Validating a bike network analysis score based on open data as a connectivity measure of urban cycling infrastructure adapted for European cities

Dissertation submitted in partial fulfillment of the requirements for the Degree of Master of Science in Geospatial Technologies

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Declaration of Academic Integrity

I hereby confirm that this thesis on *Validating a bike network analysis score based on open data as a connectivity measure of urban cycling infrastructure adapted for European cities* is solely my own work and that I have used no sources or aids other than the ones stated.

All passages in my thesis for which other sources, including electronic media, have been used, be it direct quotes or content references, have been acknowledged as such and the sources cited.

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I agree to have my thesis checked in order to rule out potential similarities with other works and to have my thesis stored in a database for this purpose.

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List of Abbreviations

BNA	Bicycle Network Analysis
CBS	Centraal Bureau voor de Statistiek
DOT	Department of Transportation
FTW	Fietstelweek
OD	Origin-Destionation
OSM	OpenStreetMap
LISA	Employment Register for the Netherlands
LSOA	Lower Super Output Area
LTS	Levels of Traffic Stress
NSW	National Survey of Wales
NTS	National Travel Survey
PfB	PeopleForBikes

Abstract

Cycling has been considered a viable option to generate a modal shift from fossil dependent transportation modes. In this framework, measurements and tools that aid connected bicycle infrastructure planning have been developed. This is the case of the Bicycle Network Analysis score, a connectivity measure adapted for the U.S. It is based on the Levels of Traffic Stress methodology and computed mainly with OpenStreetMap data. Its aim is to quantify how well the low-stress bicycle network in a city connects people with the places they want to go. For this research, the BNA open source tool is adapted to a European context to validate its ability of quantifying low-stress connectivity. Three core elements are evaluated: *stress network*, *destinations*, and the *overall score* itself. They are related to cycling behaviors from two validation data sources: travel to work data in England and Wales, and crowdsourced bicycle trip routes in The Netherlands. The results indicate that in England and Wales, there is a significantly higher percentage of bicycle trips performed between origin-destination pairs with a low-stress connection between them. Additionally, a positive correlation is found between the percentage of bicycle trips within a city and its overall BNA score. In the Dutch case, the *destinations* core element is evaluated, determining that the destinations contemplated in the BNA score calculation are also among the highly frequented by cyclists. However, their importance within the score computation might require adjustments. Although a comprehensive validation cannot be achieved due to data limitations, evidence that providing low-stress connections between origins and destinations relates to bicycle commuting in cities is found. Therefore, special attention should be given to those measures that can greatly benefit the decision-making process when planning for sustainable cities.

Key words: bicycle network analysis score; bicycle network connectivity; levels of traffic stress; OpenStreetMap; sustainable mobility; open data

Chapter 1

Introduction

Private motorized transport accounts for 47% of the trips made in urban areas worldwide (Aguiléra & Grébert, 2014). Unfortunately, private cars remain as the mainstream mode of transport, contributing largely with pollutant emissions that deter air quality and contribute to climate change (Hickman & Banister, 2014). Nonetheless, environmental awareness has increased in the past years, and a large impulse to sustainable transport is evident (Banister, 2011), notably among highly urbanized areas with congestion and traffic problems.

Active travel, i.e. walking and cycling, stand out among the sustainable mobility options, as those exhibiting a plethora of benefits. Advantages include an increase in physical activity and exercise, promoting public health (Oja et al., 2011); an improvement of social interaction, livability, and sense of community (Bopp, Sims, & Piatkowski, 2018); traffic and congestion relief (Kosha & Rudolph, 2016); and clear benefits to the environmental health of the planet by reducing fossil fuels dependency (Hickman & Banister, 2014).

In this vein, cycling has been a key focus of sustainable mobility policies that aim for a modal shift of those short distance trips too long to walk but, normally performed by car (Pucher & Buehler, 2008b). Therefore, identifying the conditions that prevent citizens from taking that leap is imperative to create real change. Motivators such as calm and clean air environments, natural beauty, and segregation from motorized traffic have been identified as those top elements that can positively influence cycling behavior (Winters, Davidson, Kao, & Teschke, 2011).

Special interest has been given to traffic variables that act like deterrents of urban cycling (Fishman, 2016). In this sense, a trend to provide citizens with low-stress bicycle infrastructure that allows them to have pleasant, safe, and comfortable bicycle rides has been encouraged (Pucher & Buehler, 2008a). Nevertheless, 'good' bicycle infrastructure is only so when it truly connects people's origins and destinations (Lowry & Hadden, 2017), by building bicycle networks that promote an integral adaption of this mode of transport.

Several measurements have been developed to quantify the connectivity of bicycle networks. These assessments can greatly assist decision-makers, transport planners, and other stakeholders to take informed decisions when planning and implementing new bicycle infrastructure that serve all population groups (Twadell et al., 2018).

1.1 Background

The *Bicycle Network Analsysis (BNA) score* (PeopleForBikes, 2019) is a tool created by the PeopleForBikes (PfB) organization (PeopleForBikes, 2018). It is essentially a connectivity measure based on the concept of Bicycle Levels of Traffic Stress. It aims to quantify how good the low-stress bicycle networks in U.S cities connect people to other people, their workplace, or other destinations such as schools, universities, supermarkets, pharmacies, doctors, etc. The score computation is based on open data sources such as governmental Open Data Portals and OpenStreetMap (OSM).

The BNA score is an overall connectivity measure assigned to an area under analysis, allowing comparisons between cities. Additionally, the score identifies zones in the city with low connectivity. This spatial analysis can help to improve the cycling conditions through a diagnosis of the priority areas. It can also aid to identify weakest links within the biking network, enhancing network connectivity.

Stakeholders in North America have already been directing their attention to the BNA score tool (Broach, Dill, Clifton, & Lust, 2018; Gardner, 2017; Lindsey, 2018; Small, 2018; Szyszkowicz, 2018; Twadell et al., 2018); raising awareness on road safety, security, and environmental issues that surround the active travel topic within a city's mobility policies. It is therefore a promising tool to measure connectivity, which can be implemented in other countries in the world.

Replicating the score for other study areas is an achievable goal. PfB released their entire methodology and workflow as an open source tool, where every step is reproducible and can be run locally. Their basic architecture consists on a combination of different programming languages scripts that run on a Virtual Machine environment. The current set-up to run the local analysis can be limiting due to its complexity, possible leading to a decrease interest from third-parties to use the tool. This reduces the enhancement opportunities by external analysts.

1.2 Motivation

The original local analysis for the BNA score computation proposed by PfB urges a simplification of its original workflow. This would allow external analysts to modify the underlying computation code without worrying about the complexities of the set-up. Removing this barrier should be the first step before diving into the research questions that emerge from the BNA score conceptualization.

One of the main doubts that rise when presented a BNA score result is: *How accurate is this number representing the bicycle network connectivity in a city?*. The PfB methodology has only been validated in an empirical way, that is, by people who know the cycling conditions in a scored city. For example, if a road segment is classified as low-stress when it actually is not, a person can report it as general feedback.

Even if these kinds of evaluations by the actual riders help to improve the score computation with small adjustments, the methods behind the score computation are taken for granted and not evaluated along with actual cycling behaviors.

1.3 Research questions

When decomposing the BNA score into its core elements (stress network, destinations, and the score itself), one can wonder how the theory or the methods behind each of these elements are reflecting peoples' actual cycling behaviors. To analyze how well the BNA score reflects people's stress levels and destination locations, three research questions are proposed:

1. *Are more people biking if there is a low stress network connecting their origin to their destination?*
2. *Are people biking more to the highly ranked destination types in the BNA score?*
3. *Is there a relationship between the BNA score, as a connectivity measure, and actual bicycling activity*

Overall, the answer to these three questions might clarify the main research question analyzed by this thesis: *How accurately can a quantitative index based on open and/or crowdsourced data serve as a tool to evaluate connectivity of low-stress cycling networks?*.

1.4 Objectives

The research questions lead into the aim of this research, which seeks to validate a bicycle network analysis score based on open data as a connectivity measure of urban cycling infrastructure. To do so, the three following objectives have been established:

- Translate the current bicycle network analysis score scripting into an R and SQL based tool that would allow the computation of the score in European cities.
- Validate the capacity of the BNA score to classify the cycling network by its stress level and to measure connectivity in the England and Wales jurisdiction making use of their Home-to-Work Origin-Destination data available at Lower Super Output Level (LSOA).
- Validate the selection and importance of the destinations included in the BNA score by comparing them to actual bicycle trips in the Netherlands making use of the crowdsourced data set 'Fietstelweek'.

1.5 General methodology

The proposed methodology to answer the research questions listed above rely on two main stages. The first one consists on translating the original BNA score workflow conceptualized for U.S. cities, into a simplified architecture (based on R and SQL scripts) that allows the local computation of the BNA score in European cities. The translation and adaption of the code results in a prototype that is fed with OSM and Open Data Portals data.

The second and main stage consists of the score validation in a European context. To do so, the BNA score is decomposed into three core elements: stress network, destinations, and the score itself. Each component is related to each of the research questions stated above. To answer them, two case studies are proposed: 1) England and Wales and 2) The Netherlands. These case studies are selected based on the validation data available, upon which statistical analyses are performed. This would ideally allow the evaluation of the BNA score performance against real cycling behaviors.

1.6 Thesis structure

The remainder of this thesis is organized as follows:

- **Chapter 2** presents a review of the relevant literature to the Bicycle Network Analysis score framework. It gives an introduction to the underlying theory within transportation networks, as well as the techniques and applications to evaluate network connectivity. The chapter also extends deeper on the BNA score itself as conceptualized by PeopleForBikes, giving particular attention to the its base data, OpenStreetMap.
- **Chaper 3** expands on the proposed methodology, describing in a comprehensive manner the steps and procedures taken to design the BNA score local analysis prototype for European cities, and the score validation process for two case studies: England and Wales, and The Netherlands.
- **Chapter 4** describes the results of the prototype implementation and the outcomes of the validation procedure. All the results are analyzed and discussed in context with their study areas and the related literature.
- **Chapter 5** portrays the limitations of the proposed approach, as well as the recommendations for future enhancements of the BNA score computation and local analysis.
- To conclude, **Chapter 6** summarizes the research work by presenting the main results and its contributions.

Chapter 2

Literature review

This chapter gives a general overview of bicycle network connectivity work. Four sections collect the main theory, methods, and applications that have been introduced to the transportation domain to analyze sustainable mobility within cities; specifically focused on bicycle usage as an utilitarian mode of transport.

General concepts of graph theory are presented according to their pertinence to an specific technique of network connectivity measurement, developed by Mekuria, Furth, & Nixon (2012), called the bicycle Levels of Traffic Stress (LTS). This technique focuses on an analysis of the bicycle infrastructure composing the cycling network within a city, and categorizes it according to how comfortable a bike ride is between origins and destinations.

The LTS approach is only one of several methodologies developed to evaluate the bicycle infrastructure network connectivity (e.g. Bicycle Level of Service (Landis, Vattikuti, & Brannick, 1997), Bicycle Compatibility Index (Harkey, Reinfurt, & Knuiman, 1998), Bicycle Quality Index (Birk et al., 2010)). Nevertheless, the methodology has gained recognition among mobility research (exemplified by a selection of research work) within cities, mainly due to the easiness of its interpretation and the usage of fairly accessible input data required (Boldry, Anderson, & Roskowski, 2017).

The data sources to classify a network based on its LTS vary between municipality, governmental, crowdsourced, or private organization's data collections, which may or may not be open to the public. Within this vast selection, OpenStreetMap (OSM) has been also a source of information that can significantly benefit researches using these types of connectivity measurements, specially in places where street network layers are difficult to obtain.

Gradually, OSM has gained popularity among transportation network research and has also been applied to compute the bicycle Levels of Traffic Stress. One of the main examples that has combined open data sources such as OSM and official Open Data portals is the Bicycle Network Analysis (BNA) score developed by PeopleForBikes (PfB). This score is aimed to U.S. cities and towns, but represents a growing effort of computing connectivity scores that are easily comparable and applicable in a nationwide context. Since, this thesis is focused on this specific score for connectivity measurement, a thorough description of its workflow, architecture, and developers is presented.

Throughout the chapter, references and links to the BNA score are always mentioned to gain a general view of the relationship between the related work performed and this particular tool. As a summary of the specific contents of this chapter, its sections are briefly described below:

- **Section 2.1** portrays the main concepts related to transportation network analysis, mainly regarding definitions within the Graph Theory domain, and focusing on the shortest path problem and Dijkstra's solution to it by presenting his algorithm shortly. These concepts and particular topics have been chosen due to their relevance when calculating the BNA score, and are meant to give the reader the basic knowledge required to understand the score. However, it is not intended as an exhaustive review of the transportation network analysis domain.

- **Section 2.2** presents the methodology to compute bicycle Levels of Traffic Stress, and its usage as a connectivity measure within sustainable transport research. As an example of the related work making use of the methodology, recent research papers are mentioned and described along with their specific objectives, focuses, and main results. A table with the main related literature summarizes the work, and includes the data sources of each analysis. This also aids as a link to the next subsection which reviews one of the data sources, also used by the BNA score, OSM data.

- **Section 2.3** is meant as a brief introduction to the OpenStreetMap project and how much it has grown within the mapping community in these 15 years. Since the BNA score uses OSM as base data, the tagging process is briefly explained with some examples of the tags used by the score. To complete the short review on OSM, some of its major limitations are described, mainly regarding the data quality of the crowdsourced database as a case of volunteered geographic information.

- Finally, **section 2.4** describes the Bicycle Network Analysis score in detail. It concentrates on the score as a connectivity measure developed for the U.S. by PeopleForBikes, and depicts the workflow to calculate the score, its basic architecture, a description of its developers' aims, objectives, and vision of the score. It finishes with previous work based specifically on the BNA score application outside of the U.S.

2.1 Transportation Network Analysis

Transportation networks are considered the key components of mobility and accessibility, shaping the lifestyle and prosperity of populated regions (Bell & Yasunori, 1997). Transport involves crossing the geographic space between two points, with an infinite number of points in between, making it an inherently geospatial activity (Lovelace, Nowosad, & Muenchow, 2018). Transport analysts then, turn to geocomputational methods, which lie on the field of *Graph Theroy* to adress these issues.

2.1.1 Graph Theory

The *Graph Theory* domain has been studied since 1736 (Biggs, Lloyd, & Wilson, 1986). Its applications span different fields such as computer science, linguistics, physics and chemistry, social sciences, biology, and transportation. From this mathematical field, a transportation network can be defined as a *graph* (Fig. 2.1). Several derived concepts are cited below from Wilson (1996), introducing the basic terminology that will be used throughout this thesis.

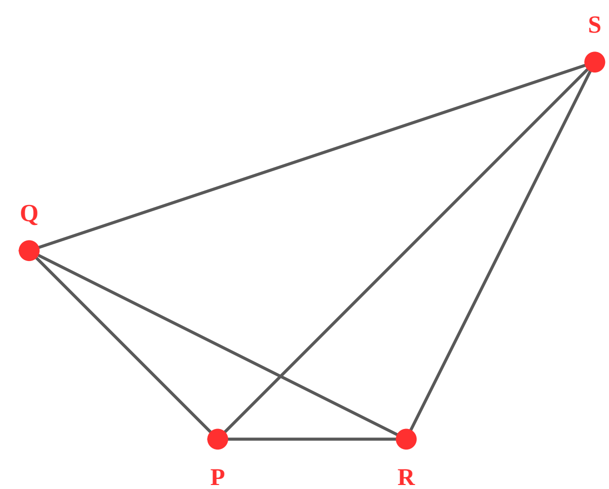


Figure 2.1: Graph representation.

Node and edge: basic units out of which a graph is constructed. A *node* is drawn as a point and is also known as a *vertex*. Nodes in a graph are connected by an *edge* or also known as a *link*. Edges can be *directed* or *undirected*; the first are also known as *arcs* or *arrows* and the latter as *lines*.

Graph and subgraph: a *graph* diagram composed of a set of nodes connected in pairs by edges. A graph with its elements can be observed in Fig. 2.1, where the red points P, Q, R, S are the *nodes* and the black lines are the *edges*. A *subgraph* of a graph G is a graph where its nodes belong to the set of nodes of G, and its edges belong to the set of edges of G.

Degree: the degree of a node is its number of incident edges. In a *directed graph*, an *in-degree* is the number of incoming edges and an *out-degree* the number of outgoing edges. From this property, an *origin or source node* can be defined as a node with *in-degree* 0, and a *destination or sink node* as a node with *out-degree* 0.

Walk, path, and cycle: a *walk* is a sequence of edges, one after the other, which indicates the way of getting from one node to the other. A *path* is a walk in which no node appears more than once. A *cycle* is a path with the same initial and end node.

Directed, connected, and weighted graph: in a *directed graph* the edges have a *direction*. A *connected graph* is a graph in one piece, so that any two nodes are connected by a path. In a *weighted graph* a non-negative number or a *weight* is assigned to each edge. A common weight is the length of the edge.

Tree and spanning tree: a *tree* is a connected graph with only one path between each pair of nodes. It can also be defined as a connected graph with no cycles. A *spanning tree* is a subgraph of any connected graph G which includes all the nodes in G and the minimum possible number of edges.

Network and flow network: a *network* is a graph where attributes are associated to the nodes and edges. It is also defined as a weighted directed graph. A *flow network* is a directed graph where each edge has a *capacity* and receives a flow. The flow of an edge cannot exceed its capacity, and the total flow into a node is equal to the total flow out of it, unless the node is an origin or a destination.

Transportation network: With these basic concepts, the definition of a *transportation network* from Bell & Yasunori (1997) can be cited as “a flow network representing the movement of people, vehicles or goods”. In the mathematical sense, the edges may refer to the movement between nodes, or the mode of transport (e.g. by car, train, bicycle, on foot), where a *path* can represent simultaneously the *route* and *mode of transport*. On the other hand, nodes can symbolize spatial elements like buildings, zones, or cities, depending on the level of aggregation and the generalization of the area.

2.1.2 Shortest path problem

Once again, from the mathematical point of view, several problems can be solved by using *Graph Theory*. There is a group of problems referring to *routing* (creating a route from one node to another), from which the most relevant problem for this thesis is the *shortest path problem*.

Fig. 2.2 helps to illustrate the problem, which seeks to find the shortest path between two nodes, for example, A and G. The figure can represent a road network connecting different towns. Every two nodes are connected by a path, so this graph can be considered as a *connected graph*. Each edge has a number marked next to it, which indicates the "cost" of traversing this edge. The cost can refer to the road length, the time it takes to go through this road, or even the economical cost it may represent. In *Graph Theory* this cost corresponds to the definition of a *weight*. Therefore, the graph is a *connected weighted graph*. In this sense, the problem translates into ***finding a path from*** A ***to*** G ***with minimum total weight***.

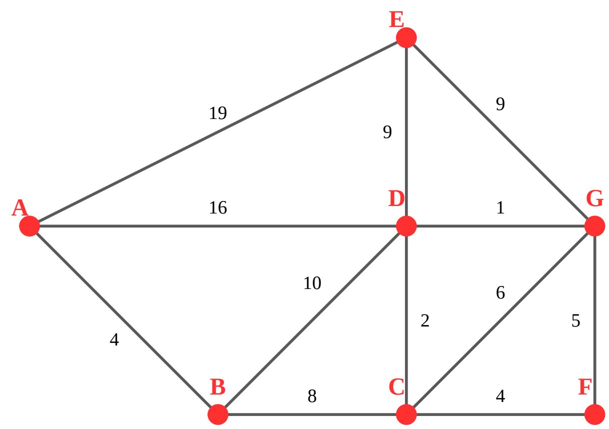


Figure 2.2: Shortest path problem illustration.

Several methods can be used to solve the problem. For example, one could list all the possible routes between town A and town G and select the shortest. If one considers the routes to be only paths and not cycles, then there would be 20 possibilities to get from A to G. For this example, calculating 20 "total weights" is rather trivial; however, if a real transportation network is considered like the German highway network, then the computational burden will get much higher. Some of the possibilities might not even be worth considering. For instance, the path of the form $A \to E \to D \to B \to C \to F \to G$, which actually includes all the nodes in the graph, but would mean making an extreme detour before getting to the destination node G.

There are more computationally efficient ways to solve this problem with algorithms such as Dijkstra, Bellman-Ford, A* search, Floyd-Warshal, Johnson's, Viterbi, among others. This review focuses on the Dijkstra algorithm, as it is the one used for the BNA score computation.

2.1.3 Dijkstra's algorithm

Edsger W. Dijkstra conceived in 1956 an algorithm to solve single-source shortest paths problem on a weighted directed graph, given that all edge weights are non-negative (Cormen, Leiserson, Rivest, & Stein, 2009). Originally, the algorithm found the shortest path between two nodes. He published the algorithm in 1959 and in 1969 was considered as the most computationally efficient procedure to tackle the problem (Dreyfus, 1969). Variants of the code allow the computation of the shortest paths from one "source" node to all the other nodes in a graph, thus generating a *shortest path tree*.

Following the algorithm explanation from Wilson (1996), each node N in the graph in Fig. 2.2 can be associated to a temporary label $l(N)$, that indicates the sum of the edge weights from node $A \to N$. Node A initially gets the label 0, while B, D, and E the temporary labels $l(A) + 4 = 4$, $l(A) + 16 = 16$, and $l(A) + 19 = 19$ respectively. The smallest number, i.e. 4, will be now the permanent label for its corresponding node, i.e. $l(B) = 4$.

The procedure is repeated for the adjacent nodes to B, without considering the already visited node A. The temporary labels for C and D are now $l(B) + 8 = 12$ and $l(B) + 10 = 14$. Among all temporary labels, the smallest is 12, and therefore C is assigned the permanent label $l(C) = 12$. Looking now at the adjacent nodes to C, temporary labels are assigned to D, F, and G as $l(C) + 2 = 14$, $l(C) + 4 = 18$, and $l(C) + 6 = 18$. Among the temporary labels, there are two smallest corresponding to 14, that belong to the same node; hence the permanent label $l(D) = 14$ is assigned.

Finally, the adjacent nodes to D, i.e. E and G are assigned the labels $l(D)+9 = 23$ and $l(D) + 1 = 15$. The smallest temporary label now is 15 which corresponds to the node G, the destination node, assigning the permanent label $l(G) = 15$. Consequently the shortest path between A to G has a length of 15. In this case there are two possible paths that can be taken to get from A to G. Both can be observed in Fig. 2.3, where the corresponding permanent label has been placed next to each node.

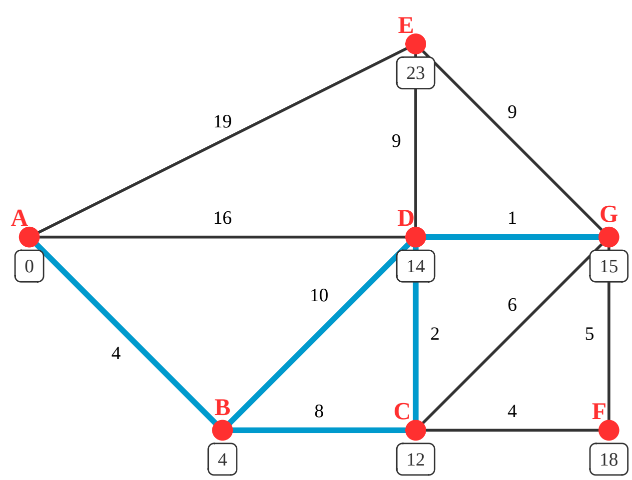


Figure 2.3: Dijkstra's solution for shortest path problem.

