Analysis and Quantification of Urban Bicycle Networks: The Example of Copenhagen

Master thesis

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Table of contents

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Abstract

This research aimed to analyze and quantify the changes in Copenhagen's urban bicycle network, which has recently been improved in favor of cyclists. My methods are rooted in network science and based on data from OpenStreetMap. To acquire network data over the research period from 2013 until 2022, the Python package OSMnx was used. Several subnetworks were defined, such as the bicyclable network and the bicycle specific infrastructure. I proposed several network measures and showed the results of a selection of measures on Copenhagen, as well as three other cities of similar size. The selection of five measures can be divided into two groups: 1) Random route lengths (compared to car route length); 2) Total network lengths (% bicycle specific infrastructure). These measures are meant to quantify changes in bicycle friendliness and differences between cities, all based on OSM data. Using combinations of different measures can mitigate the shortcomings of each measure. Therefore I recommend adding more network measures to the 'toolbox' for future research.

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1. Introduction

This thesis aims to learn from Copenhagen's development in terms of bicycle friendliness in recent years, by studying its network of bicycle infrastructure and aiming to quantify improvements. Other cities which want to enhance cycling with suitable infrastructure, can possibly take Copenhagen as an example and compare their efforts and results with this city. I hope my analysis can contribute to this, by developing objective measures for the evaluation of bicycle friendly infrastructure.

1.1 Context

In the last fifty years, car traffic has become a dominant factor in most cities – at the expense of livability. By occupying a lot of space, causing pollution and bringing danger to the streets the massive growth of car use has had an immense impact. But until quite recent years, only in a few cities the awareness of this has led to policies in favor of slower modes of transport like cycling.

Ten years ago, the outlook was still more growth of car use. According to The World Energy Council (2011), the amount of cars could again more than double in a few decades. But in more recent years, the perspectives for city transport and mobility have started to shift in more and more cities in both Europe and North and South America (Walljasper & Ballmer, 2018).

Some popular publications have even predicted the “End of the car age” (Moss, 2015). In these changing perspectives, sustainable alternatives to the car are catching the spotlights. Together with new forms of public transport, the bicycle can play an important role in this. Indeed, increasing transport by bicycles instead of cars has been recognized as a way to enhance sustainability and livability in cities as well as promote a healthy lifestyle (for example Agarwal et al., 2020; Gössling & Choi, 2015).

However, practice has shown that bicycles are more popular in some cities than others due to various and sometimes complex reasons. Parkin (2012) describes a historic pattern of how cars replaced bicycles at a certain point in time. In only a few countries and cities the bicycle has taken over again. He states that cycling is still in decline on the global scale, even as its contribution to sustainability becomes more widely acknowledged. This suggests that the shift from cars to bicycles is not easily implemented and goes hand in hand with many challenges.

One of Parkin’s (2012) conclusions is that the absence of cycling culture and infrastructure makes cycling something marginal which in turn makes it unattractive for people to do. This makes clear that good urban planning is needed to really encourage more sustainable modes of transport (Mohan & Tiwari, 2020). In this context, this thesis focuses on the development of bicycle infrastructure.

As cities are working with limited space, often the choice has to be made: either car lanes or bicycle lanes (Parkin, 2012). During my bachelor study I did fieldwork in New York, where citizens were asked for their opinion on alternatives for car transport. While bicycle lanes seemed a nice solution to some people, most interviewees were against it because they ‘stole’ room for the cars, making traffic jams worse and creating dangerous situations. The fact that cycling infrastructure depended on tax money (as most infrastructure) was one of the arguments interviewees had against it. So as the means and space for bicycle infrastructure are limited, those have to be used in the most efficient way.

One of the main barriers for large scale bicycle use according to Bonham & Wilson (2012), is the so called mobility-modernity nexus which links the bicycle to childhood and gives it the status of being not meant for adults. According to Bonham & Wilson (2012), the bicycle not being the vehicle of choice applies to most parts of the world. The common view is adults only choose the bicycle when they lack the money for a car.

As becomes apparent from the observations above, history plays an important role for current bicycle use, as it affects both the cities’ infrastructure as the perception of the bicycle as a valid transport tool. Practice has shown that it is not easy to generate a shift from high car use to bicycle use, but it has been done (Parkin, 2012; LA Times, 2019). In order to increase the use of the sustainable bicycle, one could learn from examples of cities or countries that have achieved success in this transition.

1.2 Development of Copenhagen

One city that has a long reputation of stimulating bicycle use is the Danish capital, Copenhagen. Several times already, this city has been recognized as the best cycling city of the world. In July 2022 this reputation was again confirmed broadly in international media, when Copenhagen hosted the start of the Tour de France (NOS, 2022).

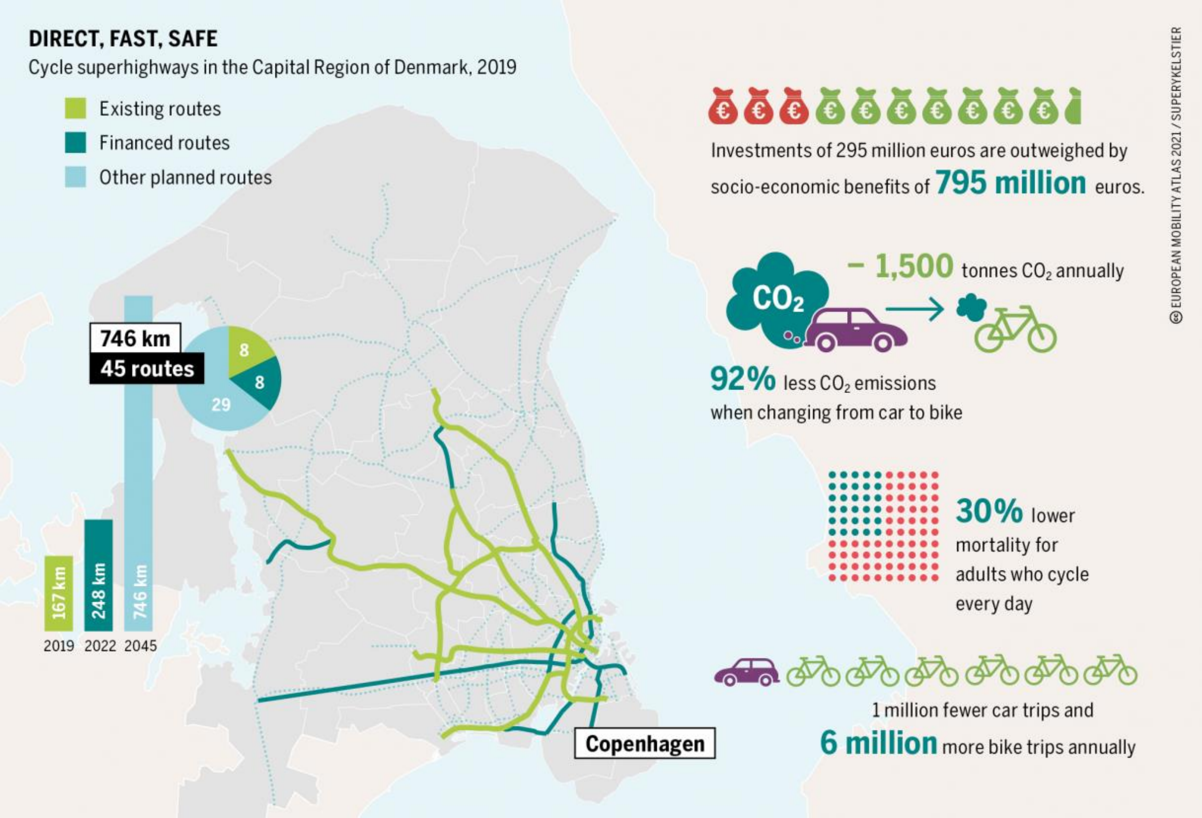


Figure 1: The ongoing addition of cycle superhighways in the region of Copenhagen. (Source: European Mobility Atlas / Supercykelstier / Heinrich Böll Stiflung)

In many articles the efforts of the Danes to increase cycling traffic by lowering thresholds for bicycle users have been described (for example Haustein et al., 2020; Nielsen et al., 2013). Bicycle traffic has been prioritized by structurally improving the cycling network (City of Copenhagen, 2011). Copenhagen has given more space to cyclists, created dedicated bicycle highways and bridges, resulting in fewer 'missing links'. And this policy was successful: more and more inhabitants of the city choose the bicycle to go to their work or study. In a 2009 interview from the Dutch Fietsersbond (Cyclist Union) with Denmark's equal Cyklistforbunded it was stated that 37% of all people who work or study in Copenhagen, come by bike. It was mentioned that the goal for 2015 was 50%. I found the most recent percentage of 44% for 2021 in the European Mobility Atlas, which points out a significant improvement for cyclists (Böll Stiftung, 2021). This number is expected to keep increasing, as bicycle infrastructure keeps being improved. An example of this is shown in the infographic of Figure 1, which is about the addition of cycle superhighways in the region of Copenhagen. It is expected that the following years, more cycle superhighways will be added.

It is interesting to study the recent improvements in Copenhagen's bicycle network with the help of detailed data from OpenStreetMap. These data show how the addition of several bridges specifically for bicycles has made Copenhagen's bicycle network more connected. A few of those bridges were already mentioned in 2011 in Copenhagen's bicycle strategy, which can be seen in Figure 2 where they are drawn as black arches. But since then the list of strategically built bridges that provide cycling shortcuts in Copenhagen has even grown longer. Looking merely at the inner city of Copenhagen, the following important bridges have been added recently:

- Proviantbroen, bicycle bridge (2014)
- Trangravsbroen, bicycle bridge (2014)

- Cykelslangen, bicycle bridge (2014)
- Cirkelbroen, bicycle bridge (2015)
- Inderhavnsbroen, bicycle bridge (2016)
- Lille Langebro, bicycle and walking bridge (2019)

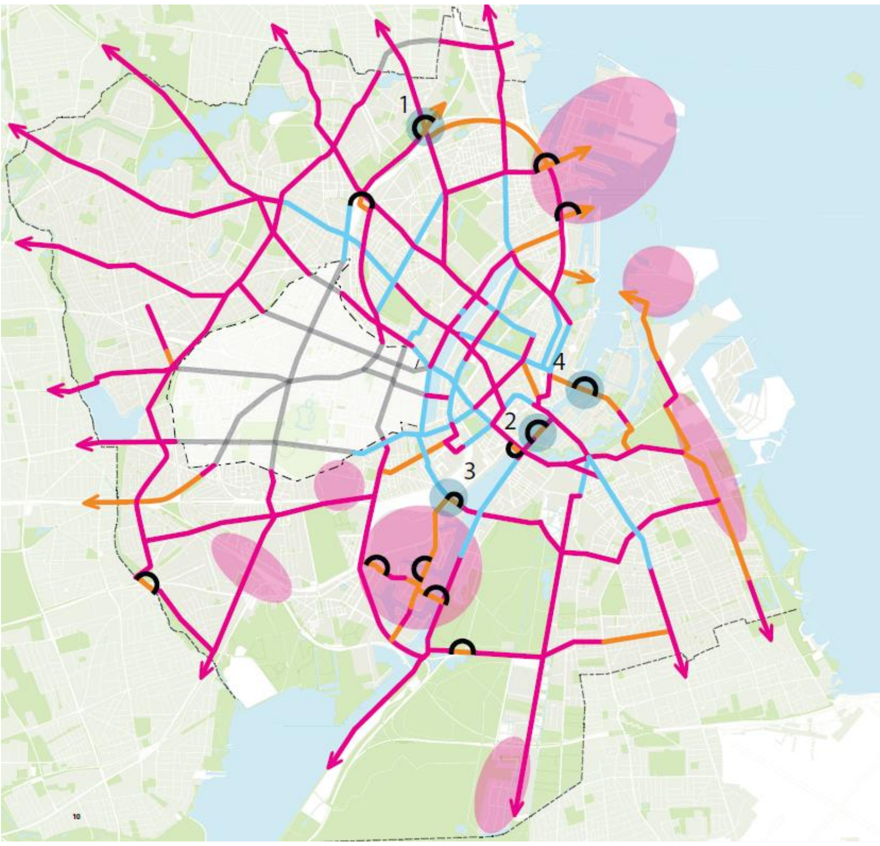


Figure 2: 2011 plans for structural improvements in Copenhagen's bicycle network (Source: City of Copenhagen, 2011). Legend: Magenta roads: OK – only minor adjustments required. Blue roads: More space. Orange roads: Large-scale improvements / start from scratch. Black arches: New bridge/tunnel for cyclists and pedestrians. Pink area: New urban development areas with perspectives beyond 2015.

Due to the reasons mentioned earlier – limited space, no dedicated infrastructure, the lack of a cycling culture and the self-reinforcing effect of these factors – the success of Copenhagen is not easily transferred to other cities. And even in this city which can be seen as an example, cycling infrastructure still remains a topic of political debate, as reflected by Gulsrud & Henderson's book (2019) titled "Street Fights in Copenhagen: Bicycle and Car Politics in a Green Mobility City". Still, improving cycling networks is one of the necessary ingredients of any policy to enhance cycling in cities. So, by studying the network improvements of Copenhagen and analyzing their effect on bicycle friendliness, possibly clues can be found which can help other cities that want to move in the same direction.

1.3 Network Science

As mentioned, bicycle usage is influenced by different factors and has also been studied from different perspectives. In this regard Copenhagen has been a test subject from, for example the perspectives of urban planning practices (for example Nielsen et al., 2013), cultural and historical factors for bicycle use (for example Haustein et al., 2020; Emanuel, 2019), and GPS-based studies analyzing cyclist behavior (for example Skov-Petersen et al., 2018).

New insights could be gained from the perspective of network science. Carstensen et al. (2015) have studied the spatio-temporal development of Copenhagen's bicycle infrastructure of 1912 until 2013. Their study documented the spatio-temporal development of Copenhagen's bicycle infrastructure throughout the mentioned period. Covering a full century of the city's history, they were able to distinguish four distinct periods in Copenhagen's development towards a bicycle friendly city: 1) first cycling city. 2) car city. 3) liveable city. 4) liveable cycling city.

My thesis also takes the approach of network science and focuses on the decade that passed since Carstensen et al. (2015) ended their research, spanning the decade from 2013 until 2022. In that respect, my research can be seen as a follow up of their work, although I will use different methods to analyze developments. In the Theoretical Framework the meaning and relevant concepts of network science are explained.

1.4 Research relevance

The societal relevance of this thesis can be found in the aim to make cities more livable. As mentioned in the introduction, the development of mobility makes cities face big challenges regarding public health, safety, environment and spatial planning.

As the example of Copenhagen shows, by making smart decisions on bicycle infrastructure, a city can make long-term improvements in livability in a financially efficient way. As said before, bicycle culture and bicycle infrastructure need each other to succeed and it is hard to create one of the two without the other. Bu on the other hand, without a good infrastructure every attempt to stimulate a cycling culture will be doomed to fail. So this thesis focuses on bicycle infrastructure as a necessary condition for bicycle friendly cities.
Scientifically, the relevance of this thesis could lay in the development of relevant network measures to monitor and compare bicycle friendliness of traffic infrastructure in an easily applicable way. I try to be innovative in finding such network measures and use them to analyze street network development over time. Also, this thesis will be almost solely based on open data and open software. This makes the research reproducible.

1.5 Research objectives and questions

1.5.1 Main research objective

My research studies the changes in Copenhagen's street network over ten successive years (2013-2022) using historical data from OpenStreetMap (OSM). The different networks for cars and bicycles are taken into account, as these share streets but also have separately allocated streets. An important goal is to quantify bicycle friendliness. In this thesis I will apply existing network measures, and present some new (combinations of) measures suitable for the specific case of bicycle networks. While following a network-scientific approach, this study also tries to contribute to the interpretation of the network measures in a human geographical way, by linking changes in results with real world phenomena.

During the work for this thesis, it appeared necessary and practical to bring some change in my research objectives. Originally, I expected to succeed in such detailed analysis of the development of bicycle networks in Copenhagen that I could pinpoint the specific network changes which were the most beneficial for Danish cyclists. This was not realistic. Instead, I chose an approach on a more macro level.

In short, my main research objective is as follows: Quantifying the development of urban bicycle networks of Copenhagen in a relevant and objective way which is also applicable to other cities of comparable size. The measurements must be fit for the evaluation of network improvements, by comparison of results and trends in different cities.

1.5.2 Research questions

My research was guided by three main research questions. In order to perform the network analysis, adequate data needed to be collected. First I had to define different network layers to compare and to indicate relevant levels of bicycle friendliness, based on the data and infrastructure. Next to defining those meaningful subnetworks, I had to find a way to efficiently collect the network data of Copenhagen (as well as other cities) of the past 10 years. Therefore, my first research question and subquestions are formulated as follows:

RQ1 How can meaningful subnetworks of the street network be defined?

RQ1.1 How can relevant car and bicycle networks be defined?
RQ1.2 How can these networks be practically extracted from historical OSM data?

As explained in the introduction, a wide array of network measures exists. As I studied developments in Copenhagen's bicycle network over the past 10 years, I looked at which (combinations of) measures give a comprehensive and realistic picture of the overall performance of bicycle infrastructure of the city. Looking for matches between these macro measures and real interventions in the infrastructure, I wanted to increase understanding of which network characteristics are essential for bicycle friendliness. This is reflected in the following research questions:

RQ2 What (combination of) measures provide a reliable quantification of Copenhagen's development towards bicycle friendliness?

RQ2.1 How did the scope of Copenhagen's street networks change over the past 10 years?
RQ2.2 Which network measures are suitable for monitoring bicycle friendliness of a city?
RQ2.3 Can changes in these measures be interpreted in terms of the geographical context by linking them to real interventions?

