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How Good Is Open Bicycle Network Data? A Countrywide Case Study of Denmark

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Cycling is a key ingredient for a sustainability shift of Denmark's transportation system. To increase cycling rates, better bicycle infrastructure networks are required. Planning such networks requires high-quality infrastructure data, yet the quality of bicycle infrastructure data is understudied. Here, we compare the two largest open data sets on dedicated bicycle infrastructure in Denmark, OpenStreetMap (OSM) and GeoDanmark, in a countrywide data quality assessment, asking whether the data are good enough for network-based analysis of cycling conditions. We find that neither of the data sets is of sufficient quality, and that data conflation is necessary to obtain a more complete data set. Our analysis of the spatial variation of data quality suggests that rural areas are more prone to incomplete data. We demonstrate that the prevalent method of using infrastructure density as a proxy for data completeness is not suitable for bicycle infrastructure data, and that matching of corresponding features is thus necessary to assess data completeness. Based on our data quality assessment, we recommend strategic mapping efforts toward data completeness, consistent standards to support comparability between different data sources, and increased focus on data topology to ensure high-quality bicycle network data.

Introduction

Our current car-dominated transport systems must become more environmentally and socially sustainable (Mattioli 2021; EEA 2022; Jaramillo et al. 2022). Active mobility, such as cycling, is an important part of the transition (European Commission 2021; Jaramillo et al. 2022; European Commission 2023). However, getting more people to cycle is a complex task and often requires bicycle infrastructure improvements (Schoner and Levinson 2014; Buehler and Dill 2016; Tait et al. 2022; Xiao et al. 2022; Fosgerau et al. 2023). The corresponding policy and decision-making process could be greatly supported by data-driven methods, as demonstrated by recent bicycle planning approaches (CHIPS 2019; Eudaly et al. 2020; ECF 2022) and by active mobility research (Lovelace et al. 2017; Natera Orozco et al. 2020; Olmos et al. 2020;

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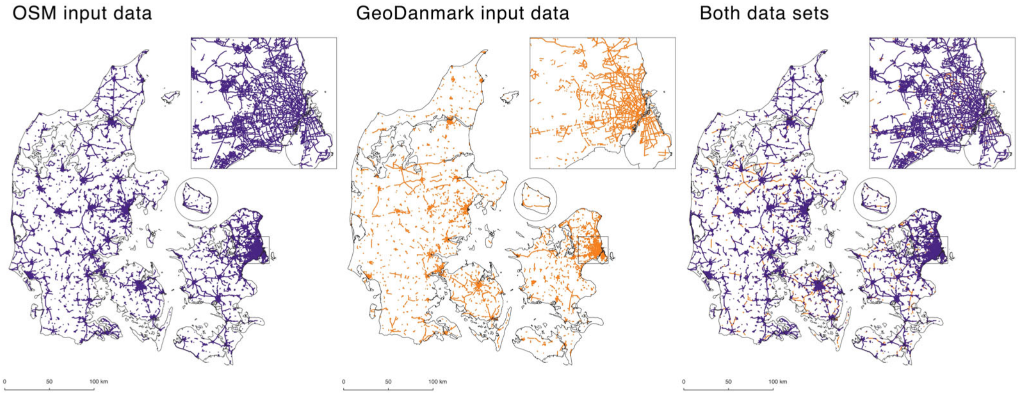

Figure 1. Spatial extent of the two input data sets. Left: OSM bicycle infrastructure. Center: GeoDanmark bicycle infrastructure. Right: Both data sets, OSM on top. Map insert: Copenhagen and surroundings.

Steinacker et al. 2022; Szell et al. 2022; Paulsen and Rich 2023; Vybornova et al. 2023). Moreover, technical and governmental guidelines on bicycle infrastructure planning often give recommendations that would require high-quality infrastructure data to implement (de Groot 2016; Parkin 2018; City of Copenhagen 2023). There is a growing number of open-source data-driven tools with a large potential for decision support in bicycle planning, such as Propensity To Cycle (Lovelace et al. 2017), Bicycle Network Analysis (PeopleForBikes 2023), and A/B Street (Carlino, Li, and Kirk 2023). Unfortunately, the often low or unknown quality of bicycle infrastructure data is a massive obstacle for these data-driven tools and methods. In terms of quality, cycling data are still lagging behind motorized transport data (Lee and Sener 2020; Willberg et al. 2021; Rambøll 2022). Despite this, to our knowledge, there is currently very little research specifically on bicycle infrastructure data. All of these issues pose a barrier for any data-informed efforts to improve cycling conditions.

To address the problem of bicycle infrastructure data of low or unknown quality, we conduct a quality assessment of bicycle infrastructure data for the entire extent of Denmark. Our results are of particular interest for country-specific applications, while our approach is transferable to other regions or countries. The two open data sets assessed in this article contain networks of dedicated bicycle infrastructure (tracks and lanes) from the global collaborative mapping platform OpenStreetMap (OSM) (OpenStreetMap Contributors 2023) and from the national public data set GeoDanmark (GeoDanmark 2023) (Fig. 1). We analyze the spatial data quality for the entire country for both data sets, with special attention to network structure and spatial patterns in levels of data quality. In particular, we pose the following research question:

Is the spatial data quality of the OSM and GeoDanmark data sets adequate to support network-based analysis of cycling conditions in Denmark?

To answer this question, we compare the two data sets through four data quality metrics: data completeness based on infrastructure density, data completeness based on feature matching, network structure, and OSM tag completeness. All metrics are computed with `BikeDNA` (Vierø, Vybornova, and Szell 2023), a Python-based open-source tool for the comparison of OSM and reference data sets on bicycle infrastructure. For each of the quality metrics, we then investigate spatial patterns, such as indications of spatial autocorrelation. This is, to our knowledge, the first investigation of spatial patterns of bicycle infrastructure data quality; the first study that assesses bicycle data quality for the entire country of Denmark; and one of the first studies to examine bicycle infrastructure data quality outside of urban areas.

An assessment of the spatial data quality of a bicycle infrastructure data set, like the one presented here, has two main purposes: identifying and correcting specific data errors, and informing data management with the goal of improving data quality. Our Denmark case study serves both purposes: we find substantial differences not just in the *amount* of bicycle infrastructure, but also in *where* bicycle infrastructure is mapped in the two data sets. Importantly, we conclude that the prevalent method for evaluating data completeness through density differences is inadequate for bicycle infrastructure data, due to the large variability in bicycle infrastructure mapping practices. Moreover, we find widespread topological errors, appearing for different reasons in the two data sets. These errors require customized solutions, particularly for network-related purposes, such as routing. Lastly, we find that the completeness of OSM "tags" (the attributes associated with a feature) relevant to bicycle conditions, such as road surface or street lighting, follow distinct spatial patterns, with large variations between the completeness of tags within compared to outside of urban centers.

The rest of the article is organized as follows: first, we give a brief overview of previous work on spatial data and bicycle network data quality and an introduction to bicycle infrastructure data in general (Section Literature review), followed by an introduction to the data sets used in this article (Section Data). Next, we introduce the methods for spatial data quality evaluation (Section Methods). We then present the results and what they tell us about the bicycle infrastructure in Denmark (Section Results). Lastly, we discuss potential applications, future work, and limitations of this article (Section Discussion), and end with a conclusion that summarizes our findings (Section Conclusion).

Literature review

The quality of spatial data in general, and of volunteered geographic information (VGI) and other crowdsourced data sets in particular, is overall well-studied (Fonte et al. 2017; Degrossi et al. 2018; Medeiros and Holanda 2019) – but much less so for bicycle infrastructure data, for which very few studies exist. Therefore, we conduct our literature review in two steps: first, we review previous work on spatial data quality assessment, with a focus on OSM bicycle infrastructure data quality (Section Previous work on spatial data quality assessment). Then, we provide a general typology of bicycle infrastructure data and an overview of common data sources and error types (Section Typology, data sources, and common quality issues of bicycle infrastructure data), which motivates the methods (Section Methods) and their applicability to other locations than Denmark.

Previous work on spatial data quality assessment

Spatial data quality encompasses both the quality of the *spatial geometries* and the *attributes and information* associated with each geometry (Fonte et al. 2017). An increasingly popular approach to spatial data quality, particularly of VGI and OSM data (Biljecki, Chow, and Lee 2023), is the "fitness-for-purpose" concept, which asks whether a data set fulfills the requirements for a given *use case* (Devillers et al. 2007; Brando and Bucher 2010; Barron, Neis, and Zipf 2014; Zhang and Ai 2015; Brovelli et al. 2017), instead of using a formalized definition of data quality, as for example the ISO 19157 standard (ISO 2013). This is the approach to spatial data quality we use in this article.

Studies on spatial data quality commonly distinguish between *intrinsic* and *extrinsic* methods for quality assessment. Intrinsic methods evaluate the internal properties of one single data set, while extrinsic methods compare the data set to an external ("reference") data set (Barron, Neis, and Zipf 2014). In the case of OSM, studies that use intrinsic methods mostly analyze edit history, contributors, network connectivity, or tag completeness (Keßler, Trame, and Kauppinen 2011; Neis, Zielstra, and Zipf 2013; Barron, Neis, and Zipf 2014; Gröchenig, Brunauer, and Rehrl 2014; Hashemi and Abbaspour 2015; Guth et al. 2021), while studies based on extrinsic methods compare OSM data with other data sets from, for example, administrative sources (Haklay 2010; Koukoletsos, Haklay, and Ellul 2012; Neis, Zielstra, and Zipf 2012; Graser, Straub, and Dragaschnig 2015; Brovelli et al. 2017).

Regardless of the method used, most studies on OSM road network data quality agree on two points: first, OSM road network data are of a *generally* high quality and completeness; and second, the quality of OSM road network data suffers from *large spatial variations*. Data quality variations are seen across city-level, national, and international scales (Haklay 2010; Neis, Zielstra, and Zipf 2012; Barrington-Leigh and Millard-Ball 2017; Brovelli et al. 2017). Moreover, these variations occur in the spatial distribution of added OSM tags (Almendros-Jiménez and Becerra-Terón 2018; Zhang et al. 2021) and between different parts of the road network (Guth et al. 2021). For example, data on infrastructure for active mobility often lags behind data on infrastructure for motorized mobility (Neis, Zielstra, and Zipf 2012, 2013). Finally, OSM data quality tends to be lower in less densely populated areas (Haklay 2010; Barrington-Leigh and Millard-Ball 2017). Due to these heterogeneities in OSM data quality, many studies see the need to subdivide study areas to present the results on a local scale (Haklay 2010; Forghani and Delavar 2014; Brovelli et al. 2017).

So far, very few studies have investigated the quality of bicycle infrastructure data specifically. Notable examples are Tait et al. (2022), which examines the London Cycling Infrastructure Database, and Hochmair, Zielstra, and Neis (2015) and Ferster et al. (2020), which both assess the quality of OSM data on dedicated bicycle infrastructure in selected North American cities through extrinsic comparisons with reference data sets. Hochmair, Zielstra, and Neis (2015) compute and compare the aggregated density of OSM bicycle infrastructure data to a reference data set and manually inspect tagging and completeness errors. Ferster et al. (2020) also compute aggregate density and additionally match corresponding features to identify overall differences and the exact locations where OSM and other open data sets disagree. Both studies conclude that, although OSM data are generally of high quality and in many places in concordance with local reference data sets, there are substantial spatial differences in data completeness, mapping practices, and tagging precision within and between the examined cities. At the same time, the two studies draw opposing conclusions regarding different bicycle infrastructure types: Hochmair, Zielstra, and Neis (2015) conclude that in the examined locations, OSM is more complete for protected than for unprotected bicycle infrastructure, while Ferster et al. (2020) find the biggest concordance between OSM and reference data precisely for unprotected bicycle infrastructure. These contradictory findings emphasize the need for local spatial data quality assessments of OSM data, particularly for less frequently studied parts of the data set, such as bicycle infrastructure.

