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RESEARCH ARTICLE

Network evolution analysis: a usage-centric approach applied on cycling infrastructure

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Abstract: Cycling practice is quickly increasing around the world, giving rise to the development of devoted infrastructure to protect its users and offer them a more enjoyable ride. Mobility infrastructure is represented in geographical databases, but these databases are often centered on car and pedestrian mobility. This causes some data quality problems like the lack of completeness or freshness. Volunteered geographical information (VGI) is affected by this kind of problem with a variable extent relying on the contributors' wish and skills. Research on VGI evolution for a network mainly focuses on the main usage of a road section, ignoring secondary information related to other road users of a specific section. This paper contains two contributions. To model the evolution, we define a multiplex graph where each layer represents a snapshot. It is implemented with an infrastructure class based on how cyclists perceive an infrastructure. We also present two complementary VGI road network evolution methods with a usage-centric approach on cycling. These approaches are adaptable for any usage of the network and are based on the multiplex graph. The first approach is based on the road sections, analyzing the evolution of each section individually. The second approach is based on randomly generated starting/ending points. These methods are illustrated in the Centre-Val de Loire region with OpenStreetMap.

Keywords: openstreetmap, cycling network, data evolution, multiplex graph, route generation

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1 Introduction

Cycling mobility has experienced a significant increase in popularity since the early 21^{st} century [31]. This trend has been further accelerated by the COVID-19 pandemic, as individuals sought alternatives to public transportation. Cycling is recognized as an environmentally friendly alternative to car travel, offering the advantage of shorter routes in urban areas. Additionally, cycling for commuting, daily activities or leisure contributes to improved human health and reduced CO_2 emissions. In response to this growing popularity, public authorities have been implementing new cycling infrastructure solutions to enhance its mobility and ensure traffic safety by protecting cyclists from motor vehicles. Consequently, numerous cycling infrastructure have been developed, predominantly in urban areas. However, these infrastructure remain limited in many rural areas, where higher car speeds are common. According to [6], in Austria, rural mobility administrators continue to prioritize car infrastructure over cycling mobility.

Cyclists typically utilize roads recommended by route planning applications. However, these applications can only provide recommendations if cycleways are present and accurately documented in road databases. Updating cycling infrastructure in road network databases in near real-time poses a significant challenge for national mapping agencies and volunteered geographical information (VGI) platforms such as OpenStreetMap (OSM), due to the rapid nature of infrastructure changes. These changes often involve modifications to existing infrastructure rather than the creation of entirely new elements (e.g., adding a new roundabout takes longer than modifying an existing infrastructure to create a new cycleway), necessitating local information and prompt updates.

In response to the increase in both cycleways and cycling mobility, the French national mapping agency revised its topographic road network model (BDTOPO®) at the end of 2023 to include diverse cycling infrastructure. However, incorporating that information into the database on a national scale is both costly and time-consuming. Conversely, while VGI platforms such as OSM have extensive coverage of the cycling network [12], maintaining quality and continuous updates remains challenging. This is because the editing activity relies on the motivation, skills, and local knowledge of contributors, leading to heterogeneities between rural and urban areas. These local differences result in variable data quality within the dataset. The only study on a high-quality dataset specifically for cycling has been conducted solely for Paris [40].

These data quality issues have inspired numerous research studies focusing on data quality and data evolution for VGI [3, 14, 16]. A primary limitation of these studies is the lack of a usage perspective, as roads within a network are typically analyzed only for their primary users (e.g., major roads for cars, tracks for pedestrians). For instance, a major 2x2 lane straight road may be highly efficient for motor vehicles due to the high speeds achievable, but cyclists often find such roads dangerous and tend to avoid them [17]. A usage-centric analysis of the road network is more beneficial for optimizing its use, particularly in specific routing scenarios.

For cycling, ensuring optimal conditions involves considering numerous factors, as demonstrated in [20]. These factors include safety, the landscape attractiveness, and the efficiency of reaching the destination, which are challenging to balance. Due to the slower development of cycling infrastructure, [25] noted that OSM data in rural areas are not updated as quickly as in urban areas, resulting in better OSM data quality in major cities compared to rural regions.

This paper examines data evolution in a road network from a usage perspective. It proposes two complementary approaches based on (i) road sections and (ii) generated routes. Both approaches utilize a classification system applied to each road section, reflecting how cyclists perceive road infrastructure. The first approach involves analyzing each OSM road section individually to determine its cycling infrastructure class. The second approach involves generating shortest path routes with a priority on using cycling infrastructure. A way centrality indicator is then computed for each road section to estimate the use of cycling infrastructure in the generated routes. Additionally, the distribution of infrastructure classes is analyzed for each route. A multiplex graph is created and instantiated to model network evolution over time [11]. These approaches are applied to the Centre-Val de Loire region where many rural areas exist as well as some important cities.

This paper presents three key contributions:

1. The development of a multiplex graph to model the evolution of road networks over time.
2. The introduction of two complementary approaches for usage-centric VGI evolution: a road section approach focused on individual road sections, and a routes approach centered on cycling network usage. Both approaches are based on the multiplex graph.
3. A case study applying both approaches for cyclists in the Centre-Val de Loire region. These contributions are generic and can be adapted to other uses, such as for cars or individuals with reduced mobility, provided the infrastructure classes are appropriately modified.

The paper is structured as follows: Section 2 reviews the state of the art in OSM data evolution and multiplex graphs. Section 3 introduces the multiplex graph and the proposed approaches. Section 4 describes the study area and the parameters for both approaches. Section 5 presents the results and Section 6 discusses them. Section 7 concludes the paper and suggests directions for future research.

2 Related work

This section reviews related work on the definition and representation of cycling networks. It then discusses methods for analyzing the evolution of these networks. Additionally, it examines studies on evolution graphs to provide a robust and user-friendly tool for our data evolution approaches.

2.1 The cycling network: definition and representation

The linear component of the cycling network, as defined in [4], encompasses all roads where cyclists are permitted. This includes dedicated cycling infrastructure such as cycleways and cycle lanes, as well as portions of the pedestrian network, and various roads without specific cycling infrastructure. A subset that includes only dedicated cycling infrastructure [36,37] would result in a fragmented network impractical for route generation in most countries. This definition is more suited to urban planners. For our purposes, a usage-centric definition of the cycling network, as proposed in [4], is required. That definition includes every road section where cyclists are allowed. In both definitions, the cycling network consists of points representing intersections and lines representing roads.

This subsection also examines and discusses various models for the cycling network. The cycling network is expanded to include other elements in [2], such as points of interest and road signalization, which are not linear. The cycling network has been modeled in urban planners' databases, such as Vélo & Territoire's database[1]. Vélo & Territoire is an association that assists local authorities in developing their cycling infrastructure and provides data models to store information about all aspects of the cycling network. Their roads database for cycling is detailed at the road section level, with attributes to differentiate the right and left sides of the road. This structure attracted the French mapping agency, which partially incorporated it into BDTOPO® for the road network. Only roads with cycling infrastructure (cycleways, cycle lanes, roads shared with other users) are represented in it. Additionally, Vélo & Territoire has modeled other components of the cycling network as defined in [2]. However, this representation is not formalized and does not accommodate all road users (e.g., pedestrians, motor vehicles).

Cycling infrastructure were previously implemented in an oriented graph by [26]. In this study, the road network is represented by an oriented graph, with vertices representing network intersections and edges representing road sections. Each edge is associated with multiple costs, including time and security costs, for each direction. This graph was implemented with a single snapshot, but its structure could be adapted to accommodate multiple snapshots. A multi-layer graph, described by [9], incorporates multiple snapshots, providing a list of snapshots where an edge or a vertex is available. However, this graph consumes excessive memory because identical objects (edge or vertex) are recreated in multiple snapshots. A potential cost reduction strategy involves using the same object (edge or vertex) across all layers of the graph.

We recognize that numerous research efforts have focused on correlating high-quality cycling infrastructure with increased bicycle usage [7]. Also, cycling level of traffic stress [13] shows how cycling policies have been oriented mainly towards the separation from other usage, which is not a way to represent every type of cyclist. There are multiple routing engines proposing cycling options with OSM data like r5r [29], OSRM [22], openrouteservice [2] or Valhalla [3]. They do include some bike dedicated roads and some cars/pedestrian dedicated roads. However, there remains an ongoing challenge concerning the usage patterns of all roads accessible to cyclists in the road network databases, regardless of their designated cycling infrastructure.

The linear component of the cycling network has been defined; however, the state of the art reveals the existence of multiple definitions [2, 4, 37]. Additionally, various representations of the cycling network exist (e.g., Vélo & Territoires, [9]), but these are either not formalized or too costly for long term data evolution analysis. The next subsection discusses how data evolution has been studied.

2.2 Spatial data evolution

Spatial data evolution is defined as the transformation of a spatial database over time, encompassing all dimensions of data quality and the evolution of the database structure to address an expanding range of problems. Within the context of VGI, our primary focus

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[1] https://www.velo-territoires.org/politiques-cyclables/data-velo-modeles-donnees/schema-donnees-amenagements-cyclables/

[2] https://maps.openrouteservice.org/

[3] https://github.com/valhalla/valhalla?tab=readme-ov-file

is on the data quality aspect of spatial data evolution. Research on spatial data evolution has predominantly centered on OSM, particularly in relation to quality assessments [14, 19, 23, 43]. Investigating OSM data quality raises critical questions regarding completeness, freshness, and other relevant quality metrics.

In this paper, we focus on data freshness that we define as the temporal aspects of data [28]. Numerous studies [14, 16] have examined data freshness in the context of network evolution, positing that increased temporal dynamics correlate with a higher number of contributors and daily usage, which may enhance both completeness and freshness. Conversely, [19,23] focus their evolution analysis exclusively from a completeness perspective, concentrating on the quantitative changes of individual road. In contrast, this paper adopts a perspective that emphasizes the analysis of evolution in relation to specific usage rather than solely through a quality lens.

From our perspective, network evolution analysis is exemplified by the work of [24], which examines the global evolution of network length categorized by road type. In this study, we will similarly investigate variations in length over time

The volume of evolution studies pertaining to OSM data is on the rise, facilitated by the Geofabrik website and the OSHDB format [32]. The Geofabrik website provides access to snapshots of OSM data across various global regions at multiple temporal points. The OSHDB format enables users to retrieve either a snapshot of a region for a specific date or the complete historical dataset for an area spanning two dates. This framework has been employed in prior research, as illustrated in [41].

