edges as lines (Figure 1).

2.2 Representation of Street Networks

Street networks can be modelled and represented in multiple ways (Marshall et al., 2018). The selection of model and representation is tightly related to the usage that will be given to the street network (e.g., cartography, topology, geocoding, routing, assignment) (Rodrigue, 2024). However, the most intuitive way to model a network is through a graph, which manages to capture its connectivity and topological aspects. Other network models, e.g., rasterisation of the street network, allow to capture

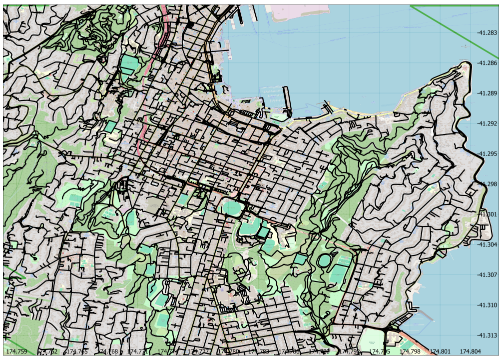

Figure 1. Example of spatial street network visualized in GIS software.

other network properties. For example, networks represented as rasters can be seamlessly integrated with other gridded data and have been shown useful for spatial analysis (Dur et al., 2014).

A graph $G = \{V, E\}$ is a data structure composed of a set of nodes (also called vertices) V and a set of edges E. Nodes are represented by points in the graph, while edges are the connections between them. In street networks, there are two widely used graph representations:

- Primal graphs: In this representation, nodes represent road junctions, while edges represent street segments (Porta et al., 2006b). Primal graphs can be directed, in particular when used for routing purposes – as the direction of streets is important; or undirected, for urban topology analysis where direction is not relevant.

- Dual graphs: Also called line graphs, are graphs where nodes represent street segments and edges represent intersections (Porta et al., 2006a). Dual graphs can represent different aspects of the street network, such as connectivity, and are the basis of the discipline of space syntax (Hillier et al., 1976).

Efficient and pertinent data representations, that reflect the intended purpose of the network for their subsequent analysis, are then required.

2.3 Multimodal Street Networks

In cities, multiple means of transportation interact with each other. The main urban means of transportation include private vehicles (also called private transportation), bicycles or micromobility (e.g., scooter, skateboard), public transportation (e.g., bus, metro, tram), and walking.

Street networks of different modalities can be represented using multilayer networks (Kivelä et al., 2014). These networks allow to study and analyse mobility in a holistic way as they manage to take into account the different mobility aspects of citizens. For example, combining multiple public transport networks to model urban transportation systems in multiple cities (Aleta et al., 2017), and representing the combination of driving, pedestrian, biking, and public networks as multiplex networks (Orozco et al., 2020) .

Although multimodal representations have the advantage of presenting the transportation system as a whole, they introduce additional complexity to an already complex network.

2.4 Street Network Generalisation

Scale is a major conditional in the analysis of street networks. Street networks get increasingly complex as the city size increases. Small and medium cities may contain a couple thousands of street segments, while big cities can reach up to hundreds of thousands. Generally, graph calculations are complex and require extensive processing power and time. Additionally, storing the street networks of big cities pose a significant space requirement. A multiscale approach is then obtained by setting different levels of generalisation to a network, depending on the scale of analysis.

The process of simplifying – or generalising – street networks have been extensively studied (Pueyo et al., 2019). In graph-based street networks generalisation is usually comprised of: i) the removal of elements within the network based on certain criteria (Chen et al., 2009, Pung et al., 2022); and ii) the combination of elements of the network by perceived similarity (Ma et al., 2024).

Proposed generalisation procedures includes an algorithm that attempts to maintain topological properties of a street network while removing certain patterns within the network such as loops, dead-ends, and gridirons. Removed sections are then aggregated to adjacent nodes, so the overall properties of the network are maintained (Pung et al., 2022). Other study proposed a natural street generalisation and removal to homogenise the number of nodes of a network in order use the resulting subgraph to train a deep learning model (Ma et al., 2024). In fact, the calculation of natural streets is already a generalisation of the network, as it merges street segments based on their name and/or their natural continuity (i.e., similar incidence angle).

2.5 Active Transportation and Sustainability

Active transportation comprises human-powered mobility. In particular, we focused on walking and biking as active means of transportation. In the framework of sustainable mobility, the role of active transportation has been studied to improve health (Rojas-Rueda et al., 2016), social capital (Kim and Yang, 2017, Stroope, 2021), built environment (Rafiemanzelat et al., 2017), and community engagement (Hassen and Kaufman, 2016).

Additionally, some studies address role of the street network configuration to measure active mobility, such as (Bielik et al., 2018), and (Hassen and Kaufman, 2016). However, it is worth mentioning that most of the studies are oriented towards walkability, while biking and micromobility get less attention.

