Assessing Walkability and Bikeability in Trento. A Spatial Analysis of Active Mobility

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Abstract
This study assesses the walkability and bikeability of Trento by analyzing its pedestrian and cycling infrastructure across its twelve districts. Walkability is evaluated through intersection density and pedestrian access to amenities, while bikeability is measured using a composite index incorporating bike lane length and coverage, bike parking density, natural area proximity, POI concentration, and bike lane steepness. The results highlight Centro Storico - Piedicastello (District 12) and San Giuseppe - Santa Chiara (District 11) as the most pedestrian- and cyclist-friendly areas. The analysis also reveals disparities in infrastructure distribution, which calls for targeted improvements such as expanding bike lanes and enhancing accessibility in underserved areas.

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1 Introduction

Understanding urban mobility is a crucial aspect for designing sustainable and accessible cities. Walkability and bikeability, in particular, are important indicators of urban livability, as they influence public health, environmental sustainability, and social equity. While widely studied, both concepts lack universally accepted definitions due to their complex, multifaceted nature.
Bikeability is often assessed through the characteristics of the built environment that either encourage or hinder cycling. In his Master's thesis, Gehring[2] defines it as the suitability of urban infrastructure for cycling, based on factors such as connectivity, safety, and accessibility. Similarly, walkability can be evaluated through various lenses, one of which focuses on the proximity of essential services. Hall and Ram[4], for example, propose measuring walkability by analyzing pedestrian access to amenities within a given distance.
In this study, I evaluate the walkability and bikeability of the city of Trento, in Northern Italy, to assess the efficiency, connectivity, and accessibility of its pedestrian and cycling networks, by leveraging open data and employing spatial analysis and network-based methodologies.
Specifically, for bikeability, I develop an index inspired by Heinemann's approach[5], which evaluates cycling conditions using five metrics. I adapt the index to Trento by considering six key factors: bike lane length, bike lane coverage, bike parking density, natural area proportion, points of interest density, and bike lane steepness. In particular, given Trento's diverse topography, I incorporate the impact of elevation on cycling accessibility.
For walkability, I follow Eemil Haapanen's approach[3] to compute the density of urban walkpath intersections using a network-based method. The underlying assumption is that a dense urban fabric indicates greater walkability, as supported by extensive research showing a positive correlation between intersection density and walking as a mode of transport (see Ewing and Cervero[1]). Additionally, I assess pedestrian accessibility to key urban amenities, drawing from the list of sociable places identified by Novack et al.[6], who explore how various urban features influence the pleasantness of public spaces.
Furthermore, for both bikeability and walkability, I focus on district-level variations to identify areas with strong or limited infrastructure. The research therefore aims to provide insights into how Trento's infrastructure supports active mobility and to suggest potential improvements for urban planning.

2 Data

This section describes the datasets used in the project, their sources, and the data cleaning operations applied.

2.1 Open Data - Comune di Trento

Most of the datasets for this project were sourced (in GeoJSON format) from the Comune di Trento Open Data portal, which provides freely accessible datasets for download and reuse. They are all detailed below. For each of them, I converted their coordinate reference system (originally EPSG:25832, corresponding to ETRS89 / UTM zone 32N) to EPSG:32632 (WGS 84 / UTM zone 32N): although both CRS are well-suited for Trento, which lies within UTM zone 32N, I selected EPSG:32632 to ensure consistency in spatial analysis and compatibility with other datasets.

2.1.1 Trento districts

The `circoscrizioni` dataset provides the **geographical boundaries** of the **twelve circoscrizioni** (districts) into which the city of Trento is administratively divided. Figure 1 shows them mapped over OpenStreetMap (OSM). The districts are:

1. Gardolo
2. Meano
3. Bondone
4. Sardagna
5. Ravina-Romagnano
6. Argentario
7. Povo
8. Mattarello
9. Villazzano
10. Oltrefersina
11. San Giuseppe - Santa Chiara
12. Centro Storico - Piedicastello