Consequently, research on data evolution can be categorized into two distinct approaches: contribution-based analysis and snapshot-based analysis. These approaches may focus on different subjects of analysis; some studies examine individual road segments, while others assess networks from a usage perspective. We refer to these methodologies as feature-centric and usage-centric, respectively.

The contribution-based analysis utilizes comprehensive historical OSM data for a given region, examining each contribution to derive results. In the feature-centric approach, [25] investigated contributions across multiple cities worldwide, categorizing them based on whether they involved OSM points of interest (POI) additions, deletions, geometric updates, or attribute updates. The differentiation between types of updates, specifically attribute and geometric updates, represents a significant and emerging area of research, as highlighted by [25]. In this context, we will propose the introduction of a third category of updates, focusing on attribute modifications that result in changes to the cycling usage of any OSM way. It is important to note that [25] analysis was conducted on a dataset of POI, which is not the primary focus of our study.

To the best of our knowledge, no contribution-based analysis has been conducted employing a usage-centric approach.

A snapshot analysis involves obtaining multiple states of OSM data for a specific area and aggregating the changes that occur between two consecutive snapshots. Several studies have employed this method using a feature-centric approach across various countries [24, 41, 43]. These studies utilize different time intervals between their snapshots and timeframes for analysis. For instance, [24] employed a three month interval over a study period of 4.5 years, while [43] used the same interval within a four year study period. However, the network usage aspect that we aim to incorporate into our analysis renders these short time intervals and limited study durations inadequate. Furthermore, these studies do not differentiate between usage patterns in their approaches to road networks.

Only two applications of snapshot methods utilizing a usage-centric approach have been identified: [33], which focuses on car usage, and [5], which examines bike usage. Both studies employ randomly generated routes to evaluate network usage. The primary aim of [33] and [5] is to compare the lengths of these routes. However, [5] additionally proposes various environments to assess the method and metrics based on the number of routes for which the length was altered by at least 1% and 20%. This study further elucidates the rationale behind specific changes and introduces the concepts of *update*, defined as a real-world change promptly reflected in OSM, and *upgrade*, characterized as a resolution to a data quality issue.

Data evolution can be categorized into two primary methods: snapshot-based and contribution-based approaches. These methods can further be classified as either feature-centric or usage-centric. Usage-centric approaches are particularly relevant to our research objective, as they focus on the perception of features from the perspective of cyclists, ensuring that each of them is analyzed based on how it is experienced by users. To facilitate the analysis of cycling network data evolution, a tool is required to store and manage multiple snapshots of OSM data.

2.3 Evolution graphs

This subsection presents various graphs that illustrate the evolution of networks. Given that road networks are commonly modeled as graphs, several extended graph-based data structures have been proposed to represent the dynamic nature of evolving networks. We define an *edge* as the line component of a graph, representing the connections between points, and a *vertex* as the point component of a graph, representing the intersections within the network. We reserve the terms *node* and *way* for their specific meanings in the OSM context, where a node represents a specific geographic point, and a way represents a sequence of nodes forming a polyline, such as a road.

In the field of spatio-temporal dynamic graphs, [10] and [27] review several spatio-temporal graph models used to represent urban networks. The model proposed by [30] challenges the conventional approach by representing streets as vertices and intersections as edges. However, a key limitation of this model is the absence of attribute properties necessary to distinguish road segments based on specific usage. Additionally, this representation is not well suited for route generation. The study also provides an extensive analysis of the concept of centrality to support the graph's structure.

Several graph models have been developed with a focus on the semantic web. [15] introduced a graph model that integrates temporal information into the RDF format, a standard defined by the W3C. In this work, two methods for incorporating the temporal dimension into RDF graphs are proposed: the timestamp approach and the snapshot approach, both closely related to the data evolution methods discussed previously. The result is a triplet extended by two timestamps that define its validity period, enabling the creation of snapshots at any point in time.

Temporal property graphs, such as those described by [18], have also been defined. These models combine the RDF format with a property graph, which allows the storage of attribute information for vertices. The temporal property feature enables the handling of time and the storage of multiple attribute values, as well as vertices and edges versioning. This aspect of versioning is particularly useful for managing OSM data, as the majority of its objects have multiple versions and numerous tags that can be treated as attributes.

However, a limitation of this approach is the authors' failure to specify whether each object in the graph must implement an attribute, as is the case in OSM. Additionally, [39] proposed a duration labeled graph where each edge is associated with a start date and a validity period, offering a low computational cost for query processing.

Temporal dynamic graphs have also been applied in other fields, such as traffic prediction, as demonstrated in [34] and [38]. In these studies, temporal dynamic graphs are integrated into neural networks to forecast traffic patterns. However, these approaches fall outside the scope of this research and are therefore not considered in our analysis.

To the best of our knowledge, no existing research has proposed a graph structure that incorporates multiple snapshots with semantic attributes and is optimized for efficiently handling multiple OSM snapshots. The structure introduced by [30] is closely aligned with our needs, but additional attribute properties are required to integrate the detailed information available for each road section in OSM. The multi-layer approach proposed by [9] is also essential for capturing data evolution, although we aim to reduce the computational cost associated with such a graph.

A multiplex graph, as described by [8], which integrates attribute properties and temporal dimensions, presents the most suitable option for our study. It offers an effective balance between ease of query processing and low memory usage. The specifics of our graph model and data evolution methods are detailed in Section 3.

3 Methods and tools to analyze the cycling network evolution

This section presents our approach to analyze the evolution of the cycling network. The overall pipeline is presented in Figure 1.

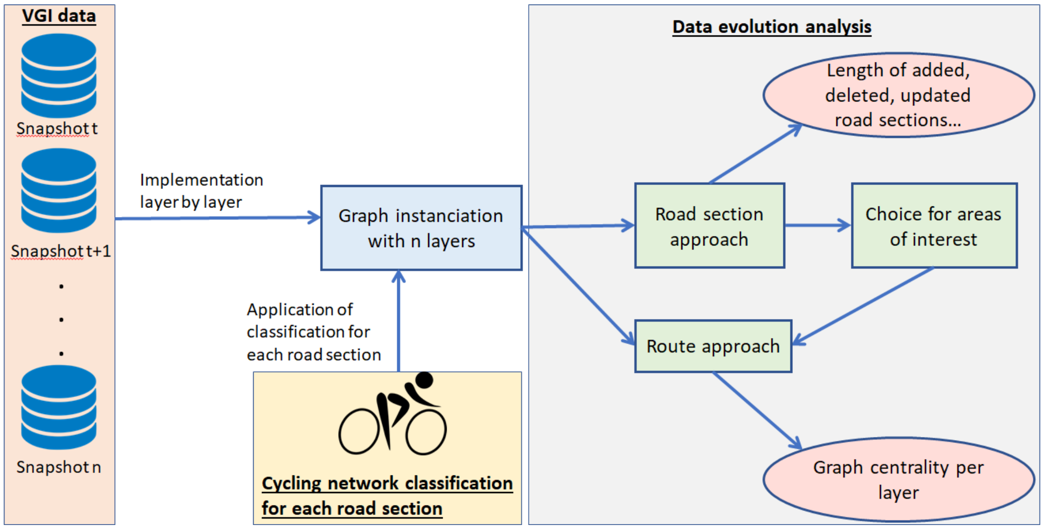

Figure 1: Pipeline to evaluate the cycling network.

We begin by acquiring OSM data from Geofabrik. Subsequently, we classify the infrastructure based on OSM tags. This classification is then used to instantiate the graph, with each infrastructure element assigned a corresponding class. During graph instantiation, both the road sections and routes-based approaches are implemented, and results are collected for each. The road section approach is performed prior to the routes-based approach to facilitate the selection of areas of interest (AoI) for the latter method.

In this section, we also present the multiplex graph model and describe the data evolution methods used in our analysis.

3.1 Multiplex graph for VGI road network evolution

As outlined at the conclusion of Section 2, we utilize a multiplex graph G to analyze the OSM cycling network. This graph is designed with multiple interconnected layers to accommodate the various data snapshots, each identified by the parameter n which is our temporal parameter in this article. Attributes are assigned to both the edges and vertices, with greater emphasis on the edges. This emphasis reflects the primary focus of our analysis, which is centered on road sections rather than intersections.

Let $G^n = (E^n, V^n)$, where G^n represents a graph layer corresponding to the snapshot at timestamp n. E^n denotes the set of all edges for snapshot n. Each edge in the graph corresponds to a road section in the real world, where its characteristics remain uniform throughout the entire segment. Equation 1 illustrates the composition of E^n.

$$E^n = \{e_0^m, e_1^m, ..., e_i^m, e_k^m\} \tag{1}$$

In Equation 1, e_i^m represents an edge with version m in snapshot n of the graph, where k denotes the total number of edges in snapshot n.

V^n represents the set of all vertices in the graph for snapshot n. Each vertex corresponds either to an intersection or a point where there is a change in the attributes of the road. The composition of V^n is presented in Equation 2.

$$V^n = \{v_0^m, v_1^m, ..., v_j^m, v_l^m\} \tag{2}$$

In Equation 2, v_j^m represents a vertex with version m in snapshot n, where l denotes the total number of vertices in snapshot n.

$$G^n = (\{e_1^m, e_2^m, ..., e_i^m, ..., e_k^m\}, \{v_1^m, v_2^m, ..., v_j^m, ..., v_l^m\}) \tag{3}$$

As shown in Equation 3, the union of E^n and V^n constitutes a single layer of the multiplex graph. Each graph layer G^n, corresponding to a snapshot, collectively forms the full multiplex graph G. The union of all E^n and V^n across snapshots creates the complete set of edges E and vertices V, respectively. For edges and vertices that remain unchanged between two consecutive snapshots, they are applied to both layers without duplication.

Edges in E correspond to ways in the OSM database that contain the "highway" key and permit cyclist access. Each edge is characterized by a linear geometry, an identifier (id), a version number (version) to its evolution, an OSM id (osmid), an OSM version (osmversion) to trace the source way in OSM, a cycling infrastructure classification (cyc) to monitor changes in infrastructure, and a field consolidating all OSM tags associated with the way (fields) to track attribute changes.