The final part of this research is an attempt to generalize outcomes of my case study of Copenhagen by studying three other cities using the same network measures. Some aspects might be unique for Copenhagen making it hard to get really comparable results in other cities. The preliminary choice of cities as well as all methods are explained in the methods section of this proposal. The research questions for generalization are as follows:

RQ3 In which ways can the outcomes of the study of Copenhagen be generalized?

RQ3.1 How can the network measures be transferred consistently to other cities?
RQ3.2 Which unique aspects of Copenhagen make a fair comparison difficult?
RQ3.3 Which conclusions can be drawn by comparing (trends in) the measures between the four cities?

1.6 Research approach

The research was divided into three main steps corresponding to the three aforementioned main research questions. Within these steps as shown in Figure 3, several tasks and processes were performed as a non-linear process. For example the data exploration and the theoretical framework depended on each other and were created at the same time and alternately. However, the main process of three steps was a more linear process. When Step 1 was completed, the defined network layers were saved to a computer disk and would remain unchanged during Step 2 and 3, unless absolutely necessary. During all research steps, I would regularly focus on the thesis writing process.

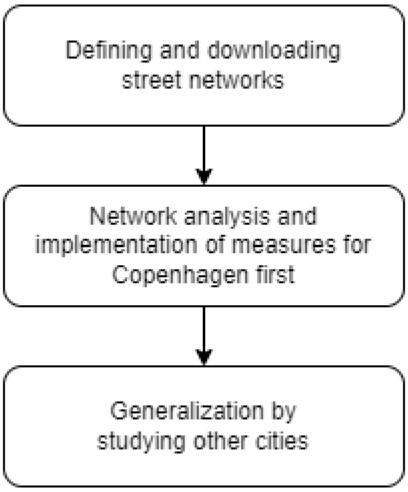


Figure 3: Three main steps of the research approach

1.7 Research feasibility/limitations

While the first part of this research focused on Copenhagen, the final outcome will be a more general way of measuring and comparing different urban bicycle networks. Doing this makes it possible to make steps towards the monitoring and evaluation of such networks in more cities over longer periods of time in an efficient way.

In this thesis, the bicycle networks of only four (4) cities will be analyzed and compared: three in Europe, one in Northern America. Reasons to limit this research to cities in the western world were the availability of data and the more or less comparable economical setting. For example, in this part of the world the debate about making cities more livable by limiting car traffic is roughly comparable, which makes the focus on bicycle networks relevant for each of these cities.

Also, the choice for this limited number of cities was practically necessary because mastering the data and developing and testing relevant measures in itself took already quite some time. Also, this number of cities appears to be enough to present quite rich results. For every city, I constructed 6 different subnetworks in 10 consecutive years. These 240 networks and 200 measurements of bicycle friendliness not only took quite some computer time to calculate. The results also give a nice basis for interpretation and for discussing the feasibility of the measures developed.

When measures like those presented here (with possibly some adjustments) are recognized as relevant and adopted for further use, it will not be difficult to roll them out for many more cities. But in this thesis, mere numbers are important. It is the proof of concept that counts here.

There are some more limitations to my research that I have to mention. First, the time span of the analyses in this thesis is limited to 10 years. This is caused by a license change to Open Database, which made it difficult for me to gather data from before September 12th (OSM Blog, 2012). For my goals, ten years are enough. For further research, access to data of a longer time period can be relevant. In that case, the reliability and completeness of these older data has to be still tested.

Data reliability is already sometimes an issue in recent OSM-data. As explained by the creator of OSMnx, Geoff Boeing, it can be tough to determine whether changes in these data are actual real world changes in infrastructure, or simply updates of digitalization. In most cases, a look at network details can give an answer to this type of question. In the data for the city of Copenhagen, I did not encounter this type of problem too often as this city has known an above average coverage in OSM for the last decade. But still, when interpreting results, I always kept an eye on the possibility of disturbing data updates.

My focus on developing general measures for bicycle friendliness on the ‘macro’-level of city centers or complete cities has the advantages that small data disturbances will be leveled out. But this also brings limitations: the results will not be to detailed enough to pinpoint specific bottlenecks or breakthroughs on a small scale street level.

In the discussion Chapter and conclusions Chapter I will elaborate more on what lessons can be learned from my research effort, the possibility to generalize the results to cities in other continents and the adjustments that can make this type of measurements even more relevant for urban planners.

2. Theoretical framework

2.1 Chapter intro

The theoretical framework is meant to provide background and justification for the concepts and methodology of this study. There are several existing studies that have specifically combined network science with bicycle infrastructure analysis, which I think should be noted first. These provide a starting point of my theoretical framework, even when not following the same approaches. My thesis is meant to build on this existing knowledge. After the review of existing studies with similarities, this chapter focuses on theories and studies relevant to my thesis in the following main categories: 1) bicycle friendliness, 2) Network science, 3) OpenStreetMap.

2.2 Existing comparable studies

A relevant existing study that combined network science and bicycle infrastructure analysis is that of Carstensen et al. (2015), who studied the spatio-temporal development of Copenhagen's bicycle infrastructure. It especially provides a starting point of my framework as it is also about Copenhagen. The main difference is the time period studied which is 1912-2013. As my thesis focuses on Copenhagen's period of 2013-2021, it can be seen as a temporal extension of the work of Carstensen et al. (2015), but using different analysis methods and new possibilities of data collection via OpenStreetMap. Carstensen et al. (2015) identified, after studying historical maps and the municipality's own data, four distinct periods in Copenhagen in which bicycle infrastructure was constructed. These four periods mentioned by Carstensen et al. (2015) are as follows:

- First cycling city (1910s to 1940s)
- Car city (1950 to 1960s)
- Liveable city (1970s to 1990s)
- Liveable cycling city (1990s to 2010)

The development of Copenhagen's bicycle network of 1912 until 2013 as studied by Carstensen et al. (2015), is shown in Figure 4. In their research area of Copenhagen they made the distinction between the inner districts and the Outer districts. Carstensen et al (2015) mention that the expansion of bicycle infrastructure first happened mainly along outbound radial roads connecting the city with the more natural areas. Over the years a more fine-meshed network of bicycle infrastructure has emerged. Carstensen et al. (2015) also mention the relation between the development of bicycle infrastructure and changing transport cultures. The relevance of the study of Carstensen et al. (2015) for my own research, is the suggestion that the overall context and history of each city should not be neglected, especially when comparing different cities.

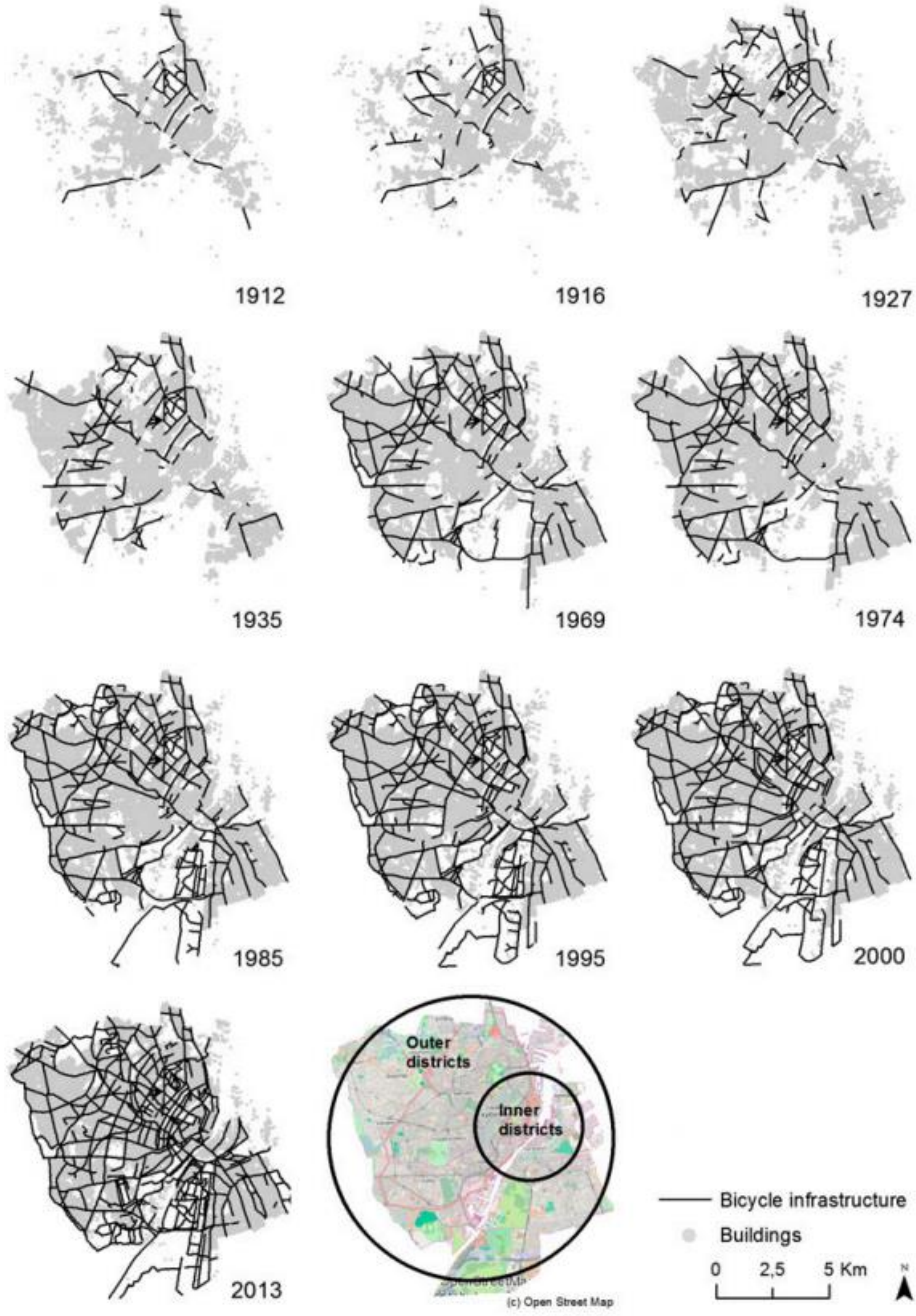


Figure 4: The spatial development of bicycle infrastructure in Copenhagen from 1912 until 2013. Source: Carstensen et al. (2015).

A study that focused on studying bicycle networks using OSM data, but with a different goal, has been performed by Ferster et al. (2020). Their goal was to compare the available OSM data to open data provided by cities. They studied the bicycle network data of six Canadian cities: Montreal, Toronto, Vancouver, Halifax, Kelowna and Victoria. What's interesting is that Ferster et al. (2020) re-coded the bicycle network into new categories during their data acquisition, for example separate cycle tracks and on-street bicycle lanes. This re-coding was based on route preference studies performed by Teschke et al. (2012)and on corresponding OSM tags. The re-coding of bicycle infrastructure by Ferster et al. (2020) resulted in five categories shown in Table 1. The queries they used to get the data are in ArcGIS format (not shown in Table 1), which is not used in my research but still provides insight in how the categorization can be done.

New category	Description	Generalized OSM tag(s)*
Cycle track	A paved facility alongside a city street, separated by a curb or barrier, intended for bicycle-only use.	Highway = cycleway Highway = * + cycleway = track
On-street bicycle lane	A painted bike lane on the street, with or without parked cars.	Highway = * cycleway = lane
Path (bicycle lane or multi-use)	An off-street paved path, either bicycle only or shared with pedestrians	Highway = path + bicycle = yes/designated Highway = footway + bicycle = yes Highway = service (or unclassified) + bicycle = yes/designated + motor_vehicle = no
Local street bikeway	A designated bicycle route with signs, and possibly cyclist activated traffic signals/traffic calming	Cycleway = shared Cycleway = designated
Ambiguous infrastructure	Uncertain	Highway = cycleway No other tags

Table 1: infrastructure types and related OSM tags (Ferster et al., 2020) *Tags have variations and additional descriptor tags.

From the research of Ferster et al. (2020) it also becomes prevalent that different cities use different terminology in their municipal data, especially between English and French speaking cities. The OSM data is seemingly more harmonized, but also facilitates a certain degree of freedom in digitalization which can cause regional and local differences. According to the OSM beginners guide (OpenStreetMap, 2021d), tagging rules and conventions change over time. More relevant background information and theories surrounding OSM are given at the end of this theoretical framework.

With the idea to quantify bicycle network connectivity, Abad & van der Meer (2018) studied the bicycle network of Lisbon for which they used OSM data. They categorized the street segments into two possible classes: low stress and high stress. These 'subnetworks' are based on conditions comparable to those used by Ferster et al. (2020) shown in Table 1, but the five variables used by Abad & van der Meer (2018) are: maximum speed, whether it is a residential area, number of lanes, the slope, and whether the edge has a bicycle tag according to the OSM data. Like the tags used by Ferster et al. (2020), this edge information is all available from OSM.

2.3 Bicycle friendliness

This section reviews articles and studies regarding bicycle use, friendliness and history. These are valuable to determine relevant subnetworks and also for further analysis. In the first place, this background knowledge provides more background for defining meaningful subnetworks of the street network. This segment will only focus on aspects of bicycle friendliness that are related to the bicycle infrastructure, as opposed to for example bicycle ergonomics.

2.3.1 Safety

One way to grasp which infrastructure is bicycle friendly, would be to look at the injury risks of different route types. The earlier mentioned study of Teschke et al. (2012) did this with the help from local hospitals by interviewing 690 injured cyclists in Toronto and Vancouver and tracing in what situation the accidents happened. They compared 14 different route types based on this injury data. Teschke et al. (2012) concluded that the risks of injury are lower when there is bicycle-specific infrastructure along busy streets and they are also lower on quiet, smaller streets. Their resulting matrix shows the injury odds per route type and can be seen as an indication for the bicycle friendliness of certain infrastructure. For example, bicycle lanes and especially bicycle tracks have lower injury odds and can be regarded to be more bicycle friendly.

2.3.2 Cyclist behavior

There has been an increasing amount of studies using GPS data from cyclists to analyze cyclists' behavior and their preferences while using the bicycle network. These preferences and route choice could be another indication of the bicycle friendliness of certain infrastructure. A good example of such a GPS behavior study has been performed in Copenhagen by Skov-Petersen et al., (2018). Their objective was to determine the extent to which human navigation is affected by their direct surroundings and infrastructure, but also their established knowledge about the area. Some of their most relevant conclusions about their were as follows (Skov-Petersen et al., 2018):

- The route length and the number of turns on a given route are associated with disutility. So, in general cyclists prefer less of both.
- Right turns are preferred to left turns, as this does not involve crossing the road.
- Cyclists prefer routes with a high number of traffic lights, which represents safer road crossing'. (Skov-Petersen et al. (2018) acknowledge that traffic lights might be installed more often along popular routes, making the parameter not very meaningful)
- Routes with bicycle specific infrastructure, such as curbed tracks and segregated bikeways, were significantly preferred.

Menghini et al. (2010) conducted a similar GPS study as Skov-Petersen et al. (2018) and claims to be the first of its kind. Their route choice model already gave several relevant conclusions, which were later confirmed by Skov-Petersen et al., (2018). In terms of bicycle friendliness, the results of Menghini et al. (2010) revealed that the route's length is in general the most important factor for cyclists' route choices. Bicycle specific infrastructure also had a considerable impact on route choice, but less substantial than the route's length. These conclusions were made using elasticity formulas and a multinomial logic model.

In the context of my study area of Copenhagen (and other cities), these conclusions are relevant because a bicycle network can change and improve in different ways. Shortening the average route length might be of a higher priority than 'simply' increasing bicycle specific infrastructure across the existing network. Copenhagen's bicycle strategy (City of Copenhagen, 2011) involves the construction of several new bridges and shortcuts, which are also bicycle specific infrastructure. The above-mentioned conclusions for bicycle friendliness will are taken into account in my network analysis, as they indicate the importance of the 'shortest path'. Network measures like the shortest path will be explained in chapter 2.4.

2.4 Network science

This section contains theory behind network science, relevant to this thesis. It is assumed that most readers of this thesis will have a basic understanding of networks. The street data I am working with consists of nodes and edges (ways) which form the networks. The origins of network science go back hundreds of years, but over the last few decades it has become more prevalent and advanced. It has mainly become more relevant because of its applications in the digital world (Najera, 2020). Network science is concerned with the study of networks, and can be seen as interdisciplinary as it uses techniques developed in disciplines like mathematics statistics, physics and computer science (Börner et al., 2007).

Also, I have made the conceptual division between 'abstract networks' and 'real networks'. With abstract networks I mean nodes, edges and network measures like centrality. Concepts like these are what's usually understood as network science, and are treated in this section. However, also relevant to my research is the interpretation of the networks in the geographical context. Looking at these real networks is about finding out what changes in the network could in reality mean to cyclists. So, real networks are abstract networks with a real world meaning attached to it. Concepts like these, which combines several factors like cyclist behavior and infrastructure of Copenhagen and other cities, are treated in the Chapter Methods. The reason for this is that the combining of different concepts and testing these with the available data is part of the methodology. This Section (2.4 Network science) focuses more on abstract network science and separate theories.

2.4.1 Geographical networks

Network science has also become increasingly applicable in geography because of data and software availability. Geographical networks possess the special attribute of space. According to Barthelemy (2017), many measures developed for complex networks are not useful when space is relevant and therefore he presented new interesting measures for street patterns. While geographical networks can be analyzed using non-spatial measures, for example degree centrality (Boeing, 2018), it can be argued that the spatial attribute should not be entirely ignored. Mocnik (2018a) found the polynomial volume law, which hypothesizes that network volume and spatial volume scale in the same way, showing that the influence of space on networks often seems to be very stable. In the same manner he also found the influence of space on street networks to be seemingly stable (Mocnik, 2018a),, meaning that that dimension could serve as an invariant. Finding what measures, either well

As geographical networks, for example street networks, represent features on the surface of the earth's globe, they are also subject to a projection when visualized. This is relevant to keep in mind, but does not have any implications for the analysis. Geographical networks can be planar or non-planar, meaning they are embedded in a two-dimensional plane (Huisman & de By, 2009). While infrastructure networks are in reality not necessarily two-dimensional, I will keep it limited to planar networks.