In the same way, as mentioned before, the shortest path can be computed from and to all the nodes in a graph. The Dijkstra algorithm was the first implemented on the *pgRouting* extension for the *PostGIS* open source software, which supports geographic objects store on a *PostgreSQL* database. The main routing computations of the BNA score are run on the mentioned database, making use of these software (see section 2.4.1).

2.2 Network Connectivity for Low-stress Bicycling

This section, named after the paper by Furth, Mekuria, & Nixon (2016), depicts the basic methods behind the BNA score. The score aim is to measure how well a ***low-stress*** bike network ***connects*** people to the places they want to go (see section 2.4). Breaking down this objective to its core, this section describes below what is understood by *low stress bike network* and *connected bike network*. As a whole, the concepts are part of Mekuria et al. (2012) method to classify the road segments that make up people's routes between origin and destination points, into their tolerance level for traffic stress, without forcing them to take large detours to do so. The method has become a standard to plan and evaluate bicycle networks, mainly in the U.S.

2.2.1 Bicycle levels of traffic stress

The concept of *bicycle stress levels* was first introduced in 1978 by the Geelong Bikeplan Team in Australia (Harkey et al., 1998; Sorton & Walsh, 1994). The concept was used to define how suitable were the roadways from the cyclist point of view, considering that they would like to minimize not only the physical effort during their bike ride, but also the mental effort or *stress* of sharing the road with motor vehicles. The team members themselves came up with a top three list of the most important variables that influence on their stress level while riding a bicycle. The list included the curb lane width,[1] motor vehicle speed, and traffic volume. Different combinations of these variables were ranked between 1, corresponding to very low stress level to 5, very high stress level.

These subjective values for the same three variables were re-evaluated by Sorton & Walsh (1994). They adapted the concept to common cyclists, who were divided into four categories: *child* (primary school), *youth* (secondary school), *casual* (recreation, utility, shopping, etc.), and *experienced* (commuting, touring, recreation). The type of cyclists were related to five levels of traffic stress, excluding children under 10 years old, who according to the authors, should not ride a bicycle on the proximity of a street without adult supervision. The stress levels include *very low* stress (level 1), which is safe for all cyclist, *low* (level 2), *moderate* (level 3), *high* (level 4), and *very high* (level 5), not suitable for bicycle use.

Different threshold were assigned to each level, and were then validated with 61 volunteers belonging to the *youth*, *casual*, and *experienced* type. They had to watch videotapes of road segments on different environments and combinations of curb lane width, traffic volume, and motor vehicle speed. Then, they rated the video segments according to the level of stress they would experience on such situation. The results indicated that the cyclists experienced differences among these variables that were reflected on their stress levels.

The type of cyclists evolved from a classification based on skills into one based on the attitudes riders have towards bicycle facilities and traffic. Geller (2006) estimated a classification of Portland, Oregon, U.S. population which broke down into the following

[1] A curb lane is the lane next to the curb. A curb or *kerb* is the edge where a raised sidewalk meets the street or roadway.

categories: *strong and fearless* (<1%), *enthused and confident* (7%), *interested but concerned* (60%), and *no way, no how* (33%).

The classification schema has been widely adopted in the U.S., targeting efforts to promote cycling as a form of transportation among the *interested but concerned* group. The proportion of the population assigned to each type was revisited twice by Dill and McNeil (2013, 2016). They conducted random phone surveys to adults, first from the Portland region and next from the 50 largest U.S. metropolitan areas, and found a similar distribution to Geller's first estimate. Their results also showed that reducing motor traffic speed and introducing bicycle infrastructure separated from the general traffic would increase cycling rates.

Based on this classification, Mekuria et al. (2012) introduced the concept of levels of traffic stress (LTS). They first classified the population, based on their tolerance for traffic stress, following Geller's schema. An additional class was added by dividing the *interested but concerned* class into two, one for children[2] and one for adults. They also ignored the *No way, no how* part of the population, since this group is characterized by people who would not ride a bicycle, even if better infrastructure for cycling was implemented into the road network. Hence, the analysis comprised four types of cyclists.

The next step was to classify the bicycle facilities. Several efforts have been shown towards this end, such as the Bicycle Level of Service (Landis et al., 1997) and the Bicycle Compatibility Index (Harkey et al., 1998). However, the authors of the LTS mention among the limitations of these methods, the difficulty to acquire the data needed (traffic volumes and lane widths); and the complexity of the formulas building the concepts, especially when it comes to interpreting their results. Hence, they proposed a new classification schema to assign levels of traffic stress to the four types of cyclists (Fig. 2.4).

The criteria developed are based on Dutch bicycle infrastructure design guidelines, roughly adapted for the LTS 2 category. This category corresponds to the *interested but concerned* level matched to the greater part of the population (between 50% and 60% according to Dill and McNeil, 2016). Dutch standards are considered given their successful attraction of male and females in almost equal shares, as well as high levels of bicycle use among all ages (Mekuria et al., 2012). LTS 1 matches the *children* cyclist type, which basically offers a comfortable ride for anyone, regardless of their skills. This group requires greater separation from the motor traffic. LTS 3 matches the *enthused and confident* who are able to expose themselves to higher traffic stress than LTS 2, normally with an exclusive bicycle lane. Finally, LTS 4 matched to the *strong and fearless*, presents scenarios of mixed traffic at high vehicle speed and greater traffic flows.

The method itself consists on classifying the road sections and intersection approaches according to six factors: number of traffic lanes, motor traffic speed or speed limit, traffic flow or number of vehicles, presence of bicycle lanes, width of the bike lane (including parking if applicable), and the presence of a physical barrier or a bike

[2]The BNA score calls the children category *"8 to 80"* to also include seniors, and in general the population of all ages and abilities.

lane blockage (Furth et al., 2016). Intersections are also evaluated by looking at their size and crossing speed, as well as if they are signalized or not (Buehler & Dill, 2016).

Different reference values are assigned to different scenarios. The criteria are summarized in a series of tables for each network element and factor. The method is adapted to compute the BNA score with minor modifications. Hence, the thresholds and criteria used are described in section 2.4.1.

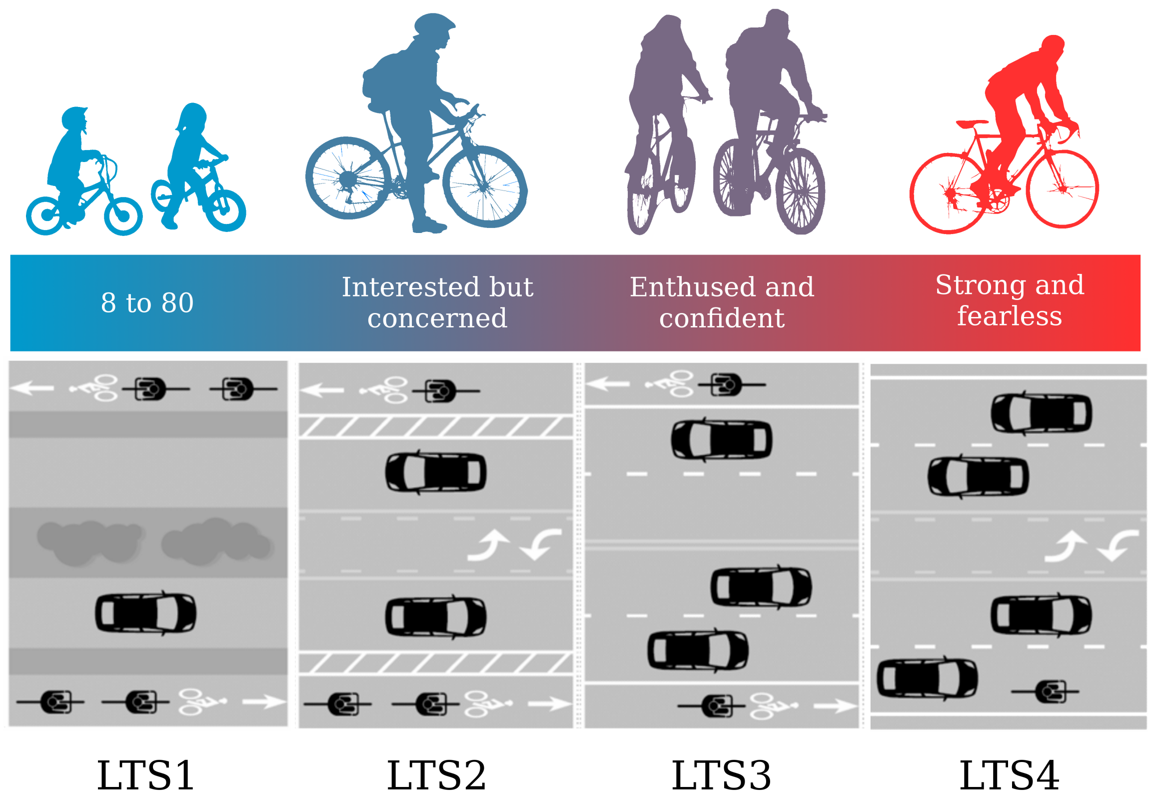


Figure 2.4: Levels of traffic stress and cyclists' types. Adapted from Pritchard & Alquist (2017) and Alta Planning + Design (2017). Vectors from Freevector.com

2.2.2 Network connectivity

Recapitulating from *Graph Theory*, a connected graph is one where any two nodes are connected by a path. *Connectivity* within transportation network analysis is defined as "the probability that traffic can reach a given destination at all" (Bell & Yasunori, 1997, p. 179). It can also describe how easily a person can travel across the transportation system (Twadell et al., 2018).

From the Level of Traffic Stress work, defining if an origin and destination are connected by a low-stress route requires the analysis of the network elements composing it. A route is governed by the *weakest link* principle, which means that the stress of a route is defined by its most stressful link. Hence, it is not a sum nor an average (Mekuria et al., 2012). If an intersection is labeled LTS 3 within a route composed of road sections LTS 1, then the whole route is assigned a stress level LTS 3, meaning that only *enthused and confident* and *strong and fearless* cyclists would ride it.

Another factor defining the connectivity of the cycling network is the *level of detour*. The willingness of cyclists to ride their bicycle for transportation can be limited if a low-stress network implies a significant detour, given their sensitivity to distance which ends up reducing the utility of the network (Furth et al., 2016; Schoner & Levinson, 2014). Acceptable route deviations have been analyzed in the literature. Studies (Aultman-Hall, Hall, & Baetz, 1997; Boisjoly & El-Geneidy, 2016; Broach, Dill, & Gliebe, 2012; Winters, Teschke, Grant, Setton, & Brauer, 2010) indicate that cyclists may add between 10% and 26% to the trip length compared to the shortest path route connecting their origin and destination. They do so in order to use bicycle facilities, low-stress networks, or even to take a path with higher green cover to get to their destination.

Based on these studies, Mekuria et al. (2012) established the level of detour within their methodology to be 25%. For the case of short trips, the lower-stress route should be no larger than 500 meters compared to the shortest path. This can be expressed as:

$$\begin{gathered} \frac{L_k}{L_4} \leq 1.25 \\ \text{or} \\ L_k - L_4 \leq 500m \end{gathered} \tag{2.1}$$

Where L_k stands for the length of a route connected at an $LTSk$ level, which avoids links $LTS > k$, and where L_4 represents the shortest path between the origin and destination of said route, with any level of stress, as long as cycling is allowed.

Hence, *connectivity* between a pair of points means "the ability to get between the two points without exceeding a specified stress threshold and without exceeding the specified level of detour" (Mekuria et al., 2012, p. 8). From this work, a definition of *bicycle network connectivity* by Boldry et al. (2017) can be stated as a low-stress and high-comfort network that allows people to go to their particular destinations in several ways in a safe and comfortable environment which suits all skills and ages, meeting the needs of all the population.

The importance of a connected network, according to Schoner & Levinson (2014), can avoid consequences such as forcing the cyclist into mixed traffic, requiring large detours to avoid this mixed traffic, or simply discouraging cycling altogether. To summarize, Lowry & Hadden (2017) mentions that, a connected bicycle network is a combination of destination potential (amount of destinations that can be reached), physical network structure (protected bike lanes, shared paths, etc.), continuity of low-stress bikeways, tolerance for traffic stress, and willingness or ability to travel farther distances.

The BNA score takes this concept within its own definition, as it measures the low-stress bicycle network connectivity between the places people want to go, without forcing them to deviate more than 25% compared to the shortest path (PeopleForBikes, 2017). The way this connectivity is measured will be expanded in section 2.4.1.

2.2.3 Low-stress connectivity research

The LTS methodology has gained popularity among transport research, and has been applied for several purposes. Research has focused on the data collection process to classify a bicycle network into levels of traffic stress, making emphasis on its simplicity compared to other methods. It has also been described as a useful technique to prioritize new bicycle infrastructure, and compared to bicycle travel behavior and accidents. This short review will present two main topics, bicycle network prioritization and LTS relation with cyclists' trips. Finally, a summary table presents a concise overview of all the discussed papers.

Bicycle network prioritization

As one of the initial ventures to prioritize bicycle network infrastructure, Lowry, Furth, & Hadden-Loh (2016) developed a tool to rank over 750 bicycle infrastructure improvement projects for Seattle, Washington. They based their analysis on the capacity of the network to connect homes and important destinations making use of a low-stress network connectivity. Their results included a GIS-based tool that could benefit transportation planners. Building on these results, they followed on Lowry & Hadden (2017) with an analysis of the differences among cyclists and neighborhoods types. Overall, the developed tool not only allowed to rank the different interventions listed on the Bicycle Master Plan, but also to focus on specific types of cyclists and neighborhoods.

Not only Seattle, but a number of cities and towns in the U.S. have been working towards enhancing their cycling infrastructure. For example, Washington D.C sought to develop a prioritization tool to identify strategic investments for their already well established bike network. Semler et al. (2017) measured bicycle accessibility in the district by applying the LTS method, in an effort to find those areas that can benefit from bicycle infrastructure, and can potentially attract a larger share of the population to cycle on a low-stress network. Their analysis is centered mainly on the data requirements. By applying a triaging approach, they reduce significantly the amount of data that would otherwise require field-work collection. Their results present a highly detailed catalog of roadway characteristics that can be easily updated according to the authors. Although a prioritization of new bicycle infrastructure is not performed, the authors affirm that the resulting map will serve this goal within the Department of Transportation (DOT). They promote their method as an innovative way to classify the bicycle network into LTS that could be imitated by other areas in the U.S.

Furthermore, the research developed by Moran, Tsay, Lawrence, & Krykewycz (2018) uses the LTS approach as a prioritization tool in a novel manner. Instead of ranking already existing proposals, they analyze the impact of individual road segments that, if intervened, could enhance the low-stress bicycle connectivity. Analyzing Philadelphia's suburbs, they applied a moving frame among low-stress islands and calculated shortest paths between one million origin-destination pairs. Their results showed that the main routes were connected by LTS 3 roads, highlighting them as those links within the network that should be improved to guarantee low-stress connectivity. Calculating the potential impact of each link, the authors successfully rank those road segments that should be prioritized.

Notably, Peter Furth, one of the main researchers behind the development of the LTS classification presented a revision of the criteria (Furth et al., 2016) and applied it in his latest paper (Furth, Putta, & Moser, 2018). The objective of the authors here is to generate a propensity model to estimate how willing a person would be to bike to work. They define a gross connectivity measure that takes into account maximum distance trips and detour levels considering a propensity function based on the trip length, instead of defining harsh thresholds. They test their tool in Delaware's existing cycling network, along with proposed improvements. They confirm how low-stress connectivity can be translated into benefits, such as number of works accessible and the potential modal shift this would generate if the proposed links are implemented.

The concept of LTS has also been viewed from an equity point of view, with two noteworthy articles. Tucker & Manaugh (2018) take the LTS concept to a Latin American context and analyze how safe, low-stress cycling can increase citizen's mobility and accessibility. They assess how bike infrastructure and connectivity to main commercial areas relate to neighborhood incomes in Rio de Janeiro and Curitiba. Their results show that Curitiba has a better accessibility to commercial areas through low-stress links regardless of the income level of its neighborhoods; whereas in Rio de Janeiro, only the wealthiest neighborhoods have a low-stress connected network. Although there was a contrast on the results, the authors still conclude that there is a need to take equity into account when planning for new bicycle infrastructure, aiming to identify those segments that would benefit the low-income proportion of the population.

Following this analysis, Kent & Karner (2018) used the LTS approach on a recent study to prioritize bicycle projects based on accessibility performance measures (PM). The analysis, developed as a case study in Baltimore City, U.S., encompassed four main steps: 1) a classification of the existing bike network according to its level of traffic stress (low or high); 2) a quantification of the service area, low stress network distance, and number of business accessible as PMs; 3) an analysis according to demographic variables such as racial segregation and poverty rates; 4) and finally a prioritization schema to identify bicycle infrastructure projects that favor accessibility especially to minority population in an attempt to include equity within sustainable transport. The method successfully applies LTS as an accessibility measure, highlighting among their results that higher service areas of the low stress network spatially correlate with segregated areas, although this network does not give them access to businesses like supermarkets or libraries.

In general, these articles have shown how the LTS connectivity approach can be largely explored to not only classify a network and identify weak links, but also to rank different proposals based on their impact to bicycle network connectivity, taking into account racial, income, gender equity among many other socio-demographic variables. The overall view of these researchers is that enhancing low-stress connectivity can effectively lead to an increase on bicycle commuting. All these analyses have been supported by those relationships between the LTS criteria for road classification and the actual bicycle behavior that commuters show when using the network, as presented on the next group of articles.

LTS and actual cyclists' trips

Some objections regarding the power LTS has to actually account for all the variables that influence a person;s comfort level when cycling has been interrogated in the literature (Chen et al., 2017; Wang, Palm, Chen, Vogt, & Wang, 2016). To analyze these effects, comparisons with travel behavior, bicycle casualties, user-centered perceptions, and bicycle modal shares are summarized below.

Wang et al. (2016) explored the LTS classification in a methodological sense, to evaluate if it is a valid option against its more data expensive alternatives. In a validation attempt, the authors test if the LTS classification can explain travel behavior. They compare bicycle trips made between origin-destination (OD) pairs at census block level obtained from the Oregon Household Activities Survey. They also account for demographic and socioeconomic variables like age, gender, race, household size. Low-stress routes are calculated between OD pairs and low-stress islands are generated for analysis. Three main contradictory conclusions are drawn: 1) there is no relation between low-stress accessibility and mode share; 2) there are significant correlations between bicycle trip production and the household's low-stress accessibility, and 3) women and children tend to take low-stress routes compared to men and adults respectively.

Another way to relate cyclists perceptions to the quality of the bicycle network is to analyze the reported accidents. Chen et al. (2017) looks into crash events and the injuries severity in four cities in New Hampshire, and correlates them with LTS classifications of their bicycle networks. One of their results show that there is an effect of LTS on the severity level of a bicycle crash, in the sense that more severe injuries are more likely to happen in LTS 4 segments compared to LTS 3. With this in mind they suggest their methodology to identify vulnerable and unsafe areas in the cycling network.

Boettge et al. (2017) propose a different approach to the level of cycling stress concept. Although they don't classify the network itself according to the criteria developed by Mekuria et al. (2012), they still maintain the concept of the type of cyclists and its relation with the stress level. They apply a user-centered procedure where 89 active cyclists in St. Louis are asked to identify their cycling experience and then draw on a road network map their latest cycling route. In the exercise, they color the segments according to the stress level they perceived, and they are also asked to mark the time of the day (differentiating between peak hours also) when the ride took place. The results of their statistical analyses show that cyclists prefer routes with bicycle facilities like bike lanes, and that they feel stressed on roads with higher speed limits and number of lanes. However, there was no relationship between the type of bike facility and their perceived stress. They conclude that the findings can aid planners to identify future projects to enhance bike infrastructure.

Again on a travel behavior approach, Crist et al. (2019) compared 1 038 GPS-recorded trips with LTS network classification to understand route preferences among

87 volunteered cyclists in San Diego. Extracting origin-destination pairs, they compare the observed trips to the shortest path and low-stress routes. They determined that over half of the trips would have not been possible on a low-stress connection. Of the remaining trips, the low-stress alternative was 74% longer than its shortest-path alternative, and 56% longer than the actual route taken. Even though cyclists did not appear to ride completely on low-stress links (27% of trips were on LTS 4 segments), the authors acknowledge that the participants might be experienced cyclists who do not seem affected by the stress level. Therefore, they still conclude that prioritizing bicycle infrastructure improvements that enhance low-stress connectivity would encourage the transport mode shift from private cars to bicycles.

Finally, Cervero, Denman, & Jin (2019) take the analysis into an European context, where they explore the relationship of bicycle infrastructure LTS connecting origin-destination points of travel to work data at MSOA level. They look into 36 English and Welsh cities and through a zero-one inflated beta model, they relate not only LTS, but also travel distance, environmental, natural, and built-environment attributes, and socio-demographic attributes. The results show that on-road stress is an important factor, as the bicycle modal share increases on LTS 1 and 2 links. Their model suggests that an increase of 10% in the number of low-stress links can boost in 0.73% percent the cycling rates. Although the gain might seem insignificant, it is important to know that current cycling rates among the cities analyzed are on average 6.2%. Taking the LTS method as certain, they conclude that improving connectivity, land-use mix, and activities along the routes can positively influence bicycle commuting.

The common thread in these research studies illustrate how low-stress accessibility enhances bicycle commuting, as it accounts for more comfortable bike rides, especially for the most vulnerable parts of the population in the study areas.

Summary table

As a way to compile the reviewed research, table 2.1 presents the publication year, goal of the analysis, study area, and data sources for each article mentioned above. The articles reviewed were limited to the last four years, to ensure an up-to-date analysis of the state of the art. It is valid to mention that the BNA score itself has not been mentioned within this part of the literature review, because a research article focused on its development and application has not been published by PeopleForBikes or their associated partners. However, an attempt to replicate the methodology will be discussed at the end of this chapter, as a precedent of this thesis work.

Table 2.1: Literature review summary table of reseach applying low-stress connectivity techniques.

Authors	Year	Goal	Study Area	Street network data sources
Lowry, Furth, and Hadden-Loh	2016	Prioritize bicycle facilities to improve low-stress connectivity.	Seattle, Washington, U.S.	Seattle DOT street network.