2.6 Measuring Walkability and Bikeability as Indices of the Street Network

To characterise and compare street networks, the calculation of indices and metrics has been widely studied (Zhang et al., 2023). Among the different ways to characterise street networks, graph-based measurements are used to interpret the network topology or urban form, which is the way in which a network is organized. For example, network centrality has been as an index to locate key portions of the urban area (Agryzkov et al., 2019), and, similarly, graph centrality measurements have been used to characterise accessibility (Ahmadzai et al., 2019).

Analysing the edge and node-wise properties of the network has also been used to characterise street networks. For example, a study calculated multiple metrics for thousands of urban centres (e.g., intersection density, elevation, orientation entropy, etc.) for analysing urban street network form (Boeing, 2019). In Malaysia, a study characterised land use changes through proximity measurements (among other indices) using street networks and distance to roads (Abdullahi and Pradhan, 2018).

Finally, composite indicators comprise the use of multiple metrics to measure specific properties. Composite indices are single values composed of the combination of normalised and weighted metrics. For example, a composite index was used to study the relationship between land use and transportation integration (Dur et al., 2014), and a second example shows how graph-based metrics, combined with demographic information, were used to compose a neighbourhood walkability index (Cowie et al., 2016).

By contextualising network indicators into the framework of active mobility, it is possible to interpret those metrics and calculate which cities are more or less walkable or bikeable. As examples, composite indices were used to calculates the walkability and bikeability in four Chinese using edge and node-wise street network characteristics (Gu et al., 2018), graph-based measures were used to characterise walkability and accessibility in the city of Weimar (Bielik et al., 2018), and neighbourhood-level walkability in Norwegian cities was calculated by analysing infrastructure, street network, urbanity, surroundings and activities (Knapskog et al., 2019) .

3. Methodology

The goal of this study is to propose and test a general methodology for measuring walkability and bikeability at the city level from a topological perspective. It means to characterise, through different metrics, the level of bikeability and walkability of whole urban areas.

Our workflow (section 3.1) is divided into data extraction (section 3.2), data preparation (section 3.4), and the calculation of indices and metrics (section 3.4).

3.1 Workflow

Our methodology is composed of the following steps: i) the extraction of driving, walking, and bike street networks; ii) data preparation for each of the extracted street networks; and iii) the calculation of metrics using a multimodal (i.e., combining networks), and multiscale (i.e., performing generalization procedures) approach. Our workflow is depicted in figure 2.

3.2 Data Extraction

The initial step for the data extraction procedure is to select an area of interest, represented as a polygon. Then, using the OSMnx library (Boeing, 2017), we extract three street networks from the area of interest, namely the driving, pedestrian, and biking networks. OSMNx downloads OSM data using predefined filters that target specific street segments for each of the networks, however, we produced specific filters for pedestrian and biking networks. In particular, the pedestrian filter leaves out segments that specify non-accessible streets, as well as segments that have sidewalks mapped separately, avoiding duplicated pedestrian paths. The biking filter eliminate streets that specify non-accessibility and that are mapped as no-bicycle streets, as well as eliminating pedestrian-only paths.

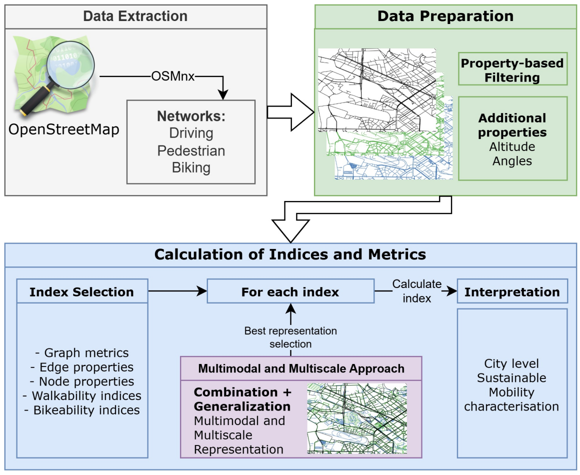

Figure 2. Workflow of the proposed methodology for calculating walkability and bikeability using a multimodal and multiscale approach through city-level indices and metrics.

3.3 Data Preparation

The data preparation step takes each of the downloaded networks and perform additional filtering based in properties of the network. In addition, one node property and two edge properties are calculated and added to each of the networks. The properties that are added to the network are node elevation, edge inclination or grade, and edge orientation.

The additional filters applied to each of the networks are the following:

- Driving: No additional filters were applied, as OSM is designed around driving streets and the downloaded street networks were of good quality.

- Biking: An additional filter based on street type was performed to eliminate inaccessible streets and other types of streets, such as parking aisles. However, it is important to mention that biking networks, as they share a large portion of the driving network, are generally well mapped in OSM.