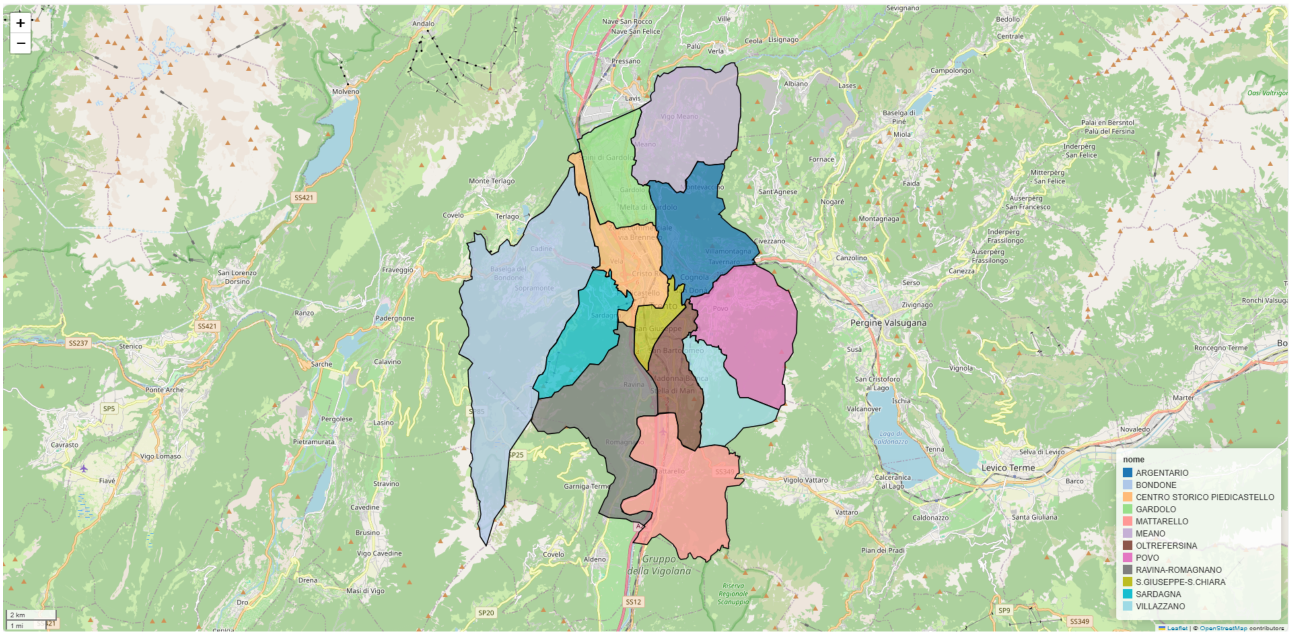


Figure 1: Geographical boundaries of the twelve districts (circoscrizioni) of Trento, mapped over OpenStreetMap (OSM).

By adding a column with the value "Trento" to each row and applying a **spatial dissolve**, I obtained the city's outer boundary, which is visualized in Figure 2 on a physical map.

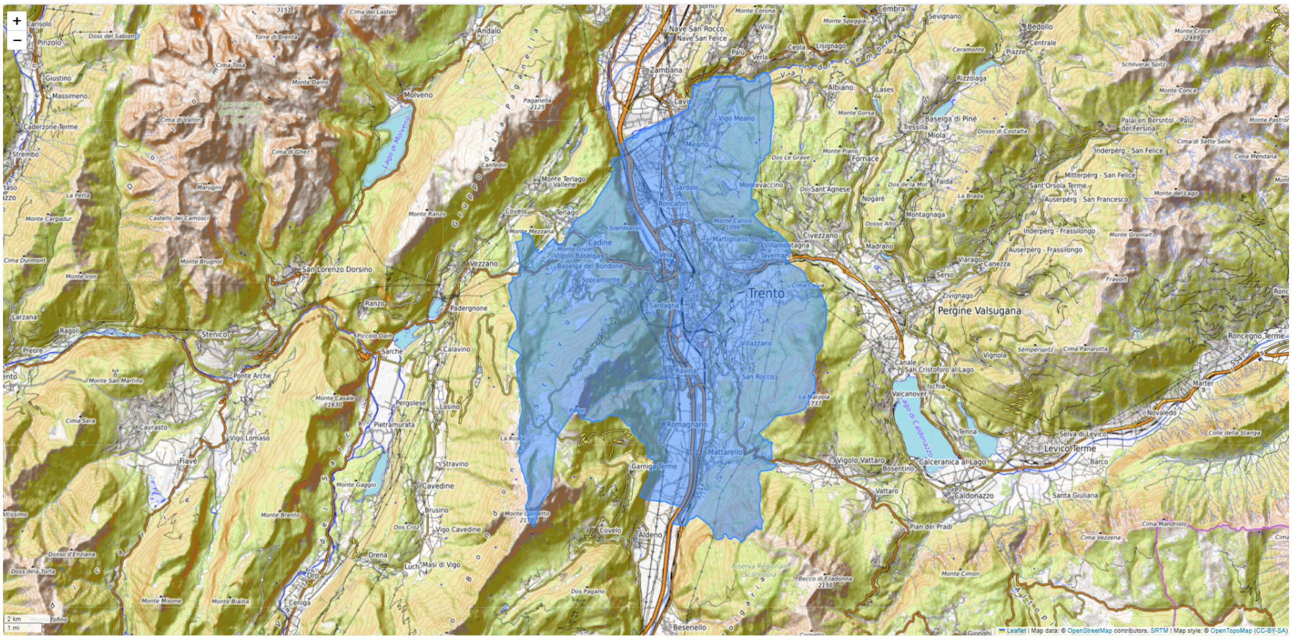


Figure 2: Administrative boundary of Trento displayed over OpenTopoMap.

2.1.2 Bike Lanes

The `bike_lanes` dataset provides information on Trento's cycling infrastructure, specifically **bike lanes** and **shared pedestrian-cyclist paths** under both municipal and provincial jurisdiction. It consists of 295 records and 11 attributes, including *descrizione*, which provides

a textual description of each bike lane segment, and *geometry*, which represents the segment's spatial structure as a LINESTRING.
To analyze the distribution of bike lanes across different districts, I overlaid the `bike_lanes` dataset with the `circoscrizioni` boundaries using a **spatial intersection**, ensuring that each bike lane segment is correctly assigned to its respective district (Figure 3).