Table 2.1: Literature review summary table of reseach applying low-stress connectivity techniques. *(continued)*

Authors	Year	Goal	Study Area	Street network data sources
Wang et al.	2016	Quantify the relationship between LTS and bicycle mode share and trip rates.	Salem and Keizer, Oregon, U.S.	Oregon DOT and Mid-Willamette Valley Council of Governments bicycle network data.
Boettge, Hall, and Crawford	2017	Relate LTS to individual cyclists stress perceptions.	St. Louis, Missouri, U.S.	Street network source not mentioned; self-conducted survey.
Chen et al.	2017	Relate LTS with bicycle injury severity.	Concord, Manchester, Nashua, Portsmouth, New Hampshire, U.S.	Bicycle & Pedestrian Transportation Advisory Committee LTS data.
Lowry and Hadden-Loh	2017	Rank proposed projects for new bicycle facility implementations.	Seattle, Washington, U.S.	Seattle DOT street network.
Semler et al.	2017	Produce an LTS network map as a baseline to prioritize future bicycle infrastructure investments.	Washington, D.C., U.S.	District DOT bicycle network data; Washington D.C. Open Data website.
Furth, Putta, and Moser	2018	Estimate the benefits of bicycle network improvements according to a weighted low-stress connectivity.	Wilmington and Newark, Delaware, U.S.	Delaware DOT street network; Google Street View for bike lanes attributes.
Kent and Karner	2018	Prioritize new bicycle infrastructure to enhance social equity.	Baltimore, Maryland, U.S.	Baltimore City DOT LTS street and bicycle network.
Moran et al.	2018	Rank street network links according to their potential to contribute to low-stress connectivity.	Philadelphia, Pennsylvania, U.S.	DVRPC's regional travel demand model based on OpenStreetMap.
Tucker and Manaugh	2018	Examing bicycle infrastructure across neighborhoods with different income level.	Rio de Janeiro and Curitiba, Brazil	OpenStreetMap street network and commercial point locations.
Cervero, Denman, and Jin	2019	Relate travel to work data with network design and built environment.	36 cities and towns in England and Wales	OpenStreetMap street network.
Crist, et al.	2019	Relate cycling network quality and utilitarian cycling behavior.	San Diego, California, U.S.	San Diego Association of Governments street network.

The study areas are mainly located in the United States, however, the methodology is also being applied in the United Kingdom and in Latin America. It is interesting to observe how the street network data for the U.S. studies usually come from the Department of Transport (DOT), which sometimes has to be enhanced by ancillary data like Google Street View. Others opt for using already classified street networks with the LTS schema. Except for Moran et al. (2018), only the studies outside of the U.S. have used OpenStreetMap as their main source of street network. PeopleForBikes has also opted for using this data source. Hence, a deeper review on OSM data characteristics is presented in the next section.

2.3 OpenStreetMap as base data

OpenStreetMap (OSM) was born in 2004 in University College London as a project to build a free and editable geographic database of the world, with an eventual goal of recording every single geographic feature on the planet (Bennett, 2010; Haklay & Weber, 2008). People who contribute to this database are volunteers, who can easily add and edit features in the map. The whole mapping process is based on a global crowdsourced task distributed among various cartographers, from amateurs to experienced, who in essence contribute to a collection of user generated content, more specifically categorized as volunteered geographic information (Goodchild, 2007).

OSM can be described as a continuously updated database, always providing the latest data to download. This asset benefits millions of people around the world who can use OSM data without restrictions, under the condition of attributing the OpenStreetMap contributors, and guaranteeing that the products generated with the data are also freely distributed under the Open Data Commons Open Database License (OpenStreetMap Contributors, 2019).

Its popularity has only shown an exponential increase along the years. By early February 2019, over 5 million users where registered on the platform (OpenStreetMap Contributors, 2019). However, not every user contributes actively. By December 2018, 1.2 million accumulated contributors per month were registered (OpenStreetMap Wiki contributors, 2019). As the numbers show, only 20% of the users are responsible for actually contributing information; however, this is a common trait of user generated content (Haklay & Weber, 2008; Neis & Zipf, 2012).

Seizing all these characteristics featured by the OSM database, PeopleForBikes used it as its basic data source to build the Bicycle Network Analysis score. Although the data is not perfect, and has not yet achieved its ultimate goal of recording every single feature in the world, it constitutes a database that can easily be improved upon and therefore, be applicable in every place in the world who count with people willing to collaborate. PfB encourages its stakeholders to improve the BNA by contributing to OSM with basic information about roads, bicycle facilities, and key destinations (PeopleForBikes, 2019).

To understand OpenStreetMap role within the BNA score, this subsection explains the tagging process, and the main tags used by PfB (2.3.1). It also presents some of the major limitations regarding OSM data (2.3.2).

2.3.1 Tagging process

The access to features' geographical coordinates in OSM is enriched by the information it is associated with, in the form of attributes. These attributes tell a user what the feature is, along with further information that would enrich its characterization. The process of assigning additional information to a feature is called tagging. A tag can be defined as a simple `key-value` pair. OSM offers an extremely flexible approach to assign tags to features, as any user can create a tag when it is needed. This sometimes can appear chaotic. However, a documentation of any new tag is well encouraged by the OSM contributors community, prioritizing the use of existing tags (Bennett, 2010).

It is the information contained within this tags that is used to compute the BNA score. Characteristics on the bike network, and the destinations are queried from a set of tags. An example of the tags used in the score calculation is presented in table 2.2.

Table 2.2: Main OSM tags used in the BNA score.

Key	Value
Roads and bicycle facilities	
highway	path, cycleway,living_street, residential, tertiary, secondary, primary, motorway
cycleway	lane, track
lanes (number/width)	<number-based>
oneway	yes, no
parking:lane	parallel, diagonal, perpendicular
crossing	traffic_signal, island, uncontrolled
Key destinations	
amenity	school, university, college, clinic, dentist, doctors, hospital, pharmacy, social_facility, community_centre
leisure	park, nature_reserve, playground
landuse	retail
shop	supermarket
public_transport	station

The tagging process is of extreme importance within the BNA score computation, since it is its major source of information. Therefore, even if a feature is mapped, if it does not contain tags, it is very unlikely that the tool will take full advantage of it. This is one of the problems with OSM data, not only the lack of mapped features but also the lack of tags (not in number but in quality) (Mooney & Corcoran, 2012). The following subsection enumerates and describes briefly the common problems associated with OSM data.

2.3.2 OSM data limitations

Along with other volunteered geographic information examples, OSM's biggest limitation can be portrayed by one single issue, data quality. OSM does not provide any measure for quality control and procedures, nor it undertakes internal quality assurance (Haklay & Weber, 2008). Nevertheless, as the concern for quality data has risen, several methods have been proposed to measure the value of the data. As analyzed by Barron, Neis, & Zipf (2014), the quality of spatial data is characterized by elements such as completeness, and positional and thematic accuracy, among others.

OSM data completeness varies from one country to another (Neis & Zipf, 2012). Although, one could argue that OSM geographical data will never be complete, and as stated by the founder of OSM, Steve Coast, one should just let go of this concept (Haklay & Weber, 2008); several researchers have invested their time into measuring the coverage of the OSM data. Different geographic features can be analyzed in this context, like points of interest (Hochmair, Juhász, & Cvetojevic, 2018), buildings (Brovelli & Zamboni, 2018), road and bike networks (Barrington-Leigh & Millard-Ball, 2017; Hochmair, Zielstra, & Neis, 2015), administrative boundaries, natural features (Girres & Touya, 2010), among others.

Some results of interest for the BNA score include the completeness of the road network, which according to Barrington-Leigh & Millard-Ball (2017) is 80% complete. Even more related to PfB concerns, a study by Hochmair et al. (2015) affirms that OSM data for bike infrastructure presents differences among U.S. cities. They suggest that areas with low coverage could be enhanced for example by data from local planning authorities. PfB, in this case has opted for encouraging communities to map their home areas, keeping up the original OSM crowdsourced spirit.

As for the positional and thematic accuracy of the data, a distrust surrounds the instruments used to map OSM features. OSM promotes mainly the use of GPS devices for data collection, which are usually prone to accuracy errors. There is also the possibility to digitize satellite imagery and obtain cartographic features for remote area. However, this approach presents problems if, for example, there is a positional shift of the satellite image, or in a more general sense, the mapper does not know the attributes that would complete the data for the feature (Bennett, 2010; Haklay & Weber, 2008; Mooney, Corcoran, & Winstanley, 2010).

Nevertheless, when compared with official data, OSM presents equivalent, and in some cases better accuracy. This is also highly prone to the areas under analysis, where highly urbanized areas present better mapping efforts (Mooney, 2015). Positional and thematic accuracy is still an open issue, and methods to compare it to official data is constantly object of research (Antunes, Brovelli, Minghini, Molinari, & Mooney, 2015; Brovelli & Zamboni, 2018; Zhang & Malczewski, 2017), in an attempt to promote the use of OSM data which integrates a quality assessment along with it.

As Goodchild & Li (2012) present it, data quality for volunteered geographic information, although free and timely, is "highly variable and undocumented". The heterogeneity of the OSM data is caused by the different technical skills and motivations of contributors around the world (Mobasheri, Sun, Loos, & Ali, 2017). In general, OSM data quality, in all its aspects, decreases when areas outside major cities are analyzed (Quinn, 2017), and so, particular attention should be given to computational results obtained in such areas by applications like, in this case, the BNA score.

Nonetheless, since the early years of the OSM project, experts have agreed that the quality will not only be eventually quantifiable (Mooney et al., 2010), but will also improve in the near future due to data collection efforts (Hochmair et al., 2015).

2.4 Bicycle Network Analysis score

The *Bicycle Network Analsysis (BNA) score* is a tool created by the PeopleForBikes (PfB) organization, with the objective of measuring how well the bicycle network in a city connects its citizens with the places they want to go. It has been designed specifically for U.S. communities as part of the program *PlacesForBikes City Ratings*. The program aims to identify and reward the best places for cycling, while also encouraging low-rated areas to improve constantly. Around 300 cities were scored in 2017 (Andersen, 2017), and subsequently the first city ranking to include the network connectivity score was launched in 2018. Soon, the new results will be available for 2019.

The BNA is essentially a connectivity measure based on the concept of bicycle Levels of Traffic Stress. It seeks to quantify how good a low-stress bicycle network in a city connects people to other people, their workplace or other destinations such as schools, universities, supermarkets, pharmacies, doctors, etc., on a comfortable network within a biking distance covered in ten minutes at an average speed of ten miles per hour or around fifteen kilometers per hour. The spatial unit of analysis is the census block. The score ranges between 0 and 100, which is assigned to each census block and then aggregated to the whole U.S city or town.

Their methodology is based almost entirely on OpenStreetMap (OSM), which, even with its quality, coverage and completeness limitations as a crowdsourced mapping project, allows the score computation to be reproduced for other areas. Ancillary data from the US-Census 2010 included the census blocks spatial boundaries, the population of each block, as well as the number of jobs, which are part of the Census Longitudinal Employer-Household Dynamics data. Hence, the BNA score is also used to compare local bicycle networks connectivity on a nationwide scale.

This section aims to introduce the BNA score as a connectivity measure of urban cycling infrastructure created for the U.S. The precedent sections on this chapter have introduced the main concepts and methods behind the BNA score (section 2.1 and 2.2) and have also presented the role that OSM takes within the score computation, along with its limitations (section 2.3). This section will include the following subsections: Subsection 2.4.1 explains the computation of the BNA score in detail as PfB has conceptualized it, subsection 2.4.2 expands on the software architecture of the PfB approach, and subsection 2.4.3 describes the main organizations involved in the creation of the score, along with the future goals of the BNA score tool. Finally, subsection 2.4.4 reviews an application of the score outside of the U.S. and its proposal for a validation procedure of the score.

2.4.1 Workflow

As indicated in the introductory section of this chapter, the BNA score measures the connectivity of the low-stress bicycle network in a town to get people to the places they want to go. The step-by-step methodology to calculate the overall score for a town can be summarized in the diagram below (Fig. 2.5).

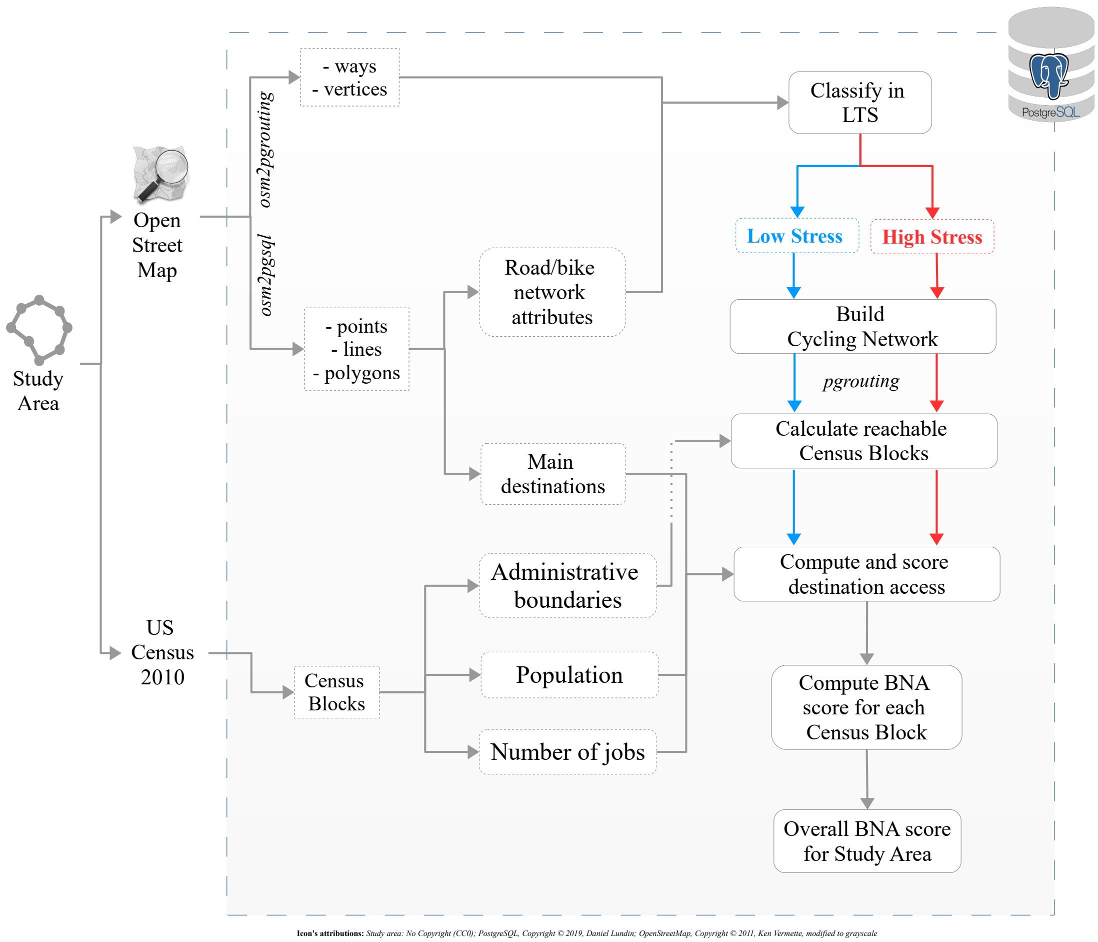


Figure 2.5: BNA score workflow.

As can be observed, the BNA score is computed for a study area, from which OSM and census data is collected. The data is loaded into the PostgreSQL database in different ways. The OSM bicycle network is classified into two simplified Levels of Traffic Stress (low and high), making use of attributes coming from the tagging system implemented in OSM. From there, the low and high stress networks are built. Then, using the *pgRouting* extension, the shortest paths between each census block pair are computed both through a high and low-stress network.

The main destinations are aggregated for each census block, and its accessibility, through a high or low-stress network, is computed and scored (in a 0-100 scale), according to the ratio of destinations accessible. Finally, the score is aggregated according to a weighting system for each destination, and an overall score is computed for the whole study area, by performing a weighted average of the individual census blocks, where the weight corresponds to the population.

The workflow is explained in detail in the following subsections, which include the data collection, the traffic stress network classification, the destination access computation and scoring, and the score aggregation.

Data collection

The first step is to select a study area. For the Pfb BNA score, a U.S. city or town. Once the area is defined, the data corresponding to its boundary is gathered from two main sources, OpenStreetMap and the US Census Bureau. The data include:

1. *Census blocks and population*

   Census blocks within the study area boundary, which include their administrative boundaries (as a `.shp` file) along with the population living in each census block. The data are obtained from the Topologically Integrated Geographic Encoding and Referencing (TIGER) cartographic data for the census year.

2. *Jobs per Census block*

   The employment data, in other words, the number of job posts or workstations per census block, is obtained from the Longitudinal Employer-Household Dynamics (LEHD), specifically from the LEHD Origin-Destination Employment Statistics (LODES) version 7. The data set includes the total number of jobs per workplace census block, which is then used within the BNA score calculation to indicate the number of work stations reachable by a low-stress bicycle network. The data also includes residence and workplace census block code, the number of jobs disaggregated by age range, income range, and industry sector.

3. *OpenStreetMap data*

   The OSM data is queried through the overpass API, which downloads a `.osm` file containing all the information available on OSM for the study area. The read-only API can be defined as a web database that returns customized selected areas of OSM geographical data.

The data is subsequently uploaded into a PostgreSQL database, previously created, which counts with two schemas apart from the `'public'`: `'received'` and `'generated'`, and has the extensions such as `hstore`, `postgis`, `pgrouting` installed. The census block administrative boundaries are uploaded to the PostgreSQL database, and the job information is joined to the table by the census block code.

For the OSM data case, the data is imported into the database making use of two import tools: `osm2pgsql` and `osm2pgrouting`. The first one takes the OSM data and uploads it into the database as points, lines, and polygons. It uses a `.STYLE` file where OSM tags can be selected and discarded according to the analyst convenience. From here, the destination types as well as complementary information for the bicycle network is extracted.

The second one, `osm2pgrouting` uploads the data as two tables, one of edges, called 'ways', and one of nodes, called 'vertices' in a format that *pgRouting* can use to run its routing algorithms. The tool uses a configuration file (`mapconfig.xml`) that generates a network with the 'highways' tag in OSM, with its corresponding vertices. It can be adjusted for bicycle networks, that is, roads where the bicycle is allowed, by changing the configuration file. Hence, from this data configuration, the bicycle network is uploaded into the database.

Traffic Stress Network

The BNA score bases its connectivity on a low-stress bicycle network (section 2.2.1). According to the Levels of Traffic Stress, there are four possible categorizations of a network according to the type of cyclists. Mekuria et al. (2012) divided the "interested but concerned" category into two, from which PfB derived the category "8-80". According to the PfB methodology, a low-stress bicycle network corresponds to the LTS levels 1 and 2. Therefore, the four LTS are re-categorized in *low stress* (LTS 1 and LTS 2), and *high stress* (LTS 3 and LTS 4).

The LTS classification takes into account the edges (road segments) and nodes (road intersections) composing the bicycle network. Several categorization criteria are applied to each of these elements, extracted from a series of OSM tags. The tables used to follow the classification criteria can be reviewed in Appendix A.

Destination access

Once the elements of the network are classified, two types of networks can be built, a low-stress network, which will only be built by road segments and intersections classified as low-stress; and a high-stress network, built up by all the segments and nodes, no matter their category.

With these two networks, PfB evaluates which census blocks are connected to each other, and can be reached with a low-stress or only with a high-stress network. To compute this, the *pgRouting* tool is applied, with its routing function `pgr_drivingDistance`. This function identifies and extracts those nodes with a cost less than or equal to a pre-determined distance by using the shortest-path Dijkstra algorithm. The corresponding edges will form the spanning tree of the graph. The function takes the following SQL command:

```
pgr_drivingDistance(
  'SELECT  id, source, target, cost, FROM edge_table',
  starting_vertices, biking_distance, directed := true
)
```

Where the `edge_table` is obtained from both the low-stress and high-stress network, containing the `source` and `target` nodes for each edge, as well as its `cost`. The network is built in a directed way, hence the boolean for `directed = TRUE`. The `starting_vertices` correspond to each source node in the network. The method only considers trips up to 2 680 meters (`biking_distance`), equivalent to a ten-minute ride at an average speed of ten miles per hour. The speed reflects an average pace for cyclists of all ages in the U.S.

The BNA score considers that a census block is connected to a road around or within its perimeter. Therefore, trips inside the same census block are always considered low-stress. The connected census blocks would be those where an unbroken low-stress route serves them, assuming a maximum level of detour of 25% as explained by equation (2.2.2), by comparing the low-stress and high-stress shortest path.

Since the population and jobs are aggregated per census block, the previously described computation allows to calculate the number of people and workplaces that can be reached with a low-stress network and with a high-stress. The same is done for the main destinations which are summarized per type for each census block.

Next, a scoring process is applied, assigning points from 0 to 100 (also expressed as percentages) to each destination type. The score is based on the ratio of destinations that can be reached with a low-stress bicycle network compared to all those that could be reached, within the established biking distance, with no restrictions, i.e. the high-stress network. The score works in a stepped way, giving higher value to the first destination reached with on low-stress. Afterwards, the score is pro-rated. The ratio depends on the type of destination under analysis, as not all destinations are equally abundant and important. For instance, reaching a park is not as important as reaching a hospital. The scoring methodology is summarized in table 2.3.

Table 2.3: Scoring criteria for different destination types.

Scoring Process	Criteria
A	Up to 3% = 10 points Up to 20% = 40 points Up to 50% = 80 points
B	First low stress destination = 30 points Second low stress destination = 20 points Third low stress destination = 20 points
C	First low stress destination = 70 points
D	First low stress destination = 40 points Second low stress destination = 20 points Third low stress destination = 10 points
E	First low stress destination = 60 points Second low stress destination = 20 points
F	First low stress destination = 70 points Second low stress destination = 20 points
G	First low stress destination = 60 points

The highest score is 100. Hence, if all the destinations can be reached, 100 points are awarded to that destination type. The scoring process A works by calculating the ratio low-stress:high-stress. The rest of the processes work in a cumulatively manner. After the number of low-stress destinations specified in the criteria is met, the points for the remainder low-stress destinations are based on the ratio low-stress:high-stress.

Subsequently, a pondered score is assigned to each census block, based on the individual scores for each destination type. The weights depend on the destination's category, as observed in table 2.4. A weighted average occurs for each category, and again for all the categories, to obtain a total BNA score for each census block. The weights are used to represent the relative importance of each destination type to the overall BNA score, and therefore, reflects how a person commuting by bicycle prioritizes these destinations.

Table 2.4: BNA destinations' weights and scoring processes.