- Pedestrian: Given the freedom of pedestrian movement, pedestrian networks are complex to map, in particular for sidewalks. OSM specifes certain rules for mapping sidewalks separately to streets. Moreover, streets must specify if they have a separately mapped sidewalk. This practice allows more granularity, but not all cities around the world have the same level of detail and, even in well-mapped cities, not all sidewalks are mapped separately to driving streets. This makes pedestrian networks a composition of most of the driving street network plus the separately mapped network of sidewalks and pedestrian paths. In the case that a sidewalk is mapped separately to the street, but the street does not specify that is has a separate sidewalk, redundancy is created in the pedestrian network. To overcome this, we compared the 2D slope (i.e., slope m of a linear regression of the street segment points) of each sidewalk with the slope of every street in a network radius of 8 (i.e., an induced subgraph of depth 8), and their proximity as the distance between their centroids. If a sidewalk and a street share similar slopes and are closer than a threshold of around 20 meters, the street is eliminated. Figure 3 shows the results of this procedure for the city of Milan. The red lines shown on the figure

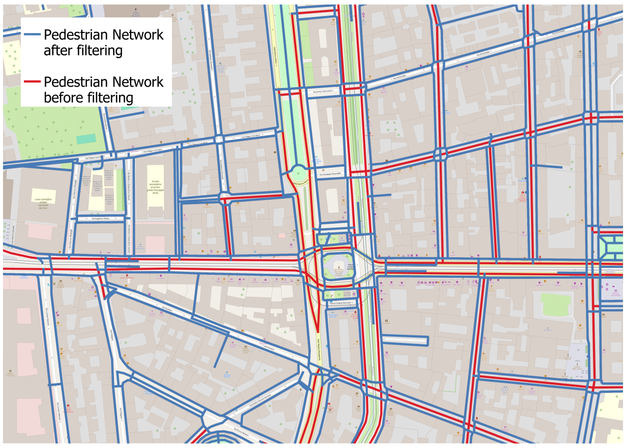

Figure 3. Pedestrian network before and after elimination of driving streets with separately mapped sidewalks.

are streets that were eliminated after the filter, while the blue lines represent the resulting pedestrian network. This filter is not perfectly accurate, but is able to eliminate most of the redundant streets with mapped sidewalks effectively, and reduce the amount of edges in the network.

After filtering, the additional properties of node elevation, edge inclination, and edge orientation were added to each of the street networks. Node elevations were interpolated from the global Digital Elevation Model NASADEM (NASA-JPL, 2020). This dataset provides global elevation data with a 30-meter resolution. Having the elevation for the nodes of the network, the inclination of each street segment was calculated as the angle of inclination with respect to a flat surface. Finally, compass bearings are calculated for each edge as proposed in (Boeing, 2017).

3.4 Calculation of Indices and Metrics

For index calculation, the driving, biking, and walking graphs were loaded and merged into a multimodal representation. Each index requires a specific network representation (and/or subsequent generalisation) that provides the best trade-off between pertinency and accuracy.

The multimodal representation is simply a combination of edges that share common nodes among the network. For the multiscale representation, two generalisation methods were implemented: i) natural streets simplification, where streets with the same name or good continuity were merged (Ma et al., 2024), and the topological-preservation generalisation (Pung et al., 2022), where loops, dead-ends, and gridiron structures, are iteratively eliminated until convergence, while maintaining topological properties.

The selected indices and metrics were extracted or derived from academic literature and are composed of multiple graph-based metrics, node and edge properties, and composite indices. Each index is calculated for walkability and bikeability, as the networks used to address each of them are different. Indices were selected to reflect walkability and bikeability from a network topology perspective. The selected indices are the following:

3.4.1 Average Circuity: Measures the curvature of street segments. It is the ratio of the real-world length of each street segment with respect to the great-arch distance between the nodes of the segment. Lower circuity (values closer to 1) has been related to more efficient street networks (Cubukcu, 2021).

3.4.2 Orientation Entropy: Calculated as the Shannon Entropy of the edge bearings of the street network. It refers to how "organised" a street network is (Boeing, 2017). In particular, the edge bearings are classified into 36 bins, each of 10 degrees. The Shannon entropy is then calculated on the classified values, with a theoretical higher value of $log_e(36) = 3.5835$. Lower entropy values represent less variability in angles between streets of the network, referring to more uniform cities that present a higher amount of organized structures, such as gridirons.

3.4.3 Road Density: Calculated as the amount of street network segments per square kilometre (km^2) of built-up area. Higher values of road density refer to more packed and compact cities, which is usually an indicator of more walkable cities.