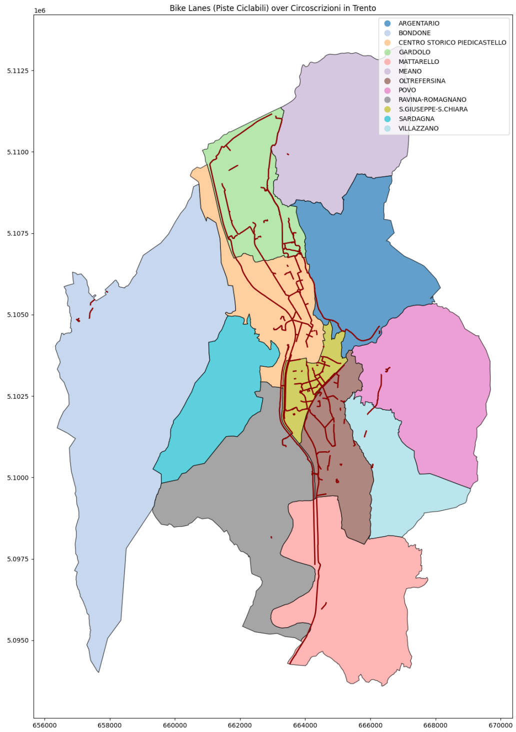


Figure 3: Bike lanes (red) by district in Trento. Note that Sardagna is the only district without any bike lanes.

2.1.3 Bike Parking and Racks

Two datasets describe **bicycle parking infrastructure** in Trento: `bike_parking` and `racks`. The first one contains information about **protected long-term bicycle parking areas**, designed to ensure safe and convenient bike storage while reducing unauthorized parking. It includes 9 records and 8 attributes, such as the facility name, street address, number of available bike spots, and spatial location.
The second dataset maps **bike racks** (*rastrelliere*) within the limited traffic zone, classifying them by type and capacity. It consists of 453 records and 17 attributes, including the number of parking spots.

2.1.4 Contour Lines

The `elevation` dataset represents **contour lines** (*curve di livello*) with a 10-meter vertical interval, depicting the topography of Trento (Figure 4). These lines are derived from the fourth edition of the Technical Map (*Carta Tecnica*), published in December 2010 at a scale of 1:2000, based on aerial surveys conducted in 2009. The dataset comprises 67,573 records and 7 attributes, the most relevant being: *length* (the length of each contour line segment), *dxf_elevat* (the elevation value), and *geometry* (the spatial representation as a LINESTRING).

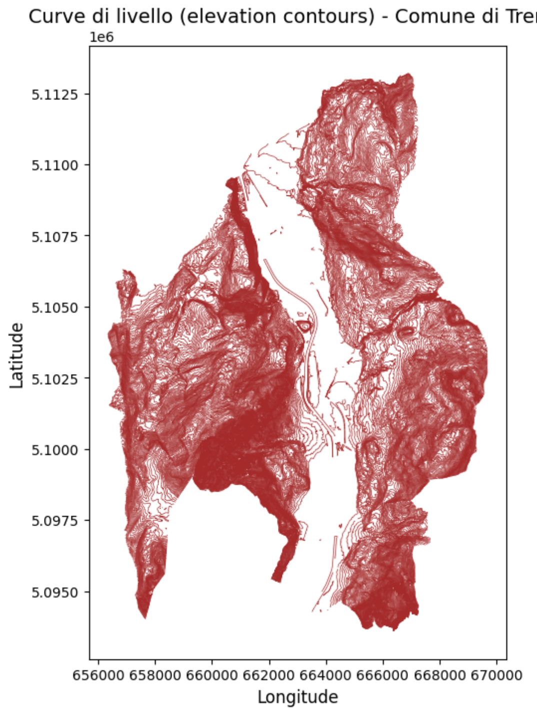


Figure 4: Contour lines in Trento.

2.2 Open Street Map

All the other datasets that were needed for the analysis but were not available as Open data from the Comune di Trento website were extracted from OpenStreetMap (OSM) using the `osmnx` library. They are detailed below.

2.2.1 Natural Areas

The `natural_areas` dataset provides information on **green spaces** in Trento, specifically parks and grassy areas (Figure 5). It was retrieved by defining the city boundary of Trento in the WGS 84 coordinate system (EPSG:4326) and then querying OpenStreetMap for features classified as:

- **Leisure**: `park` – Public parks and recreational green spaces.
- **Land Use**: `grass` – Areas covered by grass, such as meadows or green strips.

After downloading, the dataset was transformed to EPSG:32632. It consists of 3,846 records and 41 attributes, including the name of the park or green space (if available) and the polygon representation of each natural area.

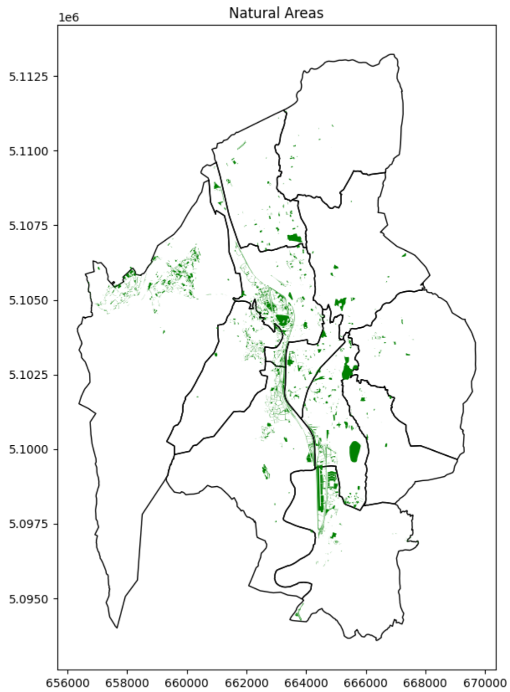


Figure 5: Parks and grassy areas in Trento, divided by district.