Additionally, Wasserman et al. (2019) have examined the potential of using OSM data for Level of Traffic Stress (LTS) classifications for cyclists (Mekuria, Furth, and Nixon 2012), and conclude that OSM data have a high accuracy for predicting the correct LTS score when compared with ground-truth reference data. Ferster et al. (2023) similarly study how well

OSM data performs compared to other open data sets for identifying high and low comfort bicycle infrastructure, and find that the accuracy of OSM data is higher or comparable to the reference data. Both studies, however, also find substantial variations in the classification accuracy depending on both the location and type of infrastructure.

In summary, bicycle infrastructure data quality is subject to substantial spatial variations: error types vary between locations, and findings cannot be generalized from one location to another. Moreover, there are many differing tagging practices and data models for bicycle infrastructure, which makes it necessary to adapt spatial data quality assessment methods specifically to this type of data. Finally, the two main studies on OSM bicycle infrastructure data quality by Hochmair, Zielstra, and Neis (2015) and Ferster et al. (2020) are specific to the North American context and cover only the aspects of data completeness and thematic accuracy, without addressing data topology. However, correct topology is required by many bicycle infrastructure data applications, such as routing and accessibility analysis. Thus, the challenge of determining the fitness-for-purpose of bicycle infrastructure data for these purposes has so far remained unaddressed.

Typology, data sources, and common quality issues of bicycle infrastructure data

Within the context of this article, we define (dedicated) "bicycle infrastructure" as the elements of the *road and path network dedicated exclusively to cyclists*. In other contexts, the term "bicycle infrastructure" might also encompass such facilities as bicycle parking and repair stations; however, here we use the term in line with the previous related literature on spatial data quality (Ferster et al. 2020, 2023). Definitions and classifications of dedicated bicycle infrastructure can vary depending on the local context (Transport for London 2014; Wien 2016; City of Amsterdam 2017; Tait et al. 2022; City of Copenhagen 2023). For the purpose of this article, and in line with the public Danish data set we analyze, we distinguish only between *protected* (bicycle tracks, physically separated from motorized traffic) and *unprotected* (bicycle lanes, with no physical separation from the motorized traffic) bicycle infrastructure, see Fig. 2. Dedicated bicycle infrastructure is crucial for encouraging cycling (Fosgerau et al. 2023), and improves both the actual and the experienced cycling safety (Kamel and Sayed 2021; Gössling and McRae 2022). However, data on where this infrastructure exists are often inadequate (Hochmair, Zielstra, and Neis 2015; Ferster et al. 2020; Winters, Zanotto, and Butler 2020; Rambøll 2022), and there is a lack of established best practice in bicycle data collection and maintenance. The approaches that do exist are mostly community-driven, such as guides for mapping bicycle infrastructure in OSM (OpenStreetMap 2023a; Ferster 2024). The low data quality for dedicated bicycle infrastructure is in contrast with the high data quality for mixed use roads that are part of the already well-mapped motorized traffic network. Moreover, physical networks of dedicated bicycle infrastructure tend to be significantly more fragmented than networks for motorized traffic, and suffer from many missing links and disconnected components (Natera Orozco et al. 2020; Reggiani et al. 2023; Vybornova et al. 2023). These two issues can therefore appear indistinguishable, creating a specific challenge for bicycle infrastructure.

There are two main sources for open data on bicycle infrastructure: online mapping platforms, where OSM is the most well known and widely used (Ferster et al. 2020; Nelson et al. 2021), and public agencies, such as municipal administrations or national mapping agencies (Winters, Zanotto, and Butler 2020; Rambøll 2022; Tait et al. 2022). OSM is the go-to data source for research on the built environment and for projects and applications relying on open road network

Figure 2. Types of bicycle infrastructure. The analysis includes dedicated bicycle infrastructure, which can be either *protected* bicycle tracks (left) or *unprotected* bicycle lanes (right).

data (Carlino, Li, and Kirk 2023; CycleStreets 2023; PeopleForBikes 2023), whereas data from public agencies to our knowledge are primarily used for planning and administrative purposes.

Bicycle infrastructure data are usually the outcome of manual data collection, land surveying, and digitizing based on aerial or satellite photos (GeoDanmark 2020; Tait et al. 2022; OpenStreetMap 2023b), although little research engages specifically with the collection of bicycle infrastructure data. Recent research indicates that data collection efforts could make use of machine learning methods applied to street view images (Biljecki and Ito 2021; Ding, Fan, and Gong 2021; Saxton 2022), but this has yet to be implemented in practice. OSM, in addition to the data collection methods already mentioned, also makes use of bulk imports of, for example, administrative data sets (Zielstra, Hochmair, and Neis 2013; Witt, Loos, and Zipf 2021).

Regardless of their source, data on bicycle infrastructure are often of an unknown, heterogeneous, or low quality (Hochmair, Zielstra, and Neis 2015; Ferster et al. 2020; Winters, Zanotto, and Butler 2020; Rambøll 2022; Hvingel and Jensen 2023a). For administrative data, the lower quality of bicycle data has been explained with a lack of resources, as active mobility is given lower priority in contrast to motorized modes (Rambøll 2022). Below, we give a brief overview of the most prominent quality issues for bicycle infrastructure data from a network research perspective. For a more detailed introduction to the different types of data quality problems in bicycle infrastructure data, see Vierø, Vybornova, and Szell (2023).

The starting point for most quality assessments is data *completeness*, which indicates whether all existing objects are represented in the data. Issues with data completeness can be divided into errors of *omission* and *commission*, referring to missing or excess data, respectively (Fig. 3). Data completeness is also affected by *thematic accuracy* (see below). Crowdsourced data that are added gradually over time are especially prone to suffer from incompleteness during early stages of data collection (Neis, Zielstra, and Zipf 2012).

Figure 3. Common quality issues in bicycle infrastructure data. Left: Different levels of data completeness, with an error of commission resulting in a longer bike path in the GeoDanmark data (orange) than OSM (purple). Center: Different data models in OSM (purple) and GeoDanmark (orange), with OSM using a center line mapping and GeoDanmark mapping all infrastructure with separate geometries. Right: Example of an undershoot in OSM data.

The next step is typically to assess data *consistency*, which, for bicycle infrastructure data, includes complete and correct *classification* (thematic accuracy), data *topology*, and the *data model* used to map bicycle infrastructure. Issues with thematic accuracy, that is, when objects are given erroneous tags or attributes (Fonte et al. 2017), appear, for example, when unprotected bicycle infrastructure is classified as protected, or vice versa. Topology issues can arise due to missing nodes at intersections or because of undershoots, that is, when infrastructure geometries are slightly too short and therefore do not connect (Fig. 3). Finally, although differing ways of mapping bicycle infrastructure are not errors in themselves, they can be a hindrance for comparing different data sets and pose problems if a chosen data model does not support the desired data application. For example, in the data sets from our article, OSM uses a combination of mapping bicycle infrastructure to the center line, where bicycle infrastructure running along a road is mapped by adding a tag to the road center line, *and* mapping bicycle tracks with their own geometries. Meanwhile, in GeoDanmark, bicycle infrastructure is always mapped with separate geometries, regardless of the infrastructure type (Fig. 3).

Data

The case study makes use of several data sets. Our two main data sources are OSM and GeoDenmark, providing a VGI data set and a public data set of bicycle infrastructure for the same area, respectively. Since previous studies have found contradictory results on data quality in OSM compared to public data (Brovelli et al. 2017; Sarretta and Minghini 2021; Smarzaro, Davis, and Quintanilha 2021), we do not make any prior assumptions regarding their comparative level of data quality. Further, we use four auxiliary data sets which provide us with the delimitation of the study area (the entire extent of Denmark), administrative subdivisions at the municipal level, municipal population sizes, and the local population density across the country.

OSM data are crowdsourced, that is, maintained by a large number of contributors on a voluntary basis (OpenStreetMap 2024a). In OSM, separate bicycle ways are usually mapped with the `highway = cycleway` tag combination and a separate geometry (rather than as

Table 1. Meta Data

Bicycle infrastructure meta data		
	OSM	GeoDanmark
Authority	OpenStreetMap Foundation	GeoDanmark
Type	Crowdsourced data	Administrative public data
Coverage	Global	Denmark
Update frequency	Continuous	Yearly major update and continuous local updates
Data collection methods	Manual mapping & bulk imports	Photogrammetric mapping & manual edits

Note: Background information on the OSM and GeoDanmark data sets.

an attribute to the road center line) (OpenStreetMap 2023c). Dedicated bicycle infrastructure running along a road is usually mapped with a tag to the road centerline, using for example the tags `cycleway`, `cycleway:left`, `cycleway:right`, or `cycleway:both` (OpenStreetMap 2023a). Additionally, OSM contributors can make use of tags such as `bicycle`, `oneway/oneway:bicycle`, `cyclestreet`, `bicycle_road` and `cycleway:separation` to add further details, or to map road space where cyclists have priority. Mapping of bicycle infrastructure in OSM is, however, contextual and dependent on the local type of bicycle infrastructure and OSM mapping traditions. For further details on OSM data structure and mapping of OSM bicycle data, see for example, Hochmair, Zielstra, and Neis (2015), Ferster et al. (2023), and the OSM Bicycle Wiki (https://wiki.openstreetmap.org/wiki/Bicycle).

The GeoDanmark road network data is a national, open data set that includes the main road network, bicycle infrastructure along the car road network, and different types of paths. The data set is collected and updated based on aerial photos and manual edits, in a collaboration between The Danish Agency for Data Supply and Infrastructure and the Danish municipalities (GeoDanmark 2020). Contrary to the OSM data model, GeoDanmark always maps bicycle infrastructure with their own geometries separate from the road center line, classified as either bicycle lanes or bicycle tracks (Figs. 2 and 3). GeoDanmark contains only a few attributes of relevance to the cycling experience, but for each feature includes information on the surface (paved/unpaved), the type of infrastructure (track/lane), as well as an attribute identifying bridges and tunnels. GeoDanmark data on bicycle infrastructure have previously been used in research on bikeability, in combination with OSM data (Skov-Petersen and Nielsen 2015; Nielsen and Skov-Petersen 2018).

Both the OSM and the GeoDanmark data sets originally contain the full road network, but only the subsets with dedicated bicycle infrastructure are used in this analysis. See Table 1 for meta-data on both data sets and Section 2 in Appendix S1 for the queries used to extract the subsets from the full network. GeoDanmark data were downloaded from the national data portal Datafordeler (Datafordeler 2023). The OSM data were downloaded from Geofabrik (2020).