3.4.4 Average Steepness: Calculated as the average inclination of the edges of the street network. Higher values of steepness indicate hillier streets. Cycling is particularly harder on steep streets, while it does not greatly affect walkability.

3.4.5 Average Street Length: Calculated as the average length of the street segments of the network. Shorter values indicate more compact and walkable street segments, while larger values indicate car-centric cities with highways or longer street segments.

3.4.6 Intersection Density: A intersection is a junction that is shared by three or more street segments. The intersection density is calculated as the amount of intersections by km^2 of built-up area, and is a measure of connectivity of the network. It is higher for urban areas with gridiron patterns and lower for curvilinear street networks with long block lengths. High values of intersection density, when combined with shorter street segments, indicate high network connectivity and are, together, an indicator of high walkability and bikeability (Cowie et al., 2016).

3.4.7 Walking and Driving Street Segments Ratio: Calculated as the ratio of the number of pedestrian street networks and the number of driving streets. It indicates how many walking streets are mapped in OSM with respect to the driving network. Higher values indicate better pedestrian infrastructure, but may also indicate more detailed mapping in OSM.

3.4.8 Biking and Driving Street Segments Ratio: Similar to the above, but calculated with respect to the biking street network.

3.4.9 Average Biking Score: Composite index roughly based on the Levels of Traffic Stress (LTS) (Furth et al., 2016) and other properties of the biking street network that affect bikeability such as street inclination. It takes into the street speed limit, the existence of separate cycling infrastructure, road type, and the street inclination to score each street segment in a scale from 0 to 5. The city biking score is then reported as the average biking score of all street segments.

3.4.10 Average Walking Score: Similarly to the biking score, the walking score is a composite index roughly based on the Levels of Traffic Stress (LTS). However it takes into account the street speed limit, the existence of pedestrian infrastructure (e.g., sidewalks or walking paths), and the road type. The city walking score is then reported as the average walking score of all street segments.

3.4.11 Connectivity: Calculated from the natural streets of the biking and walking network, it measures the connectivity of entire streets as its number of intersections. Natural streets are a generalisation of the street network where street segments with the same name and/or good continuation are merged. It is also an indicator of street importance, as streets with more intersections are more connected, and thus, are more important. The average connectivity and the standard deviation is reported for this metric. Higher values of connectivity, when complemented with lower standard deviation, indicate car-centric cities with mainly long, connected avenues, while high variation may indicate cities with long highways that connect smaller and walkable areas. Low values of connectivity may indicate shorter streets with dense and disordered patterns.

4. Results

In this section, we present the results of the calculation of the indices and metrics described in section 3.4 for the urban areas of 16 cities. The results are intended to characterise the cities' walkability and bikeability, more than to serve as a direct comparison. A discussion of some of the results of the calculations are also presented in this section, along with some insights of the limitations of working with crowdsourced and global data.

4.1 Selected Cities for Analysis

A total of 16 cities were selected for this study. The cities are all from different countries and geographical areas to provide variability. Eight geographical areas were chosen, and two cities from each area were selected. The selected cities range from middle to large, and do not follow a specific pattern. Some of them are the primate cities of their respective countries (e.g., Port Moresby - Papua New Guinea, Bogota - Colombia), others represent the countries' second largest city (e.g., Alexandria, Egypy), while others are capital cities (e.g., Ottawa, Canada, Wellington, New Zealand).

The area of each city was extracted from the GHS Urban Centre Database 2025: GHS-UCDB R2024A, produced by the European Comission's Joint Research Centre (JRC) (Rivero et al., 2024). This dataset contains information about more than 11.000 urban areas, such as population, gross domestic product (GDP), and built-up area, and their polygons at a resolution of $1km^2$.

Table 1 presents the city name, country, geographical area, total area, and built-up area, as extracted from the GHS-UCDB R2024A dataset.

City	**Country**	**Geo. Area**	**Area** (km^2)	**Built-up Area** (km^2)
Buenos Aires	Argentina	SA	2186	673.0
Bogota	Colombia	SA	534	152.0
Chicago	USA	NA	2046	524.0
Ottawa	Canada	NA	208	39.6
Panama City	Panama	CA	277	62.0
Havana	Cuba	CA	321	56.1
Milan	Italy	EU	785	176.4
Athens	Greece	EU	412	115.2
Shanghai	China	AS	3128	718.0
Hanoi	Vietnam	AS	925	161.9
Dubai	UAE	ME	854	197.8
Doha	Qatar	ME	392	107.8
Wellington	New Zealand	OC	64	13.9
Port Moresby	P. New Guinea	OC	72	8.4
Lagos	Nigeria	AF	1199	415.9
Alexandria	Egypt	AF	439	81.7

Table 1. Selected cities, their areas, and built-up areas in km^2. Geographical areas: South America (SA), North America (NA), Central America (CA), Europe (EU), Asia (AS), Middle East (ME), Oceania (OC), and Africa (AF).