Vertices in V correspond to OSM nodes that either define the endpoints of ways or indicate a change in attributes within a road section in E. Each vertex v_i^m is assigned a unique identifier (id), a version number (version), an OSM id (osmid), an OSM version (osmversion), and point type geometry (geom). Since the primary focus of this study is not on the vertices, no cycling-related attributes are included for them.

Each edge is bounded by two vertices. The relationship between an edge and its corresponding vertices is defined in Equation 4.

$$e_i^m = \overrightarrow{v_j, v_{j'}} \tag{4}$$

The graph versioning process is partially based on the versioning system used in OSM. To explain how versioning is handled in our graph, the various update scenarios are outlined as follows.

In the first case, if an OSM way remains unchanged between two consecutive snapshots, the corresponding edge in the graph is left unmodified. The second case involves geometric changes to an OSM way, which can occur in two forms: either as a geometric change to a node or as a change in the composition of nodes within the way. A geometric change in a node occurs when the geometry of a node in the way is altered, affecting all ways that use that node. In OSM, such changes are visible only at the node level. In our graph, this change is reflected in both the vertex corresponding to the node and all edges that are connected to it. This scenario highlights why it is insufficient to rely solely on OSM versioning for our graph. A node composition change, on the other hand, occurs when there is a change in the set of nodes that make up the way. This could involve the addition, removal, or modification of nodes.

The third case occurs when an OSM way experiences a version update due to an attribute modification. If multiple modifications (whether geometric, attribute-related, or both) occur between two consecutive snapshots, the changes are grouped together, and the version number in the graph is incremented by only one. This versioning logic is applied even if an edge or vertex undergoes both geometric and attribute changes. Similarly, in the fourth case, when attributes are added, removed, or modified, the edge or vertex's version number is updated. If several attribute changes occur between two snapshots, they are grouped together, and the version number is incremented by one. This same logic is applied in cases where multiple types of changes occur between snapshots. Additionally, when a new OSM way is created, it always starts with version one in the graph, even if it has been modified in OSM between its creation and the first snapshot.

If an OSM way is deleted and had been modified between the last snapshot and its deletion, a new version representing the final state of the edge is not created.

Figure 2 provides an example of how the graph operates, with the infrastructure classes in this example corresponding to the categories presented in Table 4.2.

Multiple methods have been developed to facilitate access to specific properties of the edges:

- The geometry is represented as $g(e_i^m) \rightarrow e_i^m.g$.
- The attribute information is denoted by $t(e_i^m) \rightarrow e_i^m.t$, which encompasses all tags associated with an OSM way.
- The infrastructure information is represented as $c(e_i^m) - > e_i^m.c$.
- The length is indicated by $d(e_i^m) \rightarrow e_i^m.d$.

It is important to note that all methods described above are also applicable to the vertices, with the exception of the length.

Figure 2 shows the three considered layers in this example. The first layer at timestamp n is composed of $V^n = \{v_1^1, v_2^1, v_3^1, v_4^1, v_5^1, v_6^1\}$ and $E^n = \{e_1^1, e_2^1, e_3^1, e_4^1, e_5^1, e_6^1\}$.

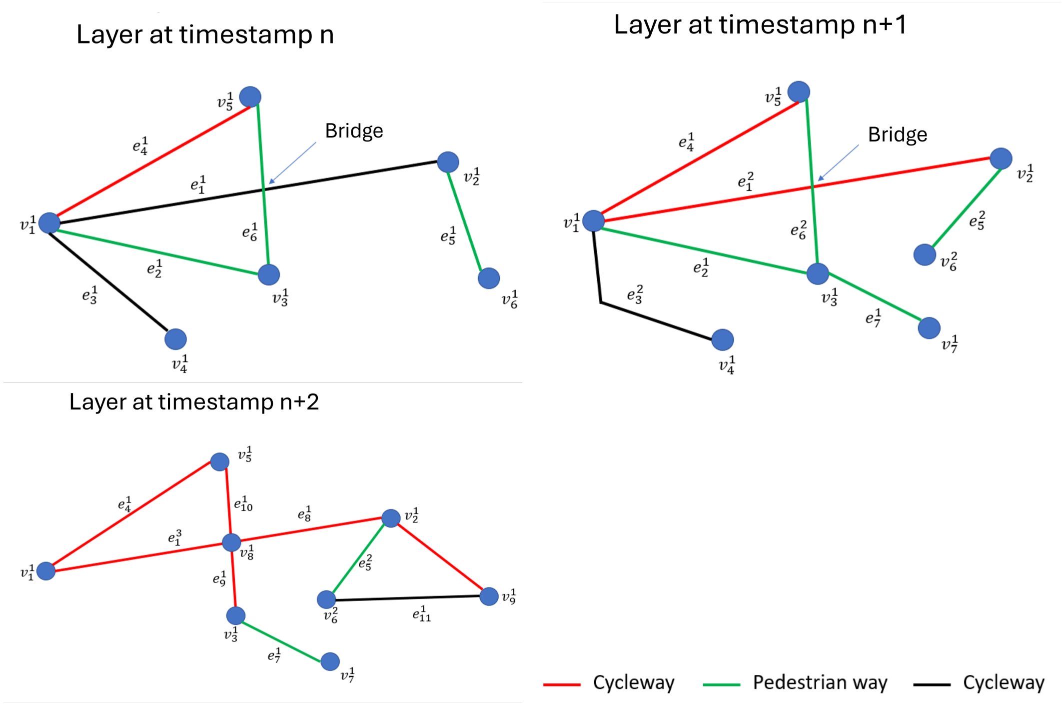

Figure 2: Example of three snapshots of the same graph.

Having established the framework for the n layer of the graph, it is important to note that several changes have occurred in the data between timestamps n and $n+1$, resulting in the formation of the $n+1$ layer.

- A new vertex v_7^1 and a new edge e_7^1 have been created.
- Vertex v_6^1 has undergone a geometric change, which subsequently altered the geometry of edge e_5^1. As a result, v_6^1 is now represented as v_6^2 and e_5^1 is represented as e_5^2.
- Edge e_1^1 has experienced an infrastructure change, as it has now been designated as cycling-prioritized. Consequently, e_1^1 is now denoted as e_1^2.
- Edge e_3^1 has undergone a geometric change without any modifications to its vertices, and is now represented as e_3^2.
- Edge e_6^1 has experienced an attribute change, although its infrastructure class remains unchanged. It is now denoted as e_6^2.

These changes are represented as written in Equation 5 and 6.

$$V^{n+1} = V^n \cup \{v_7^1, v_6^2\} - \{v_6^1\} \tag{5}$$

$$E^{n+1} = E^n \cup \{e_7^1, e_1^2, e_3^2, e_5^2, e_6^2\} - \{e_1^1, e_3^1, e_5^1, e_6^1\} \tag{6}$$

Significant changes have occurred between the $n+1$ and $n+2$ snapshots, as detailed below:

- Vertex v_8^1 has been created in the location where a bridge previously separated edges e_1^2 and e_5^2. The bridge has now been demolished, and an intersection has been established in its place.
- Edges e_{10}^1 and e_{11}^1 have been introduced to replace edge e_6^2. Both of these new edges reflect an infrastructure change, as they now prioritize bicycle transport instead of pedestrian access.
- Edge e_1^2 has undergone a geometric modification to accommodate the newly established intersection at vertex v_8^1, resulting in its designation as e_1^3.
- Vertex v_9^1 and edge e_{12}^1 have also been created.
- Edge e_3^2 and vertex v_4^1 have been deleted from the graph.

These changes are represented as written in Equation 7 and 8.

$$V^{n+2} = V^{n+1} \cup \{v_8^1, v_9^1\} - \{v_4^1\} \tag{7}$$

$$E^{n+2} = E^{n+1} \cup \{e_8^1, e_9^1, e_{10}^1, e_{11}^1, e_{12}^1, e_1^3\} - \{e_2^1, e_3^2, e_6^2, e_1^3\} \tag{8}$$

Following the explanation of the three layers that contribute to the definitions of E and V, Equations 9 and 10 represent these elements across each layer.

$$E = E^n \cup E^{n+1} \cup E^{n+2} = \{e_1^1, e_1^2, e_1^3, e_2^1, e_3^1, e_3^2, e_4^1, e_5^1, e_5^2, e_6^1, e_6^2, e_7^1, e_8^1, e_9^1, e_{10}^1, e_{11}^1, e_{12}^1\} \tag{9}$$

$$V = V^n \cup V^{n+1} \cup V^{n+2} = \{v_1^1, v_2^1, v_3^1, v_4^1, v_5^1, v_6^1, v_6^2, v_7^1, v_8^1, v_9^1\} \tag{10}$$

This multiplex graph will be utilized to implement the approaches discussed in the subsequent subsection.

3.2 Analyzing data evolution in the cycling network

This subsection presents a study divided into two parts, each focusing on distinct aspects of the data. The first part, termed the *road sections approach*, examines road sections across the entire study area, while the second part, referred to as the *routes approach*, is based on routes generated within smaller segments of the network known as AoI. Both approaches utilize information derived from the previously described graph.

The road sections approach involves a quantitative analysis of the evolution of the cycling network at the edge level. Each edge is considered individually to assess the evolution of its characteristics, thereby conducting a comprehensive evaluation of all edges within the cycling network. This approach is widely employed and deemed sufficient for analyzing extensive areas. Specifically, it considers the number of added, deleted, and updated edges, categorizing updates into three types: geometric, attribute, and infrastructure. Geometric updates pertain to changes in position and shape for an edge, while attribute updates encompass any modifications to an edge attribute. Infrastructure updates involve any changes that result in the evolution of an edge cycling infrastructure label.

The maps generated through the road sections approach serve to identify representative AoI within the study area, capturing the various patterns present. However, it is important to note that the road section approach assigns equal weight to all road sections or more precisely, to each kilometer regardless of the significance of a particular road section for cyclists. Consequently, we also conduct a routes approach, which aims to provide a more usage-centric analysis of the network and its evolution within the identified AoI.