2.4.2 Relevant measures

Finding what network measures, either well-known or lesser-known, are relevant to my case and indicative of bicycle friendliness will be one of the outcomes of my research. Here, a few of the most promising network measures are explained. According

One of the most common network measures is centrality and comes in different forms, of which the most common three are degree centrality, closeness centrality and betweenness centrality (Najera, 2020). Betweenness centrality shows which nodes act as 'bridges' between nodes in the network, by counting which nodes are passed the most after shortest path calculations between all node pairs (Najera, 2020). As my case study of Copenhagen involves actual bridges, I expect betweenness centrality to be one of the most relevant measures for my thesis. This expectation is strengthened by Demšar et al. (2007) who mentioned that betweenness centrality had been their most promising measure for analyzing Helsinki's street network.

An example of showing network measures develop in time is that of Barthelemy et al. (2013), who showed the time evolution of the spatial distribution of the betweenness centrality for Paris as shown in Figure 5. Using similar methods but trying different existing measures and new combinations of measures, I am looking for significant changes in Copenhagen's recent network development.

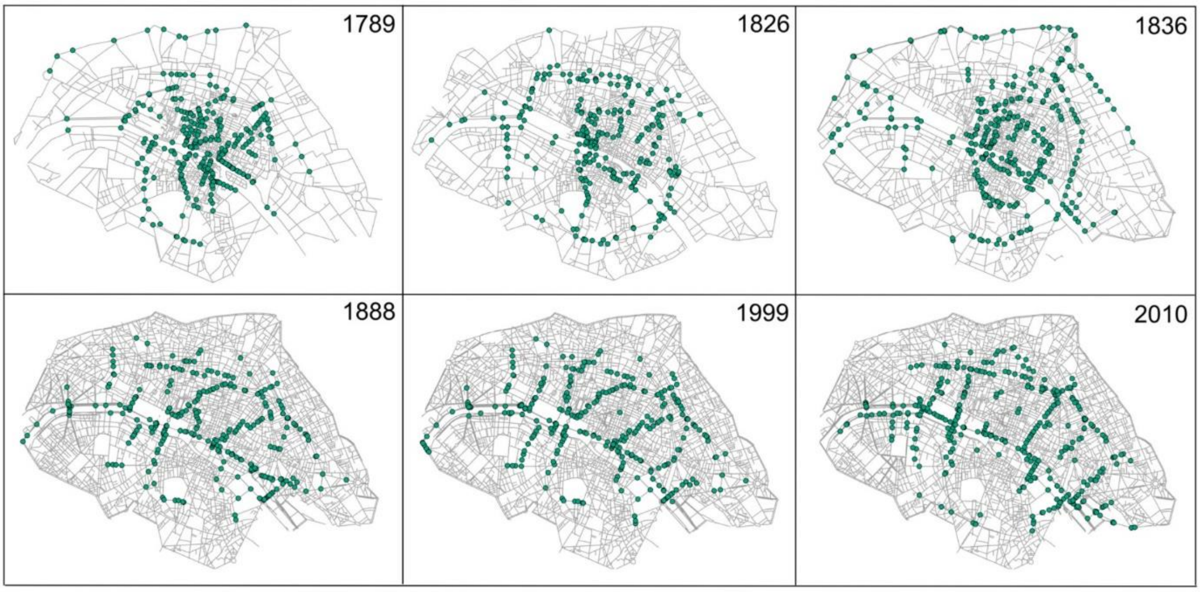


Figure 5: Change of spatial distribution of betweenness centrality for Paris. (Barthelemy et al., 2013)

Another important category of measures in street network analysis, are optimal path finding techniques. These are used to find the least-cost path between two nodes in a network (Huisman & de By, 2009). This is done based on 'costs', also called 'weights', attached as a variable to each edge. In many cases, the cost in geographical networks is defined as the distance, but can also be something different. Shortest path algorithms, like the Dijkstra algorithm, function to find the path with the least cost between two nodes (Dijkstra, 1959). While that's not directly my goal, the Dijkstra algorithm as well as many other shortest path algorithms, can be used in different ways to analyze the efficiency of a network.

Connectivity

A final measure to mention here is connectivity, which defines whether a graph is connected or disconnected (Tutorialspoint, 2021). Different types of connectivity measures exist and are available in the network analysis software NetworkX. For example, 'node connectivity' is equal to the minimum number of nodes that must be removed to disconnect the graph (NetworkX, 2021). In other words, to split the network in two separate networks with no connection between them. A network that requires many nodes to be removed before being disconnected, is considered to have high connectivity. Connectivity is mainly used in networks other than street networks, for example communication networks. New connectivity measures have been proposed by Y. Li et al. (2020), called the PCNL and the SPCNL which uses shortest paths between a high amount of node pairs. While these measures do not seem very applicable to street networks, the method of calculating shortest paths between a high amount of random node pairs could give insightful results in the network's connectivity or robustness.

2.4.3 Missing links

Relevant in the analysis of infrastructure and bicycle networks, is the search for missing links. Where could or should an extra road or bridge be constructed to improve the network? Research regarding the missing link topic has also been called 'link prediction' (L. Li et al., 2018) and for quite some time there have been methods developed to do this. Li et al. (2018) have developed a new version of a method called 'the technique for order performance by similarity to ideal solution' (TOPSIS) which is based on different similarity measures.

2.5 OpenStreetMap

As a final section of the theoretical framework, it is relevant to briefly mention how OpenStreetMap (OSM) works because it is the main data source used for this thesis. OSM is the largest open crowd-sourced mapping project on the internet and founded by Steve Coast in 2004 (Lardinois, 2014). Every day thousands of people add information to OSM, comparable to Wikipedia, and the online map is accessible on the internet for free at any time (LearnOSM, 2021). OSM and its data are used by a large variety of users, like researchers, governments and large companies like Facebook and Uber (OpenStreetMap, 2021d).

2.5.1 How OSM works

OSM has a large international community and anyone with a computer and access to the internet can create an account and add data. The data quality is said to be 'good' and often as good or better as what is commercially available (OpenStreetMap, 2021d). As a matter of fact, the map is constantly being improved in all regions of the world and is increasingly being used by governments and other large organizations.

Users can make edits to the map in their web browser (among other methods) and then save these as changesets. The history of changesets is saved in the OSM data, so it is possible to see what changes users have made. It is also possible to use historical data, provided the right tools are used (OpenStreetMap, 2021d). OpenStreetMap has an active developer community itself, and has more organizations and projects using its data than ever. Figure 6 is a screenshot of a simple visualization of OSM changesets in real time (Westman, 2021), as about every few seconds a new changeset is made. Figure 6 also shows that, at least at the time of consult (11:00 at GMT +1), especially Europe has a high frequency of updates. It can be assumed that Copenhagen and other European cities have a relatively high level of data quality and detail in OSM.

The constant updating of OSM data has advantages but also drawbacks, depending on the research area and what the data is used for. Antoniou et al. (2016) analyzed the quality of OSM with a case study of toponym (names) evolution in Paris. They aimed to understand the behavior and fitness-for-purpose of the ever-changing OSM data. An important question that remained after the study of Antoniou et al. (2016) is that when changes are made to the map, are these real-life infrastructure changes or just data quality improvements? It is not always possible to prove the nature of data changes. For my thesis research I was already aware of this from an early stage, but still expect to find interesting results. This insecurity has to be taken into account in the results, conclusions and discussion.

Figure 6: Visualization of OSM changesets in real time (Westman, 2021)

2.5.2 Data structure of OSM

Data in OpenStreetMap is stored in a simple structure of which the main elements are nodes, ways (edges) and relations (OpenStreetMap, 2021b). A node, having an id number and a pair of coordinates, represents a specific point on the earths surface. These can used to define point features, for example a statue, but are also used to define the shape of ways. A way is an ordered list of nodes, which defines a polyline to represent linear features such as roads. Ways are also used to represent boundaries of areas, to represent buildings and other polygon shaped features. The relation element can be used in different ways to document relationships between different data elements (nodes, ways, other relations), for example to group them into a certain type of infrastructure or be part of a major numbered road.

Another relevant part of the data structure is the usage of ‘tags’. Tags provide information about the particular element (node, way, relation) or changeset to which they are attached. Tags consist of a key and value(s), separated by an equals (=) sign. For example to identify roads, the main used key is ‘highway’ which can have the value ‘residential’ if it is a generic road in a residential area. Another example could be ‘highway=cycleway’ to indicate a separate cycle way. ‘Cycleway=*’ can also be added to a ‘highway=*’ to indicate cycling infrastructure that’s part of the car road, like cycling lanes. In that case the way could have the tags ‘highway=residential’, ‘cycleway=lane’ for a residential road with bicycle lanes on both sides of the road (OpenStreetMap, 2021c). From now on in this thesis, the word 'edge' will be used instead of the word 'way', as it is more commonly used and not OSM-specific.

3. Methods

3.1 Chapter intro

This Chapter explains the methods used for this research in a structured manner. In practice, the process was not always as straight-forward as I needed to learn new skills and had to go ‘back and forth’ several times. Still, this chapter contains the used methodology in a logical order and aims to make the study more reproducible. The methodology is built on the theoretical framework, but also involves new angles and newly created methods.

The structure of the methods chapter follows the earlier mentioned three steps, corresponding to the three Research Questions. First, OSMnx and other Python packages are used to define and download the right subnetworks of the right areas and period. Then, Copenhagen’s bicycle friendliness is explored and network measures are applied to the networks. Finally, the results of different cities are compared which aims to generalize the outcomes of measures and provides context. The specific methods required to answer the Research Questions are explained in the sections 3.3, 3.4 and 3.5. The Chapter begins a description of the GIS and Python workflow of this research.

3.2 GIS workflow

As this thesis deals with geospatial data, the workflow regarding GIS was an important part of the research. The core GIS software of the research is Python with several selected modules and packages. Figure 7 on the next page depicts the general workflow regarding data, software, GIS and generating results. Setting up the GIS environments to work in, was done using the Anaconda distribution which already includes many popular packages by default. According to Boeing (2021), OSMnx is an efficient way to interact with OpenStreetMap’s API. For OSMnx to work, additional packages had to be installed at the moment of creation of the environment instead of afterwards. The Python environment that was finally created and used for all steps in the progress, included: OSMnx, NetworkX, NetworKit, Spyder, GeoPandas, Descartes, Cartopy and their dependencies.

After having decided on the cities and which network extents were adequate, the networks were downloaded using specific filters for bicycle and car infrastructure. The historical data of ten years were acquired by changing the OSMnx (Overpass) settings and then downloading the data and saving the networks as a GraphML file for further use.

Initial analysis was done by checking plotted network graphs for differences and computing basic statistics like amount of edges and total length of the networks. As ideas of relevant measures arose, these were implemented into Python and tested on Copenhagen. The measures were optimized and balanced in terms of runtime and robustness of results. Next, a selection of promising measures was tested on a selection of other cities. The scripts included sections to write the results to text files.

After analyzing the results outside of GIS and Python, I went back to Python to create final and extra visualizations to bring across certain findings. To conclude, all relevant Python scripts and results were organized and saved for handing in.

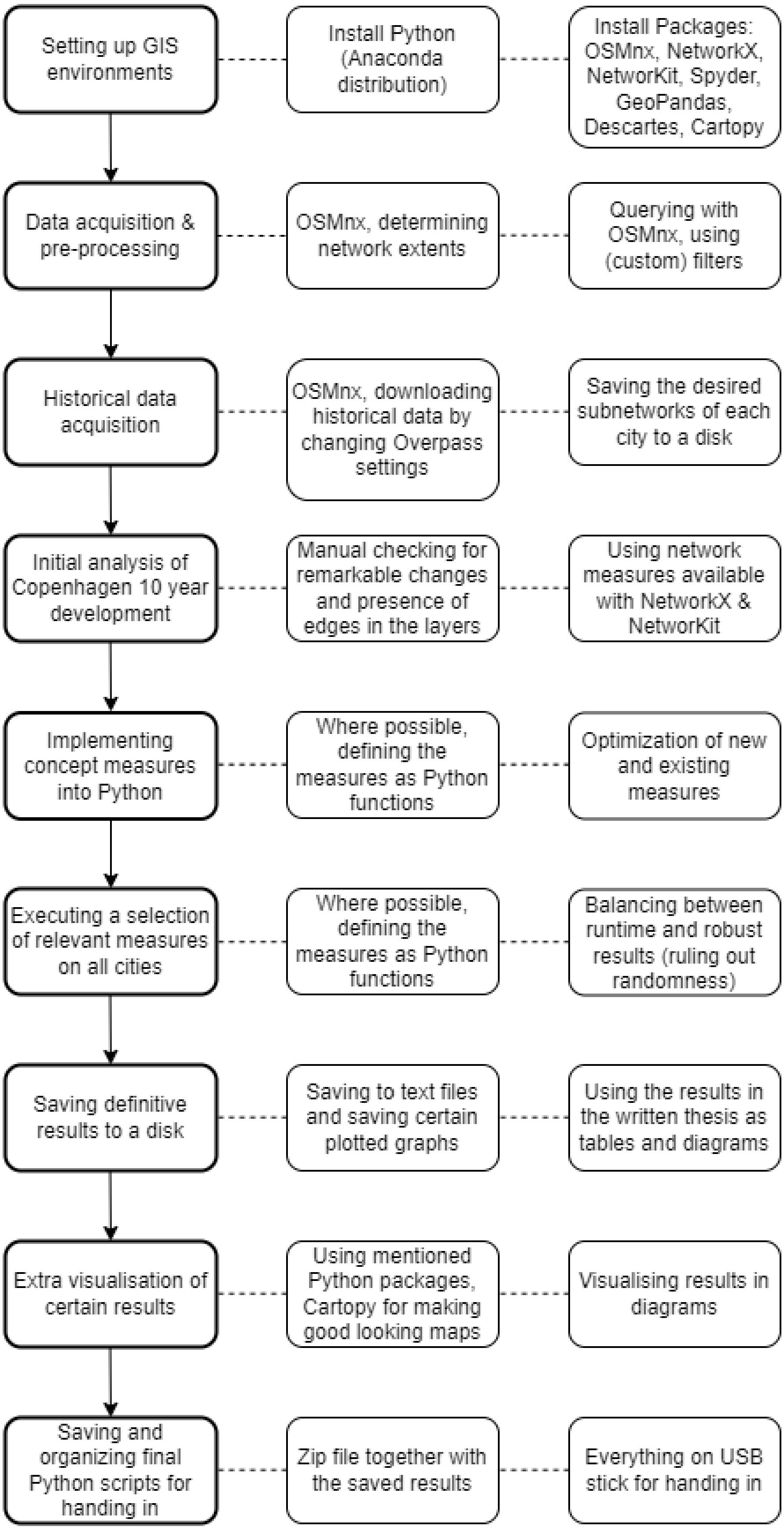


Figure 7: General Python and GIS workflow

3.3 Methods RQ 1: defining meaningful subnetworks

This section contains the methods used in regard to Research Question 1. The aim was to define meaningful (sub)networks for the bicycle and car, and to extract these for a period of 10 years using OSMnx. The choice of research areas plays an important role in the outcome of this study. The selection of cities can have an impact on the results, which will be explained in paragraph 3.5: Research Question 3. The way each city's borders are defined also plays a role, which will be explained first.

3.3.1 Network extents

Which extent of the city is used can have an impact on most network measures. Especially when comparing different cities this had to be done in a fair way. This section provides the considered options, arguments and choices that were made regarding the research areas. In the case of Copenhagen's development, the newly built bridges were relevant to be included in the network analysis. Using OSMnx, street networks of a place can be queried in different ways, using shapes or administrative borders. Also, different methods are more suitable for different purposes.

In order to perform more advanced analysis and to focus on relevant parts of the city, I focused on demarcating the inner city. The inner city networks would for example be used to compare to the surrounding neighborhoods, as well as to compare city centers of different cities to each other. In order to find the most adequate method, I tried the following methods of defining the inner city which are shown in Figure 8:

- Disk-shaped network (from a central point)
- Isochrone (from a central point)
- Administrative/official borders

Figure 8: Different definitions of the inner city: disk-shaped, isochrone, and administrative border. (basemap source: OpenStreetMap)

Querying the networks in the shape of a disk, was the first tried method. The inspiration for this was the earlier study of Carstensen et al. (2015), who used circles to represent the inner and outer districts of Copenhagen, as shown in Figure 4 in the theoretical framework. Disk-shaped networks allow to crop the network extent as desired. My main reason for using disk-shaped networks would be that they should give a more level playing field when comparing different cities. Cities have varying shapes and sizes in their administrative borders which often do not necessarily represent the area of the actual (inner) city, which would have an effect on the results. A rectangle or box-shaped network is a more standard method for downloading geographical data and maps, but would result in the four corners being further away from the center, impacting the results for no good reason. Therefore I made the more neutral disk-shaped networks as shown on the left in Figure 8.

However, the disadvantage of a disk-shaped network is that while it is neutral, it dismisses unique geographical characteristics of the city. Copenhagen for example being next to water results in a large portion of the disk not containing any edges. So I came to the conclusion that in practice cities are hard to define in standardized shapes like the circle. Another disadvantage of the disk-shaped method is that the center has to be chosen. I have not found an adequate method for choosing this center, other than arbitrarily basing it on the structure and central landmarks of the city. This makes the disk-shaped network not as unbiased as it might seem at first sight.

For an inner city demarcation method preserving the unique characteristics of the city, I have looked into the possibilities of isochrone methods. An illustration of this is shown in the middle of Figure 8. In the case of my research this means I would choose one bicycle riding distance or riding time and use this to calculate shortest routes in all directions from a central point. The result would be a polygon indicating the area reached within riding for example 3 km or 10 minutes.