4.2 Results of Indices and Metrics Calculations

After applying the methodology proposed in section 3 with the areas of each of the 16 selected cities, the results for walkability indices are presented in table 2, and the results for bikeability indices are presented in table 3. Indices for both modalities are reported in different tables as they were calculated using different networks. While the walkability indices utilised the pedestrian and driving network, the bikeability indices were calculated on the biking and driving network, yielding different results.

4.3 Results Discussion

Multiple interesting observations can be derived from the resulting calculations. Starting with the Average Walk and Bike scores (AWS and ABS), we see most of the values between 3 and 4. A bar plot of the AWS and ABS values per city is depicted in figure 4, showing in green the average walk scores, in blue the average bike scores, and in black the combination of both as the formula $(walk\_score + bike\_score)/2$. According to this metric the streets of, Chicago, Milan, and Bogotá are the most walkable and bikeable, while Oceania cities (Wellington and Port Moresby) are the less walkable and bikeable. Interestingly, the Bogota walk score is significantly higher than the bike score, mainly due to higher steepness (0.44 against 0.22 of Chicago and 0.29 of Milan), which greatly affect bikeability. Port Moresby, the least walkable and bikeable city according to the indices, has been included in multiple list of least liveable cities and suffers from deficient infrastructure, which is reflected in this results.

Observing the connectivity (ACO and SCO), and the average street length (ASL) of the walkability metrics, Shanghai and Chicago are at the top of the chart. However, the large variability in connectivity and the long ASL in Shanghai suggests that the city is composed of long avenues covering large areas and connecting smaller neighbourhoods containing long and curved streets. As of Chicago, the high connectivity and variability suggest something similar, but shorter ASL also suggests that connected neighbourhoods have a different, more compact configuration, making them more walkable. Chicago is well known for its grid-like design, which is also evident from its low Orientation Entropy (ORE) value.

Finally, by observing the results of the calculation of biking indices in the cities of cities of Buenos Aires and Lagos, we can conclude that both are car-centric, but Buenos Aires has better infrastructure and topology for bikeability. Both cities have low intersection density (3^{nd} and 2^{rd} lower values, respectively), present large average street length (3^{nd} and 4^{th} larger values, respectively), and low biking road density (3^{nd} and 2^{rd} lower values, respectively), suggesting long streets with few intersections. However, circuity and orientation entropy are significantly lower in Buenos Aires, suggesting a more organized,

City	POP	CIR	ORE	RDE	AST	ASL	IND	WDR	AWS	ACO	SCO
Buenos Aires	14’179,912	1.018	3.286	51368	0.028	86.345	326.446	0.771	3.429	8.005	10.826
Bogota	10’419,360	1.047	3.552	79835	0.048	50.608	877.276	1.405	3.863	9.242	15.193
Chicago	5’318,734	1.059	2.457	94108	0.026	54.389	929.989	3.579	3.830	29.217	59.412
Ottawa	604,618	1.062	3.366	144617	0.033	41.004	1936.544	5.263	3.594	18.898	29.599
Panama City	1’612,439	1.080	3.569	57909	0.046	72.213	431.537	1.032	3.482	7.029	10.316
Havana	1’632,771	1.049	3.555	72756	0.032	77.953	510.156	1.058	3.111	6.534	8.540
Milan	3’135,553	1.068	3.544	84354	0.035	49.257	959.704	2.576	3.805	12.988	23.377
Athens	3’166,757	1.031	3.550	86771	0.060	56.686	875.439	1.086	3.519	7.072	10.051
Shanghai	30’678,616	1.049	3.424	33536	0.027	157.808	115.765	1.184	3.140	173.804	251.134
Hanoi	4’965,520	1.059	3.574	88463	0.029	65.535	754.677	1.288	3.573	7.804	12.690
Dubai	4’565,477	1.068	3.467	77426	0.063	56.313	807.691	1.985	3.548	12.381	26.379
Doha	1’980,416	1.079	3.452	61697	0.031	66.596	541.642	1.143	3.586	6.367	8.934
Wellington	154,120	1.120	3.523	67009	0.078	52.959	676.056	3.139	3.278	6.140	11.008
Port Moresby	442,164	1.119	3.569	72745	0.046	109.971	355.963	1.023	2.947	4.267	4.417
Lagos	12’846,045	1.055	3.556	34911	0.030	100.951	196.758	0.635	3.635	6.058	9.316
Alexandria	6’931,368	1.032	3.458	74548	0.048	59.070	744.167	0.648	3.724	7.081	12.288