Before delving into the routes approach, several definitions are necessary. A route is defined as an ordered sequence of road sections (for example OSM ways) connecting a starting point to an ending point within a specified set of interconnected roads, referred to as a network. Let p denote the count of routes for a given AoI r and layer n. The notation $I_{p,r}^{n}$ represents the route corresponding to the start-end pair p for snapshot n within area r. It is characterized by a linear geometry. Let $\text{comp}(I_{p,r}^{n})$ denote the composition of the ordered road sections utilized by the route.

The routes approach, primarily based on [5], involves a quantitative analysis of the evolution of the simulated cycling network usage. Simulated usage is achieved by computing optimal routes between various start-end point pairs. These routes are analyzed over time, meaning that optimal routes are calculated for each snapshot. For this analysis, each route corresponding to each start-end point pair is examined individually, focusing on its geometric characteristics and the road sections involved. This paper builds upon the methodology presented in reference [5], which generates random starting and ending points to create a route for each pair across all available layers in the graph.

With the graph and approaches thoroughly described, the subsequent section will detail the experiments conducted.

4 Experiments

This section will present the study area and the implementation of both approaches presented above.

4.1 Study area

The Centre-Val de Loire region is situated in the central part of France (see Figure 3). This region is characterized by several medium-sized cities, such as Tours and Orléans, alongside numerous smaller towns, including Blois, Bourges, and Chartres. Predominantly rural, the region features significant agricultural areas, particularly in Beauce, as well as extensive forested regions, notably in Sologne.

The Centre-Val de Loire region boasts numerous tourist attractions, notably the Loire châteaux, including Chambord, Cheverny, and Chenonceau. In recent years, the region has promoted slow tourism through the development of a network of cycling routes that connect key tourist destinations while prioritizing safe travel. Central to this initiative is 'The Loire by Bike' [4], which is part of EuroVelo, the European cycling network. Figure 4.1 illustrates the cycling network as defined in Section 2. It is important to note that the cycling routes are not depicted in Figure 4.1 due to their classification as low traffic roads that lack dedicated cycling infrastructure.

In the study area, a significant majority of roads are part of the motor vehicle network, as illustrated in Figure 4.1 (left). While cyclists have access to these road infrastructure, they do not provide specific enhancements to facilitate cycling use and are generally not

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[4] https://www.loirebybike.co.uk/homepage/la-loire-a-velo-nature-culture-and-adventure/

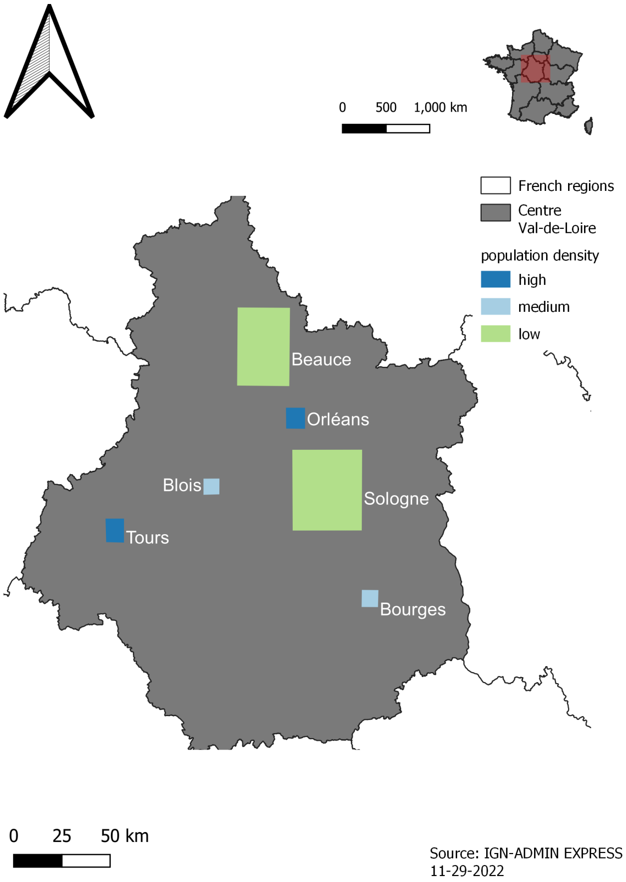


Figure 3: Area of study [5].

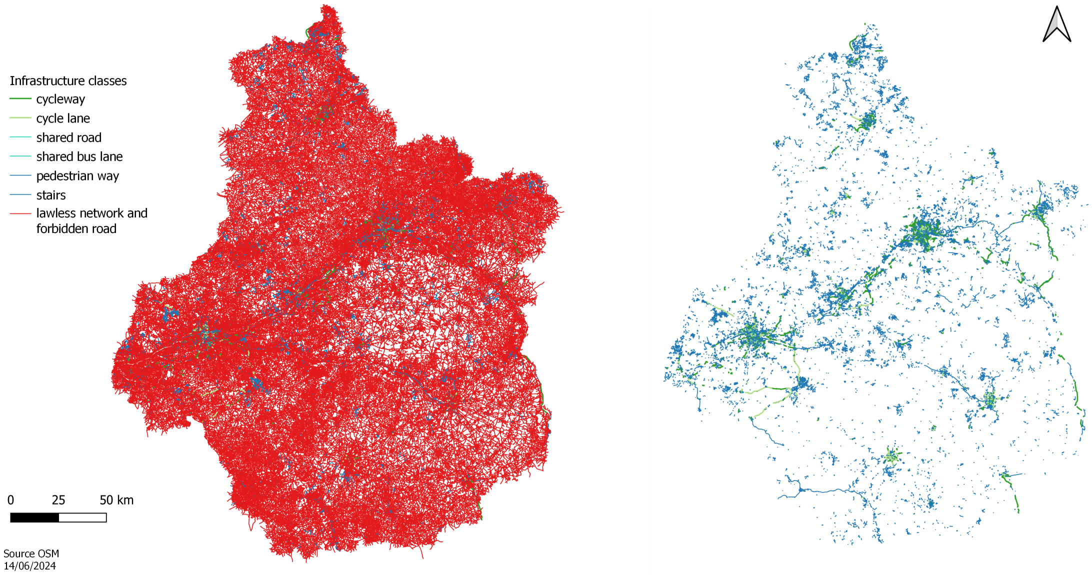
designed with cyclist convenience in mind. Consequently, cyclists must share the same roadway space with motorized vehicles. The major cities within the region are identifiable by the presence of dedicated pedestrian (indicated in blue) and cyclist (indicated in green) pathways, as shown in Figure 4.1 (left).

Figure 4.1 (right) further illustrates that green mobility initiatives are concentrated along the Loire river. The primary urban centers in this area include Orléans, Blois, and Tours; however, the remaining cycling infrastructure in the region are relatively sparse.

4.2 Implementation

In this subsection, the methodologies for implementing the road section approach and the routes approach are described in detail.

The road section approach employs various indicators that focus on the number of additions, deletions, and updates of road sections, as well as the length of the road sections affected by these operations. Updates to road sections are categorized into three types: geometric updates, infrastructure updates, and attribute updates.



Source OSM
14/06/2024

Figure 4: OSM cycling network in the area of study by classes: the left map including infrastructure dedicated to the motor vehicles and forbidden roads, and the right map without them.

A geometric update refers to changes in the position or shape of a road section and is represented in our code by the boolean variable *geomChange*. This indicator is necessary because, in OSM, a positional change in a node results in a positional change for every way associated with that node, yet there is no corresponding update to the version number of the way in OSM. In our graph, the version number must be incremented in such cases. The *geomChange* variable is set to true when the geometry of the edge differs between two consecutive snapshots, which is determined by the test $g(e_i^m) \neq g(e_i^{m+1})$, where $e_i^{m+1} \in E^n$ and $e_i^{m+1} \in E^{n+1}$.

Within the category of attribute updates, infrastructure updates are specifically highlighted. This is indicated by the boolean variable *infrastructureChange*, which is set to true when the cycling infrastructure class differs between two consecutive snapshots, as determined by the test $c(e_i^{m+1}) \neq c(e_i^{m+1})$, where $e_i^{m+1} \in E^n$ and $e_i^{m+1} \in E^{n+1}$.

Among the attribute updates, infrastructure updates are specifically identified and represented by the boolean variable *infrastructureChange*. This variable is assigned a value of true when there is a difference in the cycling infrastructure class between two consecutive snapshots. This condition is evaluated using the test $c(e_i^m) \neq c(e_i^{m+1})$, where $e_i^m \in E^n$ and $e_i^{m+1} \in E^{n+1}$.

The cycling infrastructure classes are detailed in Table 4.2, which presents two distinct classifications. The first classification, referred to as *infrastructure families*, groups multiple infrastructure types into a single category based on a shared prioritized user. The second classification, termed *infrastructure classes*, provides a more granular classification of cycling infrastructure. It is noteworthy that, in certain instances, the inclusion of prohibited roads is essential for understanding the evolution of the network. These roads will be considered in this study when deemed necessary.

Family	Class	Definition	OSM definition
Cycling infrastructure	Cycleway	Road section dedicated to bikes where cars are mostly forbidden except for local use	highway = cycleway
	Cycle lane	Space dedicated to bikes on a road section	cycleway or cycleway:both or cycleway:right or cycleway:left = {lane, opposite_lane}
	Shared road	Road section where bikes and cars, and sometimes pedestrians, share the same space together	{cycleway = {shared_lane, opposite}} or {oneway = no and lanes = 1 and cycleway = lane} or {cyclestreet = yes}
	Shared busway	Road section dedicated to buses where cyclists are allowed	{cycleway or cycleway:both or cycleway:right} and cycleway:left = share_busway} for the main direction of travel, add oneway:bicycle = no for the use of the opposite direction
Pedestrian infrastructure	Pedestrian ways	Road section where pedestrians are the only users allowed. A cyclist can use these roads only if he walks alongside his bike	highway = {pedestrian, bridleway, footway, path, sidewalk, crossing, living_street}
	Stairs	Particular pedestrian infrastructure because they are more difficult to access when pushing or carrying a bike	highway = steps
Infrastructure dedicated to the motor vehicles	Infrastructure dedicated to the motor vehicles	Road sections where the cars are prioritized and nothing exists for bikes	Any OSM way having the key highway that is not included in another class
Forbidden roads	Forbidden roads	Roads forbidden to cyclists	highway = {motorway, motorway_link, trunk, trunk_link} or bicycle = no

Table 1: Cycling network classifications.