2.2.2 Points of Interest

The `pois` dataset includes a diverse range of **points of interest** (POIs) in Trento (Figure 6), obtained by querying OpenStreetMap for features classified under the following categories:

- **Amenity**: Public and private services such as schools, hospitals, and restaurants.
- **Shop**: Commercial establishments, including supermarkets, clothing stores, and bookstores.
- **Office**: Business and professional service locations.

The retrieved POIs were reprojected to the EPSG:32632 coordinate system. The dataset contains 7,402 records and 479 attributes, from which I retained only the type of POI (amenity, shop, or office) and its spatial geometry.

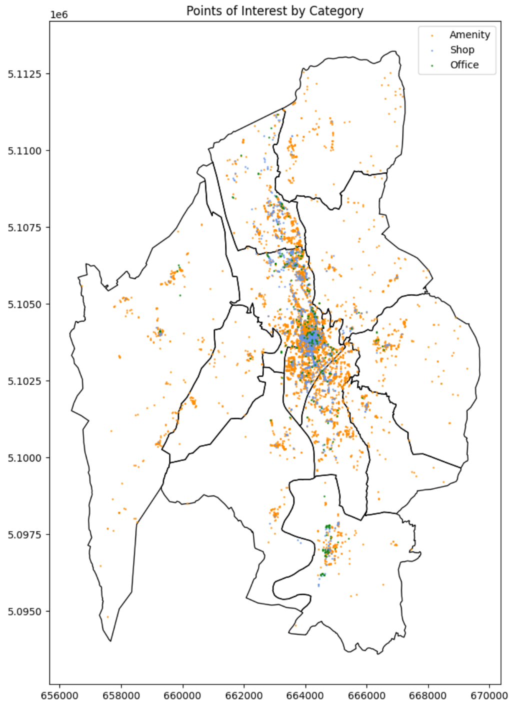
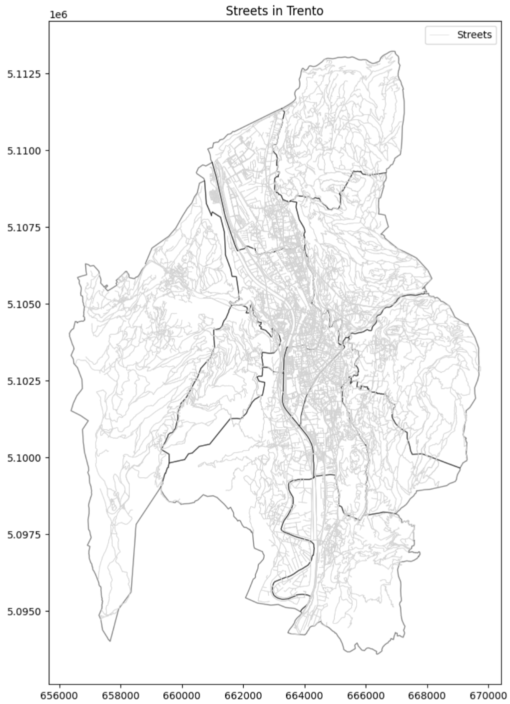


Figure 6: Points of interest for three categories (amenities, shops, and offices) in Trento districts.

2.2.3 Street and Pedestrian Networks

Finally, the `streets` and `walkways` datasets provide detailed representations of Trento's road and pedestrian networks.
The `streets` dataset includes all road types within Trento's administrative boundary (Figure 7a). It was extracted using `network_type="all"`, converted from a network graph to a GeoDataFrame, reprojected to EPSG:32632, and spatially joined with the `circoscrizioni` dataset to associate each road segment with its respective district.
The `walkways` dataset focuses on the pedestrian network (Figure 7b) and was retrieved using `network_type="walk"`, which filters OpenStreetMap data to include only walkable paths such as sidewalks, footpaths, and pedestrian streets. The dataset was reprojected to EPSG:32632 and structured as a network of nodes and edges, where edges represent pedestrian pathways.



(a)

(b)

Figure 7: (a) Trento's street network over districts and (b) Trento's pedestrian network.

3 The Analysis

3.1 Bikeability

I assessed bikeability in each district of Trento by developing an index based on six key factors:

- **Bike Lane Length** – The total length of dedicated cycling infrastructure within each district.
- **Bike Lane Coverage** – The ratio of bike lane length to total street length in a district.
- **Bike Parking Density** – The number of bike parking spots per square kilometer.
- **Natural Area Proportion** – The percentage of green spaces within a 200-meter buffer around bike lanes.
- **Point of Interest (POI) Density** – The number of amenities, shops, and offices within bike lane buffers.
- **Bike Lane Steepness** – The mean elevation gradient of bike lanes.

These factors capture different aspects of cycling accessibility and comfort, from infrastructure availability to environmental and topographical conditions; combined, they provide a comprehensive measure of how well each district supports cycling. The following paragraphs explain each factor in detail, with the final section presenting the results.

3.1.1 Bike Lane Length and Coverage

These two metrics evaluate the availability of cycling infrastructure in each district. The first, **total bike lane length**, is calculated by summing the lengths of all bike lane segments within each district. The second, **bike lane coverage**, is defined as the ratio of total bike lane length to total street length in a district: a higher coverage value indicates a more extensive cycling network relative to the road infrastructure (Figure 8).