Destination Type	Weight (%)	Scoring Process
People (15%)		
Population	100	A
Opportunity (20%)		
Employment	35	A
K-12 Education	35	B
Technical/vocational school	10	C
Higher Education	20	C
Core Services (20%)		
Doctor offices/clinics	20	D
Dentist offices	10	D
Hospitals	20	C
Pharmacies	10	D
Supermarkets	25	E
Social services	15	C
Recreation (15%)		
Parks	40	B
Recreational trails	35	F
Community centers	25	D
Retail (15%)		
Retail shopping	100	D
Transit (15%)		
Station/transit centers	100	G

The scoring process can be illustrated with an example. Assume in a biking distance of 2.68 km from an origin point there are 300 jobs (Employment (E)), five schools (K-12 education (K)), 3 universities (Higher education (HE)), and no colleges (Technical/vocational school (TS)). On a low-stress network, a commuter can reach 120 jobs, four of the five schools, and one of the three universities. Jobs correspond to the scoring process A. The ratio low-stress:high-stress is 120:300, awarding the census block 40% for the Employment destination. Schools correspond to the scoring process B. For the first three schools that can be reach, the census block receives 70 points $(30 + 20 + 20)$. There are two more schools within biking distance, and one of them can be reached using the low-stress network. Hence, of the remaining 30 points, 15 extra points are awarded for the K-12 education destination, giving a total of 85. Finally, the universities correspond to the scoring process C. Only one can be reached, and therefore a score of 70 is awarded to the census block for the Higher education destination type. All the described destinations correspond to the category *Opportunity*. Therefore the score for this category can be computed as:

$$\begin{aligned} Opportunity &= E * 0.35 + K * 0.35 + TS * 0.1 + HE * 0.2 \\ &= 40 * 0.35 + 85 * 0.35 + 0 * 0.1 + 70 * 0.2 \\ &= 57.5 \end{aligned} \tag{2.2}$$

However, the BNA score also considers those cases when there are no destinations of a determined type, in this case the Technical/vocational school, which is now represented as zero, meaning, in the computation context, that no destinations of this type can be reached with a low-stress network, when actually this is not true. To correct for these cases, the methodology assumes a weight of zero for non-existing destinations in an area, correcting the computation to:

$$\begin{aligned} Opportunity &= \frac{E * 0.35 + K * 0.35 + TS * 0 + HE * 0.2}{\sum weights} \\ &= \frac{40 * 0.35 + 85 * 0.35 + 0 * 0 + 70 * 0.2}{0.35 + 0.35 + 0 + 0.2} \\ &= 64.17 \end{aligned} \tag{2.3}$$

In this way, the score is not affected by this kind of missing destinations. The same procedure takes place for each category, and finally a weighted average for the whole census block is computed as:

$$BNAscore = \frac{P * 0.15 + O * 0.2 + CS * 0.15 + R * 0.15 + T * 0.15}{\sum weights} \tag{2.4}$$

Where P stands for *People*, O for *Opportunity*, CS for *CoreServices*, R for *Retail* and T for *Transit*.

Score aggregation

Once every census block has received an individual BNA score, a final result for the entire study area can be computed. Each census block is weighted according to its population, and finally the overall score for the town is obtained. Weighting by population is done to increase the importance of the census block in the overall computation when it is the origin of a larger amount of trips, represented by the amount of people living in it. With this approach the score not only takes into account the number of current commuters, which might not always correspond to the highly populated census blocks, but to the potential commuters that could start their journey on that census block.

Additionally, an overall score is computed for each destination type and category. The purpose is to identify the network connectivity issues to different destinations, allowing the analyst to decide which to prioritize.

2.4.2 Basic architecture

The BNA score was designed as a completely open source algorithm-based data analysis tool. The application runs on a standard application stack, including a web server, database store and an asynchronous task queue. In other words, it runs the spatial analysis on an internal PostgreSQL database using cloud computing resources (Amazon Web Services). The results are stored in the database and subsequently displayed on the web server.

The whole analysis runs on a combination of Python, SQL, JavaScript, Shell, and HTML scripts, allowing faster computation times for larger areas. This greatly benefits the developers as their aim is to rank several cities in the U.S„ requiring to run the analysis several times. However, the analysis can also be run locally by independent researchers, with the use of a Virtual Machine, adapted to a Linux operating system, which requires some basic inputs from the user to run the analysis.

The main limitation of this approach is the difficulty to follow its workflow, along with the set up of a Virtual Machine to run the computations. This can lead into a decrease interest from third-parties for using the tool, reducing the possibility of enhancements by external analysts. Overall, there is a need for a simpler implementation of the tool, compatible with the most common operating systems, that allows the analyst to focus on the algorithm to obtain the score, rather than understanding the way the scripts are structured together until finally applying technical changes.

2.4.3 BNA developers: missions and future goals

The BNA score was launched in 2017 by the ***PeopleForBikes*** non-profit organization established nationwide in the United States. THe organization started as *Bikes Belong* in 1999 with headquarters in Boulder, Colorado. It re-branded in 2013 into *PeopleForBikes*, and includes an industry coalition of bicycling suppliers and retailers, as well as a charitable foundation. The organization aims to create a better future for cycling in the U.S. by making it safer and easier to access for every citizen. To do so, it hosts several programs and projects (PeopleForBikes, 2018).

Within their *PlacesForBikes City Ratings* program, two companies were hired to develop the BNA score: Toole Design and Azavea. ***Toole Design Group*** is a planning, engineering and landscape architecture firm specialized in multi-modal transportation. Initially based in Maryland, now counts with 16 offices in the U.S. and Canada. Their mission is to "support innovative streets and dynamic communities where people of all ages and abilities can enjoy walking, biking, and access to transit" (Toole Design, 2018). They were in charge of the algorithm and data analysis tool generation for the BNA score.

On the other hand, ***Azavea*** is a B corporation applying geospatial analytics, software, and research for positive civic, social, and environmental impact. A certified B corporation is a new kind of business that balances purpose and profit (Azavea, 2018). They implemented the tool in the server and designed the website.

The BNA score is described as an evolving project, with a preliminary methodology, subject to errors and modifications (Twadell et al., 2018). It aims to collect feedback and external support to maintain it in the long term. Some of their goals for 2019 are to expand their methodology to other countries, such as Canada, as well as making it simpler for data wranglers to use the open source tool in a customized way (Rebecca Davies, Network and Mapping Specialist at PeopleForBikes, personal communication, October 30, 2018).

2.4.4 BNA score outside the U.S.

Taking advantage of the open source methodology presented by PeopleForBikes, Abad & Van der Meer (2018) make a first attempt to calculate the BNA score for a European city: Lisbon, Portugal. Although the exact workflow was not followed strictly, the basic methods and concepts behind the score were preserved.

The authors were able to categorize the bicycle street network in Lisbon using OpenStreetMap data, and applying the Mekuria et al. (2012) criteria. Common destinations were also obtained from the crowdsourced database. Lacking a spatial aggregation that could effectively comprise the level of detail that network connectivity requires (as in the case of the PfB approach, census blocks), a grid was overlayed to Lisbon's metropolitan area. The score was calculated for every grid cell according to its low-stress connectivity and the number of destinations that could be reached within it.

The results focus on analyzing the score in context to the city's available bicycle infrastructure, cycling culture, and other physical factors that hamper the common use of the bicycle in Lisbon like slope. The overall score for the city, in BNA terms was 8.6%, concluding that much efforts could be invested into prioritizing low-stress connectivity among the new projects that Lisbon's city council will build in the near future.

The major limitations of the analysis include the questions regarding the OpenStreetMap data quality, the weight of the destinations within the score computation, and the lack of validation schemes around this and other proposed connectivity measures in the literature.

This thesis work aims to address not only the mentioned limitations in Abad & Van der Meer (2018), but also its future work which seeks to adapt the PfB methodology to a European context, by adapting data from Open Data Portals and OpenStreetMaps. Additionally, the development of validation methods that could enhance the reliability on these types of scores, to be then considered with much more strength into planning policies and infrastructure implementation.

Chapter 3

Methodology

This Chapter explains in detail the steps taken to perform this research. First, a preamble on how the original BNA score computation was translated to run locally is explained in section 3.1. This section also includes the software used, a description of the modifications to the original script to compute the score for European cities, and the characteristics of the ancillary data.

Next, section 3.2 details the methodology to address specifically the research question, by proposing a decomposition of the BNA score into its core components and testing three hypotheses that would ideally confirm its validity. This section also introduces the statistical analyses performed to test the hypotheses. Lastly, it expands on the case studies selected, along with a description of the data input to the BNA score computation, as well as the data used to test the hypotheses.

3.1 Prototype design

The BNA score is a tool originally developed for the U.S. However, given that its computation relies mainly on OpenStreetMap data, it is fair to assume that given the existence of ancillary data in a region, it can be easily computed for any region in the world. This is one of the aims of this thesis, starting with European cities, where the OSM data can be considered more reliable due to its completeness and accuracy (see section 2.3). The policy of transparency of the European Union makes open data available, mainly, open geographical data, which adds an extra motivation to apply the BNA score in the continent.

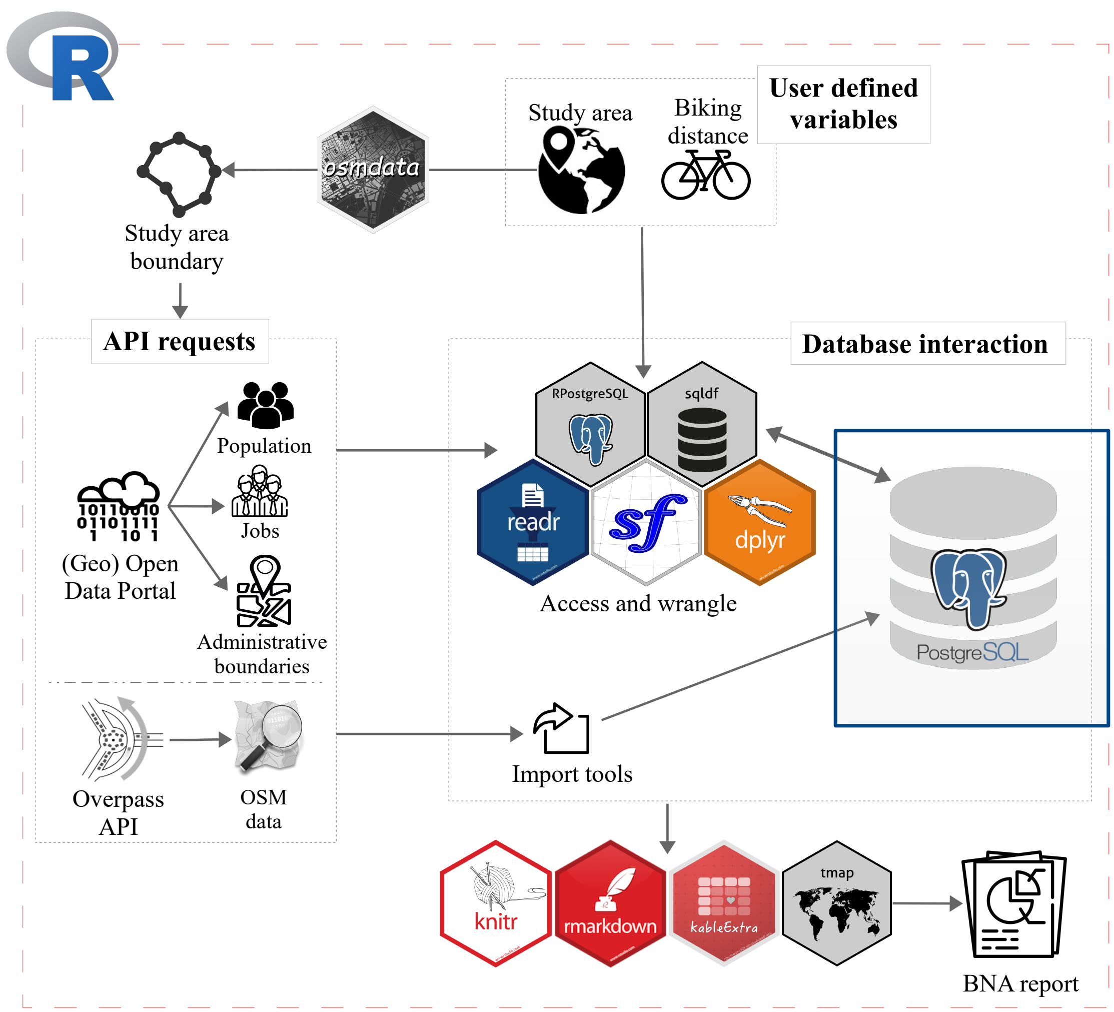
In addition, the original BNA score makes use of rather complicated software architecture. The possibility to run the analysis locally still requires the use of an application stack based on a combination of Python, SQL, JavaScript, Shell, and HTML scripts. In this thesis, a simplification of the local analysis by building a simpler architecture based only on R and SQL scripts is pursued.

The purpose is not to change the core analysis, which originally takes place inside the PostgreSQL database, but to eliminate intermediary scripts, written in various programming languages, used to set up the database, fetch data from web APIs, upload them into the database, and visualize the results. More importantly, it uses

R, a programming language that can easily be used in multiple operating systems without the need to use a virtual machine.

In addition, the proposed approach is not meant to optimize the processing times, nor to create a unique way to simplify the local analysis, as a similar procedure could have used, for example, Python scripts connected to the PostgreSQL database. It means to present an alternative architecture to the existing workflow, which might spark the interest of data scientists familiar with the R environment.

Figure 3.1 shows a diagram of the tool prototype. The R environment (red-dashed-boundary area) is used to define variables (like the study area and the biking distance for the analysis), to fetch geographical and demographic data, to bridge to the PostgreSQL database, and to generate a final report with the BNA results. To import the OSM data into the database, the import tools `osm2pgrouting` and `osm2pgsql` explained in section 2.4.1 are used. The blue-boundary area represents all the processes happening inside the database, as explained in figure 2.5.



Icon's attributions: *PostgreSQL, Copyright © 2019, Daniel Lundin; OpenStreetMap, Copyright © 2011, Ken Vermette, modified to grayscale;; RStudio, readr/dplyr/knitr/rmarkdown, No Copyright (CC0); Open data portal, study area boundary: No Copyright (CC0); Database: Icon made by Smashicons from www.flaticon.com; Import tools: Icon made by Gregor Cresnar from www.flaticon.com; Study area, administrative boundaries, biking distance, BNA report,, population, jobs : Icon made by Freepik from www.flaticon.com sf, kableExtra, Overpass API: No licensing information found; osmdata, tmap, RpostgreSQL, slqdf: Example hexagon sticker created by the author*

Figure 3.1: Prototype architecture for BNA score local analysis.

The only changes applied to the core analysis are unit conversions, from the U.S. customary system to the international system, and skipping the parallelization of the *pgRouting* function in numerous threads, since the proposed approach does not make use of cloud computing services. A description of the software, packages, and newly introduced data sources are explained in the following subsections.

3.1.1 Software

The analysis runs on two main environments, PostgreSQL and R, simplifying the complex structure of the original BNA score.

PostgreSQL is an open source database system which extends the SQL language, along with features to store and scale complicated data workloads (The PostgreSQL Global Development Group, 2014). Several add-ons can extend the database capabilities. For the database creation, setup, administration, and maintenance, an open source management tool for PostgreSQL, *pgAdmin*4 version 3.4 is used (The pgAdmin Development Team, 2018). *PostgreSQL* version 10 is used, along with three extensions:

- **PostGIS (v. 2.5):** allows spatial and geographical objects to be stored in the database. It also allows the analysis and processing of such objects (The PostGIS Development Group, 2018).
- **pgRouting (v. 2.6.1):** extends *PostgreSQL* and *PostGIS* with routing and network analysis functionality (OSGeo Foundation, 2018).
- **HStore:** a key value store inside *PostgreSQL*. Used to store simple key-value pairs without adding an extra column to a table.

R is a language for statistical computing and graphics (R Core Team, 2018). It runs on a wide range of operating systems and is extended by multiple packages that address different data analysis questions in various research fields. The Integrated Development Environment (IDE) *RStudio* version 1.1.456 (RStudio Team, 2016) is used as an execution interface of the *R* software. *R* version 3.5.2 is used along with the following packages:

- **base:** R base package, where it is important to highlight the use of the `system` function which is used to pass code to the OS command prompt by "import tools", indicated in figure 3.1.
- **osmdata (dev. v. 0.0.9.001):** Download and import of OpenStreetMap data as `sf` or `sp` objects (Padgham, Rudis, Lovelace, & Salmon, 2017). It is used inside the prototype workflow to obtain the study area boundary, by matching the user defined variable `study area` with the Nominatim. It is later used also for fetching additional destinations inside the study area in section 3.2.
- **sf (CRAN v. 0.7):** Support for simple features, a standardized way to encode spatial vector data (Pebesma, 2018). Used to read and write spatial data to and from R, the database, and system directories; manipulate geometries and coordinate reference systems.

- **RPostgreSQL (CRAN v. 0.6):** Database interface and 'PostgreSQL' driver for 'R' (Conway, Eddelbuettel, Nishiyama, Prayaga, & Tiffin, 2017). Used to get the `PostgreSQL` driver and establish a connection with the database from R. It also attaches the package `DBI` (R Special Interest Group on Databases (R-SIG-DB), Wickham, & Müller, 2018) which allows to send and get queries to and from the database, and to interpolate R variables into `SQL` scripts.
- **sqldf (CRAN v. 0.4):** Provides an easy way to perform SQL selects on R data frames (Grothendieck, 2017). It is used to write `SQL` code directly on R and sending it to the database.
- **readr (CRAN v. 1.3.1):** Provide a fast and friendly way to read rectangular data (Wickham et al., 2018b). Used to read `SQL` scripts into R.
- **dplyr (CRAN v. 0.7.8):** A fast, consistent tool for working with data frame like objects, both in memory and out of memory (Wickham et al., 2018a). Used to manipulate data frames.
- **tmap (CRAN v. 2.2):** Offers a flexible, layer-based, and easy to use approach to create thematic maps, such as choropleths and bubble maps (Tennekes, 2018). It is mainly used to create the resulting maps in an interactive leaflet environment. The maps are attached to the final report and are also used for a verification step during the computation to corroborate that the defined study area is correctly geo-located.
- **kableExtra (CRAN v. 0.9.0):** Build complex HTML or 'LaTeX' tables using `knitr` and the piping syntax (Zhu, 2019). Used to format the table of results containing the overall score for the study area. The table includes the overall BNA score, the score per destination type, and summary data for the study area regarding bicycle network length and population.
- **knitr (CRAN v. 1.21) and rmarkdown (dev. v. 1.11.3):** Both packages work together to generate dynamic reports and convert R Markdown documents into a variety of formats (Allaire et al., 2019; Xie, 2014, 2015, 2018; Xie et al., 2018). Used to present the BNA score in an interactive HTML report, including interactive maps and tables. An example can be found here.

Additionally, the following packages are used for the validation data visualization and processing (section 3.2), but are mentioned here to keep a software only section.

- **ggplot2 (CRAN v. 3.1.0):** creates elegant data visualizations using the grammar of graphics (Wickham, 2016). Mainly used for results visualization by creating plots and charts. Extended with packages like `ggrepel`, `ggpubr`, `ggthemes`, `ggspatial`.
- **stplanr (dev. v. 0.2.7.9000):** functionality and data access tools for transport planning, including origin-destination analysis, route allocation and modelling travel patterns (Lovelace & Ellison, 2019). Used to explore and manipulate origin-destination data.

The whole process runs on a series of R and SQL scripts, which are combined and called through an R Markdown file that also serves as a template for the BNA score analysis. The set-up now expects the analyst to clone the host repository and run their own local analysis.

3.1.2 Data sources

Translating the BNA score into the European context should represent no major constraints in a data availability context, mainly when referring to OSM data which is said to be more complete in areas with higher population density. In these areas, a constant data input and validation takes place, and access to internet also plays a role (Barrington-Leigh & Millard-Ball, 2017; Haklay, 2010; Helbich, Amelunxen, Neis, & Zipf, 2012). Issues like accuracy and reliability are still a big concern; however, it is expected that the data quality improves in the near future (Hochmair et al., 2015). Hence, OSM remains as the main source of geographical information for the score computation in the proposed approach.

The score computation also requires population data at a certain spatial aggregation level which allows the analysis results to be more thorough and precise. Taking the analogous U.S. census blocks, which are the smallest level of geographical data at which demographics are aggregated, it is intended to find a similar aggregation level to represent population data throughout Europe. The result is the adaption of the GEOSTAT population grid data.

The GEOSTAT data set is an effort to represent census data from all the European countries inside a population grid of 1 km^2. The data combines the last census results of 2011, and aggregates them into the population grid, currently on its version 2.0.1, as of 01/02/2016. This version provides only population data per cell, considering that cells with less than three inhabitants do not show the actual count due to privacy and data protection issues. Cells without inhabitants are not included inside the grid. The data set has undergone a process of quality assessment which meet INSPIRE metadata standards, for the geographical context and Euro SDMX metadata structure applied in the statistical context (Holst Bloch, 2012).

The data can be downloaded from the EUROSTAT website as a shapefile with coordinate reference system ETRS80/LAEA containing the geometry and a cell ID; and as a table containing the cell ID and the population count, along with additional information regarding the country, year and methods to aggregate the data. Presumably, the data is organized in this manner, as additional information would ideally be added in future releases of the data.

As an example of how the GEOSTAT grid looks like, the Netherlands has been clipped out from the general data set and can be observed in figure 3.2. The figure shows the grid filled by its population count. Areas where the OSM basemap shows land, but no grid cell is overlapping it, indicate that there is no people living in them.

The advantage of working with this spatial grid is avoiding the need to find an specific Open Data Portal to find the spatially aggregated geographic information corresponding to each European country, or city to analyze. Nevertheless, finding the same type of data set regarding number of jobs was not possible at a European level. The problem persists when looking at particular countries like Germany, or the Netherlands, where either the open data portals are highly complicated to understand due to language barriers or complex organization of the portal, as the German case; or the data was available but not as an open resource for the spatial aggregation level required by the BNA score, as the Dutch case.

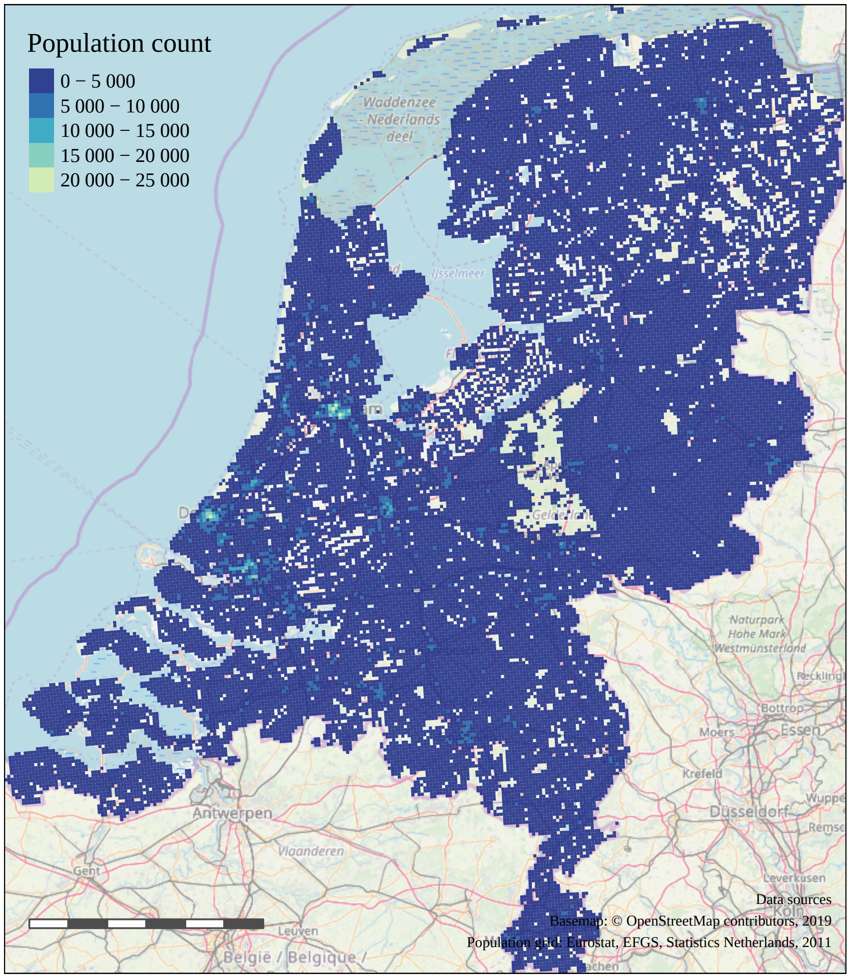


Figure 3.2: GEOSTAT example: Population grid for the Netherlands.