Table 2. Results for the calculation of walkability indices and metrics. Legend: POP: Population; CIR: Circuity; ORE: Orientation Entropy; RDE: Road Density; AST: Average Steepness; ASL: Average Street Length; IND: Intersection Density; WDR: Walk-Drive Ratio; AWS: Average Walk Score; ACO: Average Connectivity; SCO: Connectivity Standard Deviation

City	POP	CIR	ORE	RDE	AST	ASL	IND	BDR	ABS	ACO	SCO
Buenos Aires	14’179,912	1.015	3.203	49065	0.024	98.394	270.367	0.647	3.748	8.470	12.275
Bogota	10’419,360	1.048	3.551	61504	0.044	68.100	489.618	0.804	3.404	13.838	30.991
Chicago	5’318,734	1.068	2.584	66791	0.022	75.839	453.967	1.822	3.753	6.686	14.144
Ottawa	604,618	1.072	3.377	82081	0.029	64.928	586.625	1.886	3.598	8.877	16.510
Panama City	1’612,439	1.072	3.567	51913	0.044	80.275	335.305	0.832	3.300	8.974	15.316
Havana	1’632,771	1.047	3.558	64816	0.030	92.278	378.058	0.796	3.604	6.335	9.373
Milan	3’135,553	1.061	3.526	61513	0.029	70.245	461.082	1.317	3.670	51.332	86.602
Athens	3’166,757	1.028	3.546	79947	0.055	64.170	701.697	0.884	3.070	7.769	13.745
Shanghai	30’678,616	1.047	3.403	32356	0.024	176.601	98.481	1.021	3.724	78.621	128.654
Hanoi	4’965,520	1.056	3.577	80389	0.026	74.563	602.049	1.029	3.647	8.199	14.826
Dubai	4’565,477	1.070	3.454	66863	0.059	70.321	547.156	1.373	3.195	50.727	95.572
Doha	1’980,416	1.077	3.440	63745	0.030	77.212	473.217	1.018	3.579	53.867	87.018
Wellington	154,120	1.112	3.514	52335	0.069	61.568	417.051	2.109	2.901	4.219	6.099
Port Moresby	442,164	1.112	3.569	70391	0.047	111.711	334.182	0.974	2.246	4.344	4.416
Lagos	12’846,045	1.054	3.556	34729	0.030	101.862	193.692	0.626	3.590	6.605	8.622
Alexandria	6’931,368	1.032	3.449	73675	0.046	62.419	694.789	0.606	2.966	8.266	16.057

Table 3. Results for the calculation of bikeability indices and metrics. Legend: POP: Population; CIR: Circuity; ORE: Orientation Entropy; RDE: Road Density; AST: Average Steepness; ASL: Average Street Length; IND: Intersection Density; BDR: Bike-Drive Ratio; ABS: Average Bike Score; ACO: Average Connectivity; SCO: Connectivity Standard Deviation

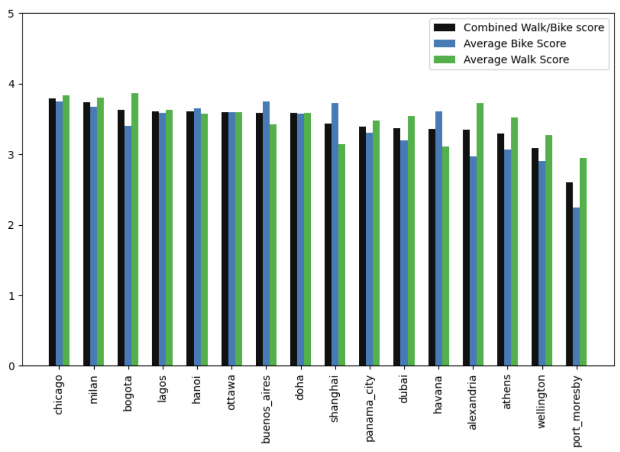

Figure 4. Plot of average bike score (blue) and average walk score (green) ordered from highest to lowest by the combined score (black).

grid-like structure in their streets, which is a sign of improved bikeability. Moreover, steepness is lower in Buenos Aires, as it is mostly flat city, and its average bike score is higher than that of Lagos, implying improved cycling infrastructure.