Both data sets were preprocessed with `BikeDNA` (Vierø, Vybornova, and Szell 2023) using the Python libraries `pyrosm` (Tenkanen 2021), `OSMnx` (Boeing 2017), and `momepy` (Fleischmann 2019). The preprocessing consists of three main steps: First, input geometries are converted to an undirected graph data structure with edges defined by their start and end nodes, but without changing the original edge geometries. Second, the tag/attribute values are

Table 2. Data Summary

Data summary		
Metric	OSM	GeoDanmark
Total edge length (km)	15,333	8,676
Edge count	88,997	50,856
Node count	90,804	51,224

Note: Summarizing of input data on bicycle infrastructure.

simplified into three attributes describing respectively the mapping type (centerline or separate geometry), allowed cycling direction, and protection level. Third, the network is simplified by removing degree-2 nodes, unless removing a node would conflate network edges with differing relevant attributes. This last step reduces the number of network edges and nodes without modifying network topology or connectivity. After preprocessing, the OSM network contains 88,997 network edges with a total length of 15,333 km and 90,804 nodes. The GeoDanmark network contains 50,856 network edges with a total length of 8,676 km and 51,224 nodes (Table 2).

The data sets on study area delimitation (geographical extent of Denmark with an area of 43,057 km^2) and municipal names and boundaries have been downloaded from Datafordeler (2023). Finally, we obtained municipal population sizes from Statistics Denmark (2023) and a population density raster from the European Commission's Global Human Settlement Layer (Schiavina, Freire, and MacManus 2023).

Methods

The main idea of our approach is to first assess four metrics of data quality (data completeness based on infrastructure density, data completeness based on feature matching, network structure, and OSM tags), and second, to examine spatial patterns in all four of them. Data completeness is usually an important aspect when evaluating data quality (Senaratne et al. 2017; Medeiros and Holanda 2019) and has also been a focus point of early work on both OSM road network and bicycle infrastructure data quality (Haklay 2010; Koukoletsos, Haklay, and Ellul 2011; Hochmair, Zielstra, and Neis 2015; Brovelli et al. 2017; Ferster et al. 2020). For research looking into, for example, the bikeability of an area, having complete data is particularly important, since the omission of dedicated bicycle infrastructure can change the assessment of an area significantly. The completeness and consistency of OSM tags can moreover be used as an indicator of spatial data quality (Mooney and Corcoran 2012; Almendros-Jiménez and Becerra-Terón 2018; Biljecki, Chow, and Lee 2023). While a consistent network structure is not of importance for all data applications, it is critical for the many projects and research applications either using OSM data for routing, accessibility evaluation, or network structure assessment (Murphy and Owen 2019; Szell et al. 2022; Reggiani et al. 2023; Vybornova et al. 2023). The consistency of network structure is however understudied for bicycle infrastructure. Finally, OSM tag completeness is crucial for, for example, evaluations of LTS using OSM data (Wasserman et al. 2019) and correct routing (Guth et al. 2021).

The four data quality metrics are computed with the previously developed tool `BikeDNA` (Vierø, Vybornova, and Szell 2023), in a version adapted to large data sets for the purpose of this article (https://github.com/anerv/BikeDNA_BIG). We compute quality metrics both globally,

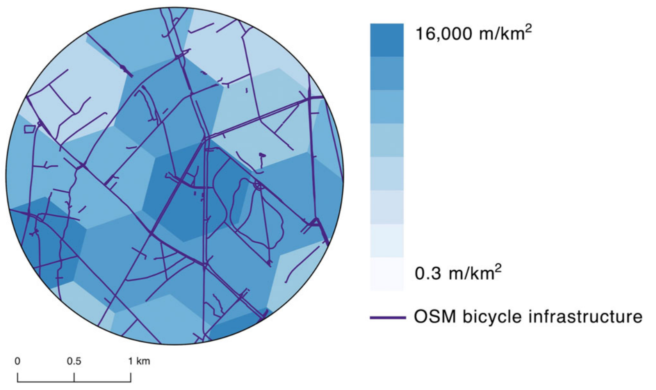

Figure 4. Example of hex grid aggregation. Hex grid cells used to compute the local infrastructure density of OSM data.

that is, for the whole data set, and locally, that is, for each cell in a H3-based hexagonal grid (Uber 2023) covering the study area (Fig. 4). The grid cell size is configurable in `BikeDNA`; here we set it to resolution 8 with an average cell size of 0.74 km^2 (see Appendix S1 for other parameter values used in the analysis). In the second methodological step, spatial patterns in data quality for all four metrics are analyzed through spatial autocorrelation (Anselin 1995; Getis 2007) and by examining the spatial correlation of quality metrics with population densities (https://github.com/anerv/bikedna_dk_analysis).

Data completeness from infrastructure densities

Computing differences in infrastructure density is a common and computationally cheap way of assessing differences in data completeness (Haklay 2010; Neis, Zielstra, and Zipf 2012). We examine data completeness based on infrastructure density in three steps: first, comparing the total lengths of the OSM and GeoDanmark data; second, comparing infrastructure densities at the municipal level; and third, comparing infrastructure densities at the grid cell level. To compensate for the different data models in OSM and GeoDanmark data (Fig. 3), our computation of data completeness is not based on the length of the geometries in each data set, but instead uses the concept of *infrastructure length*, by which we consider information on allowed cycling direction and mapping approaches. For example, an OSM center line mapping of bicycle lanes on both sides of a 100 meter long road will be counted as 200 m to allow for comparison with the data model in GeoDanmark, where the same infrastructure would be mapped with two separate 100 m geometries on each side of the road (see Section 2 in the Appendix S1 for the queries used to define allowed cycling directions). The accuracy of this approach depends on correct tagging of both bicycle infrastructure and allowed cycling direction in OSM. For this reason, previous studies have chosen to instead handle differing data models by not counting left and right lanes separately (Hochmair, Zielstra, and Neis 2015) or by conflating separate geometries to a center line mapping (Ferster et al. 2020). In dense networks, the latter method, however, necessitates information on which road centerline a bicycle geometry belongs to.

While varying levels of local infrastructure density can indicate areas with missing or surplus data, they do not reveal specific omission or commission errors. Local measures of infrastructure density are moreover aggregate measures and thus inherently prone to issues, such as hiding or exaggerating spatial differences. For this reason, we also apply a feature matching algorithm

(Koukoletsos, Haklay, and Ellul 2011, 2012; Will 2014; Vierø, Vybornova, and Szell 2023) on the two data sets to identify corresponding objects in OSM and GeoDanmark data.

Data completeness from feature matching

Feature matching (i.e., the identification of corresponding features in different data sets) is the most exact method for obtaining differences in data completeness. The feature matching procedure divides the geometries in both data sets into segments of equal length. The best (if any) match for each feature is determined using a combination of configurable maximum thresholds for segment distance, Hausdorff distance, and the angle between segments from the corresponding data sets (Koukoletsos, Haklay, and Ellul 2011, 2012; Will 2014). Just as for the comparison of data completeness, we compute results both globally (as aggregate values for the entire data set) and locally (as the total count and percentage of matched and unmatched segments in each grid cell).

Network structure

Consistency in network structure is crucial for network-based applications like routing or accessibility analysis, which are made impossible by topological errors and inconsistent network fragmentation. An analysis of fragmentation and topological errors is fundamentally an intrinsic evaluation aimed at detecting internal (in)consistencies. Nevertheless, due to the scattered nature of many actual bicycle networks, a comparison of network fragmentation and topological errors between two data sets is a useful, and sometimes necessary method for distinguishing between poor *data* quality and poor *network* quality without conducting a manual validation. Here, we focus on two aspects of network structure: *network components*, as a proxy for the fragmentation or connectivity in the data, and *undershoots* (see Section Typology, data sources, and common quality issues of bicycle infrastructure data), as an example of topological errors.

A disconnected network component is a subset of a network where all nodes of the component can reach each other internally, but no nodes of the component can reach the rest of the network. Most actual bicycle infrastructure networks are made up from many disconnected components (Furth, Mekuria, and Nixon 2016; Natera Orozco et al. 2020; Szell et al. 2022). Data on networks of bicycle infrastructure will thus often be correctly divided into many disconnected components, but can at the same time suffer from additional fragmentation due to data quality issues. Unwanted components can for example occur due to incomplete data resulting in "missing links" (Vybornova et al. 2023), snapping issues, and imprecise geographic coordinates resulting in network edges that do not actually connect. In the case of OSM or similar data sets, a missing bicycle tag on a road segment can additionally turn a single piece of infrastructure into two disconnected fragments in the data (Fig. 13). For bicycle infrastructure data created without considering routing, disconnected components can also appear if, for example, bike lanes are not explicitly connected across intersections. While most disconnected bicycle components are connected by the road network, these connections do not serve cyclists who are unable or unwilling to bike in mixed traffic. Therefore, the connectivity of the network of dedicated bicycle infrastructure is of primary importance for, for example, analysis of low stress cycling and accessibility (Mekuria, Furth, and Nixon 2012; Lowry and Loh 2017; Reggiani et al. 2021).

The distribution and location of disconnected components can indicate two aspects of data quality: First, a high local count of disconnected components indicates a large degree of network fragmentation and warrants a closer inspection of that area. Second, the absolute and relative size of the larger connected components in a network are indications of how suitable a data set is for routing and accessibility evaluations in general. The component sizes can thus indicate whether a given data set can be used in network-based data applications.

By running `BikeDNA`, we acquire the number of network components in each data set, the distribution of infrastructure length per component, the local component count (how many different disconnected components a grid cell intersects), and the local and global numbers of undershoots. For further analysis and visualization, this step also indicates which network nodes have been identified as undershoots, and which component a given network edge belongs to. In this article, we define undershoots as dangling nodes within three meters of a network edge to which the node is not connected (Fig. 3).

OSM tags

OSM tags are key-value pairs which define the core feature type of mapped geometries, as well as any additional information about the object. OSM uses an open tagging system with best practices, but no enforcement of standards (Hochmair, Zielstra, and Neis 2015). Incorrect tagging leads to errors of omission and commission for local bicycle networks in OSM (Hochmair, Zielstra, and Neis 2015; Ferster et al. 2020), and correct tagging is thus a crucial first step toward OSM bicycle infrastructure data completeness. Additional information on the infrastructure, such as surface and lighting conditions, is additionally of relevance to many bicycle planning and research projects (Wasserman et al. 2019; Ferster et al. 2023). Previous research has found large spatial variations in tagging patterns and completeness, both for the road network data and other features mapped in OSM (Mooney and Corcoran 2012; Barron, Neis, and Zipf 2014; Hochmair, Zielstra, and Neis 2015; Almendros-Jiménez and Becerra-Terón 2018; Biljecki, Chow, and Lee 2023; Ferster et al. 2023).

To examine the extent to which the OSM data in the study area contain information relevant to e.g. a mapping of LTS (Mekuria, Furth, and Nixon 2012) and bikeability, we analyze the local share of bicycle infrastructure with tags for four different attributes that are relevant to the cycling experience (de Groot 2016; Elvik 2018; Vidal-Tortosa and Lovelace 2024):

- Infrastructure surface: "surface"/"cycleway:surface."
- Presence of street lights: "lit."
- Width of the infrastructure: "width"/"cycleway:width."
- Speed limit for motorized traffic: "maxspeed."

Due to the absence of ground truth data, our analysis only considers the existence, but not the correctness of tags. Because of the limited number of attributes related to cycling in the GeoDanmark data, the analysis of OSM tags is intrinsic, i.e. no comparison to GeoDanmark attributes is made.