Some ideas have emerged for extracting the information at a very small spatial aggregation level from building footprints in OSM, however, this type of information is yet to be available for every case and cannot be generalized at the moment.

Given these constraints, the prototype is set to either compute the BNA score for any European city using the EUROSTAT population grid, but considering that the results would not take into account employment data, and therefore should be carefully interpreted; or to analyze cities in England, Wales, and the Netherlands. The reason why these particular countries are included in the prototype is that they count with uniquely interesting data sets about cycling patterns that are described and used in the second part of this research (section 3.2), where the hypotheses raised to validate the score are tested. The particular situation of the employment data in the Netherlands is also be described and discussed in the following section.

The prototype could also be modified by the analyst to include its own demographic and employment data, aggregated at a certain spatial level, for any place in the world. It is not done for this thesis, as availability of the data might not be accessible to every citizen, and the principle of openness and reproducibility is meant to be preserved.

3.2 BNA score validation procedure

Once the score has been translated into a European context, an evaluation process of its validity can be undertaken, regarding how well this quantitative score is representing the bicycle network connectivity in the analyzed city. To do so, a decomposition of the score to its basic elements is proposed as:

1. the street network classification based on the level of traffic stress (stress network),
2. the selection of the destinations' type and relative importance (destinations),
3. and the score value itself (overall score).

Each of these elements is likewise formed by a series of components, as seen in figure 3.3. However, only the top two levels are selected as the core of the methodology, following the next logic:

> The **street network classification** determines if there is a low-stress connection, where people pressumably feel more comfortable cycling between an origin and a **specific set of destinations**, which are culled from a wide range of possible options, and ranked according to the **assumed importance** a commuter would assign to it, calculating the ease of access given by said network and assigning a **quantitative score** that represents how good it is for a person commuting by bicycle to get to the places he/she wants to go to.

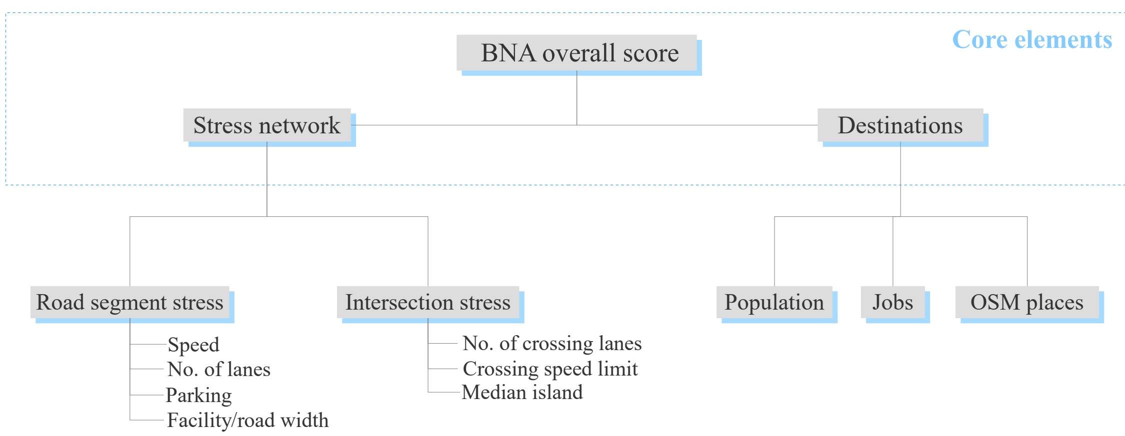


Figure 3.3: BNA core elements and sub-components.

For each element, a research question, and subsequent null hypothesis are defined. To test the hypotheses, case studies according to the validation data set available are selected, and specific statistical tests are performed to accept or reject the null hypothesis. Table 3.1 covers the hypothesis testing procedure undertaken to test the BNA score validity.

Table 3.1: Research questions and hypotheses per BNA score element.

	Stress network	Destinations	BNA overall score
Core element description	Network classification based on LTS	Destinations' type and relative importance	Quantitative score for the whole city
Research question	Are more people biking if there is a low-stress network connecting their origin to their destination?	Are people biking more to the highly ranked destination types in the BNA score?	Is there a relationship between the BNA score as a connectivity measure and actual bicycling activity?
Case study	England and Wales	The Netherlands	England and Wales
Validation data	Travel to work Origin-Destination matrix	Crowdsourced bicycle trip data	Bicycle usage
Null hypothesis	There is no difference between the percentage of bicycle trips between origin and destination zones connected by a low-stress or a high-stress network.	There is no relationship between bicycle trip destinations and the relative importance given to destination types in the BNA score.	There is no relationship between the BNA score of a city and its percentage of trips done by bike.
Statistical test	Welch t-test for unequal variances	Spearman correlation coefficient	Spearman correlation coefficient

The validation data is prepared and processed to test the hypotheses. Additionally, descriptive statistics and spatial patterns are explored. The specific procedure for each of the data sets is described under each case study sub-section below.

The following sub-sections describe the case studies' general characteristics, as well as data sources and processing (3.2.1 and 3.2.2); and introduce the basic concepts of the statistical analyses applied (3.2.3).

3.2.1 Case study: England and Wales

England and Wales is a jurisdiction of the United Kingdom, comprising two of its four nations: England and Wales. Its population by March 27th, 2011 (Census) was of 56 million inhabitants, 94.5% in England and 5.5% in Wales, in an area of 151 149 km^2. Figures on mobility and transport, according to the Census data, show that 57.5% of the working population drove to work; 16% commuted by public transport, 11% walked, and only 3% cycled to work (Office for National Statistics, 2013).

In England, according to the National Travel Survey (NTS), the average cycled miles increased in 54% from 2012 to 2017, where the average person cycled 60 miles and performed 2% of all its trips by bicycle. The main trip purposes were commuting and leisure. Men made almost three times more cycling trips than women, and traveled four times farther, as women perceived greater danger when cycling on roads (Avbulimen & Pini, 2018). In fact, the most common barrier to cycling perceived by people aged 5 or older were road safety concerns.

In Wales, according to the National Survey of Wales (NSW), 6% of people used the bicycle as a mean of transport at least once a week for 2017-2018. Men were significantly more likely to cycle than women. Younger people, between 16 and 24, cycled more than older people, aged 60 or more (Scully, 2018).

Figure 3.4: Cities selected for Case Study: England and Wales.

Thirty example cities (Fig. 3.4), are selected to compute the BNA score and validate it. The selection is based on the population size, excluding large cities with populations higher than 300 thousand inhabitants (e.g. London, Birmingham, Leeds etc.) as the computation times increase largely given the size of the OSM file for the area. Among the selected cities, the proportion of adults cycling at least once a month varied between 2.6% and 53%. Table 3.2 shows the population, area, and cycling rates among adults for travel purpose for the example cities selected.

Table 3.2: Example cities for the Case Study: England and Wales.

City	Population[a]	Cycling rate (%)[b]
England		
Bath	95 024	9.4*
Bedford	169 912	14.9
Blackpool	139 870	8.3
Cambridge	124 919	53
Canterbury	164 100	8.3
Carlisle	108 274	10.6
Chelmsford	176 194	10.8
Chesterfield	104 579	3.7
Colchester	190 098	11.4
Corby	69 540	11.1
Crawley	111 664	7.4
Exeter	128 916	24.7
Gloucester	129 083	11.1
Hastings	92 813	4.9
Hereford	55 755	4.6†
Ipswich	138 480	10.4
Lancaster	142 487	7.8
Lincoln	98 438	13.4
Luton	214 658	2.6
Maidstone	167 730	2.6
Norwich	140 353	24.9
Oxford	154 582	34.8
Plymouth	263 070	5
Slough	148 768	6.2
Warrington	209 704	8.1
Worcester	102 314	15
York	208 163	24
Wales		
Bridgend	144 288	11.3
Newport	151 485	3.8
Swansea	245 480	15

* Figure for Bath and North East Somerset.
† Figure for County of Herefordshire.
Data sources:
[a] LSOA population estimates for mid-2017 (aggregated per city), Office for National Statistics, 2018.
[b] Proportion of people cycling for travel at least once per month, England: Avbulimen & Pini (2018), Wales: Scully (2018).

The cycling rate figures include very high values, as the case of Cambridge, Oxford, Norwich, York, and Exeter, and also very low rates for Luton, Maidstone, and Chesterfield. The variability among active travel by bicycle within the case study might also indicate a variability among the bicycle network connectivity for each city, and therefore, the calculated BNA score.

For this Case Study, two core elements are evaluated: the stress network and the overall score. The data used to calculate the score and for the validation stage are described in the following subsections.

Prototype input data

The BNA score computation requires three basic elements to be extracted from an open data portal: administrative boundaries, population, and number of jobs.

The administrative boundaries for the England and Wales case correspond to the Lower Super Output Area (LSOA). An Output Area (OA) is the building block of the census in the United Kingdom. Super Output Areas (SOA) are stable and consistently size areas for Neighborhood statistics, composed by OAs. The LSOAs are, likewise composed by SOAs. They are, along with Middle Super Output Areas (MSOA), the usual levels of spatial aggregation on which statistics for the jurisdiction are released. An LSOA has a minimum of 1 000 and maximum of 3 000 inhabitants with a number of households ranging between 400 and 1 200 (Office for National Statistics, 2019).

The LSOA boundaries used for the score computation correspond to the 2011 version, obtained from the Office for Nation Statistics Open Geography Portal (Office for National Statistics, 2016a). The population data corresponds to an estimate of the usual resident population for LSOAs for mid-2017 (Office for National Statistics, 2018).

The number of jobs data is derived from the flow data also part of the 2011 Census data from the Office for Nation Statistics. The Census Flow data refers to the movement of people between places, including daily commute to work and migration to new homes. The data links two locations, an origin and a destination, turning it into an Origin-Destination data set. From the table *Location of usual residence and place of work by method of travel to work by sex by age*, the number of jobs was calculated by aggregating the total number of trips per destination LSOA, and assumed as the total number of jobs in the area (Office for National Statistics, 2011).

Validation data

This case study is selected to evaluate two core elements of the BNA score computation, the stress network and the score itself. To do so, data from the Census Flow data, described above is used. The origins and destinations do not contain information only on the total amount of trips, but also on the transport mode used to move between home and work. Therefore, the number of bicycle trips as a percentage of the total amount of trips is computed per origin-destination pair and for the whole study area comprising all the example cities selected in this case study.

3.2.2 Case study: The Netherlands

The Netherlands, by 2011, was a country with over 16.6 million people (Statistics Netherlands, 2011) in an area of 41 543 km^2. It is known as the country of bikes (Dutch Cycling Embassy, 2018), and compared to the majority of the England and Wales jurisdiction, has impressive cycling figures. The country accommodates 23 million bicycles (2 million of which are e-bikes), where 26% of its inhabitant's trips are performed by bike. The main trip purpose is leisure (37%) followed by work (24%), education (20%), and shopping (13%) (Harms & Kansen, 2018).

The increasing trends of Dutch cycling started around the 1970s, where high number of traffic casualties and the oil crisis raised awareness among the population. Consequently, urban plans started considering cycling as part of mobility and led to a program of cycling infrastructure implementation. In the 1990s, a cycling policy was adopted, and as a result, almost every city in the Netherlands counts with a cycling network (Dutch Cycling Embassy, 2018).

For this Case Study, 10 cities with population lower than 300 thousand inhabitants are selected, as can be observed in figure 3.5. The selected cities present a bicycle share as percentage of all trips ranging between 21% and 30%, as observed in table 3.3 where the population and area of each city can also be found.

Figure 3.5: Cities selected for Case Study: The Netherlands.

Table 3.3: Example cities for the Case Study: The Netherlands.

City	Population[a]	Cycling trips (%)[b]
Apeldoorn	159 945	29
Breda	149 775	25
Delft	101 215	26
Enschede	158 070	20
Gouda	71 640	21
Groningen	201 485	30
Nijmegen	163 345	27
Utrecht	295 340	30
Venlo	67 730	25
Zwolle	125 465	23

Data sources:
[a] District and neighborhood map, Centraal Bureau voor de Statistiek (2017).
[b] Bicycle trips as a percentage of all trips, Fietsberaad (2010).

In general, Utrecht and Groningen present the highest share of bicycle trips for the selected cities, whereas, Enschede and Gouda the lowest. Ideally, the cities represent the cycling trends of the middle size cities in the country.

Prototype input data

For the Netherlands, the data needed to compute the BNA score comes from two sources, the Centraal Bureau voor de Statistiek (CBS) and the Employment Register for the Netherlands (LISA).

CBS provides, within its District and Neighborhood map data, the boundaries of the neighborhoods (*buurt*), and their key figures, among them population, updated for 2017 (Centraal Bureau voor de Statistiek, 2017).

The number of jobs input for the computation is derived from LISA, a data set with the locations where paid work takes place in the Netherlands. The data provides point locations for each workplace, being an extremely detail source of information (LISA, 2019). Given the level of detail, the data is sold to interested parties and not provided as open data.

There is some free information available such as the number of jobs per Municipality (*Gemeente*), where the information to input into the prototype is estimated at neighborhood level. To do so, a spatial interpolation is made with the number of jobs in the whole municipality, half weighted by the fraction of the neighborhood area, and half weighted by the fraction of companies in the neighborhood, taken from the key figures in the Neighborhood map data.

The approach needs to be validated, and therefore, the score results should be taken with care, especially for the employment and overall score. To avoid any bias generated by this limitation, the Case Study has only been used to evaluate the core element *destinations*, not considering, among others, the employment destination type. Details are expanded in the next sub-section. In the same way, the data is not used to evaluate the overall score.

Validation data

The Dutch study case was selected to evaluate the destinations core component. The validation data for this case comes from the Fietstelweek data (FTW), a crowdsourced initiative that collects the bicycle trips made by volunteers in the Netherlands during a week (Bike Print, 2017). A mobile application records the bicycle trips that people make available to understand cycling patterns like trips distance, duration, and waiting times.

This initiative of the Fietsersbond, the Dutch Ministry of Infrastructure, Environment, and local authorities (Wardenier, 2017) is released as open data on the Bikeprint.nl site. The data is available for 2015 and 2016. Only the 2016 data is analyzed in this case, given a larger volunteer participation, and a representative sample of the nation cyclists (Vos, 2018).

In fact, nationwide, 29 thousand participants contributed with over 416 thousand routes between September 19th and 25th, 2016 (39 thousand more than the 2015 edition). The highest figures of recorded kilometers corresponded to Amsterdam, Utrecht, and Groningen with a grand total of 1 786 147 kilometers registered in the whole country (Fietstelweek, 2017).

The data provides all the edges and nodes where the trips happened, along with the start and end point of a route. The exact locations where trips start or end are safeguarded for security reasons, and the initial and final 200 meters are removed from the released data. The information is completely anonymized and is not accompanied by demographic data (Vos, 2018).

From this data, the trip end points are extracted for the 10 example cities analyzed in the Netherlands. The FTW data does not include the trip purpose. Hence, to infer if a person is biking to a certain destination considered by the BNA score, a buffer around its spatial location is performed. The buffer depends on the destination type, i.e. 400 meters for transit, university, and college destinations; 300 meters for hospital, parks, retails, schools, and supermarkets, and 250 meters for the rest.

The trip end points are then intersected with the buffers, and aggregated per destination type. From there, the number of trips ending close to a BNA destination type can be known. There might be several cases where one trip ends up in the vicinity of multiple destination types; however, since it is not possible to determine where a person was actually biking to, the end point figures in both aggregations.

3.2.3 Statistical tests

To answer the research questions that would allow to validate the core elements of the BNA score, statistical analyses are performed to accept or reject the stated null hypotheses (table 3.1).

The characteristics of the validation data are first explored to determine the statistical test that should be applied. Supported by distribution plots and descriptive statistics, two statistical tests are selected: the Welch t-test for unequal variances and the Spearman correlation coefficient. Their definitions, formulas, and assumptions are covered in this subsection.

Welch t-test for unequal variances

The unequal variance t-test, also known as Welch t-test, is an alternative to the Student's t-test, when equal variances are not assumed (Ruxton, 2006). Therefore, it is used to compare the means or medians of two groups of samples with different variance. Its calculation (Welch, 1947) involves: a) obtaining a *t'* statistic, which is compared to standard t tables, where a critical t value is obtained, and b) computing the degrees of freedom (ν).

The equation to calculate the *t'* statistic (3.1) and the degrees of freedom ν (3.2) are stated as follows, by Ruxton (2006):

$$t' = \frac{\mu_1 - \mu_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{3.1}$$

Where, μ is the mean of the group, s^2 is the variance, n is the number of observations in the group, and the sub-indices 1 and 2 represent the first and second group, respectively.

$$\nu = \frac{\left(\frac{1}{n_1} + \frac{1}{n_2}\right)^2}{\frac{1}{n_1^2(n_1-1)} + \frac{u^2}{n_2^2(n_2-1)}} \tag{3.2}$$

Where,

$$u = \frac{s_2^2}{s_1^2} \tag{3.3}$$

A null hypothesis can be stated as $\mu_1 = \mu_2$, where no difference in means is assumed. It is rejected when the absolute value of the *t'* statistic is greater than the critical t value according to the significance level α (5%), and the degrees of freedom ν.

As its name mentions, the Welch t-test does not assume equal variances; however, it does assume normal distribution. Nevertheless, with large samples, as the current case, due to the Central Limit Theorem, the test is robust to deviations from normality (Skovlund & Fenstad, 2001), and to heavily skewed distributions (Fagerland & Sandvik, 2009). Therefore, even if the data distribution would suggest to use a non-parametric test to compare the means of the samples, these types of tests are suggested mainly for small samples (Fagerland, 2012).

Spearman correlation coefficient

A correlation coefficient examines the relationship between two variables within a group of subjects to assess if the variables are associated (Freeman & Young, 2009). It is an adimensional value ranging between -1 and 1, where -1 indicates a very high negative relation, 0, indicates no relation, and 1 a very high positive relation.

The standard method to measure the degree of association is the Pearson correlation coefficient. However, given its sensitivity to outliers, assumption of linearity, finite variance and covariance, and bivariate normality of its variables (in order to run a valid hypothesis test) (Freeman & Young, 2009; Weaver, Morales, Dunn, Godde, & Weaver, 2017), its non-parametrical analogous is applied.

The Spearman rank-order correlation coefficient does not make any assumption regarding the distribution of the data, being more robust to outliers, and therefore, is appropriate for skewed distributions, given that the variables are ordinal, interval, or ratio and that the observations correspond to a process of random sampling (Mukaka, 2012; Weaver et al., 2017).

Its computation involves transforming the variables into ranks, as expressed in equation (3.4) (Bishara & Hittner, 2015):

$$g(x_i) = x_r;\ g(y_i) = y_r \tag{3.4}$$

Where x_r equals 1 for the smallest value in x, and equals 2 for the second smallest, and the same for the variables y.

The sample Spearman rank-order correlation coefficient is denoted by r_s and it is computed as (Mukaka, 2012):

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{3.5}$$

Where, n is the number of observations, and d_i is the difference between the two ranks of each observation, expressed as:

$$d_i = g(x_i) - g(y_i) \tag{3.6}$$

This correlation coefficient does not test for a linear relationship, but rather for a *monotonic relationship*. This means that the two variables increase or decrease together, or as one increases, the other decreases, not necessarily in a constant rate (as the linear case). Hence, a linear relationship is monotonic, but a monotonic relationship is not linear.

A rule of thumb to interpret the strength of the correlation (table 3.4) is taken from Hinkle, Wiersma, & Jurs (1979).

Table 3.4: Rule of thumb to determine the strength of the correlation.

(-)0.9 to (-)1.0	Very high positive (negative) correlation
(-)0.7 to (-)0.9	High positive (negative) correlation
(-)0.5 to (-)0.7	Moderate positive (negative) correlation
(-)0.3 to (-)0.5	Low positive (negative) correlation
(-)0.0 to (-)0.3	Little if any correlation

The hypothesis test in this case, will accept or reject the null hypothesis that the computed r_s is significantly different from zero. Therefore, a *p-value* below a predetermined significance threshold (0.05), rejects the null hypothesis.

It is important to notice that a strong association between two variables do not imply that one variable is the cause of another, commonly stated as *correlation does not imply causation*.

Chapter 4

Results and Discussion

The resulting BNA score implementation and evaluation in a European context is presented and discussed in this section. The first subsection (4.1) portrays the prototype implementation, and discusses its performance when running a local analysis. The following sub-section (4.2) shows the results of the validation processes performed for the core elements of the *BNA* score, discussing the results in context with their limitations.

4.1 Prototype implementation

The prototype conceptualized to run a local analysis of the BNA score adapted to European cities results on an HTML type report with interactive maps, tables, and basic information regarding the computation process.

The report template is an Rmarkdown file ideally meant to run within an RStudio IDE, as the user is prompted to add a PostgreSQL database password, and also involves an interactive step with the console to verify the location of the study area, after it is plotted with an interactive map (Figure 4.1). Inside the template, the user also sets the variables for its local analysis. The process is organized in R and SQL scripts that are called in order of analysis.

The local analysis is currently able to compute the BNA score for any European city, without considering employment data, by using the GEOSTAT grid as a population and spatial tessellation source.

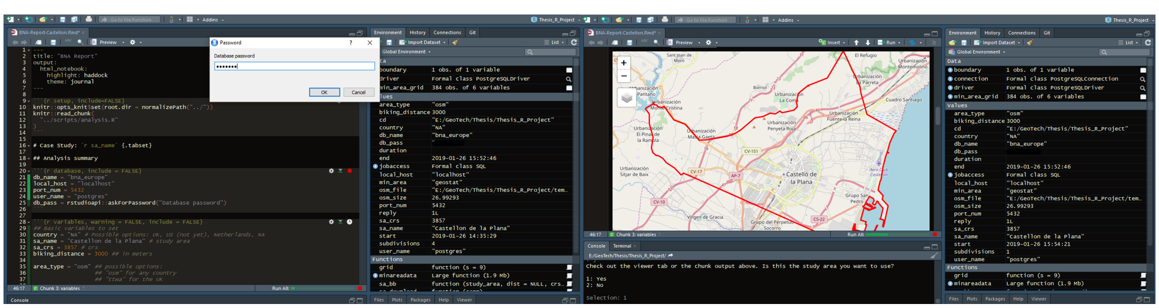


Figure 4.1: BNA score local analysis template on a RStudio IDE.

Even if there has not been a benchmark analysis between the approach by PeopleForBikes (PfB) and the proposed prototype, given that the PfB approach is meant for U.S. cities and towns; the proposed method provides an alternative to the original architecture of the local computation of the BNA score to be applied in European cities.

An example report of the BNA score analysis for Castellon de la Plana using the GEOSTAT population grid is presented in figure 4.2. General information regarding the process elapsed time and the size of the OSM data are included inside the "Analysis summary" tab (left). The study area is also shown, with the type of spatial aggregation chosen. The "Results" tab (right) shows an interactive map with the spatial aggregation layer filled by the resulting BNA score, and the bicycle network, colored by its level of stress. Below the map, a table with the overall results for the whole study area is included.