4.4 Limitations

Being a generic methodology, it is not exempt to limitations. To obtain useful information, we rely on the completeness and the quality of OSM, which is public and crowd-sourced data. Abnormal data from OSM can degrade the calculated indices, as it is the case for the city of Ottawa. The value of the ratio of walking and driving street segments is abnormally high at 5.263, while the second highest is Wellington with 3.139. After observing the resulting pedestrian network (Figure 5), we realised that Ottawa is particularly well mapped with respect to pedestrian infrastructure, even in residential zones, meaning that most streets have sidewalks mapped separately, crossings, and pedestrian paths. Such inconsistency, with respect to other cities, affects other metrics such as intersection density, road

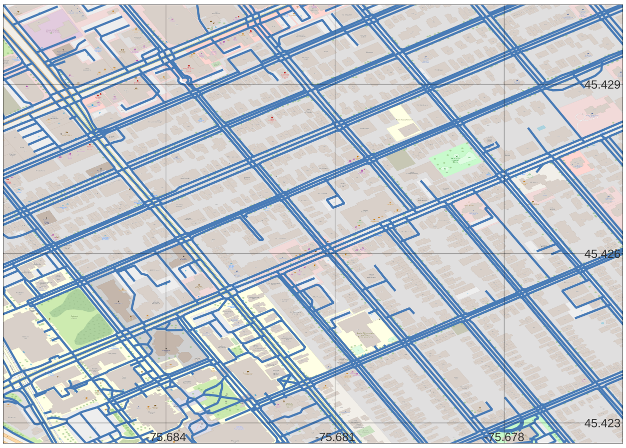

Figure 5. Ottawa pedestrian street network showing redundancy in sidewalks and residential streets.

density and connectivity, which yields values higher than expected.

Other point of failure is the usage of global DEM data for calculating altitude in the street networks. Although it is useful, the accuracy of a global DEM is not completely reliable. As an example, the city of Dubai presents abnormally high values of steepness, despite being a coastal city that lies mostly at sea level. Its steepness (0.063 for the walking network and 0.059 for the biking) is comparable to the one of the city of Athens (0.060 for the walking network and 0.055 for the biking network), which is known to be a hilly city.

As a final remark, this study does not take into consideration other fundamental factors of walkability and bikeability such as proximity to points of interest, urban greenery, or environmental conditions (e.g., weather, air quality, etc), and is an effort to understand active mobility in a quantitative way from the topology of street networks.

5. Conclusion and Future Work

In this paper we proposed a generic methodology for calculating walkability and bikeability at the city level using global, crowd-sourced, open data. Our methodology consists of the extraction of street network data from OpenStreetMap, followed by a data preparation procedure where further processing is performed to each of the extracted networks, and the posterior calculation of indices and metrics to characterise active mobility, in particular walkability and bikeability. We selected 20 indices from academic literature that helped us characterise active mobility in urban areas, which aligns with multiple sustainable development goals. Using a combination of driving, pedestrian, and biking street networks at different scale levels using generalisation algorithms, we calculated bikeablity and walkability indices for 16 cities worldwide, spanning every continent. From the results, we were able to observe certain urban patters and compare similarities among cities with respect to active mobility, as well as understand the limitations of a generic methodology, as it depends on global and crowdsourced data.

Further efforts for improving the methodology will be pursued, as improving the generalisation algorithms, multimodal representations, data extraction, and filtering. In addition, the implementation of indices based on proximity to points of interest, greenery, and environmental conditions will be implemented to the methodology, as they are fundamental for active mobility.

References

Abdullahi, S., Pradhan, B., 2018. Land use change modeling and the effect of compact city paradigms: integration of GIS-based cellular automata and weights-of-evidence techniques. *Environmental Earth Sciences*, 77, 251.

Agryzkov, T., Tortosa, L., Vicent, J. F., Wilson, R., 2019. A centrality measure for urban networks based on the eigenvector centrality concept. *Environment and Planning B: Urban Analytics and City Science*, 46, 668-689.

Ahmadzai, F., Rao, K., Ulfat, S., 2019. Assessment and modelling of urban road networks using Integrated Graph of Natural Road Network (a GIS-based approach). *Journal of Urban Management*, 8, 109-125.

Aleta, A., Meloni, S., Moreno, Y., 2017. A Multilayer perspective for the analysis of urban transportation systems. *Scientific Reports 2017 7:1*, 7, 1-9.

Bielik, M., König, R., Schneider, S., Varoudis, T., 2018. Measuring the Impact of Street Network Configuration on the Accessibility to People and Walking Attractors. *Networks and Spatial Economics*, 18, 657-676.

Boeing, G., 2017. OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Computers, Environment and Urban Systems*, 65, 126-139.

Boeing, G., 2019. Urban spatial order: street network orientation, configuration, and entropy. *Applied Network Science*, 4, 67.

Chen, J., Hu, Y., Li, Z., Zhao, R., Meng, L., 2009. Selective omission of road features based on mesh density for automatic map generalization. *International Journal of Geographical Information Science*, 23, 1013-1032.

Cowie, C. T., Ding, D., Rolfe, M. I., Mayne, D. J., Jalaludin, B., Bauman, A., Morgan, G. G., 2016. Neighbourhood walkability, road density and socio-economic status in Sydney, Australia. *Environmental Health*, 15, 58.

Cubukcu, K. M., 2021. Using circuity as a network efficiency measure: the example of Paris. *Spatial Information Research*, 29, 163-172.