Spatial patterns in local data quality metrics

Identifying areas with particularly low or high data quality can help understand why quality issues occur. Our goal is to establish whether there is a discernible, nonrandom spatial pattern in data quality. To this end, we use spatial autocorrelation to identify areas with particularly low or high data quality for results for infrastructure density, feature matching and OSM tag completeness. Results for differences in infrastructure density are moreover examined at the municipal level to examine the role of differing data maintainers. GeoDanmark data are collected on national level, but the Danish municipalities play a central role in data maintenance and updates (GeoDanmark 2020). We are thus interested in detecting whether the municipal involvement in data maintenance is reflected in the data quality, especially since there are indications that the municipalities are following different mapping practices for the classification of bicycle infrastructure (Hvingel and Jensen 2023a). For OSM, we do not expect the data quality to follow municipal boundaries – unless the local administrations contribute to OSM, of which there are some examples internationally (OpenStreetMap 2022b). To detect discrepancies between GeoDanmark and OSM, we aggregate quality metrics for both data sets at the municipal level.

An analysis of spatial patterns in data quality at the municipal level cannot stand alone, since the level of spatial aggregation makes it vulnerable to the modifiable areal unit problem, which describes how spatial aggregation can distort, conceal or exaggerate spatial patterns in data (Mennis 2019). To avoid this pitfall, we supplement the analysis of differences in infrastructure length at the municipal level with a higher-resolution grid cell-level analysis of spatial autocorrelation in differences in data completeness, feature matching success, and OSM tag completeness.

Spatial autocorrelation describes how the value of a variable varies across space by quantifying to what extent data points in close proximity have similar values (Wu and Kemp 2019). In this article, the global spatial autocorrelation is measured using Moran's I. Values for Moran's I range from −1 to 1, where values above 0 indicate a clustering of *similar* values. Values below 0 indicate that data points tend to be close to *dissimilar* values, while a Moran's I close to 0 indicates spatial randomness (Rey, Arribas-Bel, and Wolf 2020). Since we are interested not only in the degree of spatial autocorrelation, but also in the exact spatial location of potential clusters of similar values, we also calculate Local Indicators of Spatial Association (LISA) using local Moran's I (Anselin 1995). We calculate both global and local Moran's I with the Python library `ESDA PySAL` (Rey and Anselin 2007). All reported clusters of local spatial autocorrelation are significant at a pseudo P-value of 0.05.

Computing spatial autocorrelation on a fragmented network with a highly uneven network density is an analytical challenge, since there is no obvious way of defining the spatial weight matrix on which the computation is based. For this reason, we compute the spatial autocorrelation for results aggregated at a local grid cell level, using a hexagonal grid with a row-standardized spatial weight matrix based on the k-nearest neighboring grid cells, with $k = 6$. To check the sensitivity of the results to the definition of the spatial weights, we repeat part of the analysis with spatial weights based on 12 and 18 nearest neighbors and with distance bands of 1,000 and 2,000 m, and find that changing those parameters does not alter the general patterns of spatial autocorrelation (Tables S2–S4).

To explore how different methods for data completeness evaluations perform, we furthermore compare differences in local infrastructure density with the results from the more exact, but also more computationally expensive, feature matching of corresponding network segments. Finally, to establish whether the common link between OSM data quality and population densities also holds for Danish bicycle infrastructure data, we analyze how infrastructure density differences and completeness of OSM tags correlate with local population density.

Results

Below, we organize our main findings into four subsections, one for each of the four quality metrics (data completeness based on infrastructure densities, feature matching, network structure, and OSM tags). Due to the size of the input data (more than 8,600 km of bicycle infrastructure in the smaller GeoDanmark data set) and the study area (43,057 km^2), it is not feasible to present

Table 3. Extrinsic Summary

Extrinsic quality comparison		
Metric	OSM	GeoDanmark
Total infrastructure length (km)	20,681	8,676
Protected infrastructure length (km)	17,876	4,264
Protected infrastructure length (%)	86.44	49.15
Unprotected infrastructure length (km)	2,804	4,412
Unprotected infrastructure length (%)	13.56	50.85
Nodes	90,804	51,224
Dangling nodes	46,426	11,218
Undershoots	157	339
Components	10,686	4,408
Length of largest component (km)	3,433	1,018
Largest component's share of network length	22%	12%

Note: Selected metrics from extrinsic comparison of OSM and GeoDanmark data for all of Denmark.

results for all parts of the network in detail. Instead, we highlight the most relevant findings from the perspective of a bicycle network analysis. In addition, we emphasize findings that are of relevance not only to bicycle infrastructure data in Denmark, but additionally help us understand the quality and characteristics of bicycle infrastructure data in general. Results are aggregated, examined, and presented at two scales: at the global (study area) and at the local (grid cell) level. Results for differences in infrastructure density are additionally aggregated at the municipal level to explore how data completeness is influenced by differing data maintainers.

Results for data completeness: infrastructure densities

Comparing the total infrastructure length at the global level (Table 3), the OSM data set contains more than twice as much bicycle infrastructure as GeoDanmark (Fig. 5). When disaggregating these values into different categories of bicycle infrastructure (protected versus unprotected), it is clear that this large difference is mostly attributable to the mapping of protected infrastructure. While GeoDanmark contains almost equal lengths of unprotected and protected infrastructure (4,412 and 4,264 km, respectively), the OSM data only contain approximately 2,784 km of unprotected, but 17,856 km of protected bicycle infrastructure (Fig. 6). The local differences in infrastructure density (Fig. 7) furthermore reveal substantial local variation in data completeness between the two data sets: out of the 16,064 grid cells with data from either or both data sources, 81% of the cells have more bicycle infrastructure mapped in OSM, 19% have more in GeoDanmark.

At the municipal level, 96 out of 98 municipalities have more data in OSM than in GeoDanmark, with relative infrastructure length differences ranging between 2% and 94% (Table S5). The differences in infrastructure length thus vary greatly between the Danish municipalities, leading to both large discrepancies between the sum of a municipality's total infrastructure and its ranking based on infrastructure length between the two data sets. For example, Aarhus municipality is the municipality with most bicycle infrastructure data in OSM, but is only in fourth place when ranking municipalities by infrastructure length in GeoDanmark data (Fig. S10).

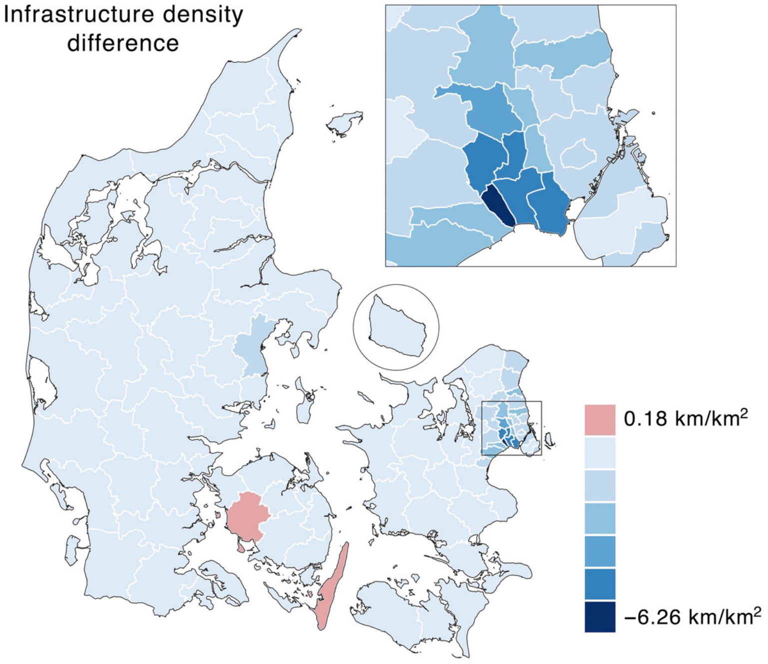

Figure 5. Difference in infrastructure density between OSM and GeoDanmark data at the municipal level. The infrastructure density difference is computed as GeoDanmark km/km^2–OSM km/km^2. Negative values (blue) indicate municipalities where OSM data have a higher density; positive values (red) indicate municipalities where GeoDanmark data have a higher density. Out of the 98 municipalities, only two have more infrastructure mapped in GeoDanmark than OSM.

At the grid cell level, the differences in infrastructure density (Fig. 7, bottom left) show a pattern of equal infrastructure density (light areas) or higher densities of OSM data (blue areas) in urban cores. Other parts of the country show no clear trend, with a combination of areas with more data in OSM and areas with more data in GeoDanmark (red areas). The insert of Copenhagen also shows that there are local exceptions to this tendency. A test for correlation between infrastructure density differences and population density indicates some correlation, with more highly populated areas having more data in OSM, but also many exceptions to this trend (Fig. S2).

To statistically confirm that there are clusters of high- and low-density differences, we analyze the local values of infrastructure density differences for spatial autocorrelation. We use Moran's I to test for any global spatial clustering and Local Moran's I to identify specific clusters of similar or dissimilar values (Anselin 1995; Rey, Arribas-Bel, and Wolf 2020). A situation of perfect spatial clustering would result in a Moran's I value of 1, while a value of 0 would indicate a random pattern. Applying the spatial weight matrix based on k-nearest neighbors with $k = 6$, as introduced in Section Spatial patterns in local data quality metrics, the global Moran's I statistic for infrastructure density differences is 0.46, with a pseudo P-value of 0.001. The results thus indicate a significant and positive, but not exceptionally strong clustering of similar values of infrastructure density differences (Fig. S4). This numerical result is also visualized in Fig. 7, bottom right: clusters of positive spatial autocorrelation of higher values of OSM infrastructure

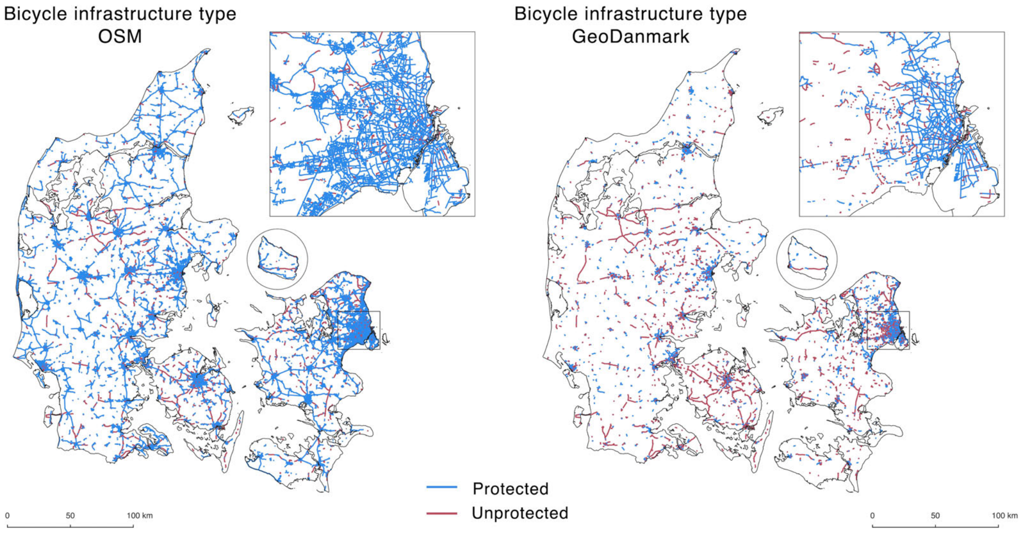

Figure 6. Protection level of bicycle infrastructure. Left: OSM. Right: GeoDanmark.

density (blue) appear in and around the major towns in Denmark, smaller clusters of higher values of both GeoDanmark (red) and OSM data are scattered across the country, while many areas show no statistically significant clustering (grey).