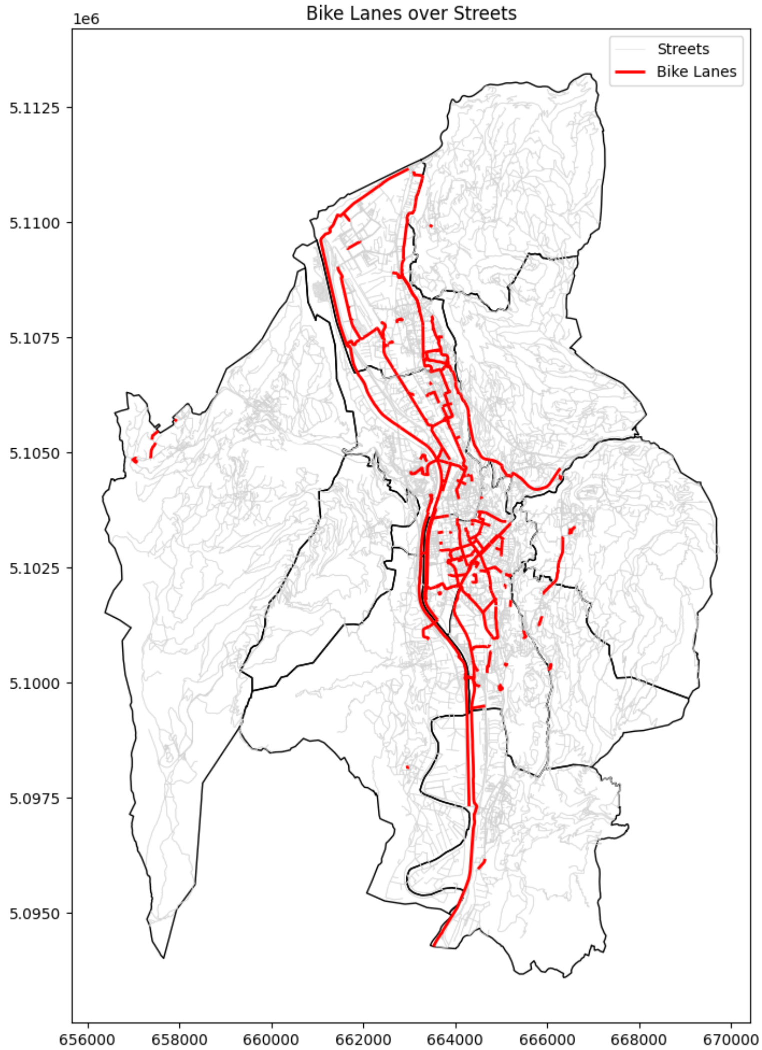


Figure 8: Bike lane coverage across districts of Trento.

3.1.2 Bike Parking Density

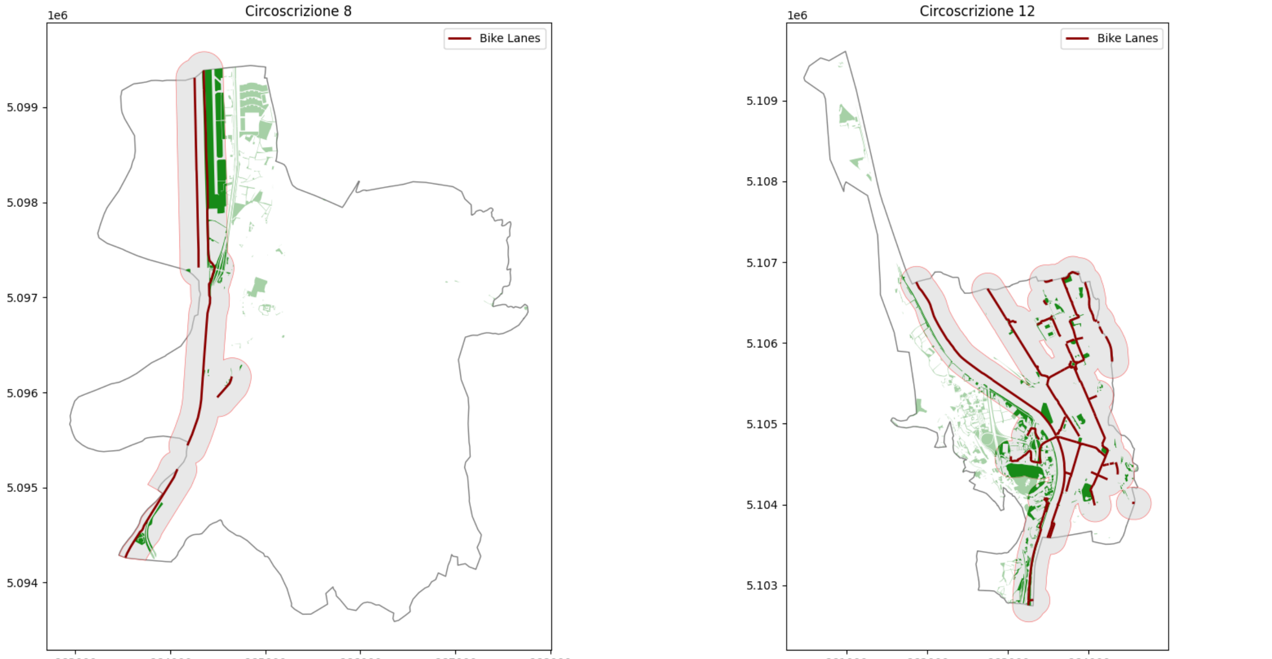
This metric quantifies bike parking availability, since providing secure and accessible bike parking is an essential factor for promoting cycling. First, I calculated the total number of bike parking spots in each disctrict by summing the counts from the `bike_parking` and `racks` datasets. To account for variations in district size, I then computed the **bike parking density** as the number of parking spots per square kilometer.