For attribute changes, any modification made to an edge is considered an evolution. In the context of OSM, if any tag associated with a feature is added, deleted, or modified, the edge or vertex is deemed to have undergone an attribute change. This condition is represented by the boolean variable *attributeChange*, which is set to true when the OSM tags of an edge differ between two consecutive snapshots. This relationship is determined using the test $t(e_i^m) \neq t(e_i^{m+1})$, where $e_i^m \in E^n$ and $e_i^{m+1} \in E^{n+1}$.

Subsequently, indicators of cycling network evolution are computed based on two consecutive layers of the graph. These indicators include the total length of added edges, denoted as $d(E_{add}^{n+1}) = d(E_{tot}^{n+1})/d(E_{tot}^{n})$, the total length of deleted edges, defined as $d(E_{del}^{n+1}) = d(E_{tot}^{n})/d(E_{tot}^{n+1})$, and the total length of modified edges. The updates are categorized into three types: geometric updates, which pertain to changes in geometry; attribute updates, which refer to changes in any properties of the edge; and infrastructure updates, which involve changes to the cycling class and are included under attribute updates. It is important to note that an update may fall into multiple categories simultaneously. All of these indicators are weighted by the length of each edge.

Regarding the routes approach, the parameters of the experiment are in accordance with [5]. For each AoI and each year, a total of 1,000 routes are generated. The starting and ending points are fixed for the same AoI across different years. A starting or ending point is initially generated within the AoI and mapped to the network. The point is retained only if it remains consistent across all temporal snapshots and is located within 100 meters of the network. The Euclidean distance between the starting and ending points ranges from 300 meters to 5 kilometers. An additional output has been integrated into this approach, which is a way centrality indicator ($cent$) calculated at the level of a road section version. This indicator, computed on edges, is similar to the way centrality as described by reference [42]. However, our method differs in that the shortest path algorithm has been adapted to identify routes that are more suitable for cycling. Specifically, we employ Dijkstra's algorithm but modify the weights of the road sections to favor cycling-friendly roads, such as cycleways.

In our analysis, we compute the way centrality indicator for a single step, utilizing the result for subsequent analyses. Let x represent the number of routes utilizing an edge e_n^i for a given year n, and let y denote the total number of calculated routes within an AoI for that year. The formula is given by $cent(e_n^i) = x$, where $x \in [0, y]$. Using this indicator, we assess the evolution of the mean, the 99th percentile, and the maximum values for each AoI and for each snapshot. Road segments with a zero way centrality indicator are excluded from the analysis to focus on road sections that have been utilized at least once within a single AoI and snapshot.

Another component of the routes approach involves the assessment of cycling infrastructure, for which we define two safety levels. The most stringent level considers only cycleways, as they provide complete separation for cyclists from other road users. The second level encompasses the family of cycling infrastructure, which includes cycle lanes designated bike-specific spaces as well as shared roadways with cars, where motorized vehicles can also operate, thus presenting a greater risk. Additionally, shared roadways with buses, while typically wide and low-traffic, pose potential challenges during interactions with buses.

Indicators have been developed to calculate the number of routes that utilize at least one cycleway and the number of routes in which cycleways comprise at least 30% of the total route length. Having outlined the experimental framework, Section 5 will present and discuss the results obtained from this study.

5 Results

This section presents the results derived from both approaches, accompanied by an in-depth discussion. The first subsection focuses on the road section analysis, where various results are examined and interpreted, including detailed commentary on specific roads. To ensure accuracy, these changes have been verified through manual investigations using Google Street View.

5.1 Road section analysis

The cycling network comprises various types of roadways, including those exclusively designated for cycling, such as cycleways, as well as shared spaces where cyclists coexist with other road users, including cars, buses, and pedestrians. The initial step in our study involves presenting the evolution of the infrastructure families discussed in Section 4. Table 2 illustrates the changes in road length across these three categories, with the percentages reflecting the evolution from the snapshot at time n compared to that at time $n-1$.

Year	Cycling infrastructure	Pedestrian infrastructure	Motor vehicles infrastructure	Total
2014	828.4	2602.2	92960.2	96390.8
2015	932.7 (+12.6%)	3227.7 (+24%)	109207.3 (+17.5%)	113367.7 (+17.6%)
2016	1086.7 (+16.5%)	3820.9 (+18.4%)	114158.8 (+4.5%)	119066.5 (+5%)
2017	1204.5 (+10.8%)	4228.7 (+10.7%)	120545.6 (+5.6%)	125978.7 (+5.8%)
2018	1209.1 (+0.4%)	6331.0 (+49.7%)	129185.6 (+7.2%)	136725.7 (+8.5%)
2019	1373.6 (+13.6%)	7092.8 (+12%)	133515.9 (+3.4%)	141983.4 (+3.8%)
2020	1370.0 (-0.3%)	7556.4 (+6.5%)	138191.7 (+3.5%)	147118.1 (+3.6%)
2021	1526.2 (+11.4%)	8047.2 (+6.5%)	140364.0 (+1.6%)	149937.4 (+1.9%)
2022	1623.2 (+6.4%)	8766.3 (+8.9%)	143278.3 (+2.1%)	153667.8 (+2.5%)

Table 2: Length in km per year of road sections according to the cycling family.

As anticipated, infrastructure dedicated to motor vehicles constitutes the majority of the road network, exhibiting a gradual increase over time. Notably, between 2014 and 2015, there is a significant growth across all types of infrastructure. The length of cycling infrastructure has notably doubled from 2014 to 2022, although there are two periods of stagnation observed in 2018 and 2020. The only decrease in cycling infrastructure length occurred between 2019 and 2020, with a reduction of 0.3%. Conversely, the pedestrian network experienced a substantial increase between 2017 and 2018, marked by a 49.7% rise, likely attributable to a surge in contributions related to sidewalks in major cities. This growth in pedestrian infrastructure length surpasses that of cycling infrastructure during the same period.

Table 3 shows the lengths of road sections belonging to each editing category between snapshots at time n and $n+1$. The percentage indicates the ratio of the length of relevant edges and the total length of edges for this snapshot.

Table 4 presents the lengths of updated edges categorized into attribute, infrastructure, and geometric updates. The percentages are relative to the road lengths of the updated edges, as indicated in Table 3. It is noteworthy that an update may encompass both ge-

Period	Added	Deleted	Same	Updated
2014–2015	18405.4 (16.9%)	1428.6 (1.3%)	59035.0 (54.3%)	29843.7 (27.5%)
2015–2016	12550.2 (10.8%)	700.6 (0.6%)	76742.6 (66.1%)	26085.2 (22.5%)
2016–2017	11062.8 (8.9%)	525.2 (0.4%)	87909.2 (70.6%)	25081.7 (20.1%)
2017–2018	13100.6 (9.7%)	497.6 (0.4%)	87305 (64.8%)	33928.3 (25.2%)
2018–2019	8218.2 (5.8%)	561.1 (0.4%)	99916.9 (71.1%)	31850.6 (22.7%)
2019–2020	7685.2 (5.3%)	514.7 (0.4%)	105156.1 (71.8%)	33005.8 (22.6%)
2020–2021	4762.3 (3.2%)	865.5 (0.6%)	116247.0 (77.9%)	27286.7 (18.3%)
2021–2022	5650.8 (3.7%)	474.8 (0.3%)	120891.5 (78.9%)	26201.0 (17.1%)

Table 3: Length in km per year of road sections according to their edition type.

ometric and infrastructure changes simultaneously, which accounts for the row totals not summing to 100%.

Period	Geometric	Infrastructure	Attribute
2014–2015	26187.6 (87.7%)	271.7 (0.9%)	10782.9 (36.1%)
2015–2016	23112.2 (88.6%)	335.1 (1.3%)	7249.8 (27.8%)
2016–2017	22829.9 (91%)	385.1 (1.5%)	5045.6 (20.1%)
2017–2018	29104.6 (85.8%)	229.1 (0.7%)	10061.8 (29.7%)
2018–2019	25246.0 (79.3%)	527.3 (1.7%)	12103.4 (38%)
2019–2020	30696.7 (93%)	292.3 (0.9%)	5511.0 (16.7%)
2020–2021	24798.5 (90.9%)	405.9 (1.5%)	5353.1 (19.6%)
2021–2022	22580.0 (86.2%)	479.2 (1.8%)	6677.2 (25.5%)

Table 4: Length in km per year of updated road sections according to their update type.

The lengths of added and deleted edges tend to decrease when the length of updated edges remains stable. Additionally, the length of updated edges decreases when compared to the total length of the network. In contrast, the length of edges that remain unchanged between two consecutive snapshots, n and $n + 1$, increases both in absolute terms and as a percentage, exhibiting increases of 54.3% between 2014 and 2015 and 78.9% between 2021 and 2022. Geometric updates constitute the majority of updates in OSM, accounting for 80% to 90% throughout the study period. Attribute updates represent between 25% and 40% of the total updates, with a notable decline towards the end of the study period, recording only 16.7% between 2019 and 2020.

This observation suggests that OSM contributors in the Centre-Val de Loire region are gradually achieving consensus regarding the data quality in this area, indicating that the number of changes driven by data quality issues is not substantial. Consequently, the remaining updates predominantly reflect actual changes in the real world.

Table 5 illustrates the evolution of the lengths of edges across different infrastructure classes between two consecutive snapshots, specifically from 2018 to 2019. The evolution appears stable across the different snapshots, and this particular year serves as a fair representation of how the data evolves over time.