From these findings on data completeness at various levels of aggregation, we draw two conclusions. First, the spatial patterns in infrastructure density differences are not adequately captured at the municipal level, and a higher spatial resolution is required to show where differences occur. Second, the large variation in relative differences between GeoDanmark and OSM data completeness at the municipal level suggests that there are differing municipal mapping practices for GeoDanmark data.

Due to incompatible classifications it is not possible to obtain exactly corresponding subsets of bicycle infrastructure: GeoDanmark data, per specification, only include bicycle infrastructure running along a road with motorized traffic, while there is no feasible way of just obtaining OSM bicycle infrastructure that runs in parallel with the car road network based on the OSM tags alone. This might explain some of the discrepancies between the total amount of *protected* infrastructure in the two data sets. Moreover, as Hvingel and Jensen (2023a) have pointed out, bicycle infrastructure might be under-reported in GeoDanmark due to imprecise labeling with bicycle tracks being classified as a "main path" instead of the more specific "bicycle track." However, this does not explain why OSM has fewer unprotected bicycle lanes than GeoDanmark, and suggests that variations in data completeness are more than just an issue with thematic accuracy.

The lack of ground truth data makes any statements on the actual data completeness difficult. Manual inspections reveal errors of both omission and commission in both data sets, but without ground truth data, the extent to which discrepancies are due to missing or surplus data is unknown. Although some of the differences in data completeness can be explained with different tagging and labeling conventions, their extent and spatial pattern suggest that OSM and GeoDanmark differ in both qualitative and quantitative terms when it comes to mapping of bicycle infrastructure. In the next section, we examine the results from feature matching to identify exactly where these differences occur.

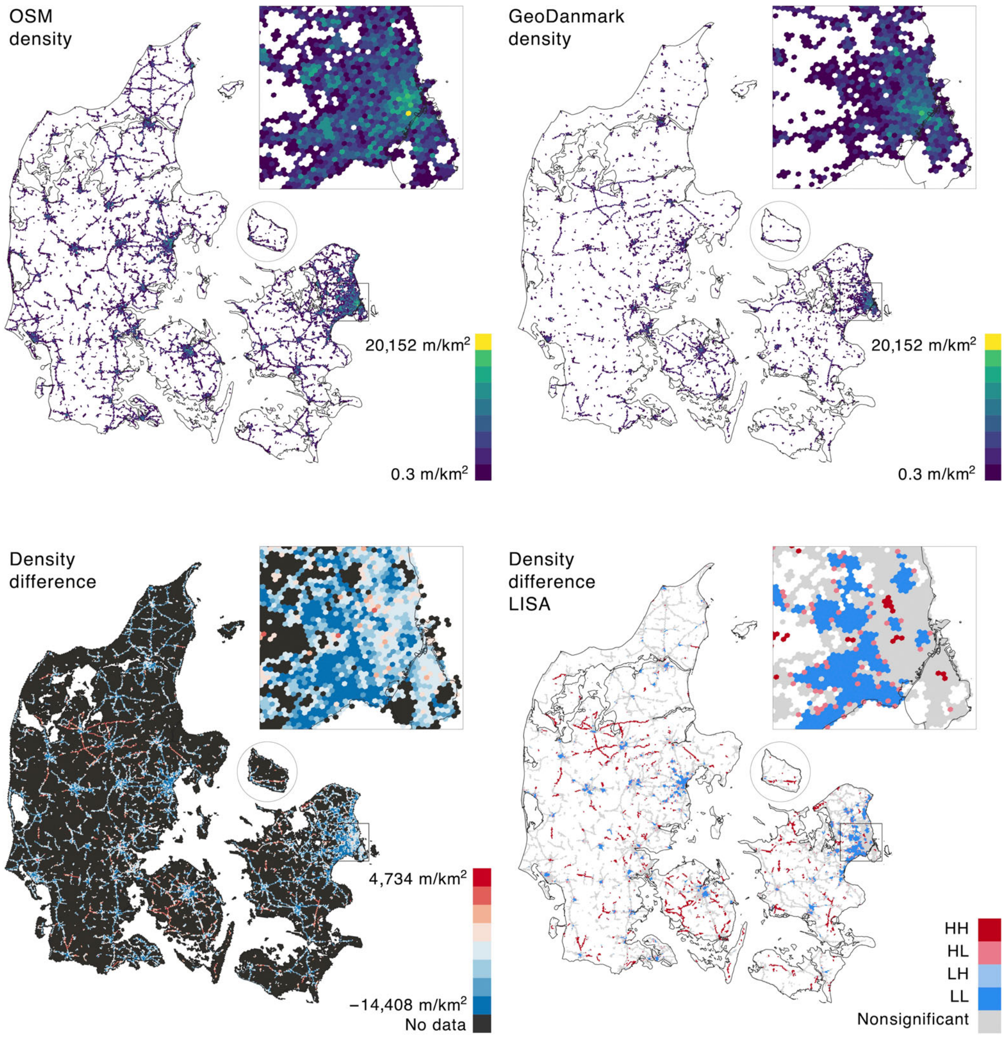

Figure 7. Infrastructure density at the grid cell level. Top left: Bicycle infrastructure density in OSM. Top right: Bicycle infrastructure density in GeoDanmark. Bottom left: Difference in infrastructure density between OSM and GeoDanmark. Areas with negative values (blues) have a higher density in OSM. Areas with positive values (reds) have a higher density in GeoDanmark. Bottom right: Analysis of local spatial autocorrelation of infrastructure density differences using Moran's I. Red areas, or "High-High" (HH), indicate significant clusters of high values ($P <$ 0.05). Blue areas, or "Low-Low" (LL), indicate significant clusters of low values. "High-Low" (HL) represent high values surrounded by low values, while "Low-High" (LH) represent low values surrounded by high values. In this context, a HL area means high relative GeoDanmark density surrounded by high relative OSM density, while LH represents high relative OSM density surrounded by high relative GeoDanmark density. Map insert: Copenhagen and surroundings in a bigger scale.

Table 4. Feature Matching Summary

Feature matching results		
Metric	OSM	GeoDanmark
Count of matched segments	351,476	564,661
Length of matched segments (km)	3,490	5,564
Percent matched segments	23%	64%
Local min. of % matched segments	0%	1%
Local max. of % matched segments	100%	100%
Local average of % matched segments	53%	83%

Note: Selected results from matching of corresponding segments in OSM and GeoDanmark data.

Results for data completeness: feature matching

In order to precisely detect where and to what extent two data sets are in agreement, their exact overlap needs to be identified. We achieve this with the feature matching method described in Section Data completeness from feature matching. Here, we present the results of the initial feature matching performed with `BikeDNA` and the subsequent analysis of spatial autocorrelation in the results.

A naive summing up of geometry lengths in each data set (disregarding differing mapping practices and data models) returns 15,333 km of bicycle infrastructure in OSM – almost twice as much as GeoDanmark with 8,676 km. Nevertheless, only 64% of the GeoDanmark segments match with an OSM segment, and only 23% of OSM segments match with a GeoDanmark segment (Table 4). We provide a detailed illustration of feature matching results through a web map at https://anerv.github.io/bikedna_webmap. A visual inspection of the results confirms that the matching procedure returns the correct result in most cases. The high levels of unmatched features in both data sets are therefore mostly explained by the two data sets containing not just *different amounts* of bicycle infrastructure, but also bicycle infrastructure in *different locations*. The spatial distribution of matched and unmatched segments (Fig. 8) thus suggest an even higher discrepancy between the two data sets than initially indicated by the differences in infrastructure density alone.

Global and local spatial autocorrelation of the local percentage of matched segments in OSM and GeoDanmark reveals a statistically significant positive spatial autocorrelation (pseudo P-value = 0.001), with a Moran's I for the share of matched OSM and GeoDanmark segments of 0.48 and 0.52, respectively. While the positive values for global spatial autocorrelation also cover large areas with no significant clustering of similar values (Fig. S5), there are clear clusters of high matching success, especially around urban centers (Fig. 8).

The correlation between the local length of unmatched segments and the differences in infrastructure density can reveal whether unmatched data occurs due to a lack of data in the other data set. For OSM data, the correlation between the local length of unmatched segments and infrastructure density differences follow an expected pattern, with more unmatched OSM segments in areas where OSM contains more data than GeoDanmark (Fig. S1). For GeoDanmark, this pattern is much less consistent: we see many locations with equal or higher amounts of data in OSM, but still high rates of unmatched GeoDanmark segments (Fig. S1). In these locations, a low matching rate for GeoDanmark data can thus not be explained with GeoDanmark simply being more complete. On the contrary, a visual analysis confirms that the low matching rates

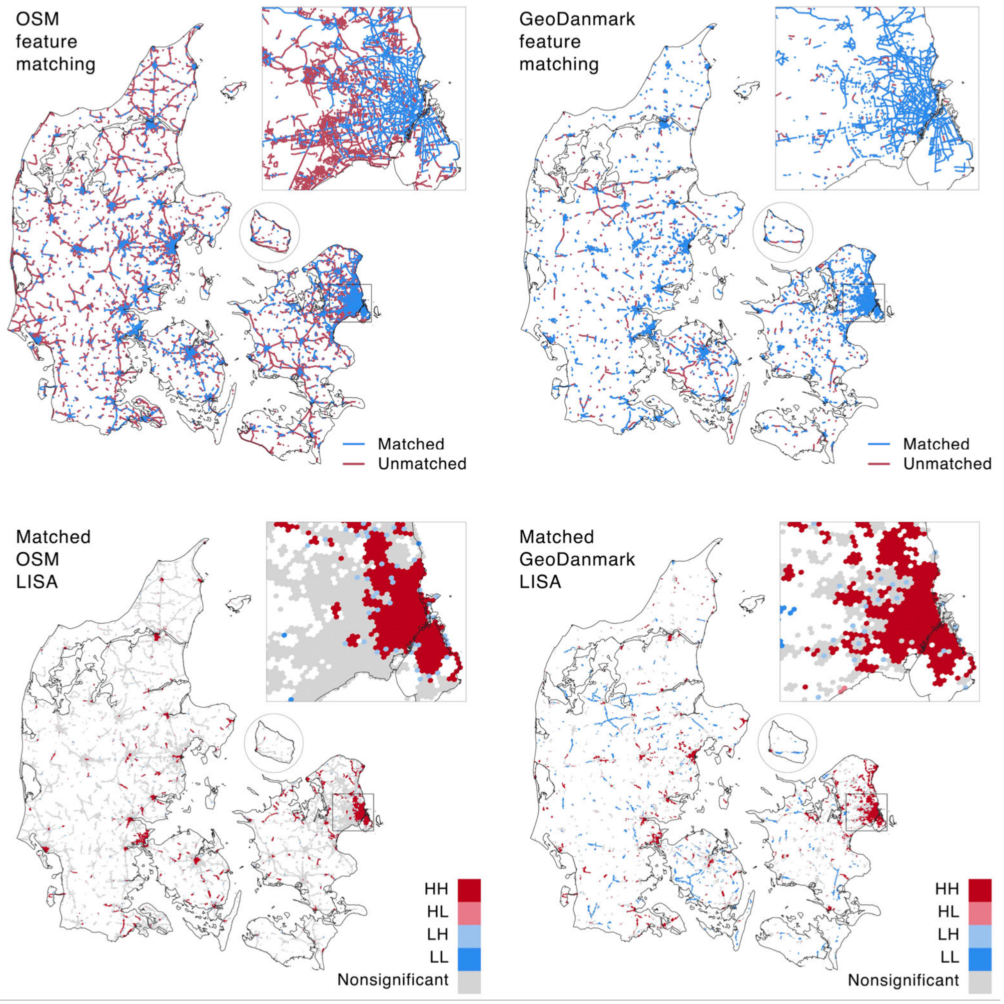

Figure 8. Feature matching results. Top row: Matched (red) and unmatched (blue) segments in OSM (left) and GeoDanmark (right). Bottom row: Local spatial autocorrelation clusters of feature matching success (% matched segments) for OSM (left) and GeoDanmark (right). Red areas, or "High-High" (HH), indicates significant clusters of high matching rates ($P < 0.05$). Blue areas, or "Low-Low" (LL), indicate significant clusters of low matching rates. "High-Low" (HL) represents high matching rates surrounded by low matching rates, while "Low-High" (LH) represents low matching rates surrounded by high matching rates. The matching rates for both data sets are highest in the larger towns and cities and lowest in less densely populated areas.

are explained by complementary or barely overlapping infrastructure data. The locations where infrastructure density differences are low, but rates of unmatched segments are high, illustrate how comparisons of infrastructure density can mask substantial differences in the actual bicycle infrastructure contained in different data sets (Fig. 9).