Dur, F., Yigitcanlar, T., Bunker, J., 2014. A Spatial-Indexing Model for Measuring Neighbourhood-Level Land-Use and Transport Integration. *Environment and Planning B: Planning and Design*, 41, 792-812.

Furth, P. G., Mekuria, M. C., Nixon, H., 2016. Network Connectivity for Low-Stress Bicycling. *https://doi.org/10.3141/2587-06*, 2587, 41-49.

Gu, P., Han, Z., Cao, Z., Chen, Y., Jiang, Y., 2018. Using Open Source Data to Measure Street Walkability and Bikeability in China: A Case of Four Cities. *Transportation Research Record: Journal of the Transportation Research Board*, 2672, 63-75.

Hassen, N., Kaufman, P., 2016. Examining the role of urban street design in enhancing community engagement: A literature review. *Health Place*, 41, 119-132.

Hillier, B., Leaman, A., Stansall, P., Bedford, M., 1976. Space syntax. *Environment and Planning B: Planning and Design*, 3, 147-185.

Kim, H., Yang, S., 2017. Neighborhood Walking and Social Capital: The Correlation between Walking Experience and Individual Perception of Social Capital. *Sustainability 2017, Vol. 9, Page 680*, 9, 680.

Kivelä, M., Arenas, A., Barthelemy, M., Gleeson, J. P., Moreno, Y., Porter, M. A., 2014. Multilayer networks. *Journal of Complex Networks*, 2, 203-271.

Knapskog, M., Hagen, O. H., Tennøy, A., Rynning, M. K., 2019. Exploring ways of measuring walkability. *Transportation Research Procedia*, 41, 264-282.

Ma, D., He, F., Yue, Y., Guo, R., Zhao, T., Wang, M., 2024. Graph convolutional networks for street network analysis with a case study of urban polycentricity in Chinese cities. *International Journal of Geographical Information Science*, 38, 931-955.

Marshall, S., Gil, J., Kropf, K., Tomko, M., Figueiredo, L., 2018. Street Network Studies: from Networks to Models and their Representations. *Networks and Spatial Economics*, 18, 735-749.

NASA-JPL, 2020. Nasadem: Creating a new nasa digital elevation model and associated products — nasa earthdata. NASA JPL doi.org/10.3334/ORNLDAAC/1523.

Orozco, L. G. N., Battiston, F., Iñiguez, G., Szell, M., 2020. Extracting the Multimodal Fingerprint of Urban Transportation Networks. *Transport Findings*.

Porta, S., Crucitti, P., Latora, V., 2006a. The network analysis of urban streets: A dual approach. *Physica A: Statistical Mechanics and its Applications*, 369, 853-866.

Porta, S., Crucitti, P., Latora, V., 2006b. The Network Analysis of Urban Streets: A Primal Approach. *https://doi.org/10.1068/b32045*, 33, 705-725.

Pueyo, O., Pueyo, X., Patow, G., 2019. An overview of generalization techniques for street networks. *Graphical Models*, 106, 101049.

Pung, J., D'Souza, R. M., Ghosal, D., Zhang, M., 2022. A road network simplification algorithm that preserves topological properties. *Applied Network Science*, 7, 1-16.

Rafiemanzelat, R., Emadi, M. I., Kamali, A. J., 2017. City sustainability: the influence of walkability on built environments. *Transportation Research Procedia*, 24, 97-104.

Rivero, I. M., Melchiorri, M., Florio, P., Schiavina, M., Goch, K., 2024. Joint research centre data catalogue - ghs-ucdb r2024a - ghs urban centre database 2025 - european commission.

Rodrigue, J. P., 2024. The geography of transport systems. *The Geography of Transport Systems*, 1-402.

Rojas-Rueda, D., Nazelle, A. D., Andersen, Z. J., Braun-Fahrländer, C., Bruha, J., Bruhova-Foltynova, H., Desqueyroux, H., Praznoczy, C., Ragettli, M. S., Tainio, M., Nieuwenhuijsen, M. J., 2016. Health Impacts of Active Transportation in Europe. *PLOS ONE*, 11, e0149990.

Stroope, J., 2021. Active transportation and social capital: The association between walking or biking for transportation and community participation. *Preventive Medicine*, 150, 106666.

Wu, C., Wang, Y., Wang, J., Kraak, M. J., Wang, M., 2024. Mapping Street Patterns with Network Science and Supervised Machine Learning. *ISPRS International Journal of Geo-Information 2024, Vol. 13, Page 114*, 13, 114.

Zhang, P., Ghosh, D., Park, S., 2023. Spatial measures and methods in sustainable urban morphology: A systematic review. *Landscape and Urban Planning*, 237, 104776.