3.1.3 Natural Area Proportion and POI Density

Another important factor contributing to the comfort and practicality of biking is the presence of green spaces and points of interest along cycling routes. To assess this, I created a **200-meter buffer** around all bike lanes and analyzed the areas within this zone.

For natural areas, I calculated the ratio of parks and green spaces relative to the total area covered by the buffers. For each district, I first merged the buffers of all bike lanes using a union operation, then clipped the merged buffers to the overall boundaries of the city of Trento—excluding any parts that fall outside. Next, I computed the intersection between these clipped buffers and the union of all natural areas, and divided the resulting area by the total area of the merged buffer. This calculation yields a **natural area proportion** for each district, that indicates how much of the bike lane network is enhanced by nearby green spaces (Figure 9 and Figure 10a).

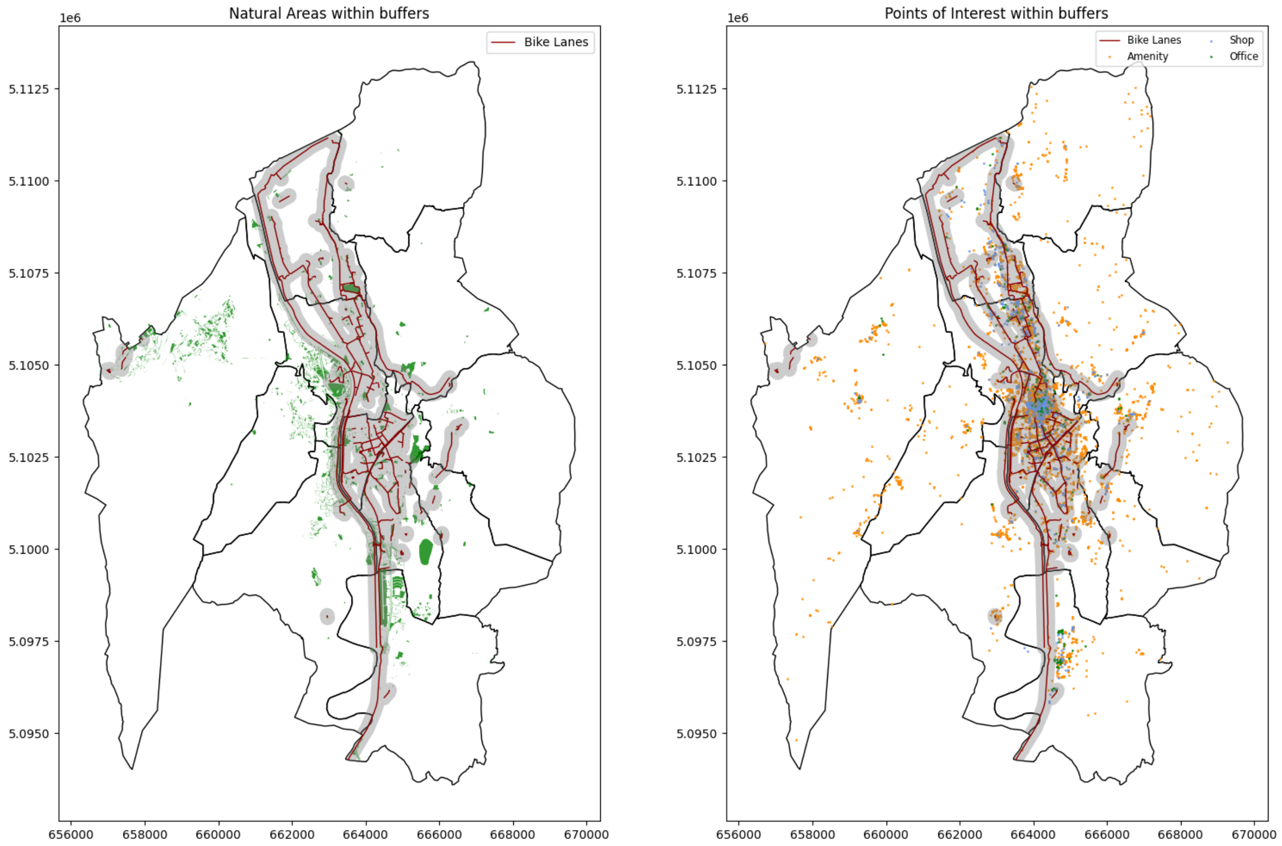
Similarly, for points of interest I performed a spatial join between the dataset of amenities, shops, and offices and the bike lane buffers to count the number of POIs within each district's buffer. I then normalized these counts per square kilometer, obtaining a **POI density** metric that reflects the concentration of accessible destinations along cycling routes (Figure 10b). Higher POI density values indicate that cyclists have more services and destinations within easy reach.