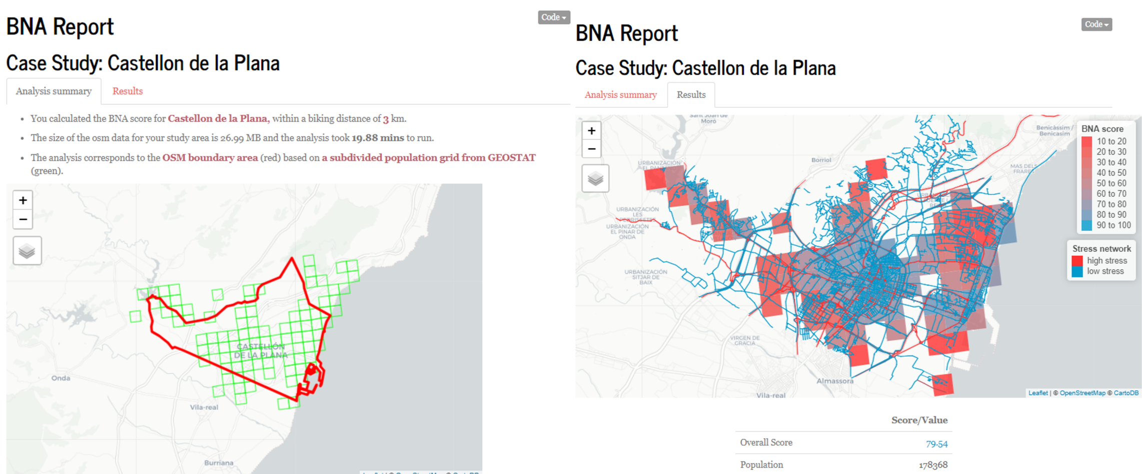


Figure 4.2: Prototype example run for a European city: Castellon de la Plana, Spain. Complete report can be found here.

The "Results" tab aims to reproduce the original BNA score viewer, which has recently adapted a series of updates, not only to the score computation code, but also to the visualization of the data. All the changes and updates can be tracked openly on the open issues of the project on Github, and on a Facebook Group that gathers people interested in using and improving the score. What is an interesting option on their site is the comparison tab, which allows to contrast up to three cities BNA score results. This was not a goal of the report generation, however, could be an enhancement for future releases of the proposed prototype.

Currently, PeopleForBikes is updating and also computing new results for their city rankings score. The new areas are being constantly uploaded to the viewer. They have added several new places to their PlacesForBikes program. On February 19th, 2019 approximately 550 cities had been scored and updated in the portal, in contrast to the 300 cities scored in 2017 (PeopleForBikes, 2019).

Another option for the proposed prototype is to compute the score for The Netherlands and England and Wales Jurisdiction, where the spatial aggregation can toggle between the GEOSTAT grid or the official administrative boundaries (*LSOA* or *MSOA* for England and Wales and *buurt* for The Netherlands). Using the official administrative boundaries, the BNA score was computed for the 40 example cities described previously in the case studies.

For all the 40 example cities, a biking distance of three kilometers is set. Nevertheless, the average bicycle trip distance is larger. For instance, in England, according to the National Travel Survey (NTS0303), in 2017 the average trip length was 3.4 miles or 5.5 kilometers (Department of Transport, 2018). For the Dutch case, the distance per trip was approximately 3.6 km in 2016 (Harms & Kansen, 2018). Data for Wales was not available. Although these figures do not differentiate between utilitarian and recreational travel, the average values are not taken into account for the analysis.

The main reasons to not increase the biking distance is, first, for making a comparable analysis between all the 40 example cities, and second, for controlling the computation time, since increasing the biking distance increases significantly the amount of time it takes to compute the shortest paths, with the current `pgr_drivingDistance` configuration. Although there has been discussion by the BNA score developers to change the shortest path computation (see further discussion here), until now, they have determined that this is the most efficient solution.

Although the driving distance variable is controlled, the local analysis still varies in its computation time, depending on the OSM file size, rather than the size of the studied area. This behavior is illustrated in figure 4.3. The time is also subject to internet speed and machine specifications. This analysis was run on an Asus F541U, Intel Core i7, 8GB RAM and 256 GB SSD, with Windows 10 OS. The figure shows the total elapsed time to compute the BNA score, against the OSM file size for each example city. The colors represent the country, and the dot size, the population.

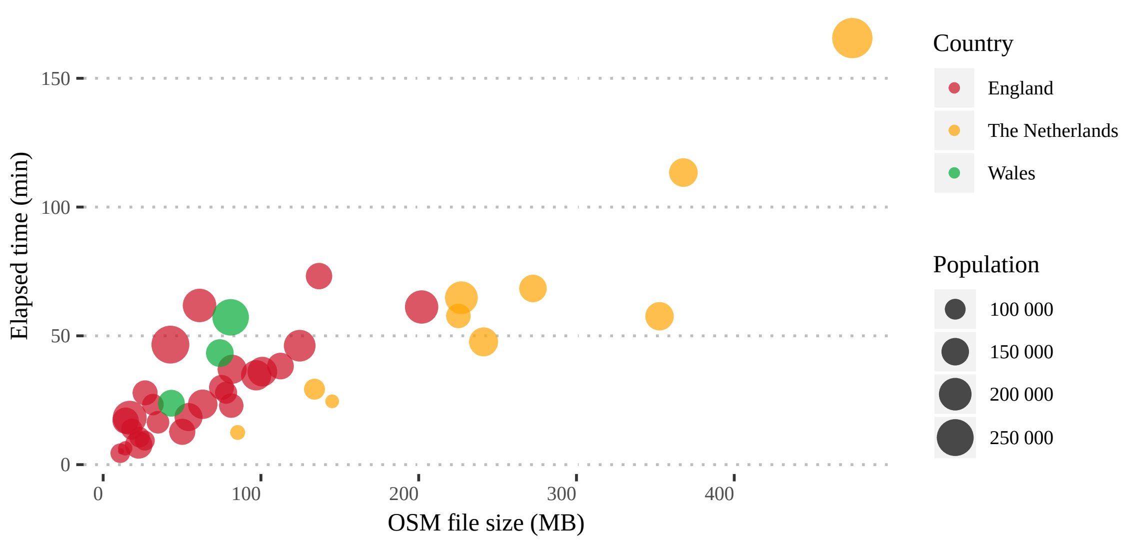


Figure 4.3: BNA score computation characteristics per example city: OSM file size vs. elapsed time.

There is a positive linear relationship (significant at the 5% level) between the elapsed time and the OSM file size ($\rho = 0.87$). The more complex and larger the OSM information in a city, the longer it will take the score to compute. This is the case of the Dutch cities (in orange), where the largest elapsed times were registered. Whereas, for the England and Wales Jurisdiction, the OSM data might not be as complete, and therefore the score is computed faster.

There is also a significant relationship between the number of inhabitants and the computation time ($\rho = 0.66$), and also a weaker relationship with the OSM file size ($\rho = 0.42$). As examined in section 2.3.2, OSM data increases its quality in areas with larger population, as these are potential active contributors to the database. These correlations show indeed that the size of the file relates to its inhabitants.

For this thesis, the example cities are selected based on small population size (< 300 thousand inhabitants), mainly to avoid large computation times, as can be predicted from the above mentioned correlation. Populations vary between 55 thousand inhabitants (Hereford, England) to 295 thousand inhabitants (Utrecht, Netherlands), as can be observed in table 4.1. Nevertheless, the focus is mainly on urbanized, populated areas, considered as cities or towns, where, as is also discussed in the literature review, the quality of the OSM data increases.

That being said, it is also important to acknowledge that although the analysis targeted built-up urban areas, the automation of the study area boundary extraction can hamper this constraint. The boundaries in OpenStreetMap are not always the official administrative boundaries (Lovelace et al., 2018), and might encompass larger areas than the official limits of the city. As a quick analysis, the example cities were intersected with functional urban areas. In the Netherlands, from the 1 161.39 km^2 analyzed, 98.3% is considered urban when compared to the functional urban area as defined by the OECD (2012). For the English and Wales case, 4 703.21 km^2 are analyzed, and only 35.45% is categorized as urban, according to the Office for National Statistics (2016b). Therefore, special care should be taken when interpreting and applying the results for transport planning purposes, considering always that knowing the study area is imperative to identify errors.

For the computation time and the size of the analyzed area, no significant correlation is observed ($\rho = 0.27$). Utrecht is the city that took longer to compute, in spite of not being the largest area in analysis. In fact, Utrecht is the 18$^{\text{th}}$ out of the forty cities analyzed when ranked in descending order by area. Similarly, the smallest computation time is 4.42 minutes, corresponding to Hastings, with an area of 30.83 km^2, only 68.4 km^2 difference from the Utrecht area (the area range difference for all the cities is 636.1 km^2).

Overall, it should always be noted that OSM data is not completely accurate, and for instance, small mistakes can change the results completely. As an example, during the thesis process, when computing the BNA score, an odd result awarded the city of York a score of 100%, and every street network link categorized as low-stress. The analysis was later reprocessed, and the new results showed a more realistic outcome. It is assumed that there was an error with the OSM data downloaded for the first run. Nevertheless, the experience also showed how the OSM contributors are able to detect and quickly correct these types of mistakes in the database.

Table 4.1: Example cities characteristics for BNA score prototype implementation

	Population (No. hab.)	Analyzed area (km^2)	OSM file size (MB)	Elapsed time (min)
England[a]				
Bath	95 024	28.68	26.40	9.31
Bedford	169 912	476.43	100.90	36.10
Blackpool	139 870	43.13	14.25	17.05
Cambridge	124 919	36.05	81.20	22.91
Canterbury	164 100	320.89	81.78	37.02
Carlisle	108 274	24.50	77.92	27.93
Chelmsford	176 194	343.00	97.00	34.68
Chesterfield	104 579	66.04	31.52	23.31
Colchester	190 098	346.71	124.57	46.17
Corby	69 540	80.27	14.00	6.32
Crawley	111 664	44.97	34.76	16.45
Exeter	128 916	47.89	75.01	29.98
Gloucester	129 083	40.83	26.58	27.86
Hastings	92 813	30.83	10.83	4.42
Hereford	55 755	20.34	11.33	5.16
Ipswich	138 480	40.30	50.13	12.75
Lancaster	142 487	654.20	112.41	38.27
Lincoln	98 438	35.69	23.06	10.64
Luton	214 658	43.35	16.84	18.21
Maidstone	167 730	393.36	63.10	23.44
Norwich	140 353	40.57	136.82	73.20
Oxford	154 582	45.60	54.12	18.47
Plymouth	263 070	84.21	42.62	46.59
Slough	148 768	32.54	22.54	7.63
Warrington	209 704	182.39	61.09	61.80
Worcester	102 314	33.28	18.17	13.77
York	208 163	272.02	201.85	61.20
Wales[a]				
Bridgend	144 288	256.16	43.24	23.83
Newport	151 485	217.77	73.96	43.31
Swansea	245 480	421.21	80.81	57.19
The Netherlands[b]				
Apeldoorn	159 945	341.15	367.78	113.40
Breda	149 775	128.68	272.44	68.40
Delft	101 215	24.06	133.94	29.28
Enschede	158 070	142.72	352.64	57.60
Gouda	71 640	18.11	85.25	12.48
Groningen	201 485	101.50	227.07	64.80
Nijmegen	163 345	57.60	241.13	47.66
Utrecht	295 340	99.21	474.85	165.60
Venlo	67 730	128.99	145.16	24.58
Zwolle	125 465	119.36	225.18	57.73

Area calculation CRS
[a] EPSG:27700
[b] EPSG:28992

Figure 4.4 presents a map of all the cities included in the analysis of the BNA score validation. These results are discussed in the next section (4.2). The aggregated score can be found next to the name of the city. Each map shows the city with its administrative boundaries, used as spatial unit of analysis, filled by their correspondent score.

The first thirty maps belong to the England and Wales Jurisdiction, whereas the last 10, to the Netherlands study case. Cities in England received a mean BNA score of 67.84%, while Welsh cities are awarded a mean score of 62.25%. The mean score for the England and Wales Jurisdiction was 67.28%. The Netherlands on the other hand scored a mean BNA of 79.88%. Surprisingly, the highest score (86.7%) is not for a Dutch city, but for Cambridge, England. The lowest score was for Worcester, England with 51.2%.

If these results are put in contrast with the U.S. cities and towns where the BNA score has been computed, the European case appears to be quite encouraging. An exploration of those U.S. cities with populations between 55 and 300 thousand inhabitants (which corresponds to the population range of the example cities sample) shows a mean BNA score of 24% (SD = 12%) for the 262 cities falling in that range. The minimum score (3%) was for Mount Vernon, NY with a population of 72 424 inhabitants. The maximum score (71%) was for Davis, CA with a population of 69 635 inhabitants.

Reviewing the top ranked cities in the U.S., it can be seen that the highest score (87%) is for Provincetown, MA, a small town with 2 669 inhabitants. In fact, the top 10 cities with the highest BNA scores have populations below approximately 100 thousand inhabitants. This trend has already been detected by PeopleForBikes, who explain their success as having low-stress connections that lead to the main streets where all the services are located (Andersen, 2017).

Thirty-two cities in the U.S. out of the 550 analyzed have a BNA score higher than 51% (the minimum score in the European analysis) with a mean score of 59.5% (SD = 8.2%). All the values referred for U.S. cities were obtained from the BNA score viewer (PeopleForBikes, 2019).

In spite of this out-performance shown for the sample cities selected for this study in Europe, it is also important to consider that the spatial unit of analysis differs between approaches, and within the European case itself, as LSOA units used for the England and Wales case are not comparable to the Dutch case. There is also a difference between the biking distance, since PfB considers 2.6 km as their maximum distance, and for this research 3 km were used. In addition, small variations might change the scores, and therefore, it is recommended to only compare areas where the input data remains similar.

The aim of this thesis is not to analyze each city individually, looking for areas where the bicycle network could be enhanced, or where good practices have been adopted inside the city. The aim is to collect all the information generated through the BNA score computation process and put it into a validation context for each of the described core elements building up the score. Hence, the next section reviews the results collectively, also acknowledging contextual information for the Case Studies.

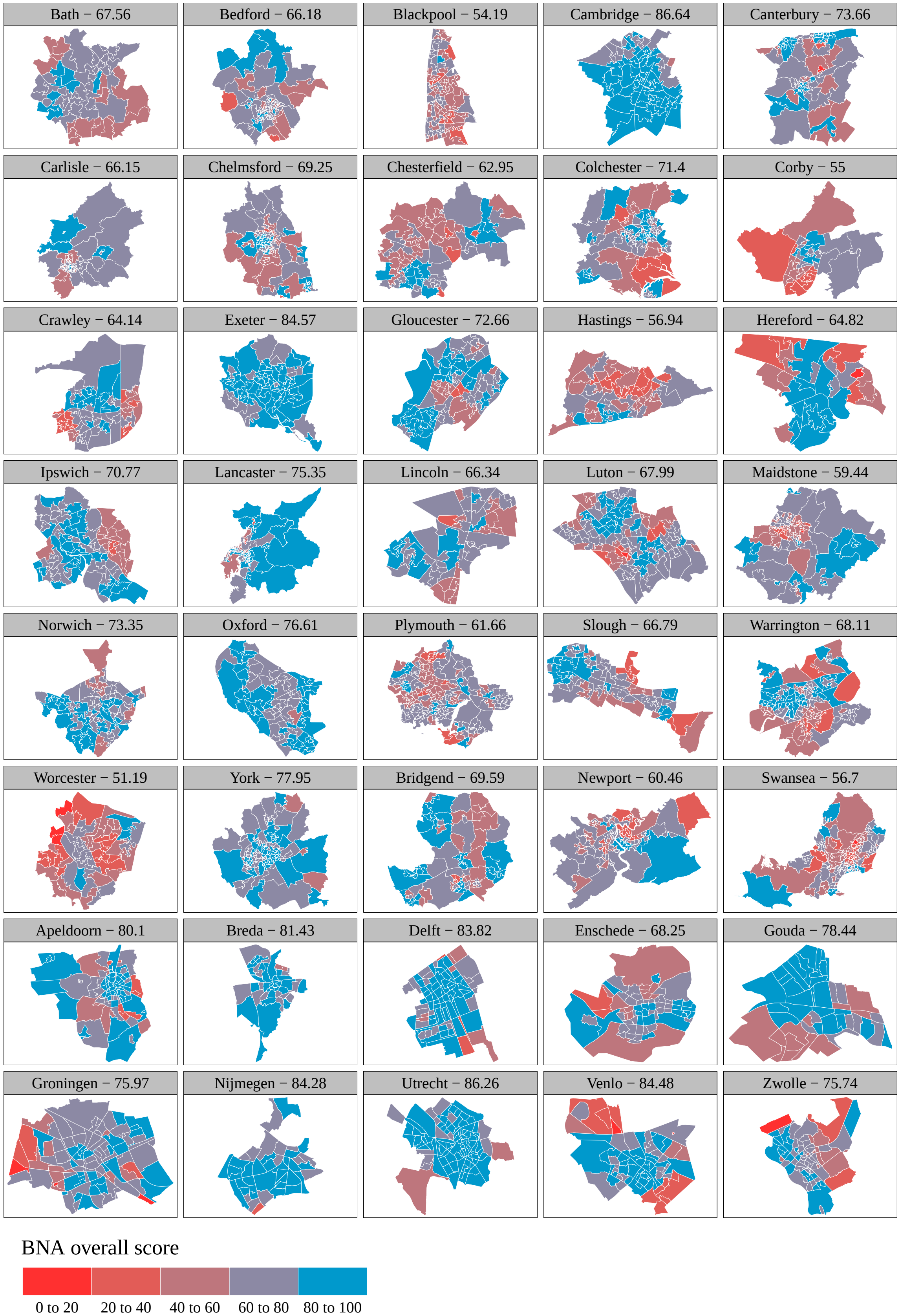


Figure 4.4: BNA overall scores per administrative boundary.

4.2 BNA score validation

This sub-section presents the result of the proposed validation of the BNA score. The validation procedure is presented in three phases, according to the core element to be analyzed. However, the evaluation resulting from the analysis of one of the core elements, might not allow a generalization of the score performance as a whole, given that each core element is evaluated on different data sets.

The main reason to do so, is that the validation data of one case study is more adequate to test one element of the BNA score, whereas another data set is more suited for a different element. In fact, obtaining adequate validation data that meets all the requirements to test the three hypothesis collectively is, to the knowledge of the author, not a feasible task. There is no one single guideline of what type of data a country's Open Data Portal should release, and not one single way of releasing mobility data, which complicates finding a standard universal data set. Ideally, the validation procedure should have also happened in the U.S., however data sets that met the required criteria were not found for the whole country. This is a major limitation of the approach and must be taken into account when interpreting the final results.

The following sections are named after the corresponding core element of the BNA score. The results of the validation of each core element are presented and discussed individually.

4.2.1 Stress network

The bicycle network connectivity classification into Levels of Traffic Stress is called, for simplicity, stress network, and is the first core element analyzed for the score validation. This element was tested with the results obtained from running the BNA score analysis on 30 cities in the England and Wales Jurisdiction. For this Case Study, home to work flow data released as part of the 2011 Census is available in the from of a geocoded origin-destination (OD) matrix by LSOA. Each OD pair contains the number of trips between them, as well as a disaggregation of the total number per transport mode.

Likewise, within the BNA score computation, a sort of OD table is generated, indicating each LSOA origin area paired with a LSOA destination area within the established biking distance, and indicating if whether there is a low-stress or a high-stress connection between both LSOA areas. Given that both tables contain a code per LSOA, the information can be joined together to analyze the number of bicycle trips expressed as a percentage of all trips (bike share) between every LSOA OD pair, per stress level of the network connection.

The data is aggregated into a single table for the 30 cities, resulting in a total of 34 326 OD pairs. A general analysis of the bike share between OD pairs is presented in table 4.2. It is important to point out that the bike share of trips between OD pairs presents a positively skewed distribution (2.5), with a high proportion (~ 54%) of OD pairs presenting zero bicycle trips between them. The maximum bike share is 100%, meaning that all the trips made between these OD pairs are entirely performed by bicycle.

Table 4.2: Descriptive statistics of bike share per LSOA OD pair.

	N	Min. (%)	Q_1 (%)	Median (%)	Mean (%)	Q_3 (%)	Max. (%)	SD (%)	Skewness
England	30 656	0.0	0.0	0.0	8.2	12.2	100.0	13.0	2.4
Wales	3 670	0.0	0.0	0.0	1.7	0.0	50.0	4.8	4.1
Total	34 326	0.0	0.0	0.0	7.5	11.1	100.0	12.6	2.5

The mean bike share for the selected cities in England (8.2%) is five times higher than in the Welsh cities (1.7%), although, it is important to consider that only 3 out of the 30 cities analyzed in the Jurisdiction belonged to this region. The Jurisdiction mean is of 7.5%. The standard deviation for the whole Jurisdiction indicates a high dispersion of the data. Putting the data into context, the mean bike share for the whole England region is 3.2%, while for Wales, 1.6%. The mean bike share for the whole Jurisdiction is 3.1% (Office for National Statistics, 2011).

The Welsh sample mean remains close to the population mean, however, in the English case the sample mean is over 2.5 times higher than the population mean. This is mainly due to the inclusion of English cities with high bicycle commuting rates due to established cycling cultures, high education rates, and touristic attractions (Aldred & Jungnickel, 2014; Cervero et al., 2019). These include cities like Cambridge, Oxford, and York, which inflate the commuting bicycle share. Nevertheless, it is important to include these cities in the samples as they can provide a greater insight regarding the cyclists behaviors and perceptions.

This data is grouped by the stress level of the network that connects each OD pair. Figure 4.5 shows the distribution of the data by group. As can be observed the distribution of the data differs from normality and presents a positive skewness.

In general, the bicycle modal share is low in the English and Wales case, with a big percentage of zero bike trips between OD pairs. The high-stress group presents 58.2% of its observations as zero bike trips between OD pairs, whereas the low-stress group, 50.8%. However, those OD pairs with no bike trips between them were kept, as they are also important indicators of network connectivity; if there is not a comfortable connection between an Origin and Destination, then not only low bicycle shares should be expected but also no bicycle trips at all.

The trend shows that a larger number of observations equal to zero are present in the high-stress group. It is also worth noticing that a larger number of OD pairs (8 959) with registered bicycle trips between them remain on the low-stress group, if the zero observations are extracted, while the high-stress group presents 6 733 OD pairs with bicycle trips. This could be an indication of commuters preference towards comfortable connections between OD pairs to travel to work by bicycle.

Analyzing the bicycle trips as a percentage of all the trips, it is observed that the mean percentage for the low-stress group is slightly higher (7.88%) than the high-stress group (7.05%). The standard deviation in both groups, although not equal, suggests large variability in the data, which mainly comes from those OD pairs presenting high bike share (up to 100%), and can be considered extreme values.