Summing up the assessment of data completeness from both infrastructure density differences and feature matching, it is not possible to provide a conclusive answer to how much bicycle infrastructure there is in Denmark. OSM contains substantially more data than GeoDanmark,

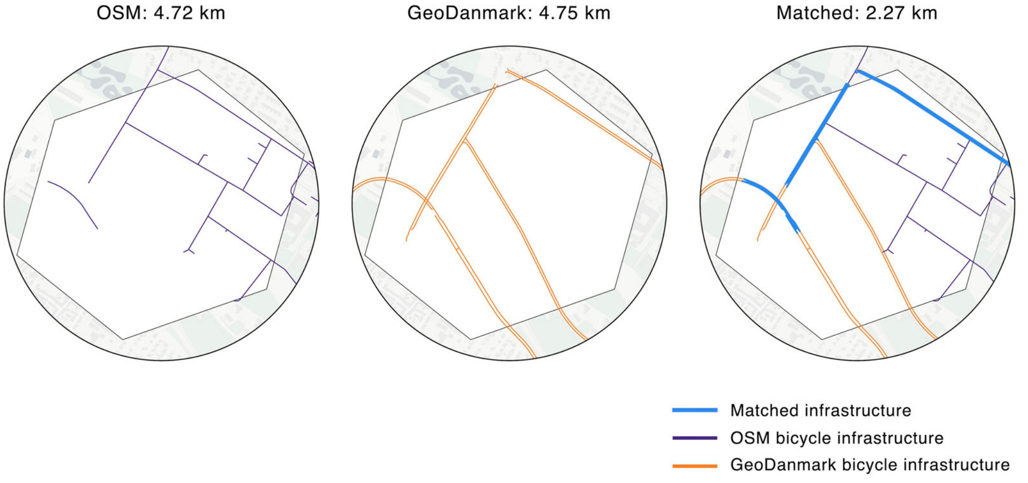

Figure 9. An example of a grid cell (in white) with very low difference in the length of infrastructure between the two data sets, but high rates of unmatched OSM and GeoDanmark data. Left: OSM data. Center: GeoDanmark data. Right: Both data sets, matched data in blue. Despite having almost the same length of bicycle infrastructure, the two data sets barely overlap.

which could indicate that the OSM data set is more complete. However, the large discrepancies in where the two data sets include bicycle infrastructure, as well as the very different ratios of protected to unprotected infrastructure, suggest that either OSM is still missing a lot of data, that GeoDanmark data suffer from many errors of commission, or both. As both the completeness of OSM and GeoDanmark data are unknown and the size of the study area makes manual verification with e.g. street view images unfeasible, we cannot conclude with certainty whether differences are due to errors of omission or commission. We are, however, able to identify where and to what extent differences exist. Notably, the concordance between the data sets is larger in more densely populated, urban areas. Although there is no unequivocal correlation between data concordance and population density (Fig. S3), the high matching rates for denser urban areas are in line with previous research, which found data completeness to be higher in areas with higher population densities (Barrington-Leigh and Millard-Ball 2017; Fonte et al. 2017).

Results for network structure

To assess data quality from a network perspective, we examine two aspects of network structure: network fragmentation, which we measure by counting the disconnected network components, and the number of topological errors, which we measure by identifying undershoots errors present in the data. As explained in Section Data, the two data sets partly make use of different data models. Moreover, the GeoDanmark data set in its current shape has already been shown unsuitable for routing (Septima 2019). We therefore expect to see some differences in network fragmentation at the local and possibly also at the global level.

The ratio of kilometers of bicycle infrastructure to number of network components (Table 3) is almost identical between OSM and GeoDanmark, with a ratio of 1.94 and 1.98, respectively. However, large discrepancies arise in the fragmentation at local (grid cell) level, that is, by counting how many different disconnected components each grid cell intersects with. In some locations OSM has a much higher number of disconnected components than GeoDanmark, in

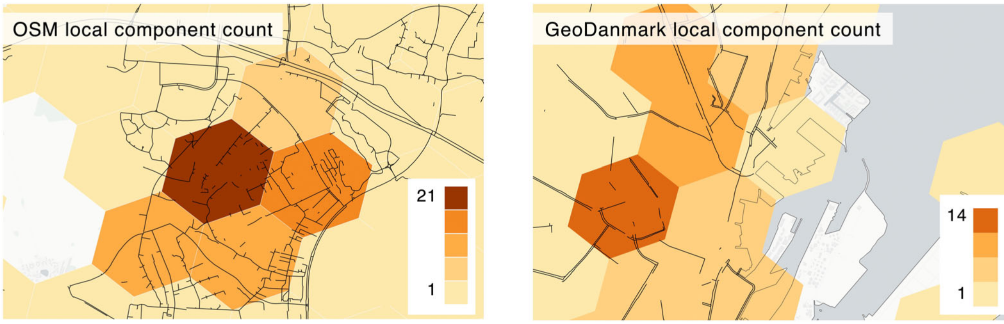

Figure 10. Local component count. Examples of areas with a high local component count in OSM (left) and GeoDanmark (right). The local component count for both data sets is relatively homogeneous, but with a few outliers with many disconnected components.

other locations the opposite is true. The value range for the local component count is notably wider in OSM (1–21) than in GeoDanmark (1–14) (Figs. 10 and S6).

A high number of disconnected components in close proximity to each other mostly occurs due to highly detailed mapping, where, for example, bicycle lanes of a few meters length result in several disconnected components on the same road. For OSM, erroneous fragmentation also occurs because of missing tags of bicycle infrastructure, which leads to many small missing links and consequently disconnected components. In GeoDanmark, disconnected components often occur due to the data model, which uses separate geometries on each side of a road with no connecting links at e.g. intersections.

Although OSM has a higher maximum count of local disconnected components (Fig. 10), its largest connected component is bigger than GeoDanmark's. The OSM network can therefore be considered more connected. The largest connected components of OSM and GeoDanmark are 3,433 and 1,018 km long and represent 22% and 12% of the total network length, respectively (Table 3 and Fig. 11).

The differences in network fragmentation can also be seen in the Zipf plot (Fig. 12), which ranks the lengths of all components by descending order on a log-log scale. For both data sets, the plot shows several data points which represent components that are much larger than the remainder of the components (top left in Fig. 12). Compared to the GeoDanmark data, the OSM data however have several very large components (starting at the leftmost top marker at rank $10^0 = 1$), and the second highest ranked OSM component is the same size as the highest ranked component in the GeoDanmark data. Although the aggregated values (ratio of kilometers of bicycle infrastructure to number of network components) indicate that OSM and GeoDanmark data have a similar fragmentation, these aggregate values cover a substantial variation in the distribution of component size (Fig. S6). At grid cell level, the OSM data have more tiny components (the lowest ranked components with length $10^{-3} = 0.001$ km, see purple tail on the right side in Fig. 12), but also more very large components with several thousand kilometers of bicycle infrastructure. The OSM network thus both contains large components that can support a cycling network analysis, but also many components which are too small for any meaningful analysis of, for example, cycling accessibility. In summary, disconnected components occur in both OSM and GeoDanmark data partly because of the scattered nature of the actual infrastructure, but also due to missing links and imprecisely mapped geometries.

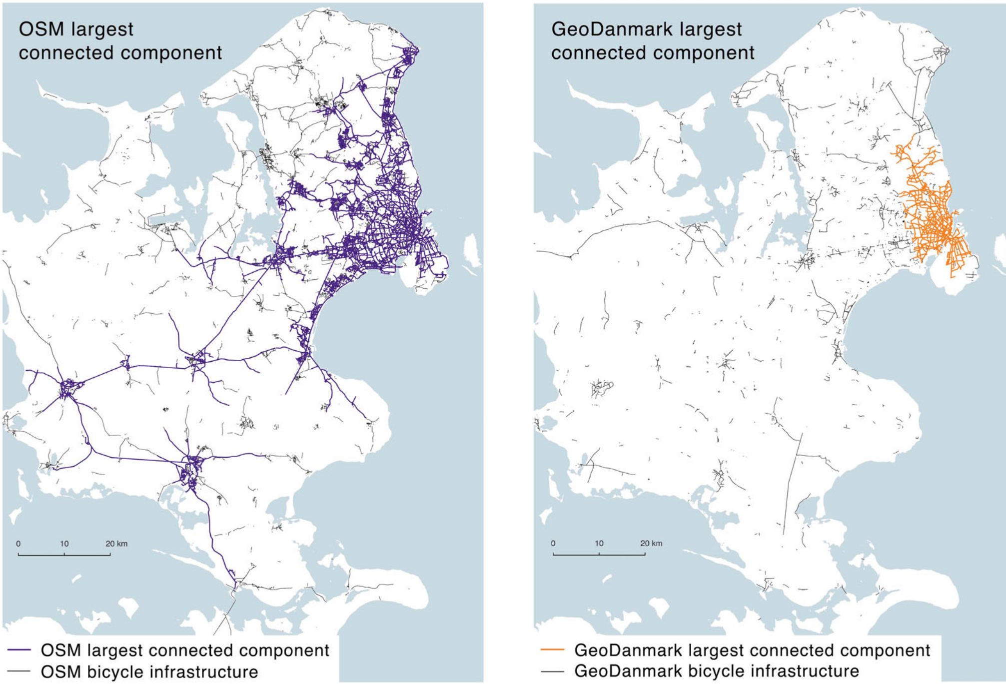

Figure 11. Largest connected components. Left: Largest connected component in OSM (purple). Right: Largest connected component in GeoDanmark data (orange).

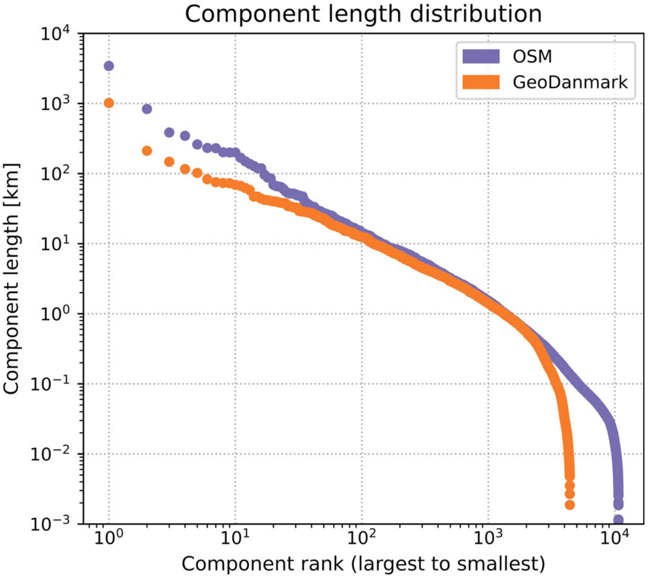

Figure 12. Zipf plot ranking the length of OSM components and GeoDanmark components on a log-log scale.