Figure 5 illustrates the usage conflict between cyclists and pedestrians, revealing that 3% of the cycle paths from 2018 are now classified as part of the pedestrian network. This shift is primarily attributed to the incorrect classification of these pathways, which were originally designated as shared spaces for both cyclists and pedestrians. The increasing

2019 2018	Cycleways	Cycle lane	Shared way	Pedestrian	Motor vehicles	Forbidden	Do not exist	Total
Cycle path	90.2%	0.0%	0.0%	3.0%	0.8%	0.0%	6.0%	100%
Cycle lane	0.0%	97.6%	0.6%	0.0%	1.6%	0.0%	0.3%	100%
Shared way	0.0%	0.2%	96.5%	0.1%	3.0%	0.0%	0.3%	100%
Pedestrian	0.2%	0.0%	0.0%	93.4%	4.9%	0.0%	1.5%	100%
Motor vehicle	0.0%	0.0%	0.0%	0.1%	99.6%	0.0%	0.3%	100%
Forbidden	0.0%	0.0%	0.0%	0.0%	0.3%	98.1%	1.7%	100%
Do not exist	1.4%	0.3%	0.1%	13.2%	81.8%	3.2%	0.0%	100%
Total	0.5%	0.3%	0.2%	5.0%	91.6%	2.1%	0.4%	100%

Table 5: Evolution of the length of the edges of each infrastructure class between 2018 and 2019.

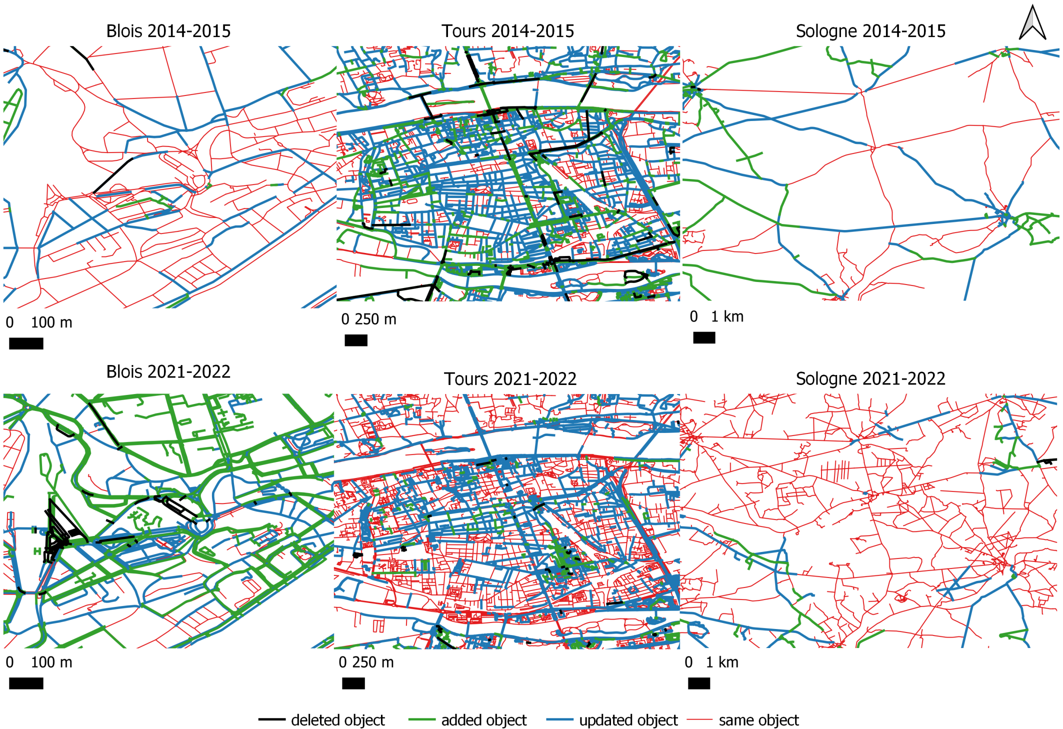
number of cyclists utilizing these shared infrastructure has created safety concerns for pedestrians, leading to the decision to restrict many of these pathways exclusively for pedestrian use [35]. Additionally, it is noteworthy that a substantial number of pedestrian infrastructure have been established, accounting for 13.2% of all road creations, in contrast to the mere 1.4% for cycleways.

Figure 5 displays the edges categorized by editing type for the periods 2014-2015 and 2021-2022 across three distinct areas: Tours, one of the two major cities; Blois, a medium-sized city; and Sologne, a predominantly forested and rural region.

Figure 5 illustrates that the Sologne area exhibited a denser network in 2022, with numerous road sections remaining unchanged between 2021 and 2022. In contrast, Tours displayed a significant number of updates across both maps, revealing clusters of activity, such as the green cluster on the 2021-2022 map, and red clusters indicating road sections with minimal changes. This pattern may suggest that OSM contributors have reached a consensus regarding those areas. The overall network density remains consistent with the density observed on the 2014-2015 map. Conversely, Blois experienced an extensive campaign between 2021 and 2022 focused on adding sidewalks in the city center, which accounts for the substantial number of new edges added. This has contributed to a greater overall density compared to the 2014-2015 map.

Overall, our findings indicate that the cycling networks in the two major cities, Tours and Orléans, the medium-sized cities (Blois, Bourges, Chartres, Châteauroux), and the rural areas exhibit distinct characteristics. To conduct a detailed analysis of the evolution in these areas, we selected six zones categorized into three groups: the major cities represented by Tours and Orléans, the medium cities comprising Blois and Bourges, and the rural areas including the Sologne forest and Beauce valley. These zones are depicted in Figure 3.

The road section analysis provides general insights into road infrastructure and its evolution within our study area, treating each road section uniformly. However, from a cyclist's perspective, certain road sections warrant prioritization over others. Consequently, the routes analysis serves to complement the road section analysis by focusing on the sections utilized by cycling routes over time.



Bres et al, Source: OSM, january 2024

Figure 5: Change types in Tours, Blois, and Sologne between 2014–2015 and 2021–2022.

5.2 Routes analysis

Firstly, the AoI encompass varying numbers of road sections, as illustrated in Table 6, which depicts the evolution of the number of edges utilized by at least one generated route for each AoI. It is important to note that any road section within an AoI that is not employed in the generated routes is excluded from this table.

Year/AoI	Tours	Orléans	Blois	Bourges	Sologne	Beauce
2014	4058	2433	1467	1342	945	1087
2015	4788 (18.0%)	2466 (1.4%)	1603 (9.3%)	1533 (14.2%)	1032 (9.2%)	1136 (4.5%)
2016	4892 (2.2%)	2588 (4.9%)	1701 (6.1%)	1718 (12.1%)	1098 (6.4%)	1231 (8.4%)
2017	5004 (2.3%)	2832 (9.4%)	1720 (1.1%)	1842 (7.2%)	1122 (2.2%)	1453 (18.0%)
2018	5171 (3.3%)	2857 (0.9%)	1745 (1.5%)	1894 (2.8%)	1178 (5.0%)	1588 (9.3%)
2019	5339 (3.2%)	3191 (11.7%)	2049 (17.4%)	1933 (2.1%)	1310 (11.2%)	1643 (3.5%)
2020	5413 (1.4%)	3646 (14.3%)	2120 (3.5%)	1995 (3.2%)	1372 (4.7%)	1681 (2.3%)
2021	5525 (2.1%)	3906 (7.1%)	2099 (-1.0%)	2081 (4.3%)	1408 (2.6%)	1690 (0.5%)
2022	5679 (2.8%)	4043 (3.5%)	2408 (14.7%)	2215 (6.4%)	1457 (3.5%)	1718 (1.7%)

Table 6: Number and evolution of road sections per year used by at least one generated route for each AoI.

AoI / Year	Tours	Orléans	Blois	Bourges	Beauce	Sologne
2014	11135	6272	2661	2650	2023	2244
2015	14977	6978	3406	3652	2539	2701
2016	16658	7868	3919	4428	2890	3327
2017	17874	8934	3978	4849	4052	3591
2018	19076	9317	4161	5059	4703	4244
2019	20917	14267	4849	5410	4969	4757
2020	21861	17738	5450	5798	5125	5288
2021	22899	20324	6497	6194	5243	5585
2022	24793	21689	8931	6973	5411	5776

Table 7: Evolution of the road sections number in the AoI.

In major cities, the number of road sections is significantly higher, indicating that there are numerous routing options available for any given origin-destination pair with minimal impact on routing time. Conversely, rural areas offer fewer optimal options for navigation between origin-destination pairs, resulting in a lower number of utilized road sections.

Regarding the evolution of road sections, its number for the same AoI consistently increases between consecutive snapshots, with the exception of Blois between 2020 and 2021, where the count decreased from 2,120 road sections to 2,099. This decline can be attributed to the rectification of a data quality issue concerning a major road (i.e., Boulevard des Cités Unies), which comprises multiple road sections. This road had been designated as prohibited for bicycles since at least 2005 but had not been accurately represented in OSM prior to this correction.

The overall increase in the number of road sections is of a similar magnitude across all AoI. Notably, Tours experienced a significant increase in its number of road sections between 2014 and 2015, while the other areas exhibited a more linear progression in their growth.

Following the examination of the number of edges involved for each AoI, we proceed to analyze the evolution of the mean way centrality indicator. This analysis is visually represented in Figure 6.

The overall trend of the mean way centrality indicator exhibits a gradual decline over time for each AoI. However, notable local increases are observed between consecutive snapshots, such as the increase in Blois between 2020 and 2021, attributed to the classification of a major road as prohibited for cyclists during that period. It is important to note that this trend does not exhibit significant variation based on the type of AoI. To gain deeper insights into the higher values of way centrality, the analysis of the 99^{th} percentile values for each AoI across the years will be presented.

In Table 8, the 99^{th} percentile of way centrality demonstrates a decreasing trend for Orléans, Bourges, Sologne, and Beauce. The values for Blois and Tours remain stable, although the indicator for Blois exhibits fluctuations over time. Notably, there is considerable variability observed in Bourges, Beauce, and Orléans, with values of 146 for Bourges and 195 for Orléans in 2014, contrasting with 128 for Bourges and 214 for Orléans in 2015.