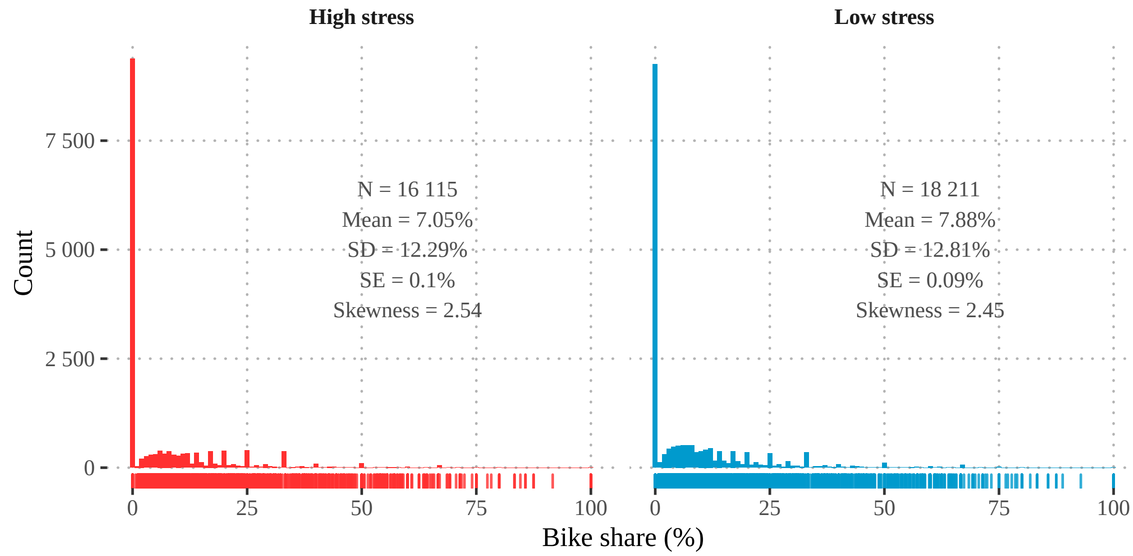


Figure 4.5: Bike share histogram per level of traffic stress.

To test if the difference between the mean of both groups is significant, a hypothesis test is performed. As stated above, both groups present high skewness, with slightly different means, therefore, a non-parametric test is applied. Applying the Welch t-test for unequal variances, the comparison of both groups aims to answer the question: *Are more people biking if there is a low stress network connecting their origin to their destination?*. The null hypothesis assumes no difference between the means. Table 4.3 shows the results of the statistical test.

Table 4.3: Welch Two Sample t-test: Bike share of trips between OD pairs by connecting network stress level.

Test statistic	df	P value	Alternative hypothesis	mean in group High stress	mean in group Low stress
-6.11	34 099	9.943e-10 * * *	two.sided	7.05	7.88

The results reject the null hypothesis that states: *there is no difference between the percentage of bicycle trips between origin and destination zones connected by a low-stress or a high-stress network*, given a significance level of 5%. Hence, there is enough evidence to state that there is a significant difference between groups. Nevertheless, it is important to consider that the number of observations is very large, which increases the degrees of freedom in the test, and could lead to a Type I error (false positive).

Cervero et al. (2019), in their analysis, which has similarities with the research question for the stress network core element (data and methodology wise), filtered out all those OD pairs where less than 30 trips with any transport mode were recorded. They do so considering those OD pairs with high bicycle commute as a result of a low number of overall trips. This is the case for the 100% observations in this research, where OD pairs have for example three overall trips, from which three of them are done by bicycle. Although this would effectively eliminate extreme values influence in the obtained results, there is not a clear explanation on Cervero et al. (2019) that indicates how to select a threshold. Attempts to filter the observations with distinct threshold values resulted in different results, which seemed arbitrary, and are therefore not reported. Hence, the analysis is presented with the complete data.

Under these results, it can be said that people bike more when there is a low-stress connection linking their origin to their destination. However, given the low bicycle shares that the data presents, it is hard to assure to which type of cyclist people in England and Wales belong to. The means, even if significantly different, are still similar between groups. Then, one could assume that the type of people commuting to work by bike belong to the *'Strong and fearless'* or the *'Enthused and confident'* group who would bike in any level of traffic stress.

A study by Jones et al. (2013) tested the relationship of active travel (i.e. walking and cycling) frequencies with connectivity measures and land use activity in the UK, and correlated it with a qualitative research to understand people's perceptions. Some of the results show that citizens in general perceive cyclists as those few brave enough who would share a road along motorized traffic. They prove how cycling is only a habit for a low proportion of the population who present the skills to create their own routes, regardless of the infrastructure. These outcomes, contemporary to the travel to work data set period, supports the hypothesis of the type of cyclists that ride to work in English and Welsh cities.

Furthermore, given that the number of OD pairs connected by a low-stress network is only slightly higher, relatively, to those pairs connected by a high-stress, it could be hypothesized that if the bicycle network would guarantee more low-stress connections inside a bicycle network, then a higher number of *'Interested but concerned'* people would commute to work by bicycle. This hypothesis is backed up by studies by Cervero et al. (2019), Jones et al. (2013), Aldred & Jungnickel (2014), who analyze the UK cycling behaviors and culture, and conclude that giving cyclists their street right will ensure and promote utilitarian cycling among the citizens.

4.2.2 Destinations

The second core element is the main destinations selected by the BNA score and the relative importance that is given to them. The importance is derived from the weighting system established to aggregate the BNA score into a single value for a unique administrative unit. To analyze if this importance corresponds to the real places people are biking to, The Netherlands study case was selected.

Dutch cycling is described as a part of the country's culture, and even considered as part of their national identity (Pelzer, 2010). Cycling comes as an activity so mundane and embedded in the citizen's routine that people do not tend to think about the reasons why they ride a bicycle as a mode of transport (Fishman, 2016). Therefore, examining those countries and regions where cycling is part of the daily life is a way to express that this is the model of city that sustainable transport policies should aim for. Extracting where people cycle to in such cities can indicate where efforts should be invested for future cycling infrastructure in other areas.

As described in the methodology, the validation procedure uses bike trips from the crowdsourced FTW data set, from which the end points of all the routes ending inside the selected cities is extracted, and aggregated by the destination type it intersects with. One same trip can figure as finishing in different destination types. The destination type referring to population is not considered in this analysis, given that accurate location of residential buildings along with its number of residents is not information available through OSM. In addition, the population per neighborhood cannot locate with a point coordinate precision the places where people live. Workplaces are also not included due to the uncertainty with which the employment data was generated for the Dutch study case. Recreational trails are also excluded because of the complexity of snapping the FTW geometry to the OSM data in a comprehensive manner.

Figure 4.6 shows the number of trips ending on a BNA destination type. The main destination people are biking to are **parks**, with almost a billion trips ending in a 400 meter buffer from them. They are followed by **supermarkets** and **schools**, representing almost 200 million trips each. From the next destination, *colleges*, until *hospitals*, there is a gradual decrease in the number of trips ending in their surroundings ranging from 26 million to 400 thousand trips.

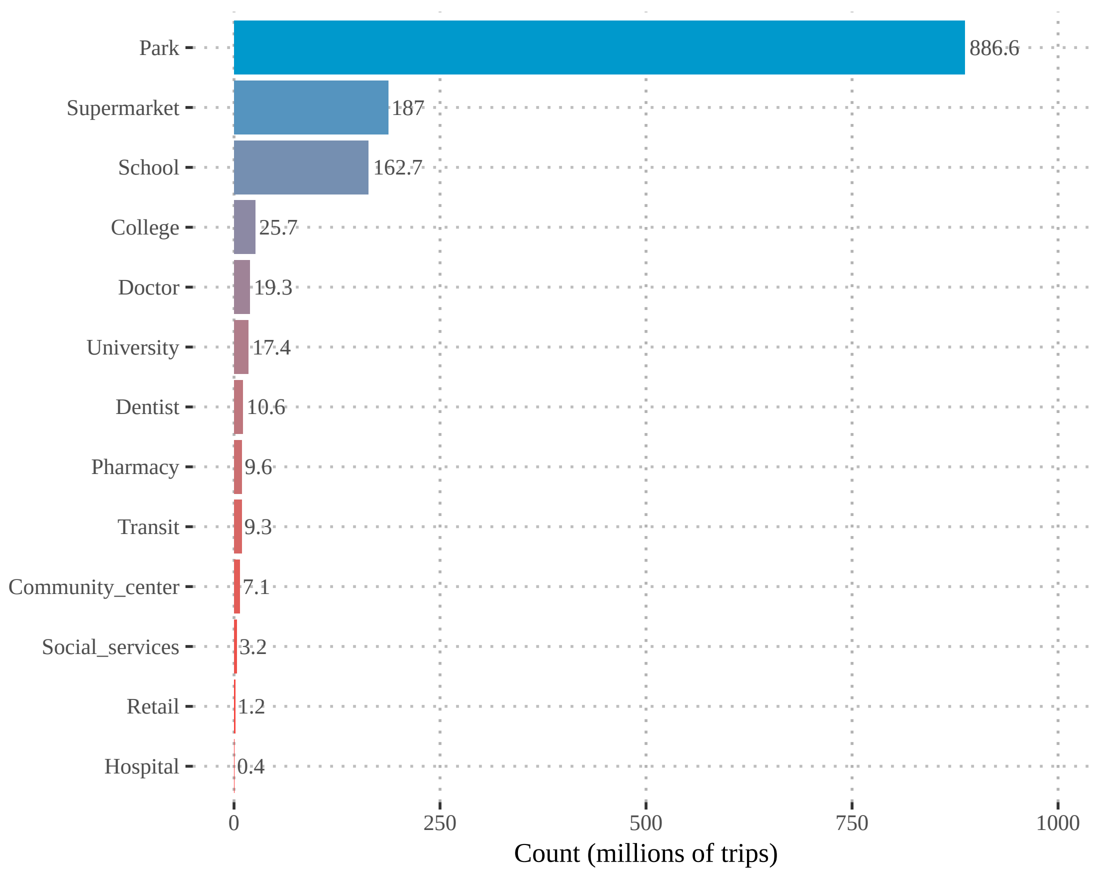


Figure 4.6: Number of trips ending in the sorroundings of BNA destination types.

Of course, the abundance of a destination type in a city will be a high determinant of how many times a trip would intersect with its buffer zone. That is the case of the parks, given that usually, there are a high number of recreational areas, playgrounds, and parks as green areas within a city. The same could be said for supermarkets and schools, usually present at least in each neighborhood. Places like colleges and universities are not as frequently found in a city, but are still important destination points.

To quantify their relevance, each of these destination types is indirectly assigned an importance level within the BNA score calculation. Table 4.4 shows the relative importance that each destination has within the score computation. This is computed by multiplying the group importance times the importance inside the group of each destination type, generating the overall importance of the destination. This is then re-weighted when excluding those destination types that are not analyzed (Population, Employment, Recreational trails).

Table 4.4: BNA destination type importance within score computation.

Destination type	OSM name	GI	IWG	OI	RI
Population	-	15	100	15.0	NA
Employment	-	20	35	7.0	NA
K-12 Education	School	20	35	7.0	9.6
Technical/vocational school	College	20	10	2.0	2.7
Higher Education	University	20	20	4.0	5.5
Doctor offices/clinics	Doctor	20	20	4.0	5.5
Dentist offices	Dentist	20	10	2.0	2.7
Hospitals	Hospital	20	20	4.0	5.5
Pharmacies	Pharmacy	20	10	2.0	2.7
Supermarkets	Spermarket	20	25	5.0	NA
Social services	Social_services	20	15	3.0	4.1
Parks	Park	15	40	6.0	8.2
Recreational trails	-	15	35	5.2	NA
Community centers	Community_center	15	25	3.8	5.2
Retail shopping	Retail	15	100	15.0	20.6
Station/transit centers	Transit	15	100	15.0	20.6

Note:
GI: Group Impotance (%)
IWP: Importance within group (%)
OI: Overall importance (%)
RI: Relative importance (%).

Comparing the relative importance of the destination types under analysis to the proportion of trips ending on their buffer area, a correlation coefficient to measure the relationship between the variables can be computed. As table 4.5 shows, there is not a significant relationship between the variables. This may suggest that the way the weights are assigned to the score computation might not be reflecting the actual behaviors of the people commuting by bicycle.

Table 4.5: Spearman correlation coefficient between relative importance of BNA destination types and proportion of FTW trips.

Test statistic	P value	Alternative hypothesis	rho
336.7	0.8073	two.sided	0.07511

In fact, the BNA score seems to be overestimating the importance for some of the variables and underestimating others. Figure 4.7 illustrates this point. Above the red dotted line, two main destination types can be observed: retail and transit, both assigned a high weight within the score computation, but not being an important destination for the bike commuters. Likewise, below the line, three important destinations can be observed, which are underestimated by the BNA score weighting system: parks, schools, and supermarkets. The rest of the destinations seem to have an adequate weight within the overall computation.

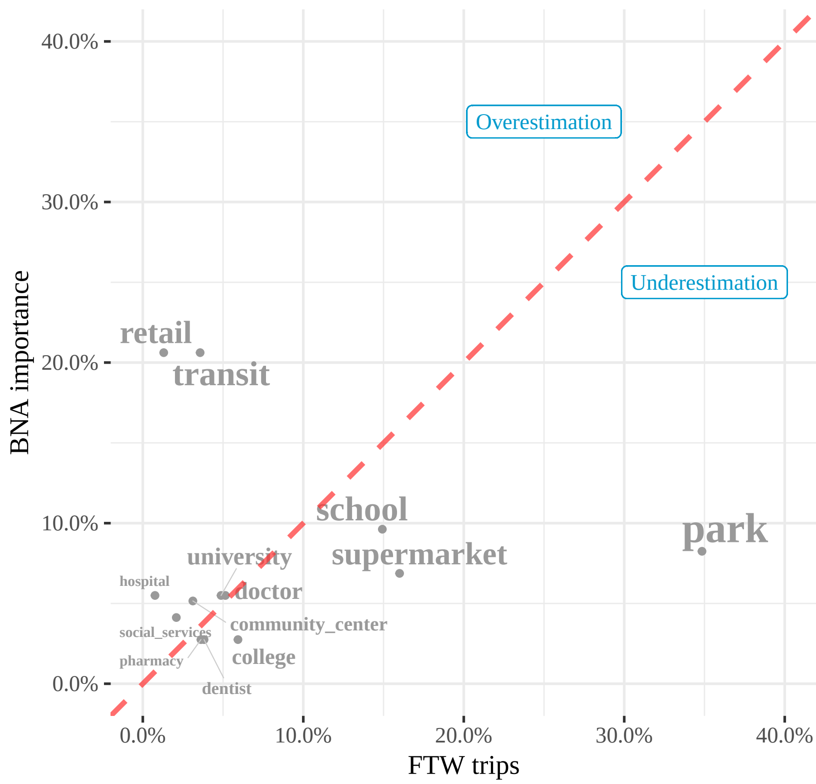


Figure 4.7: Over and under estimation of destinations' relative importance according to bike trips ending points.

Surely, it is not conclusive that people necessarily bike to this destinations willingly, as the purpose of the trip is not a variable within the FTW data. It might also be the case that a person is biking to a destination close to a park and that, consequently, the results are duplicated and show parks as popular destinations. Nevertheless, it is valuable to note that if such a destination intersects so frequently with bicycle trip ends, then there must be other services around it that attract people to these areas, and therefore, investing in comfortable and connected cycling infrastructure could benefit a greater part of the population.

Moreover, the destination types included in the original BNA score are merely a selection of the vast possibilities of destinations a commuter could go to. In this sense, the score aims to create a basket of destinations that might not serve every case, but still represents the general trends of the population (Lowry et al., 2016).

Nevertheless, the selected variables might be missing some important destinations on the daily life of the commuter. To explore the possible destinations missing, additional points of interest, based on a wide variety of OSM tags, are located within the example cities. Again, a 250 meter buffer is generated around them, and the number of trips ending within this buffer area is aggregated per missing destination type.

The results of this exploration are illustrated in figure 4.8. Only those destinations with more than 3 000 trips are shown. Although the number of trips ending on these destinations is smaller than the previous group considered in the BNA score, it is evident that one recurrent destination category is missing inside the BNA score, which could be named is Restaurants and Bars, including restaurants, fast food, cafe, pubs, and bars. Among the top results, bicycle parking also appears, indicating that people might be leaving their bicycle either to take another transportation mean, or due to proximity to their workplace, among infinite possibilities. Therefore, this destination can be disregarded as a possible addition to the score computation. The rest of the destination types are in fact alluring points of interest that could be included inside other categories of the score.

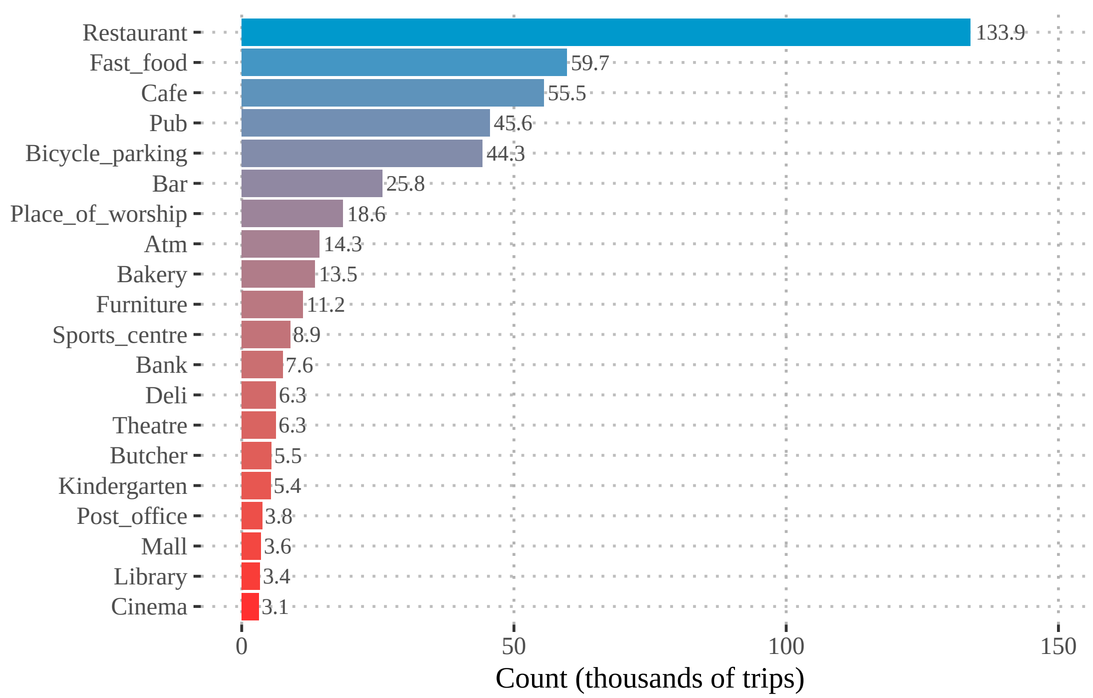


Figure 4.8: Number of trips ending in the sorroundings of destination types not considered by the BNA score.

4.2.3 Overall score

The final, and most important core element of the BNA score is the score itself. This quantitative measure intends to assign an overall score to a complete study area based on how well its low-stress network connects people to main destinations. The advantage of computing a quantitative score is that different areas can be compared to each other, under the assumption that the data input for its computation presents the same quality and spatial aggregation.

To evaluate this core element of the score, again the Case Study England and Wales is considered. Using the same home to work flow data, the OD matrix is aggregated per city to obtain its total number of commute trips and the number of those trips performed by bicycle. With these two values, the percentage of trips by bicycle can be computed. This percentage is compared to the overall BNA score for the whole city, and an statistical test to compute the correlation coefficient is applied.

The correlation coefficient method is selected according to certain data assumptions. Table 4.6 shows some descriptive statistics for the bike share and BNA scores corresponding to the 30 example cities for this case study. The BNA score presents a skewness value close to normality (0). Its mean value is 67.28% with a dispersion of 8.44%, and a standard error of the mean of 1.54%, within a range of 51.19% and 86.64%. For the bike share summary statistics, the data presents high positive skewness, with a mean value of 4.35% (SD = 4.42%, SE = 0.81%), ranging from 0.97% to 22.11%. Based on the skewness of the bike share data, the Spearman correlation coefficient was selected to measure the variables' relationship.

Table 4.6: Descriptive statistics of bike share per city and BNA score.

	Min. (%)	Mean (%)	Max. (%)	SD (%)	SE (%)	Skewness
Bike share	0.97	4.35	22.11	4.42	0.81	2.70
BNA score	51.19	67.28	86.64	8.44	1.54	0.24

Figure 4.9 presents a scatter-plot of both variables, with the results of the correlation coefficient measure included inside the plot area. The values corresponding to the Welsh cities are highlighted in green, whereas the English cities are colored red. The results show that there is a significant monotonic relationship of 0.57 between the bike share and the BNA score for the cities selected within the England and Wales Jurisdiction. According to the rule of thumb presented in table 3.4, there is a moderate positive correlation between the variables, i.e. as one increases, the other one also. The variables density plots are presented on the margins, illustrating the descriptive statistics presented above.

The results show how English cities with cycling cultures such as Cambridge, Oxford, and York have a high bicycle modal share which correlates with a resulting high BNA score. This corroborates Cervero et al. (2019) findings, who catalogued these cities as university towns, with car-restricted city centers, and bike-friendly environments. They also mention Cambridge surroundings as specially prepared for long-distance cycling by connecting the periphery to the city center.

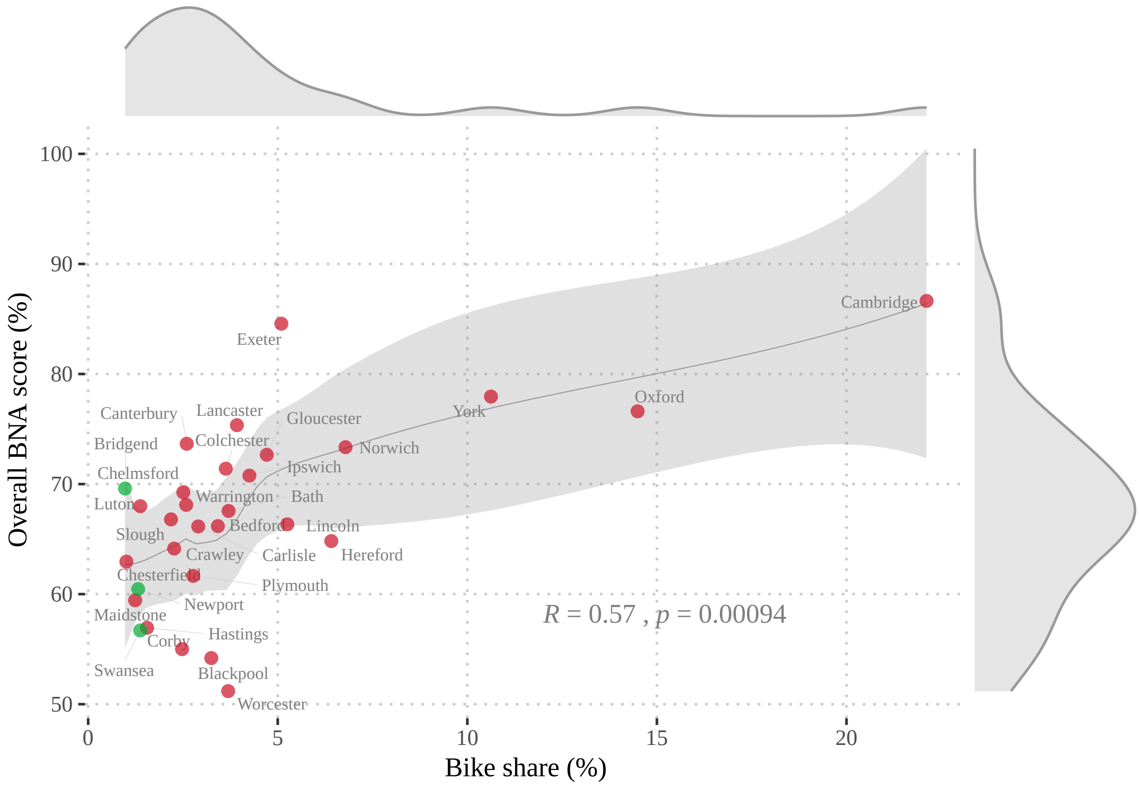


Figure 4.9: Relation between bicycle share and overall BNA score per city.