Being an interesting measure by itself or in combination with other measures, the isochrone technique is mentioned as one of the relevant network measures in paragraph 3.5. Still, this method has one disadvantage which it shares with the disk-shaped networks: the central point has to be chosen in a rather arbitrary manner. For this reason, I decided to not use the isochrone method as one of the main tools for my network analyses of cities.

I found a more common sense approach which is both feasible and relevant in the context of policies for cycling mobility. In this approach the administrative borders of the city and of the 'official' inner city are taken as starting point of analysis. In the case of Copenhagen, the whole city can be defined by combining the municipalities of Copenhagen and Frederiksberg, where the latter is a separate smaller municipality within Copenhagen. A similar method is used for demarcation of the inner city, as shown on the right of Figure 8.

For both Copenhagen as well as in other cities, the area officially named 'inner city' takes into account the unique geography and does not rely on arbitrarily choosing a central point. However, this approach is not suitable for all cities, because some cities don't have a well-defined 'inner city' or the area is too small or too large for analysis. So, choosing this method brings some limitations in which cities can be included in the analysis.

I downloaded the polygons for the administrative inner cities from government websites sources, and used these to define the borders of my networks. For Duisburg, it sufficed to use the OSMnx function graph_from_place('Duisburg-Mitte', network_type='bike', simplify=True) but this does not work for every city as the desired boundaries are not always defined in OpenStreetMap.

3.3.2 Filtering bicycle infrastructure

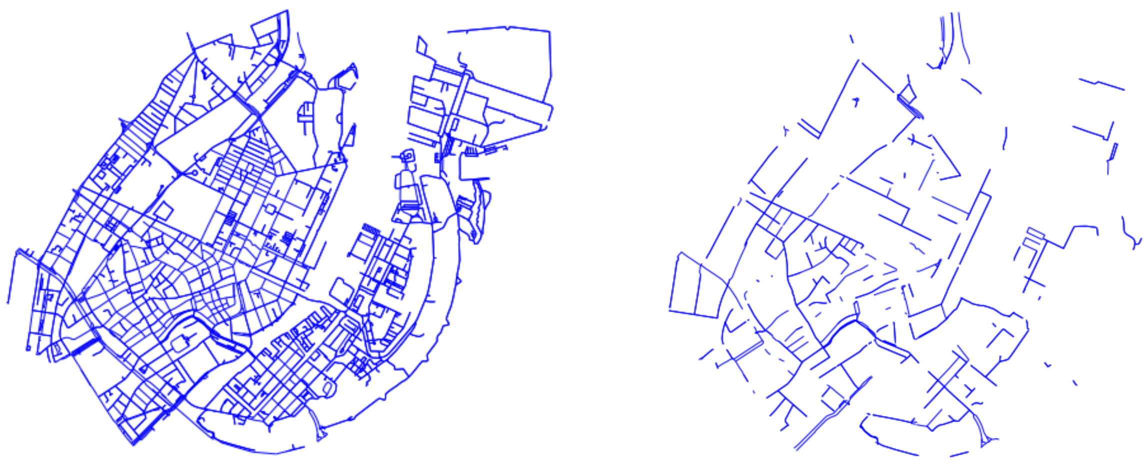
Next to bicycle infrastructure, the complete network data available from OSM include regular streets, car highways, and foot paths. In order to get meaningful networks for analysis, the data had to be filtered. This could be done based on tags (keys and values) in the OSM data. There are different tags that can be related to bicycle infrastructure. For different subnetworks and measures, adequately filtered data had to be used. First, I will explain an important distinction between two types of bicycle network. These are:

- **Bicyclable infrastructure**: any road or path where cycling is a legal and realistic option. This ranges from roads that also allow cars, to specific bicycle infrastructure.
- **Bicycle specific infrastructure**: these are cycling lanes, cycling paths, cycling bridges and other infrastructure specifically meant for cyclists.

Considering which of these two types of subnetworks to use as a basis for my analyses, both have their advantages and disadvantages. Intuitively, the second (bicycle specific) seemed the most interesting as it can be indicative of development of dedicated bicycle infrastructure over the years. However, downloading these data appeared to result in rather incomplete and fragmented networks.

In principle, this fragmentation could be solved when allowing certain non-specific pieces of road as connection between dedicated cycling roads. But this would make network analyses more complicated. Also, manual checks demonstrated that fragmentation varied over the years. This was partially caused by changes in data quality. Whether certain streets were marked as bicycle specific differed between years.

Because of this, I concluded that the bicycle specific infrastructure is an interesting network but not feasible for advanced network measures. For those, I chose to focus on the more general 'bicyclable infrastructure'. This provided more reliable data as it uses a more standard filtering method. Any edge that includes the OSM-tag 'non bicycle = no' is eligible for inclusion. The resulting subnetwork includes any road or path suitable for cycling. One can imagine this network gives less guarantees for cycling safety, but at least it is mostly complete and therefore more apt for analysis and comparison. Both types of bicycle network are shown in Figure 9.



A. B.

Figure 9: A) The bicyclable infrastructure of Copenhagen's inner city as of 01-01-2022. B) The bicycle specific infrastructure of Copenhagen's inner city at the same moment in time. The scattered nature of this subnetwork, and data inconsistency, makes it unsuitable for advanced network measures but there are possibilities with more basic network measures.

The (simplified) Python script shown in Code Snippet 1 was used to download the bicyclable infrastructure using OSMnx. This uses a polygon named Indre By, Copenhagen's inner city as mentioned in paragraph 3.3.1, as the network's extent. The network data is downloaded with the OSMnx function graph_from_polygon, which has the parameter network_type. This can have the values 'walk', 'bike', 'drive', 'drive_service', 'all', or 'all_private'. In order to get the bicyclable infrastructure, the standard filter 'bike' turned out to be adequate. For cars, the service roads included in drive_service seemed irrelevant, so the regular ‘drive’ was chosen.

```
import osmnx as ox
import geopandas as gpd

filepath = "C:/Users/phili/Desktop/GIMA/Module 7/2022/B1.
Dataverzameling/bestanden/indre_by.geojson"
indre_by = gpd.read_file(filepath)
indre_by_polygon = indre_by.iloc[0]['geometry']
G = ox.graph_from_polygon(indre_by_polygon,
network_type='bike', simplify=True)

fig, ax = ox.plot_graph(G, bgcolor='w', node_color='k',
node_size=0, edge_color='b')
```

Code Snippet 1: Downloading bicyclable infrastructure.

In order to get the second type of bicycle network, the ‘bicycle specific infrastructure’, a custom filter had to be used. This required an understanding of the useful_tags in OSMnx, which is a settings parameter to define which tags have to be taken into account. The custom filter for bicycle specific infrastructure is shown in Code Snippet 2, which was based on a method suggested by OSMnx’ creator Geoff Boeing (Boeing, 2018), and works as follows. The useful tags are defined as all default tags plus the ‘cycleway’ tag. Then, the bike network is downloaded in the same way as the bicyclable network. For the resulting Graph G, ‘non cycleways’ are defined. These ‘non cycleways’ are all edges where the key is not ‘cycleway’, or where the value for ‘highway’ is not ‘cycleway’. Subsequently, these ‘non cycleways’ are removed from graph G. While for the bicyclable network a simplification step was included in the graph_from polygon, this had to be done separately for the bicycle specific network in order to have all data available during the filtering step. This final step was done using the OSMnx functions remove_isolated_nodes() and simplify_graph().

```
import osmnx as ox
import geopandas as gpd

useful_tags = ox.settings.useful_tags_way + ['cycleway']
ox.settings.useful_tags_way = useful_tags
filepath = "C:/Users/phili/Desktop/GIMA/Module 7/2022/B1.
Dataverzameling/bestanden/indre_by.geojson"
indre_by = gpd.read_file(filepath)
indre_by_polygon = indre_by.iloc[0]['geometry']
G = ox.graph_from_polygon(indre_by_polygon, network_type='bike',
simplify=False)
non_cycleways = [(u, v, k) for u, v, k, d in G.edges(keys=True,
data=True) if not ('cycleway' in d or d['highway']=='cycleway')]
G.remove_edges_from(non_cycleways)
G = ox.utils_graph.remove_isolated_nodes(G)
G = ox.simplify_graph(G)

fig, ax = ox.plot_graph(G, bgcolor='w', node_color='k', node_size=0,
edge_color='b')
```

Code Snippet 2: Downloading ‘bicycle specific infrastructure’ using a custom filter, based on a method suggested by Geoff Boeing (2018).

3.3.3 Acquiring the desired historical data

Because I wanted to study a period of ten years, the remaining step was to find ways to get historical data from OSM using OSMnx. There are different methods to acquire historical OSM data. I found success by changing the Overpass settings at the start of the script. For example in Code Snippet 3, the date of data acquisition is 01-01-2013. To download each subnetwork over a period of 10 years with 1 year intervals, the acquisition code (as explained in the previous paragraph) was run 10 times with the date changed a year.

```
ox.settings.overpass_settings =
'[out:json][timeout:180][date:"2013-01-01T00:00:00Z"]'
```

Code Snippet 3

With this method OSM data can be downloaded at the time-level of seconds, as far back as September 12th, 2012. Before this date it was not possible to download data because of license issues (OSM Blog, 2012). According to the OSMnx documentation, changing the data acquisition time in the overpass settings has to be done with caution.

Using the methods of this paragraph, the following subnetworks were acquired:
- A: bicyclable network ('bike') inner city.
- B: bicyclable network ('bike') entire city.
- C: car network ('drive') inner city.
- D: bicycle specific infrastructure (custom filter) inner city.
- E: car network ('drive') entire city.
- F: bicycle specific infrastructure (custom filter) entire city.

Downloading these networks for several cities and 10 years, results in having many files. I have downloaded the following networks:
- 4 cities
- 6 subnetworks (per city)
- 10 years (per subnetwork per city)

This resulted in a total of 240 network files in the extension GraphML which preserves the necessary properties. These files have been ordered as follows: CITY_SUBN_YEAR. For example, the bicycle specific infrastructure for Amsterdam's inner city for 2015 is saved in the file named AMS_D_2015.

3.4 Methods RQ2: Quantifying bicycle friendliness in Copenhagen

In order to find and create measures for bicycle friendliness, the main strategy was to define concept measures and try these to see if they change over the years for Copenhagen. This strategy is derived from the general consensus that Copenhagen's bicycle network has improved significantly over the past ten years. This paragraph contains an overview and explanation of the network measures of which some are existing and some are new, or a combination of both.

3.4.1 Overview of measures

As many of my network measures did not have existing names yet, mentioning them throughout this thesis would make it unclear which ones I am referring to. For this reason I have created an overview of measures shown in Table 2 on the nest page, which summarizes all measures described in this chapter. Each measure has been given a code name, mu_1, mu_2, mu_3, etcetera, to easily mention them throughout the rest of the thesis. These code names are also used in the results. Not shown in this table is the fact that most measures can be applied to different subnetworks/parts/years of different cities, resulting in a high amount of comparisons.

Category: type of measure	**Code name and short description of measure**	**The resulting value unit**
Computing route lengths between random point pairs.	Mu_1: bicycle route length vs straight distance. Mu_2: bicycle route length vs car route length.	A ratio
Comparing total network lengths of 2 or more subnetworks.	Mu_3: Bicycle specific infrastructure divided by car network length (inner city). Mu_4: Bicycle specific infrastructure divided by car network length (entire city) Mu_5: Mu_3 divided by Mu_4 (inner/entire city)	A ratio
Bicycle friendliness weights added based on OSM tags and research. ('Spectrum of bicycle friendliness')	Mu_6: Weighted edges based on OSM tags and a spectrum of bicycle friendliness. Most other measures can be computed using these weighted edges.	Depends on the use case
Isochrone measures	Mu_7: Calculating the isochrone of cycling 15 minutes from a central point. Then calculating the area of this polygon. Mu_8: Calculating the isochrone of cycling 5 km from a central point. Then calculating the area of this polygon.	Area in m^2 Area in m^2
Existing advanced measures (adjusted to my use case)	Mu_9: Edge betweenness centrality. Mu_10: Edge connectivity.	Mu_7: Normalized value per individual node. Mu_8: Amount of indispensable edges.

Table 2: Overview of measures

3.4.2 Measures mu_1 and mu_2: random route lengths

The first category of measures is: to sample a high amount of random point pairs and then compute route lengths between these points. The shortest route length between each pair of points is calculated using the Dijkstra shortest path algorithm, by using the NetworkX function shortest_path_length. The idea is to calculate the length between the same point pairs for different subnetworks and then compare those. First, I will explain mu_1 and mu_2.

Mu_1: bicycle route length versus straight distance
The absolute route length between each pair is not very relevant in this measure, so I had to compare it to other distances. For that reason, mu_1 compares the bicycle route length to the straight distance (also named Euclidean distance, or 'as the crow flies'). Dividing bicycle route length by the straight distance, always gives a value higher than 1. This process is shown in Code Snippet 4 on the next page. The calculation is done for 10.000 random point pairs and then the average value of these 10.000 ratios is taken. This measure should indicate how directly one can navigate through the city by bike.

As each route is different, taking a high amount of point pairs minimizes the random variation of the results. The average value of the 10.000 ratios is what counts, which is reflected in the functions in my Python script, where 'avgratio' is returned. For further elimination of variation in the results, the whole function is executed 10 times. So the final results are the average of 10 iterations (10 X 10.000 pairs). This result is then printed to a text file.

These values on their own don't say a lot other than: the lower the value, the more direct the cycling routes are on average. The resulting value is mainly interesting as a relative value for the following comparisons:

- Comparing different years of the same network.
- Comparing different subnetworks of the same city.
- Comparing the values of different cities.
- Comparing the 'trends' of different cities; whether it increases or decreases over the years.

These comparisons can be done by displaying the series of values in a single diagram. The results of these comparisons are shown in the results chapter.

To get an idea of what values to expect when applying mu_1 and mu_2 to cities, I also wanted to compare them to an ideal scenario. An example of an almost ideal scenario would be a 'Manhattan grid'. In a perfect Manhattan grid I expect the value to be around 1.3, so the values of real cities are expected to not go below 1.3.

Mu_2: bicycle route length versus car route length
Mu_2 works similar to mu_1. Only this time, the bicycle distance between the two points is not divided by the straight distance, but by the car route length. The Dijkstra shortest path algorithm is used again to calculate the car route. As the bicycle network and the car network are two different subnetworks with their own nodes and edges, I have come up with a method to use the same point pairs for routes in these networks.

To link the two subnetworks, the coordinates of the initially selected bicycle network nodes are used to select the 'nearest nodes' within the car network. This is shown in Code Snippet 5 where osmnx function distance.nearest_nodes is used. This calculates the distance to the nearest node(s) and also selects the preferred node(s). These nodes of the car subnetwork are then used to calculate the shortest path.

After this, the bicycle distance (routedist) is divided by the car distance (routedist_drive). Similar to mu_1, the average value of a high amount of iterations is used to eliminate variation between different runs of the script. The measures mu_1 and mu_2 are defined as Python functions and can be executed multiple times, which is shown in the Results Chapter.

```
def mu_1(g):
    ratios = []
    for _ in range(0, 10000):
        d_node = choice(list(g.nodes()))
        o_node = choice(list(g.nodes()))
        if nx.has_path(g, o_node, d_node):
            routedist = nx.shortest_path_length(g, o_node, d_node,
weight='length')
            eucldist =
ox.distance.euclidean_dist_vec(g.nodes[o_node]['y'],
g.nodes[o_node]['x'], g.nodes[d_node]['y'], g.nodes[d_node]['x'])
            if eucldist >= 100:
                ratiodist = routedist / eucldist
                ratios.append(ratiodist)
    avgratio = sum(ratios) / len(ratios)
    return avgratio
```

Code Snippet 4: the function of mu_1

```
def mu_2(g, h):
    ratios = []
    for _ in range(0, 10000):
        d_node = choice(list(g.nodes()))
        o_node = choice(list(g.nodes()))
        if nx.has_path(g, o_node, d_node):
            routedist = nx.shortest_path_length(g, o_node, d_node,
weight='length')
            d_drive = ox.distance.nearest_nodes(h,
g.nodes[d_node]['x'], g.nodes[d_node]['y'], return_dist=False)
            o_drive = ox.distance.nearest_nodes(h,
g.nodes[o_node]['x'], g.nodes[o_node]['y'], return_dist=False)
            if nx.has_path(h, o_drive, d_drive):
                routedist_drive = nx.shortest_path_length(h,
o_drive, d_drive, weight='length')
                eucldist =
ox.distance.euclidean_dist_vec(g.nodes[o_node]['y'],
g.nodes[o_node]['x'], g.nodes[d_node]['y'], g.nodes[d_node]['x'])
                if eucldist >= 100:
                    if routedist_drive > 0:
                        ratiodist = routedist / routedist_drive
                        ratios.append(ratiodist)
    avgratio = sum(ratios) / len(ratios)
    return avgratio
```

Code Snippet 5: the function of mu_2

In a city where car and bicycle networks are identical, the value of this measure will be exactly 1. In reality, car and cycle traffic are often more or less separated. So we expect differences between the average bike and car distances. In cities with much bicycle specific infrastructure (or: many car free roads) this measure can be lower than 1. On the opposite, in cities which are less bicycle friendly I would expect values above one.

3.4.3 Measures mu_3, mu_4 and mu_5: total network lengths

Mu_3, mu_4 and mu_5 are based on taking different subnetworks and comparing their total edge length. Where the first set of measures (mu_1 and mu_2) takes a long runtime to compute, the following set of measures is computed much faster: 10 times 1 minute instead of 10 times 60 minutes per city. While being a bit less complex measures, these measures are capable of giving insightful results.

Mu_3 and mu_4: Bicycle specific infrastructure divided by car network length
For mu_3, the following subnetworks were used:

- Bicycle specific infrastructure of the inner city.
- Car network of the inner city.

For mu_4, the following subnetworks were used

- Bicycle specific infrastructure of the entire city.
- Car network of the entire city.