(a) District 8: Mattarello

(b) District 12: Centro Storico - Piedicastello

Figure 9: Bike lanes in (a) District 8 and (b) District 12 are shown in red, along with their surrounding 200-meter buffers in gray. Within these buffers, natural areas are highlighted in green, while natural areas outside the buffers are in light green. Note that the buffers may extend beyond district boundaries, except where they coincide with the city's outer limits (as seen in the lower section of bike lanes in District 8).



(a) Natural areas within 200-meter bike lane buffers.

(b) POIs within 200-meter bike lane buffers.

Figure 10: Overlay of bike lane buffers with (a) natural areas and (b) points of interest in Trento.

3.1.4 Bike Lane Steepness

The last factor in determining bikeability is the steepness of bike lanes, as higher slopes can make cycling more strenuous. To assess this, I calculated the **average slope percentage** of bike lanes in each district using elevation data from contour lines (Figure 11).
The method involves sampling elevation points along each bike lane at regular intervals (every 30 meters). By spatially joining these points with the contour dataset, I extracted the elevation values along each lane. I then computed the maximum elevation change—specifically, the difference between the highest and lowest elevation values recorded along the bike lane. The slope percentage is determined by dividing the elevation difference by the total horizontal length of the lane and multiplying by 100:

$$\text{slope} = \frac{\text{elevation difference}}{\text{lane length}} \times 100$$

Finally, I aggregated slope values by district, computing mean, median, minimum, maximum, and standard deviation (Figure 12).

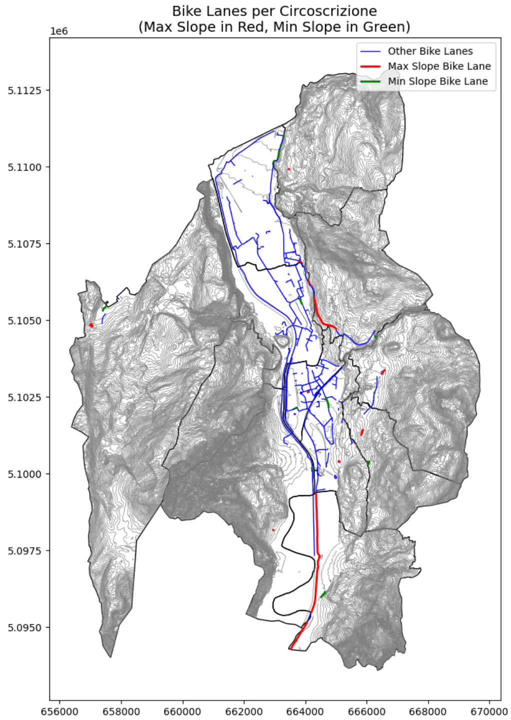


Figure 11: Bike lanes (blue) overlaid on contour lines. In each district, the steepest bike lane segment is highlighted in red, while the least steep is shown in green.

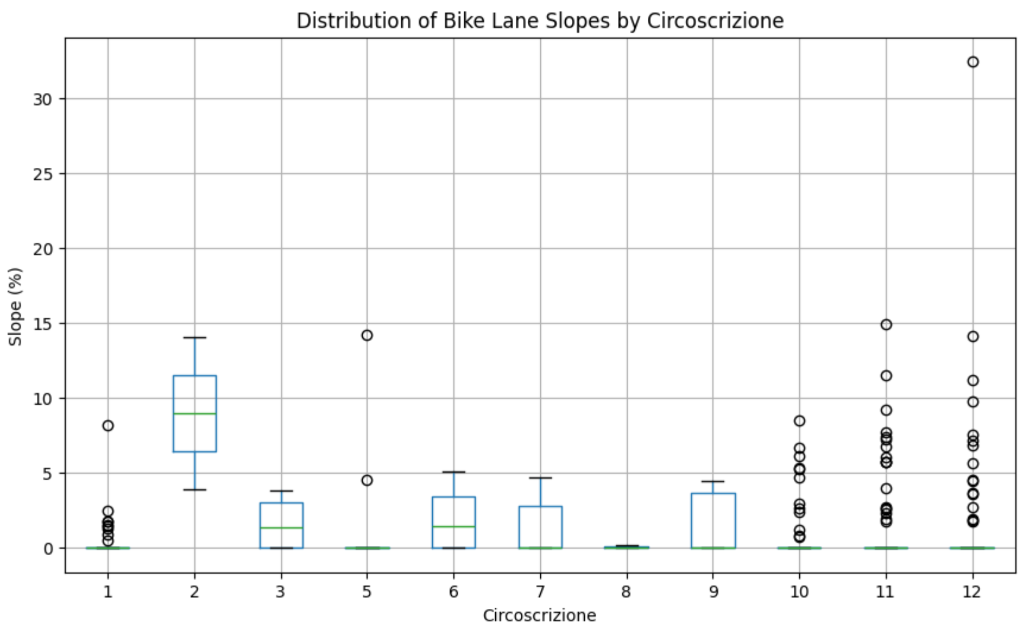


Figure 12: Boxplots displaying the distribution of bike lane slopes across districts in Trento. For all districts except district 2 (Meano), the median slope is well below 5%—often near 0%, as expected since most bike lanes are in flat areas. Only district 12 (Centro storico - Piedicastello) shows an outlier with a slope exceeding 30%, which could be due to an anomaly in the data.