It is important to note that the purpose of the trips is only commuting to work, and therefore, the wide range of destinations that the BNA considers is disregarded, possibly interfering in the relation between the variables. Nevertheless, the BNA score results for this case study are all above 50%, which should already suggest a good enough network that would account for higher cycling rates.

This fact can be contextualized by the cycling culture in the UK. Jones et al. (2013) mentions in his qualitative analysis how citizens in the UK perceive pedestrians and cyclist as second class citizens, who cannot afford better transportation modes. Equity analyses in the UK have also shown how utilitarian cycling is related to socio-economic deprived areas (Goodman, 2013; Kent & Karner, 2018)

Finally, an analysis of the relationship between the bike share and the BNA score can also be performed per LSOA level. Figure 4.10 shows bivariate choropleth maps for each example city, where colors following the diagonal of the matrix presented in the legend would indicate the monotonic relation between the variables. The figure illustrates how cities with high bike shares present homogeneity with their BNA score results per LSOA, like Cambridge, Oxford, and Exeter. However, areas like Corby, Hastings, Swansea, and Worcester often have connectivity problems in the outer-most LSOA areas. Overall, the BNA score gives a good indication of how well connected a city's bicycle network is, and this connection is evident on the bicycle behaviors of its inhabitants.

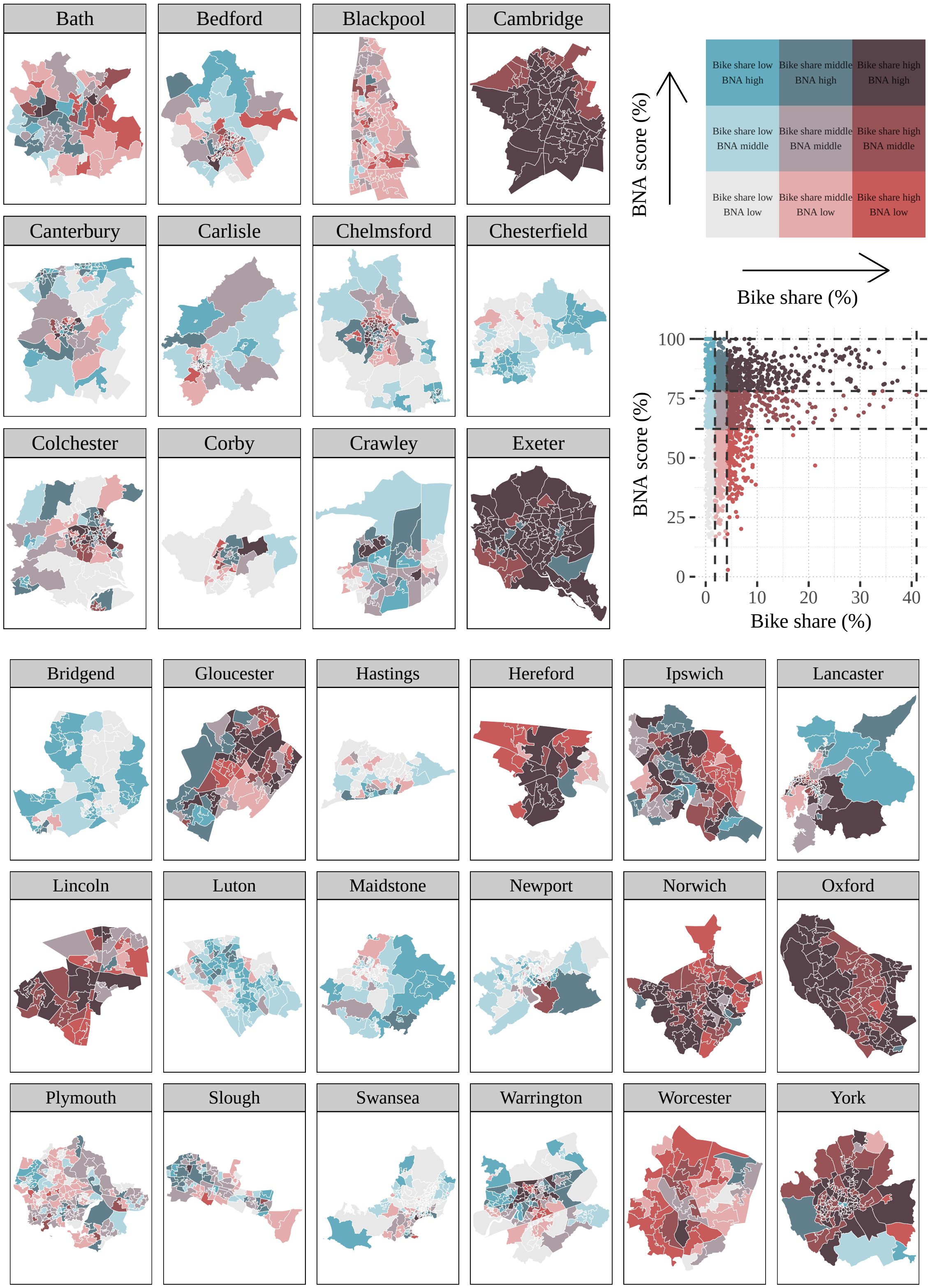


Figure 4.10: Bivariate choropleth maps of BNA score and bike share per LSOA.

Chapter 5

Limitations and Recommendations

This chapter aims to overview the major limitations of the study and also to provide recommendations for future studies or applications of the connectivity measure analyzed in this thesis, i.e. the BNA score, and the validation procedure presented.

5.1 Limitations

The limitations of the study are analyzed and discussed from two points of view, the BNA score computation and adaption to a European context, and the validation procedure of the BNA score itself.

5.1.1 BNA score limitations

As already discussed in section 2.3.2, one of the major barriers to obtain a good quality measure for bicycle network connectivity is the quality of the OSM data. As PeopleForBikes has already mentioned, the score is only as good as the OSM quality, and therefore encourages people to enhance their own community maps. Although a major enhancement of the data quality is predicted for the near future, being prone to human mistakes or incompleteness is definitely, a weak spot for the score computation.

Additionally, issues with the BNA score computation itself should be noted. The first issue contemplates the fact that the maximum biking distance applied for the analysis was kept below the national average for the English and Welsh, and Dutch cases. This is mainly due to the computational performance and technological limitations. Probably, larger biking distances could have changed the results drastically, and given a more realistic view of the cycling behavior in the example cities.

The second question is the size of the spatial unit of analysis. In the U.S. case, the BNA score is computed per census block, the smallest area available for census data release. In the Dutch case, a somehow comparable level of aggregation was used by looking at the neighborhood or *buurt* level. Nevertheless, for the English and Welsh case, the analysis was performed at LSOA level, when there are actually two levels below it. The reason was data availability, since LSOA is the Census level publicly available. Cervero et al. (2019) mentions this also as a limitation for their study, and considers that an improvement in spatial granularity could enhance their model results. Furth et al. (2016) also discussed this issue and considered that for the LTS analysis, having large spatial units of analysis is not recommended, since one zone might be connected by a low-stress network and other not. This applies also to the BNA score, since low-stress is assumed inside the spatial unit of analysis, no matter its area size.

The third concern rises from the variables considered in the LTS classification. Mekuria et al. (2012), and later, Furth et al. (2016) mention how external sources of stress could be included to the LTS analysis. Variables like slope, intersection delays, weather, pavement type and quality, crime, natural beauty, lightning, are not consider to date among the criteria. As Mekuria et al. (2012) state, they have not been included because their primary focus was the stress caused by motorized traffic. Nevertheless, they support that these criteria could be included, like has been proven by Abad & Van der Meer (2018), including slope, or Cervero et al. (2019) including weather variables and natural aesthetics. The BNA score does not include these elements, as Jennifer Boldry, head of the initiative, states that the aim of the score is to measure if people are connected by a low-stress network, and not how enjoyable it is to ride a bicycle (Andersen, 2017).

Finally, the last limitation refers to the input data other than OSM. Population data is somehow a generalized requirement that every city in the world would actually counts with, at different spatial aggregation levels. On the other hand, workplaces data present a whole different status. In the PeopleForBikes case, a fairly complete source counts the number of jobs per census block in the whole country. In the England and Wales case, the number of jobs is inferred from the travel to work data, where the number of jobs is considered as the cumulative number of trips made to a LSOA marked as a destination. However, the Dutch case showed how these data is not always available or easily estimated. The figures obtained for the Dutch case for number of jobs per neighborhood are not reliable, since they come from a quick interpolation regarding area and number of commercial buildings. This has already limited the extent to which the BNA score can be interpreted for the Dutch example cities. This case shows how, if in a European country, with a fair amount of open data, it is difficult to obtain this information, in developing countries around the world it would be even harder. Therefore, alternative sources, or even different input data might be required to replicate these studies and measurements in other areas around the world.

5.1.2 Validation procedure limitations

The major drawback of the validation procedure is the validation data availability and quality. For the English and Welsh case, the travel to work data set (although comprehensive and geographically aware, in the sense that it can be matched to the geographical space) is still lacking a relation with demographic and socioeconomic data that would help to analyze the results in context. Furthermore, it only analyzes, as its name says, travel to work trips, which do not involve all the possible destinations included in the BNA score. Additionally, Cervero et al. (2019) mention that the data set is not presenting transport "mode share as defined by travel demand models", but still considers the data as the best available in the UK, nationwide, for such analyses.

In the Dutch case, the Fietstelweek data is used as the main validation data. Although the bike count mobile application is gaining popularity among the Dutch, and an increasing number of people are volunteering their bicycle trips to improve bicycle research, the data still remains as a volunteered crowdsourced data source. Actual trips are not matched to socio-demographic characteristics of the user, to ensure privacy, and are anonymized in the sense that one cannot know exactly how many people are recording information in a city, but only how many trips are recorded. Trip purpose is also not recorded. Additionally, the application nature of the data collection requires the use of a mobile phone, which could leave some individuals invisible to the data analyst eyes, either for a technology lack from the potential application user, or just a lack of interest. Nevertheless, it represents a big initiative regarding the citizen science domain, that should be maintained, and perhaps enhanced in the future.

Moreover, the generalization of the results is directly linked to the previous points. Not having a unique validation data set that allows a general inspection of the core elements composing the BNA score constrained the potential generalization and ultimate validation of the score. Having performed different analysis on different data sets complicates a unique conclusion to whether the BNA score is completely apt to measure bicycle network connectivity. Nevertheless, given that the score is gaining popularity in the U.S., and that it seeks to expand its study areas, it would be interesting to see increasing research on its relevance and reliability, specially if it will be used as an urban planning tool. Hence, the methods proposed in this thesis could represent a set of examples on how to compare actual bicycle behavior with this type of measures.

5.2 Recommendations

This section points out the possible enhancements that the prototype could have, as well as a review of additions that could benefit the scoring methodology based on the obtained results.

The proposed prototype has translated PeopleForBikes local analysis into a popular coding language among statisticians and data scientists. This is only one of the many presentations the scoring technique could have. Exploration on Python coding and different libraries and modules could also enhance the local analysis, mainly speed and memory-wise, which are common problems when working with big data in R. Therefore, new combinations of different coding languages are encouraged, in a way that does not complicate the usage of the BNA score for local analyses, but that simplifies and speeds the process. The prototype itself could benefit from a R package or a Shiny Application that combines different engines inside its main code, but that provides a simple interface to the user.

As for the scoring methodology itself, the results presented on this research indicate how a bicycle network connectivity score, like the BNA score, relates to high cycling figures in the example cities analyzed. Although the comparison was only done with travel to work data, a broader analysis with cycling trips for different purposes would enhance the score validation.

The destinations validation procedure also pointed out the need to re-balance the importance given to the diverse destinations considered in the score computation, always ensuring that the citizen's needs are taken into account. In addition, the score could gain from adding new destinations like the Restaurant and Bars category. Nevertheless, it is important to consider that needs vary among study areas, and that including destinations that also enhance gender, age, and socio-economic equality are imperative to make low-stress cycling accessible.

Regarding the LTS classification criteria, it is important to acknowledge that changes are constantly made to the method, and new bicycle facilities or variables can enhance the stress level estimation. This technique was developed for U.S. cities, and even within them, specific state cases, like predetermined speed limits, or particular laws, obstruct the generalization of the LTS variables. This is definitely something worth noticing when adapting the score to the European context. In this thesis, the criteria itself were not adapted for the BNA score computation, as this was not the aim of the thesis. However, it is highly recommended that if such connectivity measurements are to be applied to a particular study area, all the dimensions regarding transportation policies should be considered, preferably by experts in the area.

Chapter 6

Conclusions

Bicycle connectivity measures have been continuously developed and applied as tools to evaluate and enhance the bicycle network infrastructure in a community. These measures consider distinct factors to their analyses, that allow the appraisal of the network from distinct perspectives. Several of them are applied in scientific research, while others, are used by non-profit organizations who seek to develop tools that can encourage cycling, as the PeopleForBikes case.

This thesis focuses its analysis on their bicycle network analysis tool, the BNA score, to put into a scientific research context their methodology to quantify connectivity. To do so, it contrasts the score performance with real world cycling behaviors. The ultimate aim is to answer a main research question: *how accurately is the BNA score truely representing low-stress bike network connectivity?*. This question is posed in an attempt to validate the scoring methodology, to generalize it for other study areas outside its original target, the U.S.

By translating their methodology into a straightforward local analysis, based on SQL and R scripts, a prototype is developed to compute the score for European cities, restricted to the limitations previously discussed. Then, the score is computed for 40 example cities in England, Wales, and The Netherlands, with distinct input data. The objective is to evaluate three distinct core elements of the score: the stress network, the destinations, and the score itself.

The results show that in England and Wales there is a small but significant difference between the number of bicycle trips registered between residence and workplace connected by a low-stress bike network, and a those connected by a high-stress bike network. Although the citizens who cycle to work are described in the UK as those with enough skills to expose themselves to stressful traffic conditions, there is still evidence to conclude that they prefer low-stress connections for their trips.

The destination element evaluated in The Netherlands show that the destinations contemplated in the original BNA score calculation are also among the highly frequented by Dutch cyclists. However, the importance that is given to them might appear in some cases over or underestimated.

Finally, the overall score element indicates that the score outputs do relate with cycling figures in England and Wales. As the bicycle modal share increases in a city, its BNA score also increases. This exposes evidence on how cyclists are encouraged by low-stress, well-connected networks that allow them to reach their daily destinations.

To answer the research question, it is required to consider that although the results show that the score relates positively with cycling activity in the example cities selected, the core elements can not be examined as a whole, since the validation procedure occurred in different study areas with different data sets.

In conclusion, this research has showed how translating the score into a European context is possible, considering the data input constraints. One of the benefits of the score is its great dependence on an open cartographic database of the world, as is OpenStreetMap.

This means that it allows the score to be computed in any place in the world, especially those where access to road network data, and points of interest are not easily obtained. Encouraging volunteers to contribute to the OSM initiative can enhance this type of studies immensely.

On the other hand, it is worth noting that population and workplace locations at an adequate aggregation level is not always available. Alternatives should be explored for these specific inputs, which allow an adaption of the score in different areas.

Ultimately, this research has also confirmed what other analyses regarding bicycle levels of traffic stress have found. Providing low-stress connections between origins and destinations can encourage commuting by bicycle in cities, and therefore, special attention should be given to those measures that can greatly benefit the decision making process when planning for sustainable cities.

Appendix A

LTS classification criteria

The classification of the network according to the LTS takes into consideration the road segments (edges), and intersections (nodes). This appendix includes all the classification criteria considered by PfB for this task, as presented on their methodology (PeopleForBikes, 2017).

It is important to point out that for all the tables presented below, the original units have been converted from feet to meters, and from miles per hour to kilometers per hour. The conversion is an approximate and reflects the values that were used to adapt the BNA score to European cities.

First, considering that the OSM tags might not always be complete, PfB introduced default assumptions based on the roads functional class, allowing the criteria to be complete for the whole network (table A.1). One of the latest updates to the code changed these assumptions to take into consideration speed limits varying per state. However, by the time the methodology was implemented for this thesis, the update had not been launched yet, and it is also considered irrelevant for the European case.

Table A.1: Default assumptions for road segments

	Primary	Secondary	Tertiary	Unclassified	Residential
Speed (km/h)	70	70	50	40	40
Number of lanes	2	2	1	1	1
Parking	Y	Y	Y	Y	Y
Parking lane width (m)	2.5	2.5	2.5	N/A	N/A
Buffered bike lane width (m)	2	2	2	N/A	N/A
Bike lane width with parking (m)	1.5	1.5	1.5	N/A	N/A
Bike lane width no parking (m)	1.2	1.2	1.2	N/A	N/A
Roadway width (m)	N/A	N/A	N/A	8	8

Note:
N/A: Not applicable

The road segments have different criteria depending on the type of bicycle facility they represent, which can be: cycle tracks, buffered bicycle lanes, bicycle lanes with/without parking, and shared lanes. The criteria to classify each of these facilities are based on the adjacent motorway speed, number of lanes, the presence of a parking lane, and the width of the bike facility, as observed in table A.2.

Table A.2: Road segments LTS classification criteria

Facitlity type	Speed (km/h)	Number of lanes	Parking	Facility width (m)	Stress
Cycle track	—	—	—	—	Low
Buffered bike lane	> 60	> 1	—	—	High
		1	—	—	High
	60	> 1	—	—	High
		1	Yes	—	High
		1	No	—	Low
	50	> 1	Yes	—	High
		> 1	No	—	Low
		1	—	—	Low
	≤ 40	—	—	—	Low
Bike lane without parking	> 50	—	—	—	High
	$40 - 50$	> 1	—	—	High
		1	—	—	Low
	≤ 30	> 2	—	—	High
		≤ 2	—	—	Low
Bike lane with parking	—	—	—	≥ 5	a
		—	—	$4 - 4.5$	b
		—	—	< 4	c
Shared lane	≤ 30	1	—	—	Low
		> 1	—	—	High
	> 30	—	—	—	High

[a] Treated as buffered lane;
[b] Treated as bike lane without parking;
[c] Treated as shared lane

PfB included in their BNA score additional bicycle facilities compared to the Mekuria et al. (2012) analysis. Four bicycle facilities types are taken into account. Below a description of each type taken from the Urban Bikeway Design Guide (National Association of City Transportation Officials, 2014) can be found. Pictures by Richard Drdul.

1. ***Cycle track***

An exclusively bicycle facility, physically separated from the motor traffic and sidewalk. They can be one-way or two-ways, and be at sidewalk level or intermediate level, usually with a different pavement color/texture.

2. ***Buffered bike lane***

Conventional bike lanes with an adjacent buffer space which separates the cyclist from the motor traffic. It allows the cyclist to, for example, have more freedom for overpassing another cyclist, and gives an extra safety feeling compared to a conventional bike lane.

3. ***Bike lane without parking***

A conventional bike lane, which is a part of the roadway designated for the preferential or exclusive use of cyclists. It is commonly marked by striping, signage, or pavement markings. It has no physical barriers and runs next to the curb, Normally, they run in the same direction as traffic, although there are also counter-flow lanes.

4. ***Shared lane***

A roadway that is both used by bicycles and motor traffic. It is usually marked with sharrows or Shared Lane Markings. Usually, the speed for motor traffic is low in this road segments. An example are the *"fahrradstraße"* in Germany.

The score also makes a difference between residential or unclassified streets, as seen in table A.3. Usually these types of streets are calmer and tend to be a more comfortable environment to cycle. However, the presence of parking and the road width can be a challenge mainly on shared lanes.

Table A.3: Residential and unclassified road segments LTS classification criteria

Facility type	Speed (km/h)	Number of lanes	Parking	Roadway width (m)	Stress
Cycle track	—	—	—	—	Treat as tertiary
Buffered bike lane		—	—	—	Treat as tertiary
Combined bike / parking lane		—	—	—	Treat as tertiary
Bike lane		—	—	—	Treat as tertiary
Shared lane	≥ 50	—	—	—	Treat as tertiary
	40	> 1	—	—	Treat as tertiary
		1	One side or none	≥ 6	Low
		1	One side or none	5.5	High
		1	One side or none	< 5.5	High
		1	Both sides	≥ 8	Low
		1	Both sides	7.9	High
		1	Both sides	< 7.9	High
	≤ 30	> 1	—	—	Treat as tertiary
		1	One side or none	≥ 6	Low
		1	One side or none	5.5	Low
		1	One side or none	< 5.5	Low
		1	Both sides	≥ 8	Low
		1	Both sides	7.9	Low
		1	Both sides	< 7.9	Low

Note that the table above indicates to treat as tertiary the road segments complying with these criteria. Therefore, one should use either the default assumptions given in table A.1, or consider the values of the road segment and refer to table A.2.

For the intersection case, the criteria depend on the type of intersection control, which can vary between: none or yield to cross traffic, a RRFB, or signalized, HAWK, four way stop or priority based on class. The criteria to classify are the number of crossing lanes, the crossing speed limit, and the presence of a median island (table A.4).

Table A.4: Intersections LTS classification criteria

Intersection control	No. of crossing lanes	Crossing speed limit	Median island	Stress
None or yield to cross traffic	> 4	—	—	High
	4	> 50	—	High
		50	Yes	Low
			No	High
		≤ 40	—	Low
	< 4	> 50	Yes	Low
			No	High
		≤ 50	—	Low
RRFB	> 4	—	—	High
	4	≥ 70	—	High
		60	Yes	Low
			No	High
		≤ 50	—	Low
	< 4	> 60	Yes	Low
			No	High
		≤ 60	—	Low
Signalized, HAWK, four way stop, or priority based on class	—	—	—	Low

New terms for intersection control elements on the table above can be defined, according to the Urban Bikeway Design Guide as:

1. ***RRFB***

Stands for Rectangular Rapid Flash Beacons (RRFBs) and are used to alert the motor traffic of possible cyclists' crossings. Picture by Gary Cziko.

2. ***HAWK***

Stands for High-Intensity Activated crossWalK beacon. It is a traffic control device that stops motor traffic to allow a cyclist or pedestrian to cross safely. Picture by William F. Yurasko.

3. ***Median refuge island***

An island usually in the middle of an intersection which allows a cyclist to cross one direction of traffic at a time. Picture by Richard Drdul.

The default assumptions for the signal control between functional class roads are showed in table A.5. These correspond to the priority based on class intersection control. Note that uncontrolled intersections assume a low stress crossing for travel along the higher-order roadway.

Table A.5: Default assumptions for signal control

Street classes	Signalized
Primary-Primary	Y
Primary-Secondary	Y
Primary-Tertiary	N
Primary-Residential	N
Secondary-Secondary	Y
Secondary-Tertiary	N
Secondary-Residential	N
Tertiary-Tertiary	Y
Tertiary-Residential	N
Residential-Residential	N

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