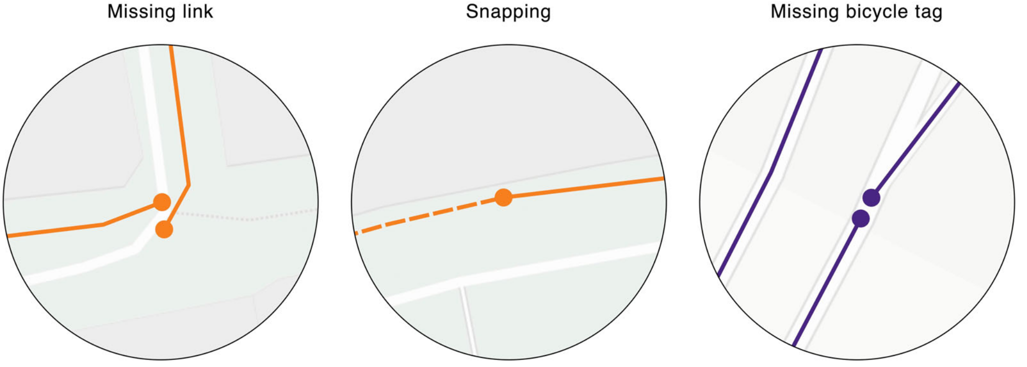

Figure 13. Different causes for undershoots. Left: Undershoots detected in GeoDanmark due to unconnected infrastructure. Center: Undershoots because of snapping issues in GeoDanmark: due to linestrings not being properly connected, the solid and dashed lines are not actually connected. Right: Undershoots detected in OSM due to a missing bicycle tag in the underlying road network.

As a final aspect of the network structure analysis, we compare the number and locations of undershoots in the two data sets. GeoDanmark data contains 339 undershoots, which is much more compared to OSM's 157 undershoots, particularly when considering that the GeoDanmark network is only half as long as the OSM network. Based on manual verification of a randomly drawn sample of undershoots in the OSM and GeoDanmark data, we find that a threshold of three meters leads to correct identification of most undershoots with only few false positives: out of 40 inspected OSM undershoots, 36 were correctly classified as undershoots, four were false positives. For the inspected GeoDanmark undershoots, 26 out of 40 were correctly classified, 13 were undershoots introduced by the GeoDanmark data model, and one was a false positive. Through the manual inspection of the undershoots subset, we also find that undershoots appear in OSM and GeoDanmark for different reasons. In OSM, most undershoots are due to missing tags, where small segments of the road network have not been tagged as having dedicated bicycle infrastructure (Fig. 13). Due to the differing data model used in GeoDanmark, undershoots mostly appear because of geometry errors, such as snapping issues and missing links (Fig. 13). The undershoots are somewhat unevenly distributed across Denmark within each data set (Fig. S7), but do not exhibit any significant spatial clustering. The discrepancy in the locations of undershoots between the two data sets suggest that the undershoots indeed are errors, rather than the consequence of a precise mapping of a fragmented infrastructure network.

In conclusion, both data sets suffer from network fragmentation and topological errors, which poses a problem for network-oriented applications, such as bicycle routing. Due to the diverse reasons for these errors, we cannot issue any universal recommendation for achieving high-quality, routable bicycle infrastructure data. Nevertheless, our findings underline the importance of detailed data quality assessments. Lastly, judging by the sizes of the largest connected components, the OSM network is more connected, and thus *more* suitable for, for example, routing and accessibility analysis than the GeoDanmark data set.

Results for OSM tags

The completeness and accuracy of OSM tags is crucial for a proper classification of the road network (Guth et al. 2021) as well as any efforts to use OSM data for more detailed analyses

Table 5. Summary of Tag Completeness

Tag completeness			
Tag type	Values	Unique values	Completeness
Lit	"yes," "no," "sunset-sunrise," "automatic," "24/7"	7	40.39%
Surface	"asphalt," "gravel," "paving_stones," "fine_gravel," 'paved'	25	64.46%
Maxspeed (km/h)	4–50	10	26.84%
Width (m)	0.5–10	75	3.43%

Notes: Overview of OSM tag values, count of unique tag values, and the share of edges with a value for each of the four examined tags. For brevity, only the 5 most commonly used tag values are shown for 'lit' and 'surface'.

of the cycling experience (Wasserman et al. 2019; Ferster et al. 2023). Since no ground truth data on the correct tag values are available, our analysis only considers the completeness, not the accuracy of tags. For an overview of common tag values, Table 5 summarizes the value ranges for numeric tags and the five most commonly used values for categorical tags. Although no assessment of the accuracy of tag values is available, an analysis of tag values revealed that most values were within the expected value ranges and matched the common value type for the tag (i.e., numerical values for "width" and "maxspeed," categorical for "lit" and "surface"). Only very few features had obvious errors (three edges had a "width" value of 0 and six edges had a nonmeaningful value for the "lit" tag).

The completeness of OSM tags related to cycling follows notable spatial patterns across Denmark. For all included tags (*"surface"/"cycleway:surface"*; *"width"/"cycleway:width" "lit"*; *"maxspeed"*) we find a large spatial heterogeneity, exhausting the full range from 0% to 100% local tag completeness (Fig. S8). Notably, the distribution of tag completeness for the different tags is not random, but instead shows clear spatial clusters of low and high tag completeness (Fig. 14).

A test for spatial autocorrelation, using the same k-nearest neighbors ($k = 6$) spatial weight matrix as in Section Spatial patterns in local data quality metrics, is positive for all tags (Fig. S9). Interestingly, although the completeness of all the investigated tags has evident clustering tendencies, the locations of clusters with low or high tag completeness follow very dissimilar patterns for different tags, with some tags showing almost reverse patterns. For example, for the bicycle infrastructure within the city of Copenhagen, values for the "surface"/"cycleway:surface" tags are mostly missing, while the "lit" tag (for street light) mostly is present (Fig. 14). Based on the clusters from the spatial autocorrelation (Fig. 14), this pattern is also visible in several other larger towns across the country, with a cluster of low use of the "surface" tag in the town centers coinciding with a cluster of high use of the "lit" tag. More specifically, out of the 2,460 hex grid cells determined to be in a hot-spot for the "lit" tag, 37% are also in a "surface" cold-spot. On the other hand, 38% of the 2,396 hex grid cells in a "surface" cold-spot are also in a "lit" hot-spot.

Missing tags are a hindrance for detailed mappings of bicycle conditions (Wasserman et al. 2019; Ferster et al. 2023). Our findings, however, also show that if the presence of tags

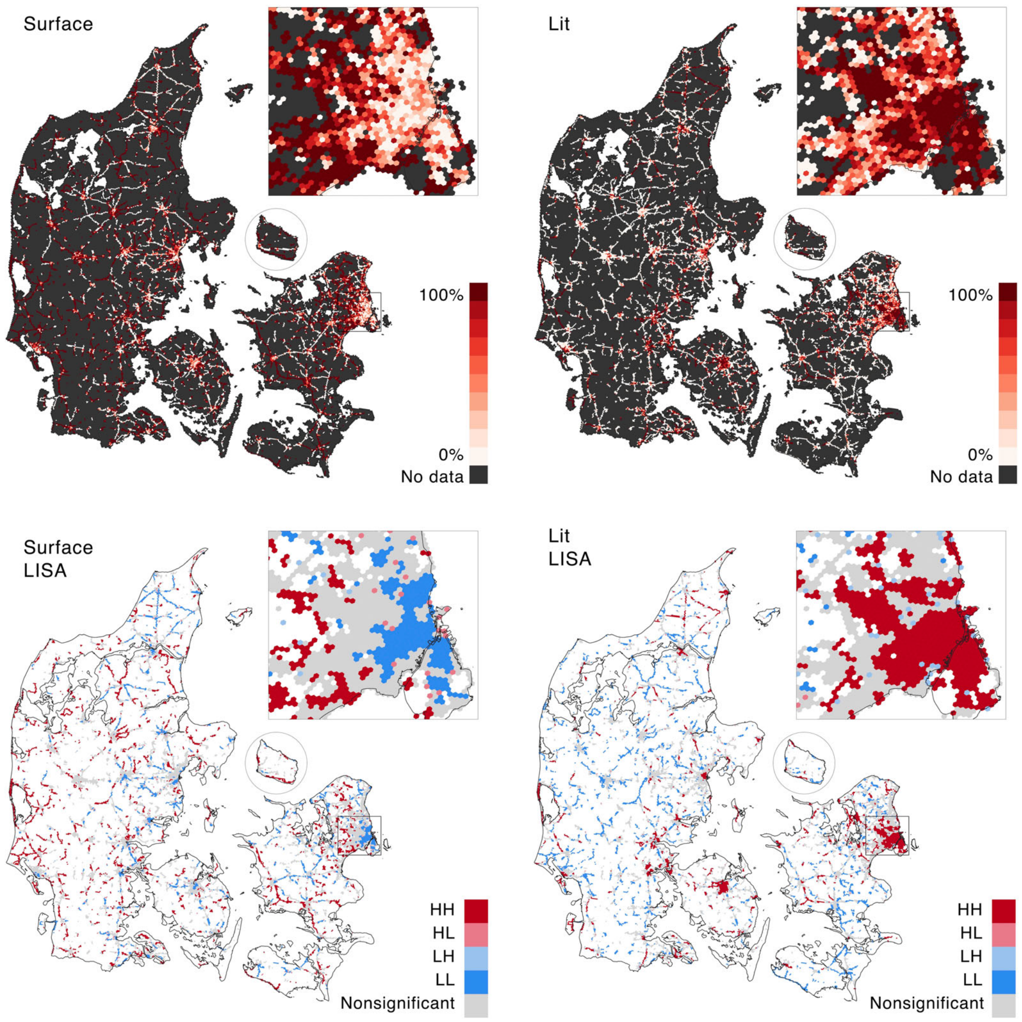

Figure 14. OSM tag completeness. Differences in OSM tag completeness: Percent length of network geometries with information for the tag "surface" (top left) and "lit" (top right). In some areas, there is a negative relationship between the tag completeness for different tags. Bottom row: Statistically significant ($P < 0.05$) clusters of share of infrastructure with the "surface" tag (bottom left) and "lit" tag (bottom right). In several locations, areas with a statistically significant cluster of low "surface" tagging coincide with clusters of high rates of "lit" tagging.

is to be used as a quality indicator, the type of tag has to be chosen with great care, since different tags have very different levels of completeness. Further, our results reveal that missing tags should not be interpreted as a lack of mapping efforts. Instead, the absence of a specific tag might indicate that it was not deemed relevant by the contributors. For example, the lack of information about the surface of bicycle infrastructure in some city centers can be explained by the fact that dedicated bicycle infrastructure in Danish cities almost always has a paved surface, usually asphalt. For bicycle infrastructure mapped as an attribute to the road center line, the surface of a "cycleway" is therefore often assumed to be the same as of the main road. Tagging completeness is furthermore not necessarily an indicator of a lack of mapping efforts, since a high number of contributors editing a OSM feature is no guarantee for many tags being added (Mooney and Corcoran 2012).