An unexpected finding is the minimal influence of urbanization on this variable. Whether an AoI is classified as a major city, a small city, or a rural area appears to have little impact on the way centrality values. Conversely, the internal structure of the city is

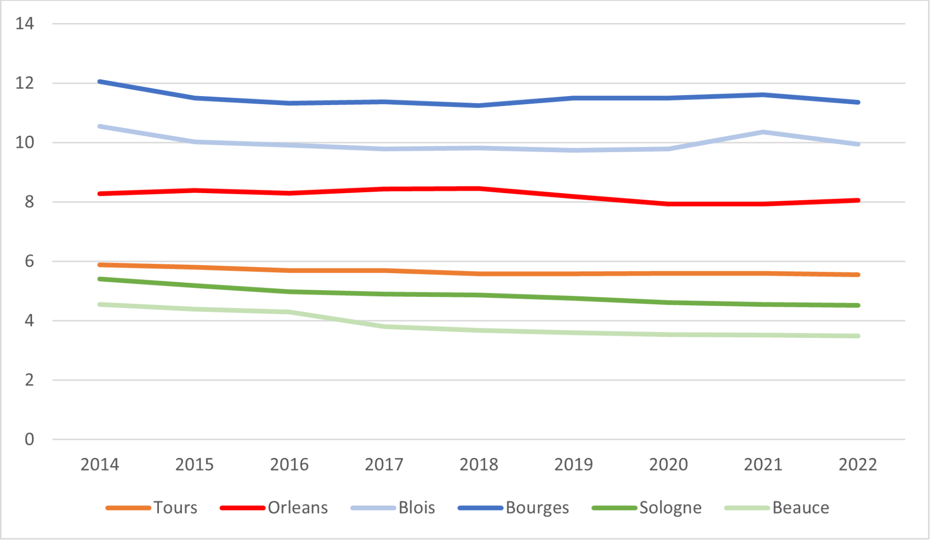


Figure 6: Evolution of the way centrality mean.

Year/AoI	Tours	Orléans	Blois	Bourges	Sologne	Beauce
2014	37.43	70.68	65	85.59	30	27.14
2015	36.13	71.7	61	87.36	28	26.65
2016	34	71.26	61	72.83	28.03	21.7
2017	34	64	60.81	75.95	25.79	18.96
2018	32	63.44	62	75.28	25.23	16.13
2019	35	65	54	79.68	23	16
2020	35	65.1	54	79	23	16
2021	36	57	62.04	81.2	29.93	16
2022	36	57.58	64	77	22	16

Table 8: Way centrality 99^{th} percentile per year for each AoI.

more significant. For instance, the most frequently utilized roads in Blois are consistently the bridges, which can be attributed to the presence of the Loire river. A major alteration to one of these bridges resulted in a substantial increase in the way centrality indicator between 2020 and 2021.

For Beauce, the way centrality indicator has stabilized at a value of 16 over the past four years, indicating that the majority of the roads in this area have already been established and that the AoI is not experiencing rapid evolution. Additionally, the infrastructure class of the most utilized road sections primarily consists of those dedicated to motor vehicles, with sporadic presence of cycle lanes. Therefore, modifications to the route generator may be necessary to more effectively prioritize cycling infrastructure.

The subsequent section of the results concerning the routes approach focuses on analyzing the proportion of cycling infrastructure incorporated into each generated route over time. Notably, the Beauce AoI was excluded from the results, as it consistently produced 999 out of 1000 routes each year that utilized 100% of the motor vehicle network. Figure 7 illustrates the number of routes that include at least one cycleway over the observed time period.

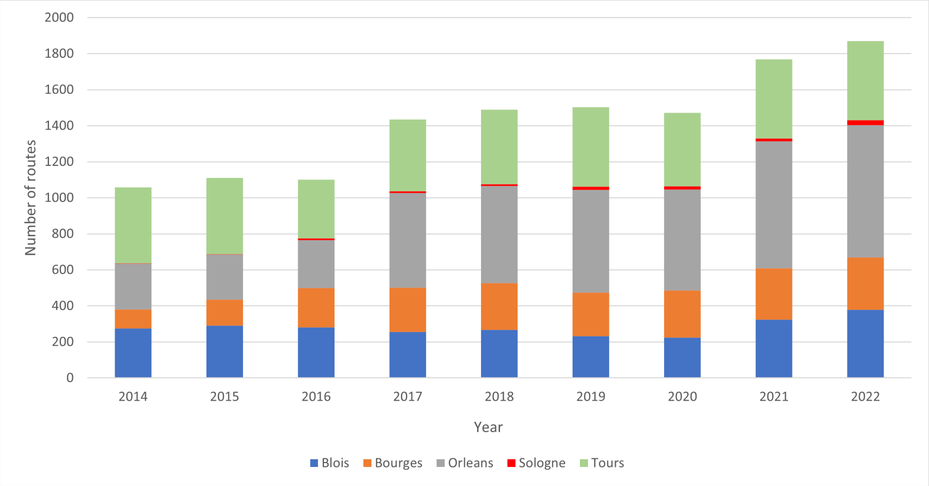


Figure 7: Number of routes per year using at least one cycleway.

The analysis reveals that urban areas are generally more conducive to cycling, with a significantly greater availability of cycling infrastructure compared to rural regions, where only 26 routes utilized at least one cycleway in 2022. However, there is a pronounced upward trend in the number of routes incorporating a cycleway over time, with the exception of Tours, where the number of routes using at least one cycleway fluctuates and remains relatively constant from the beginning to the end of the study period.

Notably, there is no discernible difference in cycleway usage between large and small cities throughout the study. Even among cities of similar sizes, patterns in cycleway utilization are inconsistent; for instance, Tours shows stagnation across the entire study period, while Orléans exhibits a significant increase in cycleway usage, suggesting an important underlying trend. This increase is particularly evident between 2016 and 2017, as well as between 2020 and 2021.

Figure 8 illustrates the number of routes that incorporate at least one cycling infrastructure over time. The results from this analysis are comparable to those presented in Figure 7.

The distinction between rural areas and urban centers is further emphasized in this analysis. While there has been a marked increase in the utilization of cycleways over time, rural areas continue to exhibit a lower number of routes incorporating cycling infrastructure by the conclusion of the study period. For instance, Tours experienced an increase from 466 to 754 routes, whereas Sologne saw a more modest rise from 2 to 32 routes.

Significant spikes in data are evident in Figure 8, particularly between 2018 and 2019 for Blois and Bourges. However, it remains challenging to ascertain whether these increases are correlated. Further investigation is warranted, particularly focusing on the behavior and editing activities of OSM contributors during that period. Analyzing whether the same contributors made significant contributions in both areas concurrently, or if bulk imports [21] from open data sources occurred, could yield insights.

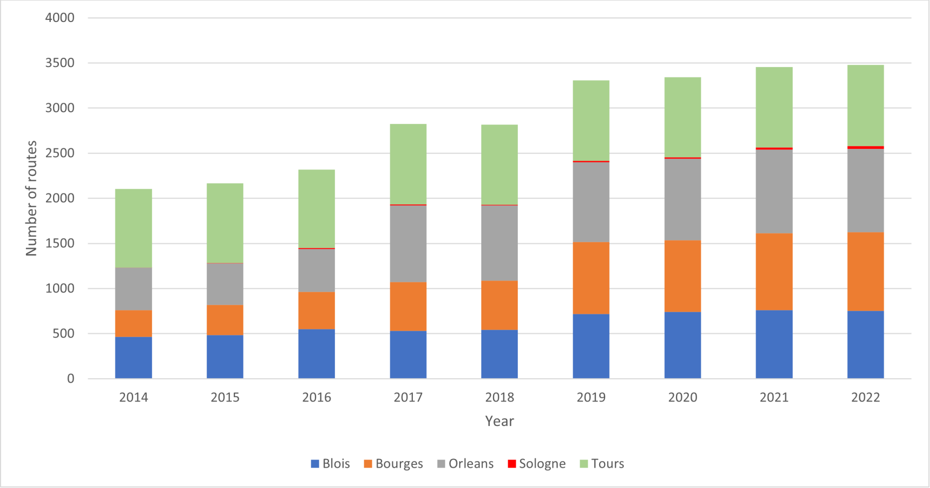


Figure 8: Number of routes per year using at least one cycling infrastructure.

Overall, the number of routes utilizing at least one cycling infrastructure increased by over 1,000 between the beginning and end of the study period. Notably, the most substantial increases were observed in Bourges and Orléans, suggesting that the scale of a city does not significantly influence the usage of its cycling infrastructure. Although the increases for Blois and Tours are less pronounced, they remain noteworthy. Meanwhile, Sologne's growth in cycling infrastructure usage is gradual, but it still lags considerably behind the levels seen in urban areas.

Following the observation that many routes incorporate only a limited amount of cycling infrastructure, Figure 9 illustrates the evolution of the number of routes in which at least 30 percent of the route comprises cycleways over time.

Initially, it is important to note that Sologne does not exhibit any routes utilizing at least 30% of cycleways. In contrast, the evolution observed in the four cities varies significantly. Tours demonstrates a decrease in routes using cycleways between 2014 and 2016, followed by a modest increase thereafter. The notable decline between 2015 and 2016 can likely be attributed to an infrastructure change in which a cycleway was reclassified as a pedestrian infrastructure. This particular road, segmented into multiple sections, previously had a way centrality indicator ranging from 40 to 50.

Orléans shows a substantial increase in the number of routes incorporating cycleways, particularly following the onset of the COVID-19 crisis. Conversely, Bourges experiences a trend similar to Orléans; however, the COVID-19 pandemic resulted in decreased theoretical utilization of cycleways rather than an increase. This significant reduction for Bourges is primarily linked to a cycleway, which is part of the *Coeur de France à vélo* bike route, being incorrectly tagged as a pedestrian infrastructure over half of the AoI.