Both these measures do the same for different extents of the city. The subnetwork for bicycle specific infrastructure is downloaded using the custom filter as described at the end of paragraph 3.3.2. Then, the car network is downloaded using the standard OSMnx filter 'drive'. The subnetwork bicycle specific infrastructure does not lend itself for computing routes due to its scattered nature. However, a reliable network measure has been to compute the total length of the network.

The total edge length of the bicycle specific infrastructure of the inner city, is divided by the total edge length of the car network of the inner city. This results in a ratio between . A higher value means a higher relative amount of bicycle infrastructure, compared to road where cars are allowed. I

It can be expected that a bicycle friendly city, like Copenhagen, would have a higher mu_3 and mu_4 than the average city or a less bicycle friendly city. Also, as mu_3 uses the same network extents as mu_1 and mu_2, these can be compared to see whether they have similar trends. If the trend is similar, this would be a plus for all measures involved as they are more likely to point at bicycle friendliness. In case of different trends in the results of these measures, it is probable that one or more of the measures is less effective at indicating bicycle friendliness.

The (simplified) Python script shown in Code Snippet 6 loads the input subnetworks that had been saved to a disk earlier, and projects them using default settings to avoid anomalies. Then, statistics for each subnetwork are computed using the OSMnx function basic_stats(). This creates a Python library of different statistics, of which the edge_length_total can be saved to a variable. This edge_length_total of the different subnetworks is used to calculate mu_3 and mu_4, which are then saved to a text file.

```
G1 = ox.load_graphml('... D_2013.graphml',)
G1_projected = ox.project_graph(G1)
G2 = ox.load_graphml('... C_2013.graphml',)
G2_projected = ox.project_graph(G2)

G3 = ox.load_graphml('... F_2013.graphml',)
G3_projected = ox.project_graph(G3)
```

```
G4 = ox.load_graphml('... E_2013.graphml',)
G4_projected = ox.project_graph(G4)

stats_bike = ox.basic_stats(G1_projected)
length_bike = stats_bike['edge_length_total']
stats_car = ox.basic_stats(G2_projected)
length_car = stats_car['edge_length_total']
mu3 = length_bike/length_car

stats_bike_mu4 = ox.basic_stats(G3_projected)
length_bike_mu4 = stats_bike_mu4['edge_length_total']
stats_car_mu4 = ox.basic_stats(G4_projected)
length_car_mu4 = stats_car_mu4['edge_length_total']
mu4 = length_bike_mu4/length_car_mu4
```
Code Snippet 6

Mu_5: mu_3 divided by mu_4 (inner/entire city)

To the same Python script as mu_3 and mu_4, another measure is added, which is called mu_5. This is calculated by simply dividing mu_3 by mu_4 as shown in Code Snippet 7. This results in a ratio between the relative amount of bicycle specific infrastructure in the inner city to the entire city.

```
mu5 = mu3 / mu4
```
Code Snippet 7

My expectation was that a bicycle friendly city, especially aimed to keep cars out of the inner city, would have a relatively high amount of bicycle infrastructure in the inner city. A Dutch city known for its bicycle friendliness, Groningen, is an example of where it has been made intentionally difficult to navigate through the inner city by car.

Mu_5 on its own might not be a decisive indicator of bicycle friendliness, as cities with different amounts of bicycle specific infrastructure can end up with similar values. A city with very little bicycle specific infrastructure, can have the same mu_5 as a city with a lot of bicycle specific infrastructure, as long as the relative ratio between the inner city and the entire city are the same. However, I did think this measure could provide useful insights. Especially so when the three measures of this paragraph, mu_3, mu_4 and mu_5, are analyzed together.

3.4.4 Measure mu_6: spectrum of bicycle friendliness

In order to further analyze the quality of the bicycle network, edges can have 'weights' assigned to them. To determine the weights, I have created a 'spectrum of bicycle friendliness' based on literature and data availability. The intention was to apply this to the subnetwork 'bicyclable infrastructure'.

The process was to first look at what information is present in the OSM data that could be indicative of bicycle friendliness, followed by finding sources and literature to rank the different types of infrastructure. The infrastructure types have been given a value between 0 (not bicycle friendly) and 1 (bicycle friendly). There are also extra factors or attributes that can add to or detract from the given base value. So the weights for edges could be below 0 and above 1, which then had to be corrected as negative weights don't work. The resulting table, called the spectrum of bicycle friendliness, is given in Table 3.

The initial ranking was largely based on the research of Ferster et al. (2020) who also worked with OSM data and compared different road types on bicycle friendliness. After all these plusses and minuses have been taken into account, the weights can be assigned based on the available OSM tags. Then, sub-networks with a bicycle friendliness above or below certain values can be defined through filtering. The spectrum and its values are subject to change in further research.

Type	Bicycle friendliness	OSM tags
Cycle track	1	Highway=cycleway Bicycle=designated
Car road with separate cycling lane	0.8	Cycleway=track
Cycling lane, but only separated by (dotted) line	0.6	Cycleway=lane
No separate cycling lane. Road shared with cars	0.2	Cycleway=no Bicycle=yes
Extra attributes	Bicycle friendliness	OSM tags
Traffic lights present	+0.3	Highway=traffic_signals
Max speed ≤ 30 km/h	+0,3	Maxspeed=*
Surface	+0.2, +0, -0.2	Surface=*

Table 3: Spectrum of bicycle friendliness. Based on: the OSM wiki/bicycle (OpenStreetMap, 2021a), Ferster et al. (2020), Skov-Petersen et al. (2018) and Teschke et al. (2012).

Because of practical consequences and issues with linking the desired weights to the right edges, this measure is not fully carried out. If it would be carried out successfully, most of the other measures could be computed using these weighted networks. A variation on measure mu_1 or mu_2 would be interesting, with the most 'bicycle friendly' routes to be calculated, instead of the shortest path. I still found it relevant to include this in the methods section.

3.4.5 Measures mu_7, mu_8, mu_9 and mu_10: other advanced measures

Isochrone measures

Measures mu_7 and mu_8 would be based on isochrones, a concept which I have mentioned earlier mentioned for the definition of network extents in 3.3.1. The idea was to analyze the area that could be covered when riding a certain amount of minutes from a point of interest.

However, due to technical limitations and a limited amount of time these measures have not been carried out successfully. Still the idea of using the distance travelled within a certain amount of cycling time (mu_7; as well as a certain cycling distance, mu_8) from a point of interest, could be a good indicator of bicycle friendliness. Then, the larger the potentially covered area, the better.

I would expect these measures to give similar results as measure mu_1 (and other measures), as mu_7 and mu_8 would also reflect the directness of available bicycle routes. Therefore I decided to focus on the other measures.

Existing advanced measures
The idea was to implement existing advanced measures as an indicator of bicycle friendliness. For betweenness centrality, as mentioned in literature paragraph 2.4, the results would be different than the previous measures as there would not be a resulting single value. For each edge (or node) within the network, a betweenness centrality would be calculated. So it would be necessary to focus on one or several specific nodes to see how their betweenness centrality has changed over the years. An alternative result would be to create a visualization of betweenness centrality as done by Barthelemy et al. (2013), but the ever-changing nature of the subnetworks retrieved from OSM data, is not ideal for this. The same argument goes for the advanced measure ‘connectivity’, where the data required extensive editing in order to be usable to get clean results.

3.5 Methods RQ3: Generalizing outcomes to more cities

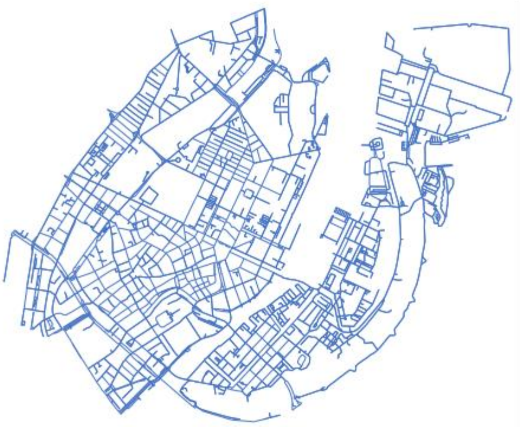
The third research question aims to take the lessons learned from Copenhagen’s network analysis, and analyze other cities using the newly found network measures related to bicycle friendliness. This is done in order to generalize the results found.

Regarding which other cities to analyze, the main question was whether I want cities comparable to Copenhagen or the opposite: varying from Copenhagen to study the suitability of bicycle friendliness measures with different aspects, for example hills. I have chosen for cities of more or less similar size as Copenhagen, all in western economies in temperate climate zones. In this way, I avoid unforeseen influences of difference in scale, climate, economy and culture. I expect this choice gives a higher chance of getting relevant comparisons and results.

Of course, still each city is different and brings complications when compared to others. The other cities than Copenhagen that I have chosen to analyze are:

- Amsterdam: another city well-known for its many cyclists for many decades.
- Duisburg: a more average European city in terms of cycling.
- Indianapolis: a more average American city in terms of cycling.

The measures for bicycle friendliness which I developed (see Methods RQ2) will be tested on these cities. The bicyclable networks of these cities are shown in Figure 10 on the next page which are downloaded using OSMnx. The cities will be compared in terms of these measures based on the infrastructure and OSM data. I will use my results to interpret the network analyses in the wider geographical context.


A)

B)

C)

D)

Figure 10: A) Copenhagen. B) Amsterdam. C) Duisburg. D) Indianapolis. The inner city bicyclable networks as of 01-01-2022. For illustration purposes, Indianapolis is from 01-01-2013 which is explained below.

At this stage I found one of the anomalies in data, this one being in the networks acquired from Indianapolis. The bicylable networks were downloaded how it was done for the other cities, using the filter ‘bike’. However, from 2014 onwards this also included car parking lots. Technically it is possible to bike on parking lots, but it was undesirable to include these in the data, as the sampling methods of mu_1 and mu_2 involve the use of nodes. This way, the random selections of nodes are skewed towards places with parking lots as these include many nodes. Figure 11 below shows the visible difference between parking lots. As I did not find a solution, and this anomaly did not seem to enormously impact the measures, I decided to use these subnetworks as I acquired them.

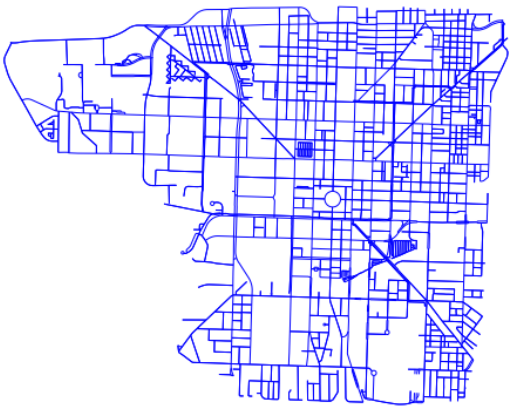
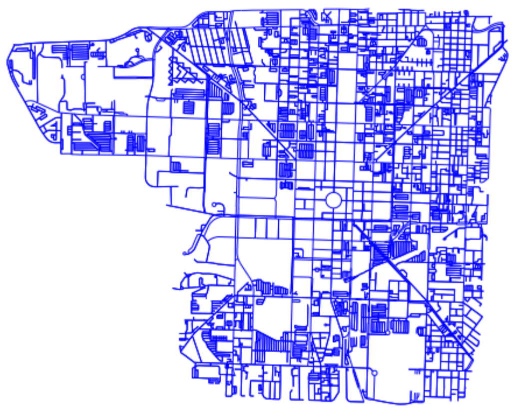

A)

B)

Figure 11: A) 2013. B) 2014. From 2014 onward, the Indianapolis bicyclable network data is cluttered with car parking lots.

4. Results

4.1 Chapter intro

My research focused on selecting and developing relevant and applicable measures for judging bicycle friendliness of mobility networks in cities. And as planned, these measures have been applied to four cities. In this chapter, I will present the results for different measures in the following way.

For each measure, I will usually first present the analysis of Copenhagen, then add the results for three other cities and compare the results (and trends) between the cities. This leads to a section with interpretation and remarks about the meaning and limitations of the results found. The results are aided by graphs and visual representations of the networks.

As mentioned earlier, I selected three different measures which could give the most meaningful and realistic results. These are the following:

- Mu_1: bicycle route length vs straight distance.
- Mu_2: bicycle route length vs car route length.
- Mu_3: inner city bicycle specific infrastructure vs car network length.
- Mu_4: entire city bicycle specific infrastructure vs car network length.
- Mu_5: mu_3 divided by mu_4 to compare the inner city to the entire city.

Next to covering the quantitative results of the selected measures, this Chapter will include interpretation of these results, aided with contextual information and visual analysis of certain networks. To keep this chapter uncluttered, not all results are mentioned here. The full numeric results of all selected measures for all cities for 10 years are given in the table in Appendix 2

4.2 Results of mu_1: bicycle route length vs Straight distance

The first measure, mu_1, compares the shortest bicycle routes to the straight distance between a set of random point pairs. To get stable results that reflect the average directness of bicycle routes in a city, I made runs with 10000 random point pairs and repeated this 10 times. First, I have applied this measure on the ten years of bicyclable network of the inner city of Copenhagen. The average values and standard deviation of 10 iterations are rounded to three decimals and shown in Table 4.

Bicyclable network, inner city CPH	Result mu_1	Standard deviation
2013	1,687	0,006
2014	1,688	0,007
2015	1,665	0,009
2016	1,667	0,008
2017	1,552	0,003
2018	1,555	0,004
2019	1,549	0,006
2020	1,525	0,003
2021	1,529	0,005
2022	1,533	0,004

Table 4: Results mu_1 for bicyclable network, inner city Copenhagen.

These results can be plotted as a line graph shown in Figure 12, where the value on the y-axis is the ratio between bicycle route length and the straight distance. At the start of the research period, 2013, the value is 1,687 which is quite far above the assumed ideal value of 1,3 in a imaginary Manhattan grid.
In these results for Copenhagen's inner city we see one year with a remarkable drop in this measure (2017) and two years with slight but notable drops (2015 and 2020). For all other years, the measure appears to be stable with variations of 0,06 at its most.

The drops of the value in three years are probably no coincidence. It appears possible to link them with real improvements in directness of bicycle routes. These improvements consist of several new (bicycle) bridges which have been built over the past 10 years. In the years I studied, the following bicycle bridges were constructed in Copenhagen:

- Proviantbroen, bicycle bridge (2014)
- Trangravsbroen, bicycle bridge (2014)
- Cykelslangen, bicycle bridge (2014)
- Cirkelbroen, bicycle bridge (2015)
- Inderhavnsbroen, bicycle bridge (2016)
- Lille Langebro, bicycle and walking bridge (2019)

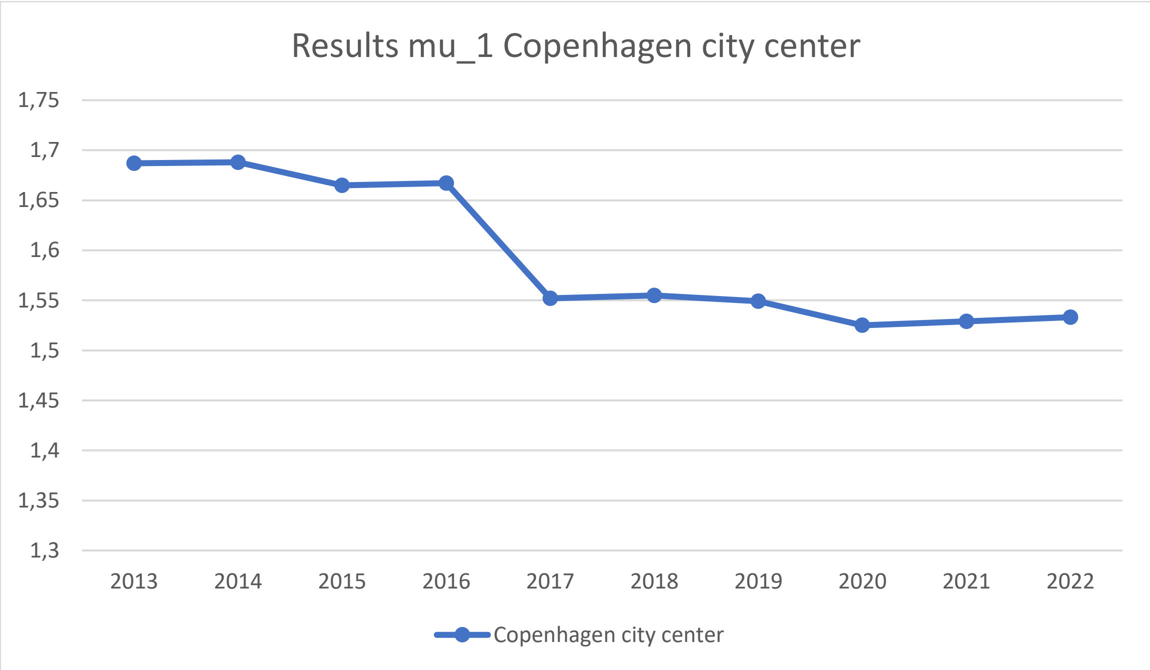


Figure 12: Results mu_1 Copenhagen city center

Figure 13: The bicyclable network of Copenhagen in 2013 and 2022. Indicated with a black arrow is the Inerhavnsbroen, which was completed in 2016.

By far the most significant drop in mu_1 value is measured in 2017, after the construction of the Inderhavnsbroen (the Inner Harbour Bridge) was completed. In Figure 13 this bridge is indicated with a black arrow. It makes sense that this bridge, connecting west and east, will cause many bicycle routes to be more direct and less of a detour.

Within Copenhagen, apart from comparing the values of different years, the values of different subnetworks can be compared. This will be done in the next paragraph (4.3), where mu_2 gives a comparison of bicycle and car networks.

Comparing different cities

The next step in regard to mu_1 is to compare the values of different cities with each other. First, the results are plotted in the graph of Figure 14. A comparison between the four chosen cities shows quite a variety of values and trends.