Discussion

In this section, we leverage the results from the Denmark case study to issue recommendations for bicycle infrastructure data quality improvements. We then discuss the limitations of this article and offer suggestions for future work.

Recommendations for data quality improvements

An initial requirement for an analysis like the one presented here is open data. In the case of Denmark, open data on bicycle infrastructure is provided by OSM and GeoDanmark, but up-to-date open data is often unavailable (Nelson et al. 2021). Under the condition that open data is available, we provide recommendations for both immediate improvements to the two data sets and more long-term upgrades of data collection and processing:

Data conflation

Our findings suggest that outside of the main urban centers in Denmark, a conflation (merging) of OSM and GeoDanmark data is necessary to achieve a more complete data set. For both OSM and GeoDanmark data, it might furthermore be beneficial to close network gaps below a certain distance threshold, or to convert the network to a coarser scale to circumvent inconsistencies from topological errors and smaller missing links, as seen in, for example, Schoner and Levinson (2014) and Reggiani et al. (2021).

Strategic mapping efforts

Our results indicate that there is a need for more strategic data collection and mapping efforts in Denmark, particularly in areas with large discrepancies between OSM and GeoDanmark data. No large-scale imports of GeoDanmark data into the OSM database have been made (OpenStreetMap 2024b), and given the advanced stage of OSM data in many areas of Denmark, a bulk import of GeoDanmark might not be appropriate nor necessary. The spatial concentration of under-mapped areas however suggests that, for example, mapathons aimed at particular areas could help close the gap between the two data sets (Gomez-Barron, Manso-Callejo, and Alcarria 2019). For example, in OSM, unprotected bicycle infrastructure appears to be particularly under-mapped outside of urban centers.

As pointed out by other researchers, it is important that also the research community that uses OSM data takes an active part in data improvement and maintenance, possibly considering which areas or feature types require particular attention (Ferster et al. 2023). The increasing number of commercial contributors to OSM (Anderson, Sarkar, and Palen 2019) might also provide resources for more systematic efforts toward high-quality data.

For GeoDanmark data, missing bicycle infrastructure data can mostly be addressed by using a more precise labelling that identifies all paths dedicated to cycling, according to a study by Hvingel and Jensen (2023a). While OSM cannot replace other open data sets, such as GeoDanmark – for example, due to the use of centerline mapping, OSM does not offer the same positional accuracy for bicycle infrastructure data – it should be considered if OSM data could be used to inform improvements of other open data sources, as seen in a recent project on improving GeoDanmark and other municipal bicycle infrastructure data sets (Local Government Denmark 2023). Although efforts usually are aimed toward improving OSM on the basis of other open data sets, the increasing quality of OSM entails that improvement efforts can go both ways.

Consistent standards and classifications

Our comparison of two data sets which use a combination of different mapping approaches and various infrastructure classifications highlights the need for more consistent standards and classifications in bicycle infrastructure data. For GeoDanmark data, we recommend an improved classification of bicycle infrastructure that indicates both the protection level and whether the bicycle infrastructure is running in parallel with a road with motorized traffic. For OSM, an explicit tagging of whether bicycle infrastructure is part of a road with motorized traffic would likewise be an improvement. Bicycle infrastructure that is not part of a road is marked with the tag `highway = cycleway` (OpenStreetMap 2023c), but this tag is used both for separate protected bicycle tracks and tracks that run in parallel with a road. Similarly, the large discrepancies in mapping of unprotected bicycle lanes between OSM and GeoDanmark data might originate in disagreements about when a lane qualifies as a bicycle lane. This could for example be solved with an increasing use of the `cycleway:lane=advisory` tag for lanes that are not reserved exclusively for cyclists (OpenStreetMap 2022a).

The need for consistent and precise classifications has also been highlighted by previous studies, which also emphasize the need for detailed instructions for how best to map bicycle infrastructure (Winters, Zanotto, and Butler 2020; Ferster et al. 2023). Technical and strategic guidelines on bicycle planning often presuppose good quality data, but rarely contain specific instructions on how to collect and maintain them (de Groot 2016; City of Copenhagen 2023). Currently, most research on bicycle data collection focuses on ridership and flow data (see e.g., Lee and Sener 2020; Nelson et al. 2021; Willberg et al. 2021; Reggiani et al. 2022). There is thus a knowledge gap on the collection of bicycle infrastructure data.

Topological consistency

Lastly, there is a need for more automated enforcement of topological consistency. For OSM, this could for example include an automated detection of short stretches with no bicycle tag on a road that otherwise has been tagged as having bicycle infrastructure. For GeoDanmark, automatic snapping of geometries and automated detecting of missing links between bicycle infrastructure would greatly improve data consistency. Nevertheless, it will require a larger update to the GeoDanmark data model if the data set is to be used for routing, such as adding consistent connections across intersections (Septima 2019).

Limitations

Although we designed our article with the aim of capturing data quality as precisely as possible, there are a few limitations to the precision of our results. The first one originates from the queries used to obtain the subsets of the road networks with dedicated bicycle infrastructure. As explained in Section Data, OSM and GeoDanmark use different data models and classifications, and there is therefore no feasible method for obtaining exactly corresponding subsets, or to ensure that no errors have been introduced when converting geometric length to "infrastructure length." While this is important to have in mind when interpreting results on, for example, data completeness, the lack of consistent classification, and mapping practices is also an important lesson in itself.

Next, the lack of ground truth and data of a known quality means that findings must be interpreted with care, and that interpretations of what the differences mean are "speculative" to some extent. Some familiarity with the study area is thus required to correctly distinguish between errors of omission or commission, as well as to establish whether network fragmentation is a consequence of low quality *data* or low quality *infrastructure*. Since our study is limited to available, open data, there might exist more high-quality data sets in, for example, road management systems, which however are not available to researchers, bicycle advocates, routing applications, etc.

It is also worth noting that the results are based on the data quality at the moment of data download. GeoDanmark data should in theory be complete and static, apart from additions of newly constructed infrastructure. However, OSM data are updated and edited frequently due to the data's crowdsourced nature, especially during early stages of mapping of a new area (Neis, Zielstra, and Zipf 2012; Seto 2022). The historic development in the use of OSM tags related to bicycle infrastructure nevertheless indicates that the amount of bicycle infrastructure in OSM in Denmark has been stable in the past two years (HeiGIT 2023).

In addition, several of the methods in this article make use of customizable settings, such as the distance threshold for undershoots or the maximum distance and angle between corresponding segments in the feature matching process. The best value for these settings depends on the specific data sets and the local context, but will in any case be a potential source of error, since there rarely will be one single and unambiguous threshold applicable to the entire data set. Additionally, many of the exact results are aggregated and generalized to the grid cell resolution, which, as all spatial data aggregation, can exaggerate or conceal spatial patterns.

Lastly, given that Denmark does not provide open socioeconomic data at high resolution, our analysis could not include potential correlations of data quality and socioeconomic factors.

The most important outcome of the analysis are thus not the exact differences in, for example, infrastructure density or the precise number of undershoots, but rather the general patterns in data quality and what they can tell us about the state of bicycle infrastructure data in Denmark.

Future research

More work remains within the area of quality assurance of bicycle infrastructure data. Our article has identified some relevant quality issues in the examined bicycle infrastructure data, but tools for actually improving the quality in an automated or efficient manner are still lacking. Therefore, developing reproducible and automated methods for, for example, conflating bicycle infrastructure data sets from different sources and data models would be a valuable contribution to the fields of bicycle research and sustainable mobility.

Further, there is still no straightforward method to distinguish between gaps and missing links in the data and in the infrastructure. There are suggestions that using street view imagery and image recognition could help solve this problem (Biljecki and Ito 2021; Ding, Fan, and Gong 2021; Saxton 2022), but these methods are still at an early stage of development.

Finally, more research on standardizing and homogenizing mapping and classifications of bicycle infrastructure is needed in order to ensure comparability and compatibility across data sets. Several local projects on improving the quality and consistency of bicycle infrastructure data classifications are already underway, for example in Canada and Denmark (Winters, Zanotto, and Butler 2022; Hvingel and Jensen 2023b).

Conclusion

In this article, we have examined the spatial data quality of OSM and GeoDanmark, two different data sets on bicycle infrastructure in Denmark, to understand whether these data sets can support a network-based analysis of cycling conditions. Our results reveal large and heterogeneous spatial variations in data completeness and consistency, meaning that the fitness for purpose of the data depends on the geographical location. The highest data quality in terms of data completeness and concordance between the two data sets is found in cities and larger towns. For more rural areas, we found that the information in the two data sets is not sufficient to confidently detect neither how much bicycle infrastructure exists, nor exactly where it is located. For the use case of a network-based analysis of Danish bicycle infrastructure, a conflation of the two data sets is a potential solution – assuming that the differences in data completeness between the two data sets are due to errors of omission, rather than commission.

In their network structure, both data sets display some unwanted fragmentation due to missing tags, snapping errors, or missing links. If data are to be used for purposes where network structure and topology are of importance, both OSM and GeoDanmark data will thus require some preprocessing, such as closing gaps at intersections or transforming the network to a coarser resolution. The OSM data not only contain more bicycle infrastructure than the GeoDanmark data, but also seem to be better suited for routing and connectivity applications, based on the larger connected components and the smaller number of topology errors. Due to the data model used in GeoDanmark, with all infrastructure mapped with separate geometries rather than a road center line mapping, the GeoDanmark data however offer a higher positional accuracy. This is essential for applications where the exact location of infrastructure is important.

Due to the lack of ground truth data, no claims about the exact spatial data quality can be made, but we can conclude that open data on dedicated bicycle infrastructure in Denmark still are of an insufficient quality for most use cases, due to the uncertainty of both the extent and location of bicycle infrastructure. We have furthermore demonstrated that the commonly used method of comparing data completeness based on density differences can obscure substantial differences in the exact infrastructure mapped in different data sets. Our article reveals that for more exact and detailed measurements of differences in data completeness, it is necessary to apply more computationally intensive methods like feature matching.

In order to overcome the challenges posed by insufficient data quality, research on networks of dedicated bicycle infrastructure has to either include a substantial amount of automated and/or manual data verification, or to perform analysis of bicycle conditions at a coarser spatial scale, which leads to more uncertainties than desired. However, the results and conclusions presented in this article are valid for data sets with only dedicated bicycle infrastructure; when considering the entire road network, both data sets are substantially less fragmented.

Data quality improvement is not an end goal in itself, but only a means to an end. Working toward improving the quality of the available data on bicycle conditions means supporting more data-informed bicycle research and planning. Efforts to improve conditions for active mobility should not be hindered by a lack of reliable data on foundational aspects such as the extent and location of existing infrastructure.

Author contributions

A.R.V. designed the study and performed the analysis. A.R.V, A.V and M.S. wrote the article.

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Conflicts of interest statement

The authors declare no conflict of interest.

Data availability statement

All data and code used in the analysis and needed to reproduce the results can be found at https://github.com/anerv/BikeDNA_BIG and https://github.com/anerv/bikedna_dk_analysis. All input data and results from the analysis can be found at https://doi.org/10.5281/zenodo.8340383 and https://doi.org/10.5281/zenodo.10185500. The complete documentation and code of `BikeDNA` needed to replicate the computation of data quality metrics for other locations are available at https://github.com/anerv/BikeDNA.

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