In the case of Blois, it was discovered that a bridge was not accurately represented in OSM until the 2016 snapshot. The sidewalks were mistakenly labeled as cycleways, although the actual infrastructure consisted of two sidewalks adjacent to a four-lanes road and two cycle lanes. Given the limited options for crossing the Loire rver, this bridge features prominently in many routes, and the absence of the inaccurately classified cycleway

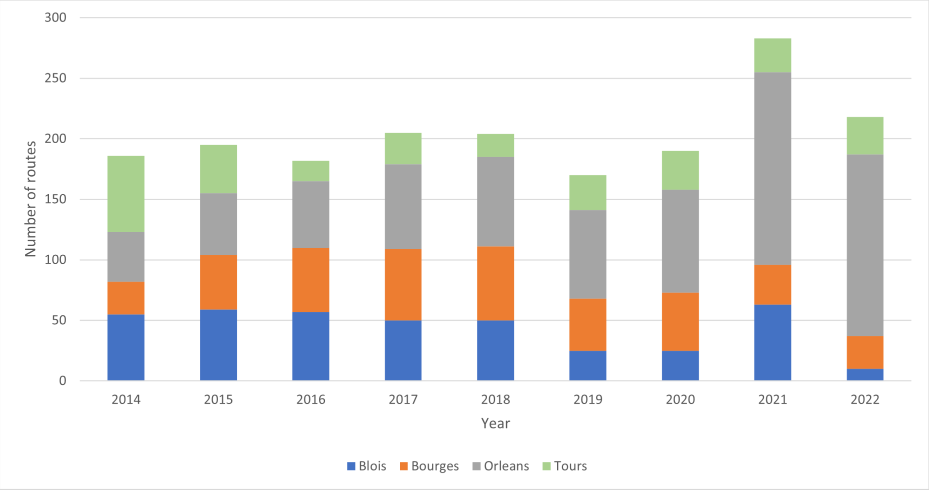


Figure 9: Number of routes per year using at least 30% of cycleways.

is reflected in the results. Notably, the data for 2021 in Blois presents a minor decrease in the number of routes utilizing at least 30% cycleways between 2020 and 2022, despite 2021 being the year with the highest proportion of routes achieving this threshold. This phenomenon may be attributed to temporary cycleways that were mapped in OSM during the COVID-19 crisis, which were subsequently removed before the 2022 snapshot.

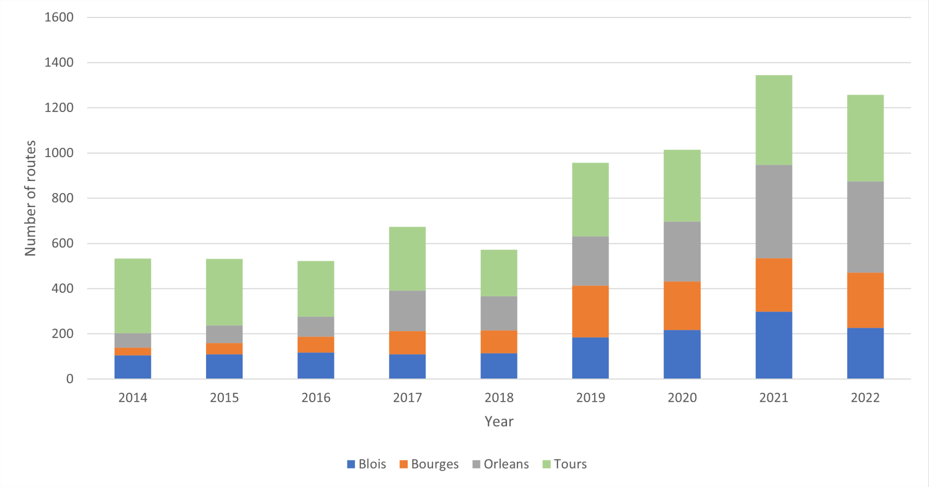


Figure 10: Number of routes per year using at least 30% of cycling infrastructure.

In Figure 10, with the exception of Sologne which consistently exhibits routes with less than 30% cycling infrastructure across all years—each city shows an increasing trend in the number of routes utilizing a higher percentage of cycling infrastructure. By the end of the study period, Tours and Orléans demonstrate comparable figures; however, Tours had a significant number of routes incorporating cycling infrastructure from the outset.

Orléans began with a number of essential cycleways and gradually expanded its network to include cycle lanes and shared paths over time. The COVID-19 crisis played a pivotal role in this development, with the most substantial growth occurring between 2020 and 2021. Additionally, a notable increase is observed between 2016 and 2017.

Bourges experienced a significant rise in routes using cycling infrastructure between 2018 and 2019, with subsequent years reflecting only modest increases. Blois exhibited a gradual growth in this area from 2018 to 2021. When combined with the data from Figure 9, it can be inferred that cycleways were likely replaced by other types of cycling infrastructure, such as cycle lanes or shared paths, by 2022.

For Tours, the trend is consistent with Figure 9, where a slight decrease is noted at the beginning of the study period, followed by an increase toward the end. This increase in cycling infrastructure is more pronounced than the growth in cycleways.

6 Discussion

The proposed multiplex graph offers an effective solution for analyzing data evolution while minimizing computational costs. Given that OSM snapshots are extensive, even for small areas, managing numerous snapshots can become resource-intensive. Our graph design allows for the incorporation of only the data relevant to the area of study and the selected snapshots, making it operationally efficient.

This multiplex graph facilitates an insightful analysis of OSM data evolution through two complementary approaches. The first is the road section approach, which, although comprehensive for a large area like a French region, may be too broad and diverse to capture every evolutionary pattern effectively. However, this approach enables the visualization of data evolution and provides insights into the trends within the cycling network.

Additionally, the infrastructure classification utilized in the confusion matrix offers valuable information regarding the current trends in an area from a cyclist's perspective. This could pave the way for identifying similar roads in analogous regions that may require updates, potentially utilizing machine learning algorithms to enhance the analysis and application of OSM data.

The application of both approaches provides valuable insights into the evolution of the OSM road network from a cyclist's perspective. The road section analysis reveals that road infrastructure predominantly cater to motor vehicles, particularly outside major cities. Over time, the network has become denser, thanks to the addition of new roads and smaller paths to OSM. This trend aligns with findings in the existing literature on OSM data evolution, which indicates an overall increase in the number of features.

The COVID-19 crisis significantly influenced many cities, leading to the creation of numerous cycleways. This period marked a pivotal shift in urban planning, as cyclists began to be recognized as a legitimate mode of transportation that requires dedicated infrastructure. While motor vehicle infrastructure continues to dominate the network, some roads have been repurposed for pedestrians and cyclists. Additionally, certain routes that were once designated for cyclists have transitioned to pedestrian-only pathways. These changes reflect a broader trend toward slowing down urban environments, as evidenced by many cities reducing speed limits from 50 km/h to 30 km/h to enhance the safety of vulnerable road users.

The road section approach indicates a growing consensus regarding the OSM motor vehicle network, with a similar agreement developing for cycling infrastructure, albeit at a later stage, alongside that for pedestrian pathways. The frequency of updates reflects the ever-changing nature of the real world, underscoring the continuous need for contributions to OSM, a sentiment that aligns with findings from previous research.

In contrast, the routes approach highlights a clear disparity between urban and rural areas. Rural regions often lack sufficient cycling infrastructure, and where it does exist, it tends to cater primarily to tourism around significant landmarks, rarely serving as the fastest routes. To foster cycling as an effective means of transportation across the country, enhancing infrastructure in rural areas is crucial.

While some differences were noted between cities, it remains inconclusive whether a city's size impacts its cycling usage. An important variable absent from this study is the political orientation of city officials over time; ecology-minded decision-makers could potentially correlate with significant increases in cycling infrastructure, observable one or two years following their election.

Another key discussion stemming from the routes approach is the allocation of space between cyclists and pedestrians. When infrastructure for both groups were originally designed, urban planners underestimated the volume of cyclists and their impact on pedestrian safety. The recent surge in cycling has highlighted this issue, as the infrastructure often prove too narrow to accommodate both cyclists and pedestrians safely. Consequently, urban planners have begun redirecting cyclists to the road or implementing measures that slow them down on pedestrian prioritized pathways.

Enhancements to the route generator are also warranted, particularly in weighting cycling infrastructure more heavily and minimizing reliance on major highways. As noted in [1], bikeability encompasses safety, comfort, attractiveness, directness, and coherence. The current routing system tends to prioritize directness over these other important criteria, potentially leading to cyclists navigating dangerous roads intended for motor vehicle traffic.

Moreover, creating different cyclist profiles such as families, commuters, and tourists could introduce diverse routing patterns. This approach mirrors initiatives like the Geovélo route generator, which aims to accommodate the varied purposes cyclists may have for their journeys.

Finally, the observed trend of increasing routes utilizing at least 30% cycling infrastructure signals that more such infrastructure are being developed in the real world. Integrating these facilities into road databases is essential to ensure they are well-known and effectively used by cyclists.

7 Conclusion

In this article, we present a novel approach for analyzing VGI with a focus on user perspectives. This method has been applied to the OSM road network from the viewpoint of cyclists in the Centre-Val de Loire region, covering the years 2014 to 2022. Our analysis reveals the evolving state of OSM data in this region, where data is still in flux, but overall stability is increasingly evident. The primary reason for changes made by OSM contributors in this area is to align the OSM dataset with real-world developments. Notably, our study identifies differences in the development of efficient cycling networks between major cities like Tours and Orléans compared to medium-sized cities such as Blois and Bourges. In rural areas, while cycling infrastructure is lacking, low-traffic roads often substitute for designated cycleways, although they typically offer lower safety.

We have instantiated a multiplex graph to facilitate the analysis of VGI road data. This graph enables the integration of multiple snapshots of any VGI road dataset, with OSM being the most suitable choice for implementation. The methodology we employed is reproducible for any other road users, provided that relevant infrastructure classes can be defined and instantiated.

Numerous future research perspectives exist. For instance, the graph could be enhanced with additional attributes at the vertex level. Integrating road intersections into the analysis is another significant improvement, as intersections are critical points in any navigation system, particularly for cyclists, who face heightened danger at major junctions.

Improvements could also be made to the routes approach. Increasing the weight of cycling infrastructure during the route generation phase would promote its usage. Additionally, starting and ending points for routes could be determined based on GPS data, selected semi-randomly from points of interest or residential areas. This method would reduce major biases associated with network density. The AoI could include diverse settings, such as densely populated regions (like the Paris agglomeration) or mountainous areas, where slope plays a crucial role in routing. Another potential area of investigation involves understanding route changes between two consecutive snapshots for the same starting and ending points. Currently, there is no method for identifying which specific modifications caused a change in the routing. Furthermore, we could develop a bikeability index calculated first on the edges and then on the vertices, utilizing the graph developed by [26] from a routing perspective.

The usage conflicts highlighted in our research offer a pathway for further exploration by adapting our methodology to other use cases, as it is fully generic to any user perspective. We anticipate that by applying this study framework across various usage scenarios, we can identify road sections that are frequently utilized by multiple users, making usage conflicts more pronounced.

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