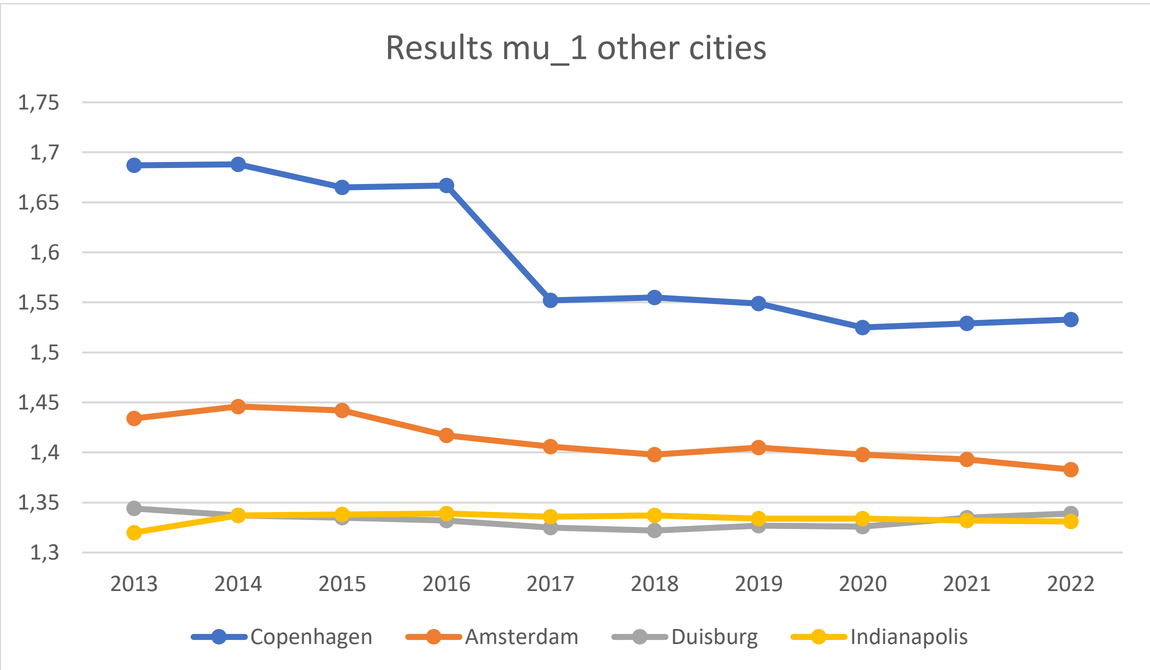


Figure 14: Results mu_1 other cities.

Copenhagen
Despite Copenhagen being considered a bicycle friendly city, it has the highest values or the longest 'detours' for bicycles compared with the straight distance. At first glance, this seems to suggest Copenhagen is less bicycle friendly then its reputation. But the unique geographical charactaristics of Copenhagen give a better explanation: a broad water canal runs through the middle of the research area. This forms a barrier which forces not only cyclists to make extra miles compared with the crow. This can be seen when bicycle and car distances are compared (see mu_2).

Also, one snapshot of the value of mu_1 does not tell the whole story. It can be more relevant to look at the *trend* of this measure. And as told before, this trend is positive in Copenhagen's inner city. This means that, within the city's physical limitations, there is notable improvement of traveling distance for cyclists.

Amsterdam
Amsterdam starts the research period with a mu_1 value lower than Copenhagen's mu_1 value, which means the cycling routes are in general more direct than in Copenhagen. This can be explained by the fact that there is not a large canal dividing the inner city. The large 'IJ canal' does run through Amsterdam, but the part of Amsterdam north of this canal is never defined as being part of Amsterdam's city center. Would I have included it in order to emulate Copenhagen's situation, the values of mu_1 could have been a lot higher for Amsterdam.

While having relatively direct cycling routes compared to Copenhagen, routes in Amsterdam are not as direct as in the following two cities, Duisburg and Indianapolis. This can be explained by the many small canals that have to be crossed when navigating through the city. At the end of the research period, Amsterdam is getting closer to the mu_1 values of Duisburg and Indianapolis.

So, also Amsterdam shows some decrease in the value of mu_1 over the past 10 years. Cycling routes have become more direct, which suggests that the cycling infrastructure has been improved and missing links have been addressed.

Duisburg
Computing mu_1 for Duisburg results in, tied with Indianapolis, the lowest values. The values for Duisburg range from 1.32 to 1.35. A plausible explanation is that there aren't many natural barriers like waterways in the central part of Duisburg, so rather direct routes are easier to realize.

There is not a very clear trend in the mu_1 of Duisburg for the past 10 years. If one could speak of a trend, it would be a slight decrease in this measure from 2013 until 2018, and a slight increase from 2018 until 2022. It has to be mentioned that the bicyclable network of Duisburg in 2013 looks a bit less detailed than in 2014. Such a change is likely due to changes in the data in regard to allocated OSM tags which causes the first dip from 2013 to 2014. If so, the seeming improvement between these years can be an artefact.

Summing up for the whole time span, the value of mu_1 for the center of Duisburg has not improved (=decreased) over the past 10 years . Mu_1 stayed roughly the same. This is a clear difference with Copenhagen and Amsterdam.

Indianapolis
The results of mu_1 for Indianapolis, a city traditionally not catered towards cyclists, seem surprisingly in favor of bicycle friendliness. The values of mu_1 are low, which indicates cyclists can navigate relatively direct through the inner city. These low values can be attributed to the grid-structure which aids the directness of random routes through the city.

It is important to mention that these values do not reflect the size of the bicycle specific network. They are based on the complete bicyclable network, that is: all roads where bicycles are formally allowed. So, while it might be officially allowed to bike on most streets, the experience can be quite different and less safe then for example in Copenhagen.

Still, the city of Indianapolis did also invest in bicycle infrastructure. An example of this is the Indianapolis Cultural Trail (https://indyculturaltrail.org/) which is a 13 km long cycling path that crosses the city in several directions. It was completed in 2013, in the first year of the time period covered by my research. So my data will not show any impact of this new piece of infrastructure.

Overall, there is no clear trend in the value of mu_1 for Indianapolis. There is not a significant increase or decrease. The values and (lack of) trend are similar to those of Duisburg.

4.3 Results of mu_2: bicycle route length vs car route length

The second measure, mu_2, is a variant of mu_1. Again in every run 10000 random point pairs were used to compute bicycle route lengths. But now, the bicycle route length was divided by the car route length. This procedure was repeated 10 times . The average and standard deviation of the ten resulting ratio's was taken as the definitive result. The results for the 10 years of Copenhagen's inner city are given in Table 5.

Bicyclable network, inner city CPH	Result mu_2	Standard deviation
2013	0,979	0,002
2014	0,980	0,004
2015	0,970	0,004
2016	0,974	0,003
2017	0,927	0,004
2018	0,917	0,004
2019	0,905	0,003
2020	0,906	0,003
2021	0,907	0,003
2022	0,926	0,004

Table 5: Results mu_2 for bicyclable network, inner city Copenhagen.

These results show that in general, in Copenhagen's inner city the bicycle route is usually shorter than the car route. Even more so, the trend shows a growing advantage for cyclists compared to car drivers. This is illustrated with the descending line of Figure 15. The improvement for cyclists can be seen especially in 2017, just after the Inderhavnsbroen opened, a cycling bridge connecting the east of the inner city to the west.

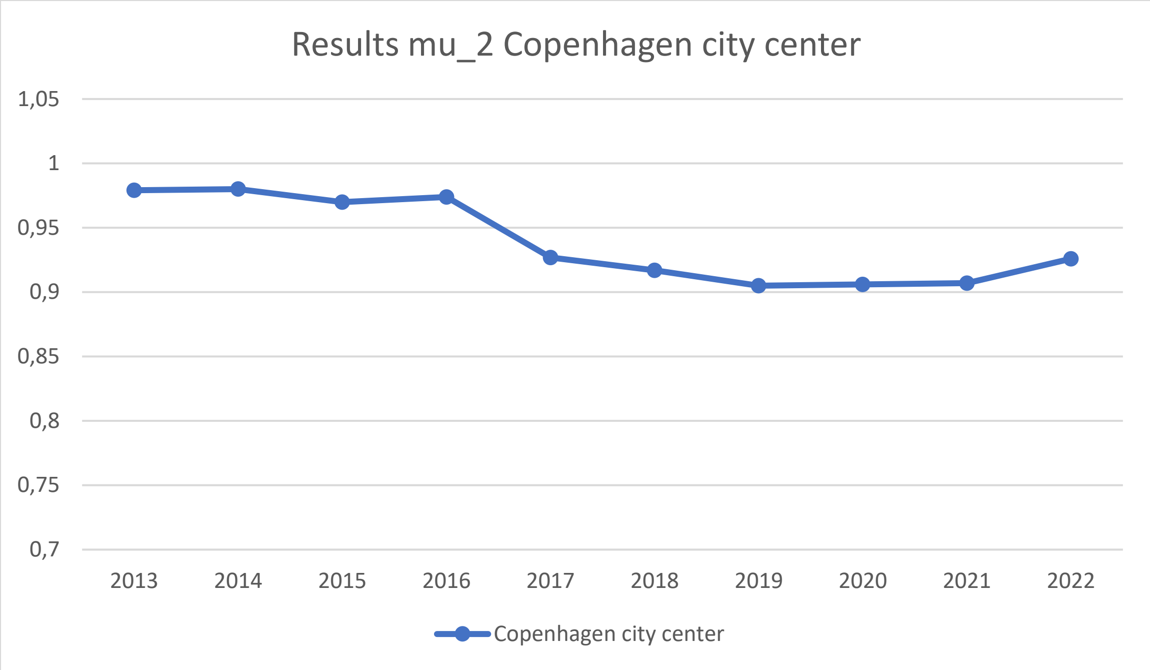


Figure 15: Results mu_2 Copenhagen city center

Comparing different cities
A comparison of the results of mu_2 for different cities is shown in Figure 16.

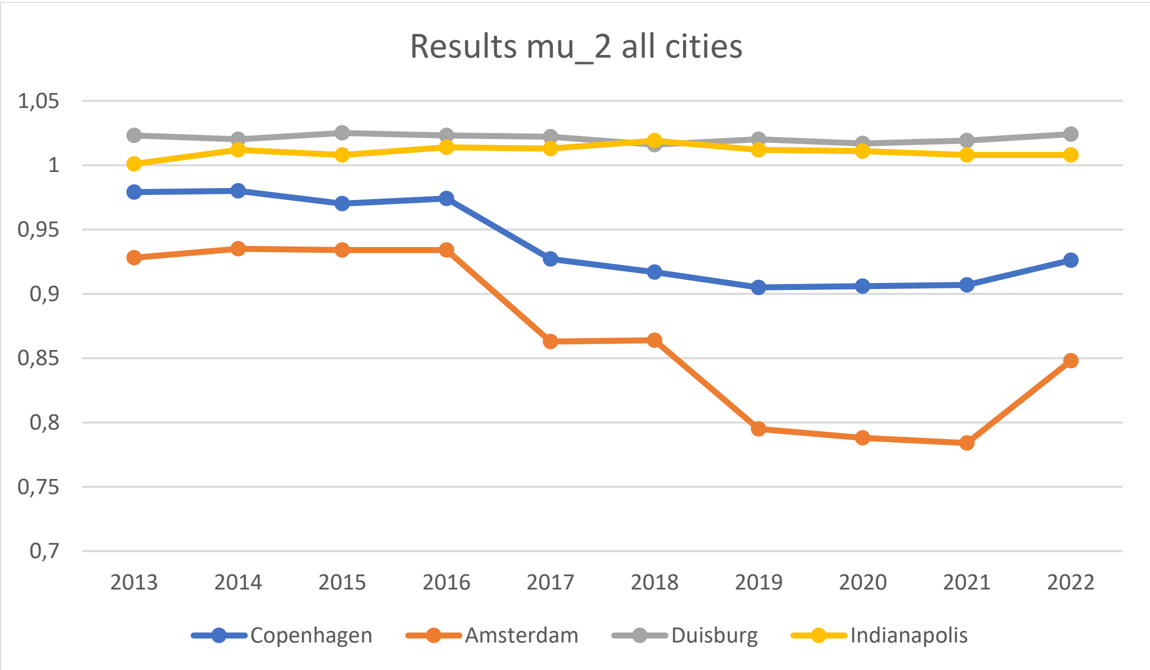


Figure 16: Results mu_2 all cities.

Relative to the other cities, Copenhagen scores well on this measure, as a lower value is indicative of bicycle friendliness. Amsterdam scores even better, as the bicycle route length relative to the car route length is in all years the shortest of the cities studied.

Duisburg and Indianapolis do not show an advantage for the cyclist, as their value is just above 1, indicating that car drivers in general have a shorter route. Also, in both cities there is no clear trend: in ten years' time the values stay more or less the same. So, according to mu_2, there has been no improvement for these two cities.

The trends for Copenhagen and Amsterdam are actually remarkably similar. The value of mu_2 for Amsterdam drops at times when this also happens for Copenhagen, and at the end (2022) both these cities show a surprising increase of mu_2. I have not yet found an explanation for this increase. Further explanation of surprising results like this is given in the discussion Chapter.

4.4 Results of mu_3: bicycle specific vs car network length (inner city)

Measure 3 focuses on the inner city where it divides the total length of the bicycle specific infrastructure by the total length of the car network. First, the results for Copenhagen are given in Table 6.

Bicycle specific infrastructure length, compared to car network length, for inner city Copenhagen	Result mu_3
2013	0,378
2014	0,372
2015	0,435
2016	0,725
2017	0,690
2018	0,514
2019	0,493
2020	0,494
2021	0,494
2022	0,501

Table 6: Results mu_3 for inner city Copenhagen

Copenhagen shows a substantial length of bicycle specific paths and roads. In 2013 this covers already 38 percent relative to the total car network and this ratio increases to 50 percent at the end of the period. This is a clear positive trend, with a short and puzzling climax in the years 2016 and 2017. I do not have a well-substantiated explanation for this ‘up and down’. However, when looking at the visual plots of the network graphs of each year for Copenhagen, a possible explanation seems to lay in abnormalities in the data. The network graphs for each year’s bicycle specific infrastructure for Copenhagen’s inner city is provided in Appendix 1. This shows that in the years 2016 and 2017 suddenly many streets, mainly in the southwestern area, were marked as bicycle specific. And after that, from 2018 on, the values return to a more expected trend, but the the network looks more scattered as can be seen in Appendix 1A. I would explain some fluctuations by either the abovementioned streets being incorrectly marked with OSM-tags which I have used to define the subnetwork, or by an imperfection in the custom filter used.

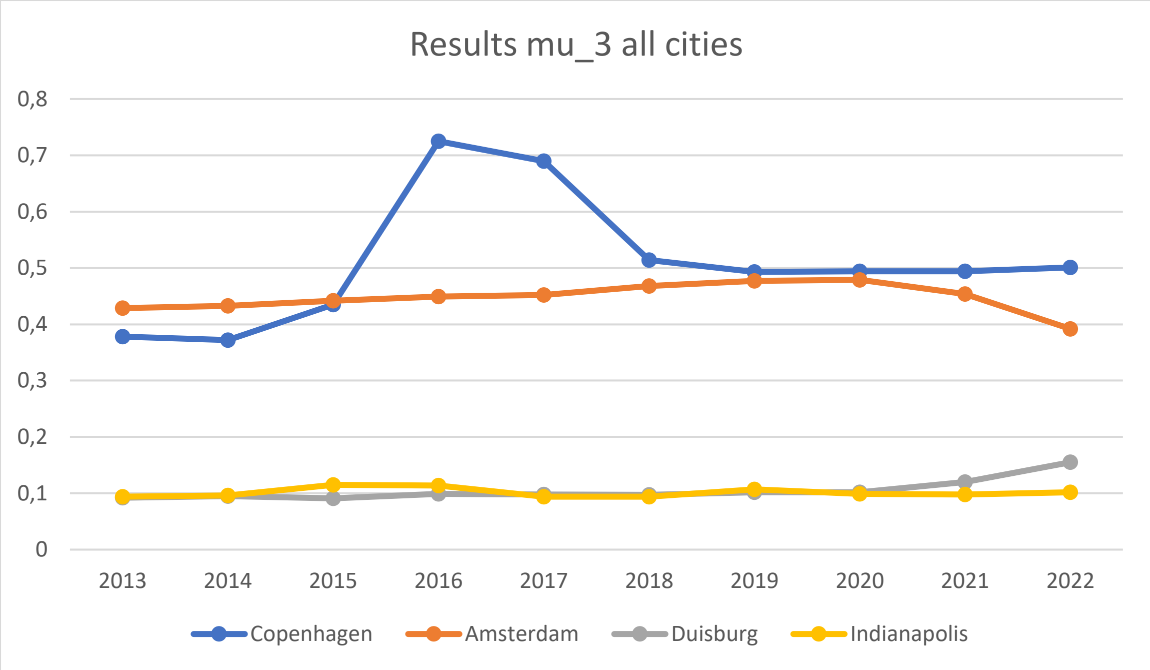


Figure 17: Results mu_3 all cities

The results of mu_3 are plotted in Figure 17. Just like Copenhagen, Amsterdam also has a large bicycle specific network, averaging between 40 and 50 percent relative to the total car network. This stands in stark contrast with the cities of Duisburg and Indianapolis, where this percentage fluctuates largely around 10 percent. So, Copenhagen and Amsterdam clearly offer much more bicycle specific infrastructure then the other two cities, which is an indication for their higher bicycle friendliness. However, the results for Copenhagen show that this measure can be sensitive to anomalies in the data.

Speaking of trends, Amsterdam shows a gradual increase of this value until 2020, but this is followed by a remarkable drop. If the data were perfect, this would suggest that this city recently gave cars more freedom, or closed some specific cycleways. But since I did not find confirmation of this, the relative fall in bicycle specific infrastructure can also be caused by data anomalies.

For the other two cities, there is little change over the ten years studied. Only in the last two years, the data for Duisburg show an increase in bicycle specific infrastructure. Trying to check this with local sources, I did not find a good explanation for this. According to a national survey in 2020 by the German union of cyclists (ADFC), the city of Duisburg even had the worst cycleways of the whole country (Ahlers, 2021a). At the end of 2021, this resulted in new plans of the city to invest 1,9 million Euro in improvement (as opposed to an earlier budget of 100.000 per year), but this operation still had to start when the last OSM-data about Duisburg were collected (Ahlers, 2021b).

4.5 Results of mu_4 bicycle specific vs car network length (entire city)

Measure 4 works similar to measure 3, but now the comparison is performed on the entire city instead of only the city center. The results are given in Table 7.As the city center is also still included, the results are slightly similar. For Copenhagen we again see a short climax in the years 2016 and 2017, likely caused by the same abnormalities as explained in the previous paragraph. As the networks analyzed are larger in size, the changes and fluctuations are less pronounced now. Over the whole period of ten years we only see a small improvement, roughly from 31,5% to 34,5% bicycle specific network. In the last five years, the score is just stable.

Bicycle specific infrastructure length, compared to car network length, for entire city Copenhagen	Result mu_4
2013	0,316
2014	0,313
2015	0,341
2016	0,416
2017	0,412
2018	0,354
2019	0,343
2020	0,348
2021	0,347
2022	0,343

Table 7: Results mu_4 for entire city Copenhagen

When the results of all cities are compared, as visualized in Figure 18's graph, mu_4 gives a different picture than mu_3. With this measure, there is a more clear distinction and possible ranking between the cities. The entire city of Amsterdam has relatively the longest distance of bicycle specific infrastructure and Copenhagen is in second place for all years of the research period.

The other two cities again show a much lower share of bicycle infrastructure, but now there is more difference between Duisburg and Indianapolis. In the entire city of Indianapolis, bicycle specific infrastructure has less than 5% of the length of the car network. At best, the value is about half of that for Duisburg. Apparently, cycling paths are mainly concentrated to the inner city (where the score is 10%). Still, there seems to be some positive news for cyclists in this America city: the value of mu_4 slowly tripled, from 1,4% at the start of the decade to 4,2% now.

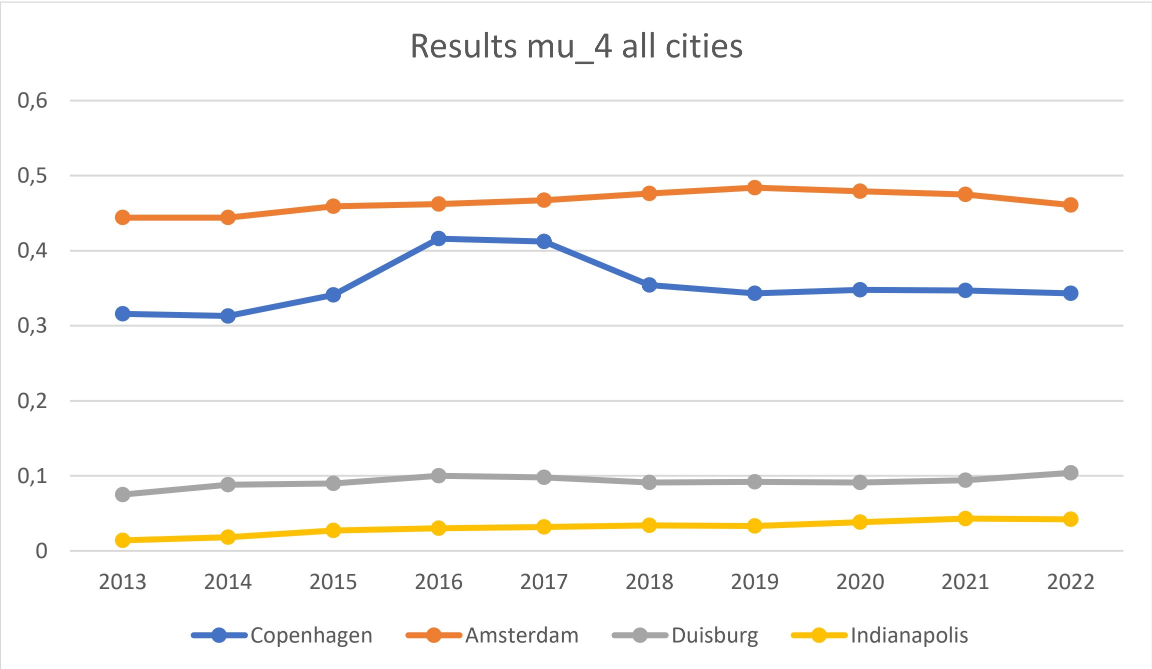


Figure 18: Results mu_4 all cities.

4.6 Results of mu_5: mu_3 divided by mu_4 (inner/entire city)

Measure 5 is simply computed by dividing mu_3 by mu_4, which gives a ratio between the relative length of bicycle specific networks of the inner city versus the entire city. This ratio is not a simple and direct indicator of bicycle friendliness, but says something about the balance between the central part and the whole city in this respect. First, the results are shown for all cities in figure 19.

The most remarkable result is seen in Indianapolis. Especially in the earlier part of the research period, the value of mu_5 is very high, which means that bicycle specific infrastructure is almost completely confined to the inner city. But in the years after 2013, the ratio of center versus inner city has fallen gradually from almost 7 to roughly 2,5. This is still the biggest contrast of the four cities studied, but also a clearly improved balance.

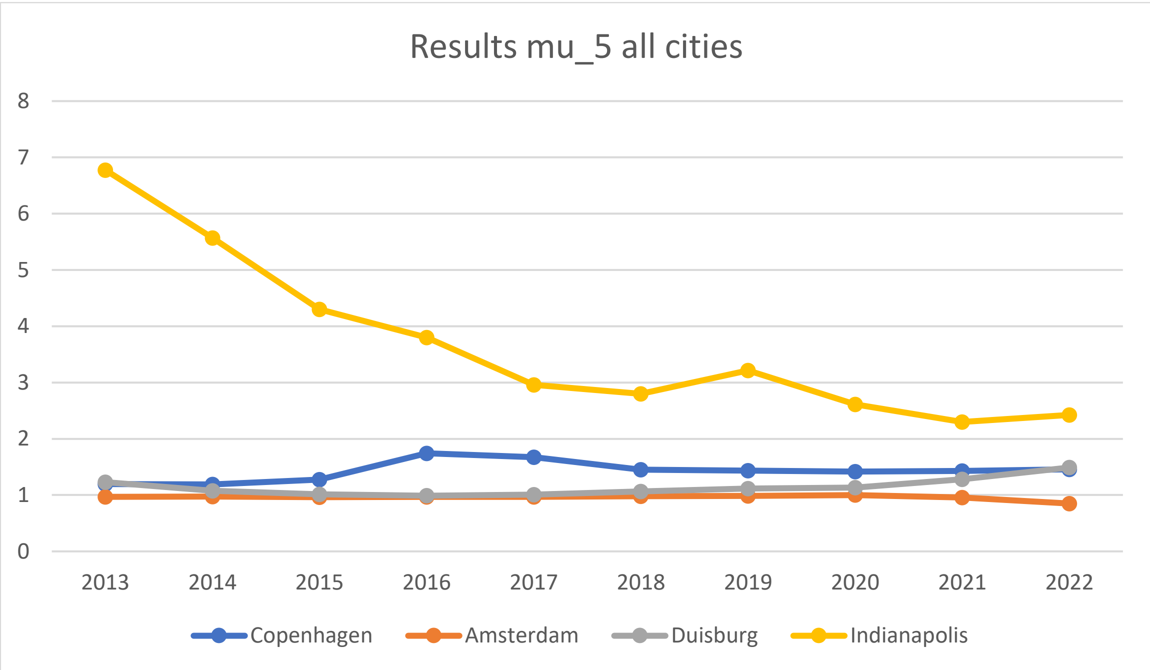


Figure 19: Results mu_5 all cities.

In order to look more closely at the results of Copenhagen, Amsterdam and Duisburg, in the graph of Figure 20 Indianapolis is excluded. In Copenhagen, this measure stabilizes around a value of 1,5 in recent years, which means that the inner city scores around 50% higher than the complete city in terms of bicycle specific infrastructure. In Amsterdam, the score stays close to 1,0, which suggests there is a balance in bicycle friendliness between the central part and the entire city.

In Duisburg, for quite some years the situation seems comparable with that of Amsterdam: a balance between inner and outer city, although much lower in absolute terms (see mu_3 and mu_4). But in more recent years, there appears to be a shift towards more growth of the bicycle specific infrastructure in the center.

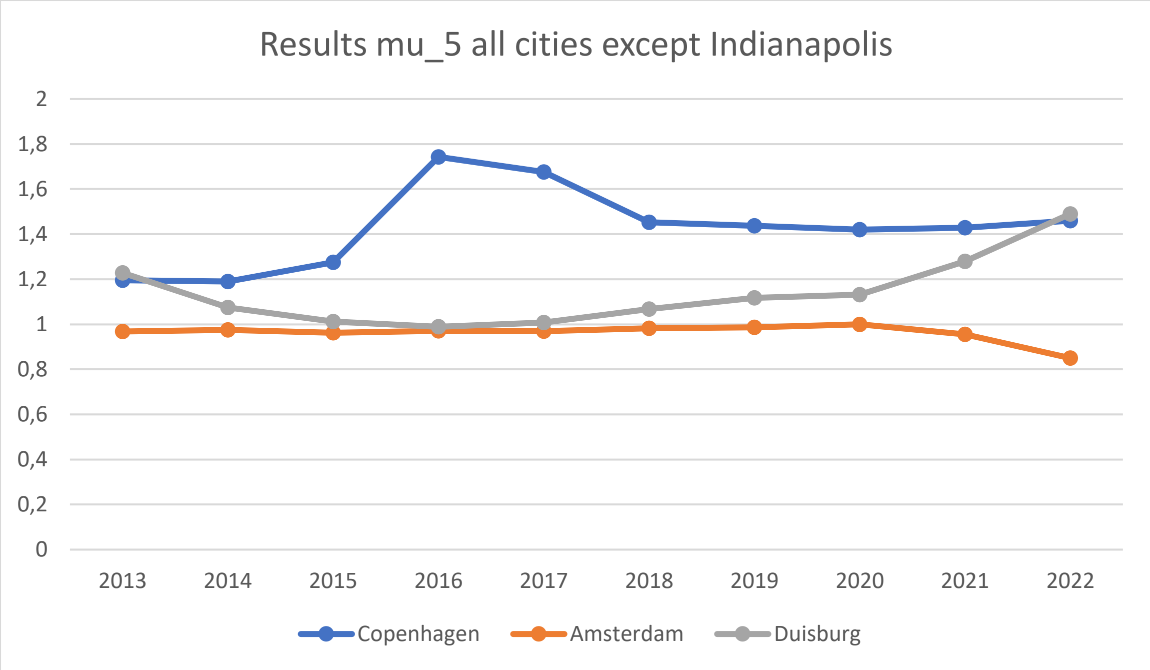


Figure 20: Results mu_5 all cities except Indianapolis.

5. Discussion

During the research for this thesis, I have used five different measures to analyze the development of traffic infrastructure of cities in terms of bicycle friendliness. Having presented the results of each measure for each city, it is now time for discussion to get an overall picture. This chapter starts with looking back and discuss the merits of the data and measures that I used. Thereafter, I will draw general conclusions and give recommendations for further research.

5.1 The data: reliability

My analyses of bicycle infrastructure in cities are fully based on data from Open Street Map. Because these data are by definition public and free, they were an attractive source to use. Another advantage is that much documentation is available about their quality and application.

Still, it is unavoidable to discuss the quality and reliability of these data. Is the improvement of measure A in city X a reflection of real developments in bicycle infrastructure? Or is it an illusion, caused by changes in data definitions or by improved input? Knowing that OSM depends on the effort of thousands of volunteers, these questions always have to be asked when using these data. But there are also some reassuring answers to them.

An important fact is that Open Street Maps has quite strict mechanisms for quality control. Similar to Wikipedia and other open source data collections, when anyone wants to add new elements to the map, they have to be checked and approved by another member of the community who is higher in rank. Also, the massive use of Open Street Map for different applications (for example the navigation apps of Garmin) both shows the trust of professional parties in the data quality and also forms a pressure for quick correction of any faults. These mechanisms for quality control should ensure the reliability of OSM-data, at least in areas where these data are massively used. The European and America cities which I studied, meet this condition.

However, even in these cities I did encounter some changes which could only be explained by data disturbances. So I am quite aware that this data sources is not perfect. And I am sure that application of measures to cities in other continents would be accompanied by more questions and doubts of this type. This is not only a matter of mistakes, but also cultural and societal differences can play a role here. For example: are the standards for a main road in Africa the same as in Denmark?

Ideally, when looking at the infrastructure in detail, one would like to calibrate OSM-data with data from other sources like those of Google Maps. Within the scope of my thesis this was not a serious option. It would have been if my analyses would have focused on specific details in a few cities. In that case, Google Street View or Google Earth could have helped. But for the measuring of the complete bicycle infrastructure within hundreds of square kilometers in four cities and ten consecutive years, this type of checks was not feasible.

Also, my focus on trends in of the complete bicycle network of cities generally meant that I could expect small faults to be leveled out in the measures. This proved to be true. Besides some exceptions, my measures showed trends which were in line with expectations and plausible interpretations.

5.2 What do these measures say?

Having seen the results of each measure with their trends and fluctuations and having seen their possibilities for interpretation, I can now discuss the actual usability and meaning of each measure.

Random route lengths (Mu_1 and Mu_2)
These measures, based on shortest cycle routes between 10 x 10.000 random pairs of points within the inner city, make use of 'brute computational force'. The advantage of this massive approach is that results are quite stable and reproducible. Possible disadvantages are that no distinction is made between more and less important routes. Also, the quality of calculated routes (like safety, or cycle specificness) is not taken into account.

Admitting these limitations, we saw that mu_2 (bicycle route vs car route) gave the most meaningful results for the evaluation of bicycle friendliness. Natural or other barriers which force all traffic to make a detour, are filtered out in this measure, which is not the case in mu_1 (bicycle route vs straight distance)

So, when trying to make overall judgements about the bicycle friendliness of the four cities, I would use mu_2 as the best indication for efficient bicycle route length.

Total network lengths (Mu_3, mu_4 and mu_5)
Contrary to the first pair of measures, these three do focus on dedicated bicycle lanes, paths and roads. This clearly is important, but a disadvantage is that these measures don't tell anything about possible routes. Even bicycle infrastructure which in the real world is scattered and misses vital connections can result in positive scores (or: a favorable picture). Also, these measures show more fluctuations caused by abnormalities in the data, as the allocation of relevant OSM tags sometimes changes between years.

Still, the fact that these measures show the amount of specific infrastructure makes them essential for any assessment of bicycle friendliness. And all three contribute to this. Mu_3 en Mu_4 indicate the size of the bicycle network in the inner and entire city. And mu_5 shows the balance between both, which is just as relevant.

So, when discussing the bicycle friendliness of the four cities, I would use mu_2, mu_3, mu_4 and 5. Only mu_1 will be left out, as it is too heavily impacted by unique characteristics of the city like waterways which results in an unfair comparison between cities.

5.3 Comparison and grading of the four cities

By all measures, it is quite clear that Copenhagen and Amsterdam offer a more bicycle friendly infrastructure than Duisburg and Indianapolis. In recent years according to popular belief, Copenhagen often 'won' the race for most bicycle minded city of the world. But using the objective measures of this thesis, the Dutch capital does perform better: in the last five years, bicycle routes in Copenhagen were on the average 5 to 10 percent shorter than car routes between the same places. Amsterdam gives cyclists an even bigger advantage, which fluctuates between 14 and 22 percent. Until 2021 both cities show gradual improvement on this measure, with Amsterdam improving the fastest. In the year 2022, the score of both cities deteriorates. It will take another year to see if this is a new trend or just a fluctuation in the data.

Looking at the bicycle specific network, Copenhagen seems to score slightly better when just focusing at the inner city. But when the whole city is taken into account, Amsterdam takes a decisive lead. Here, the total length of the bicycle network counts up to 45 percent relative to the car network, while Copenhagen recently scores 34 percent. The conclusion can be drawn that Copenhagen gives relatively more priority to cycle infrastructure of the inner city, while in Amsterdam such a division does not seem to be made.

Duisburg and Indianapolis clearly show less developed bicycle infrastructure. When we only look at route lengths (mu_1 and mu_2), both cities score reasonably well. The average cycling route in both inner cities is only slightly longer than the corresponding car route. But as said earlier, this doesn't say much about real bicycle friendliness.

The relative amount of bicycle specific network is a better indicator for this. With this measure, both Duisburg and Indianapolis show meagre scores compared to the other two cities. In the inner city (mu_3), the bicycle network sums up to some 10 percent of the car network – with Duisburg showing a small rise in the last two years. Looking at the entire city (mu_4), Indianapolis has been running far behind with bicycle specific infrastructure. There has been some improvement over the years, but this city still scores lower than 5 percent in this measure, while Duisburg is hovering around 10 percent since quite some years.

The cities and their development in regard to bicycle infrastructure can be graded based on the different types of measures. After having studied the average values, I have created a dashboard-like overview of how each city can be graded in qualitative terms in Table 8.

	Route length (mu_2)		**% Bike infra (center) (mu_3)**		**Balance inner/outer (mu_5)**	
	Score	Trend	Score	Trend	Score	Trend
Copenhagen	Good	Good	High	Rising	Moderate priority inner city	
Amsterdam	Excellent	Excellent	Very High	Rising	In balance	
Duisburg	Reasonable	No change	Low	Rising	Recent priority inner city	
Indianapolis	Reasonable	No change	Low	No change	Outer city far behind	

Table 8: Grading of the cities in qualitative terms

6. Conclusions

This final Chapter aims to summarize the findings of my research and give concluding answers to the Research Questions where possible.

RQ. How can meaningful subnetworks of the street network be defined?

I have investigated and come up with methods to define relevant car and bicycle networks. Looking for a consistent way to demarcate network for different cities, I decided to take administrative borders, for the entire city as well as the 'official' inner city. However, the latter does not work for all cities, as not every city has a well-defined city center.

Using these network extents as the research area, relevant car and bicycle subnetworks have been defined based on the available OSM data. This resulted in six different subnetworks to analyze each city:

- A/B: bicyclable network ('bike') inner city and entire city;
- C/E: car network ('drive') inner city and entire city;
- D/F: bicycle specific infrastructure (custom filter) inner city and entire city.

All subnetworks were acquired using OSMnx with the Overpass settings changed to get historical data.

<u>Conclusion</u>*. The chosen network extents are indeed meaningful. They offered solid and fertile ground for measuring bicycle friendliness on a city level, giving relevant results and insights.*

RQ2. What measures provide a reliable quantification of Copenhagen's development towards bicycle friendliness?

By experimenting several network measures have been implemented. The combination of them gives insight in the development of bicycle networks in the selected cities in a ten year period. The most suitable and fit for implementation were five measures which can be divided into two groups:

(a) Random route lengths (compared to car route length);
(b) Total network lengths (% bicycle specific infrastructure).

As pointed out in the discussion chapter, both sets of measures have their limitations. But using the combination of them largely compensates this.

<u>Conclusion</u>*. The selected measures give at least a meaningful quantification of the development of the bicycle network of Copenhagen, which lends itself for interpretation. But there are some reliability issues, which could be better judged by calibration with network data from a different source than OSM.*

RQ3. In which ways can the outcomes of the study of Copenhagen be generalized?

The OSM data which I used and the measures derived from them, appeared to be a fruitful basis for generalization. OpenStreetMap is being used and maintained by many thousands of volunteers in at least the western world. Comparable data covering European and America cities are generally available.

As a first step to generalization, I chose a limited set of four cities of similar size, in Europe and Northern America. Apart from Copenhagen, this included Amsterdam, Duisburg and Indianapolis. For these four cities, a total of 240 networks was calculated (4 cities, 10 years, 6 subnetworks). To compare the cities' level and development of bicycle friendliness, the measures were applied to the networks of these cities. All this showed to be technically feasible and resulted again in meaningful results. (See the dashboard-like comparison of the four cities at the end of the discussion Chapter)

<u>Conclusion</u>. *My methods turned out to be fit for generalization. They generated meaningful results and trends for this limited set of cities, which gives some perspective on applying them to a larger collection of cities. I see this as a step towards a more complete 'toolbox' to evaluate bicycle friendliness of cities.*

Recommendations

For further research, an important improvement would be to make use of weighted networks. This way, scattered and incomplete subnetworks like bicycle specific infrastructure can be integrated into more complete subnetworks. Combining the data would result in less or no missing edges, even if there were to be gaps in specific data.

A final recommendation would be to use more different network measures. As shown, a combination of network measures provides better insights than single network measures as they can rule out each others shortcomings. The use of several more advanced network measures, like mu_6 and onward given in Table 2 in the Methods section, is therefore advised.

7. References

Agarwal, A., Ziemke, D., & Nagel, K. (2020). Bicycle superhighway: An environmentally sustainable policy for urban transport. *Transportation Research Part A: Policy and Practice*, *137*, 519–540. https://doi.org/10.1016/j.tra.2019.06.015

Ahlers, M. (2021a, March 16). *Duisburg hat bundesweit die schlechtesten Radwege*. https://www.waz.de/staedte/duisburg/duisburg-hat-bundesweit-die-schlechtesten-radwege-id231814659.html

Ahlers, M. (2021b, November 22). *Duisburger Politik will 1,9 Mio Euro in Radwege investieren*. https://www.waz.de/staedte/duisburg/duisburger-politik-will-1-9-mio-euro-in-radwege-investieren-id233906765.html

Barthelemy, M. (2017). From paths to blocks: New measures for street patterns. *Environment and Planning B: Urban Analytics and City Science*, *44*(2), 256–271. https://doi.org/10.1177/0265813515599982

Barthelemy, M., Bordin, P., Berestycki, H., & Gribaudi, M. (2013). Self-organization versus top-down planning in the evolution of a city. *Scientific Reports*, *3*(1), 2153. https://doi.org/10.1038/srep02153

Boeing, G. (2018). *Download multiple OSM way fields using "infrastructure" parameter in graph_from_* (e.g. "cycleway", "surface", "bicycle")? · Issue #151 · gboeing/osmnx*. GitHub. https://github.com/gboeing/osmnx/issues/151

Boeing, G. (2018, January 19). *Urban Street Network Centrality*. https://geoffboeing.com/2018/01/urban-street-network-centrality/

Boeing, G. (2021). *OSMnx documentation*. https://osmnx.readthedocs.io/en/stable/osmnx.html

Böll Stiftung, H. (2021). *European Mobility Atlas 2021: Facts and Figures about Transport and Mobility in Europe* | *Heinrich Böll Stiftung* | *Brussels office - European Union*. Heinrich-Böll-Stiftung. https://eu.boell.org/en/European-Mobility-Atlas

Börner, K., Sanyal, S., & Vespignani, A. (2007). Network Science. *Blaise Cronin Annual Review of Information Science & Technology*, *41*, 537–607.

Carstensen, T. A., Olafsson, A. S., Bech, N. M., Poulsen, T. S., & Zhao, C. (2015). The spatio-temporal development of Copenhagen's bicycle infrastructure 1912–2013. *Geografisk Tidsskrift-Danish Journal of Geography*, *115*(2), 142–156.

https://doi.org/10.1080/00167223.2015.1034151

City of Copenhagen. (2011). *Good, better, best. The city of Copenhagen’s bicycle strategy 2011-2025*.

Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische Mathematik*, *1*(1), 269–271. https://doi.org/10.1007/BF01386390

Emanuel, M. (2019). Making a bicycle city: Infrastructure and cycling in Copenhagen since 1880. *Urban History*, *46*(3), 493–517. https://doi.org/10.1017/S0963926818000573

Ferster, C., Fischer, J., Manaugh, K., Nelson, T., & Winters, M. (2020). Using OpenStreetMap to inventory bicycle infrastructure: A comparison with open data from cities. *International Journal of Sustainable Transportation*, *14*(1), 64–73. https://doi.org/10.1080/15568318.2018.1519746

Gössling, S., & Choi, A. S. (2015). Transport transitions in Copenhagen: Comparing the cost of cars and bicycles. *Ecological Economics*, *113*, 106–113. https://doi.org/10.1016/j.ecolecon.2015.03.006

Gulsrud, N., & Henderson, J. (2019). *Street Fights in Copenhagen: Bicycle and Car Politics in a Green Mobility City*. https://doi.org/10.4324/9780429444135

Haustein, S., Koglin, T., Nielsen, T. A. S., & Svensson, Å. (2020). A comparison of cycling cultures in Stockholm and Copenhagen. *International Journal of Sustainable Transportation*, *14*(4), 280–293. https://doi.org/10.1080/15568318.2018.1547463

Huisman, O., & de By, R. (2009). *Principles of geographic information systems: An introductory textbook*.

LA Times. (2019). *Copenhagen has taken bicycle commuting to a whole new level*. https://www.latimes.com/world-nation/story/2019-08-07/copenhagen-has-taken-bicycle-commuting-to-a-new-level

Lardinois, F. (2014). *For the love of open mapping data* [Interview]. https://techcrunch.com/2014/08/09/for-the-love-of-open-mapping-data/

LearnOSM. (2021). *LearnOSM*. https://learnosm.org/en/

Li, L., Bai, S., Leng, M., Wang, L., & Chen, X. (2018). Finding Missing Links in Complex Networks: A Multiple-Attribute Decision-Making Method. *Complexity*, *2018*, e3579758. https://doi.org/10.1155/2018/3579758

Li, Y., Jiang, G.-P., Wu, M., & Song, Y. (2020). Methods to Measure the Network Path Connectivity.

Security and Communication Networks, *2020*, 1–10. https://doi.org/10.1155/2020/8836590

Mocnik, F.-B. (2018a). *Dimension as an invariant of street networks*. 455–457.

Mocnik, F.-B. (2018b). The Polynomial Volume Law of Complex Networks in the Context of Local and Global Optimization. *Scientific Reports*, *8*(1), 11274. https://doi.org/10.1038/s41598-018-29131-0

Mohan, D., & Tiwari, G. (Eds.). (2020). *Sustainable approaches to urban transport*. Taylor & Francis Group.

Moss, S. (2015, April 28). End of the car age: How cities are outgrowing the automobile. *The Guardian*. https://www.theguardian.com/cities/2015/apr/28/end-of-the-car-age-how-cities-outgrew-the-automobile

Najera, J. (2020, February 11). *Measuriing Network Centrality—An Intro To Quantifying "Ïmportance" Through Graph Theory*. https://medium.com/cantors-paradise/measuring-network-centrality-2a76b0045410

NetworkX. (2021). *NetworkX documentation*. https://networkx.org/documentation/stable/index.html

Nielsen, T. A. S., Skov-Petersen, H., & Agervig Carstensen, T. (2013). Urban planning practices for bikeable cities – the case of Copenhagen. *Urban Research & Practice*, *6*(1), 110–115. https://doi.org/10.1080/17535069.2013.765108

NOS. (2022, July 2). *Brede paden en speciale stoplichten: Kopenhagen koestert de fiets*. https://nos.nl/collectie/13905/artikel/2434948-brede-paden-en-speciale-stoplichten-kopenhagen-koestert-de-fiets

OpenStreetMap. (2021a). *Bicycle*. https://wiki.openstreetmap.org/wiki/Bicycle

OpenStreetMap. (2021b). *Elements*. https://wiki.openstreetmap.org/wiki/Elements

OpenStreetMap. (2021c). *Key:cycleway*. https://wiki.openstreetmap.org/wiki/Key:cycleway

OpenStreetMap. (2021d). *OpenStreetMap Welcome Mat*. https://welcome.openstreetmap.org/about-osm-community/

OSM Blog. (2012). *OpenStreetMap data license is odbl*. https://blog.openstreetmap.org/2012/09/12/openstreetmap-data-license-is-odbl/

Parkin, J. (Ed.). (2012). *Cycling and sustainability*. Emerald.

Skov-Petersen, H., Barkow, B., Lundhede, T., & Jacobsen, J. B. (2018). How do cyclists make their way? - A GPS-based revealed preference study in Copenhagen. *International Journal of*

Geographical Information Science, *32*(7), 1469–1484. https://doi.org/10.1080/13658816.2018.1436713

Teschke, K., Harris, M. A., Reynolds, C. C. O., Winters, M., Babul, S., Chipman, M., Cusimano, M. D., Brubacher, J. R., Hunte, G., Friedman, S. M., Monro, M., Shen, H., Vernich, L., & Cripton, P. A. (2012). Route Infrastructure and the Risk of Injuries to Bicyclists: A Case-Crossover Study. *American Journal of Public Health*, *102*(12), 2336–2343. https://doi.org/10.2105/AJPH.2012.300762

Tutorialspoint. (2021). *Graph Theory—Connectivity*. https://www.tutorialspoint.com/graph_theory/graph_theory_connectivity.htm

Walljasper, J., & Ballmer, M. (2018). *Promise of Bicycling Report*. Pedal Love. https://www.pedallove.org/promise-of-bicycling-report

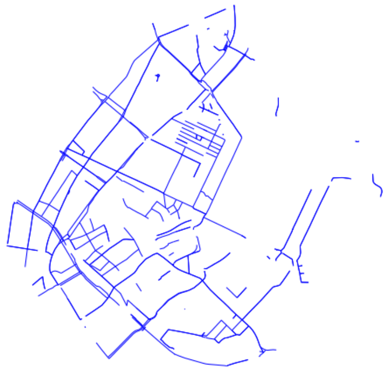
Westman, J. (2021). *OSM in Realtime*. https://jwestman.gitlab.io/osm-in-realtime/

World Energy Council (Ed.). (2011). *Global Transport Scenarios 2050*. World Energy Council.

Appendix 1A: Copenhagen's bicycle specific infrastructure (inner city)

2013

2014



2015

2016

2017

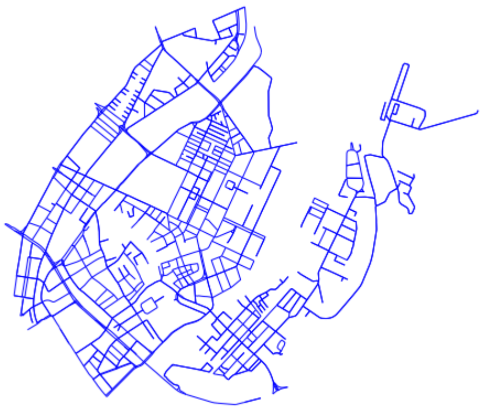
2018

2019

2020

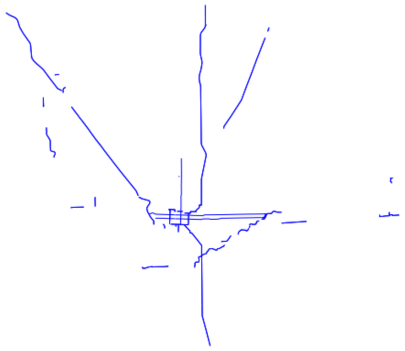
2021

2022

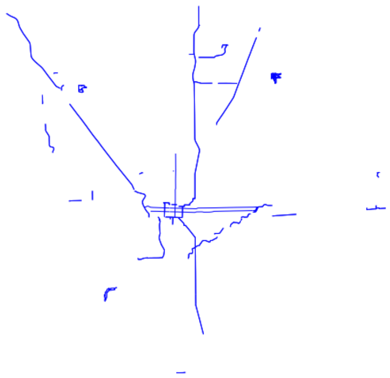


C_2022 (car network, for context)

Appendix 1B: Indianapolis’ bicycle specific infrastructure (entire city)



2013



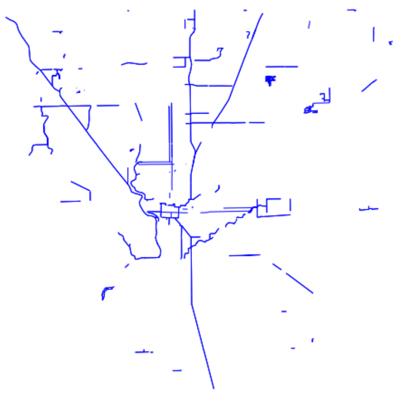
2014

2015

2016

2017

2018

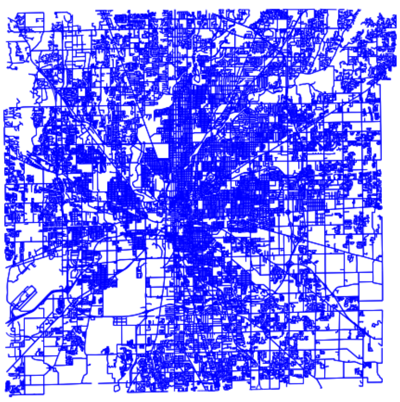


2019

2020

2021

2022



E_2022 (car network, for context)

Appendix 2: Results of all selected measures for all cities for 10 years

	Mu_1	Mu_2	Mu_3	Mu_4	Mu_5
Copenhagen					
2013	1,687	0,979	0,378	0,316	1,195
2014	1,688	0,980	0,372	0,313	1,190
2015	1,665	0,970	0,435	0,341	1,275
2016	1,667	0,974	0,725	0,416	1,743
2017	1,552	0,927	0,690	0,412	1,676
2018	1,555	0,917	0,514	0,354	1,453
2019	1,549	0,905	0,493	0,343	1,437
2020	1,525	0,906	0,494	0,348	1,420
2021	1,529	0,907	0,494	0,347	1,429
2022	1,533	0,926	0,501	0,343	1,460
Amsterdam					
2013	1,434	0,928	0,429	0,444	0,968
2014	1,446	0,935	0,433	0,444	0,975
2015	1,442	0,934	0,442	0,459	0,963
2016	1,417	0,934	0,449	0,462	0,971
2017	1,406	0,863	0,452	0,467	0,969
2018	1,398	0,864	0,468	0,476	0,982
2019	1,405	0,795	0,477	0,484	0,986
2020	1,398	0,788	0,479	0,479	1,000
2021	1,393	0,784	0,454	0,475	0,956
2022	1,383	0,848	0,392	0,461	0,850
Duisburg					
2013	1,344	1,023	0,092	0,075	1,228
2014	1,337	1,020	0,095	0,088	1,075
2015	1,335	1,025	0,091	0,090	1,012
2016	1,332	1,023	0,099	0,100	0,989
2017	1,325	1,022	0,098	0,098	1,008
2018	1,322	1,016	0,097	0,091	1,068
2019	1,327	1,020	0,102	0,092	1,118
2020	1,326	1,017	0,102	0,091	1,131
2021	1,335	1,019	0,120	0,094	1,280
2022	1,339	1,024	0,155	0,104	1,490
Indianapolis					
2013	1,320	1,001	0,094	0,014	6,776
2014	1,337	1,012	0,096	0,018	5,568
2015	1,338	1,008	0,115	0,027	4,300
2016	1,339	1,014	0,114	0,030	3,799
2017	1,336	1,013	0,094	0,032	2,958
2018	1,337	1,019	0,094	0,034	2,799
2019	1,334	1,012	0,107	0,033	3,213
2020	1,334	1,011	0,099	0,038	2,610
2021	1,332	1,008	0,098	0,043	2,299
2022	1,331	1,008	0,102	0,042	2,425