3.1.5 Bikability Index

As the final step, the six bikeability indicators were normalized using a min-max scaling approach to ensure all values fall within the range [0,1]. Since lower slopes are more favorable for cycling, the normalized slope values were inverted by subtracting them from 1, transforming the measure from ”steepness” to ”flatness”. Therefore, districts with gentler slopes receive higher scores and higher values consistently indicate better cycling conditions across all indicators.
Figure 13 presents a radar chart for each district, visualizing its relative performance across the six indicators.

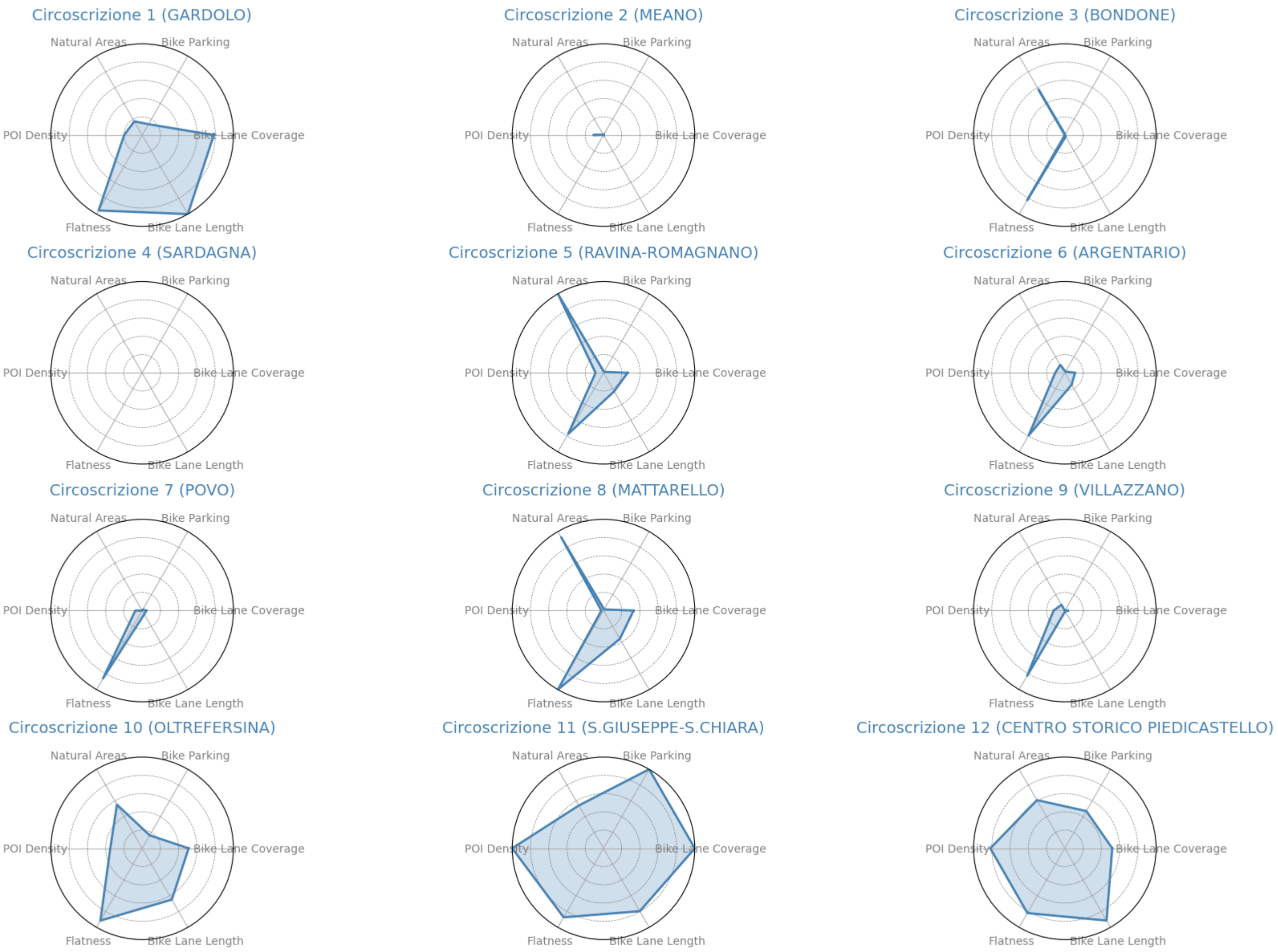


Figure 13: Radar charts displaying the six bikeability indicators for each district. District 11 (S. Giuseppe-S. Chiara) achieves the highest overall bikeability score, ranking first in three out of six indicators. Its only relative weakness is in the proportion of natural areas. Districts 12 (Centro Storico - Piedicastello), 1 (Gardolo) and 10 (Oltrefersina) also perform well, though to a lesser extent. District 4 (Sardagna) receives a score of zero across all indicators, as it lacks bike lanes and is therefore not classifiable.

The bikeability index is then computed as the average of the six normalized indicators, each given equal weight. Figure 14 presents a choropleth map of the index, where green indicates high bikeability and red represents low bikeability. The most bike-friendly district is District 11 (S. Giuseppe-S. Chiara), a relatively small area situated between the historical city center and the Fersina River. It features a high concentration of points of interest and of bike parking spots, along with excellent bike lane coverage; however, there is room for improvement in the availability of natural areas.

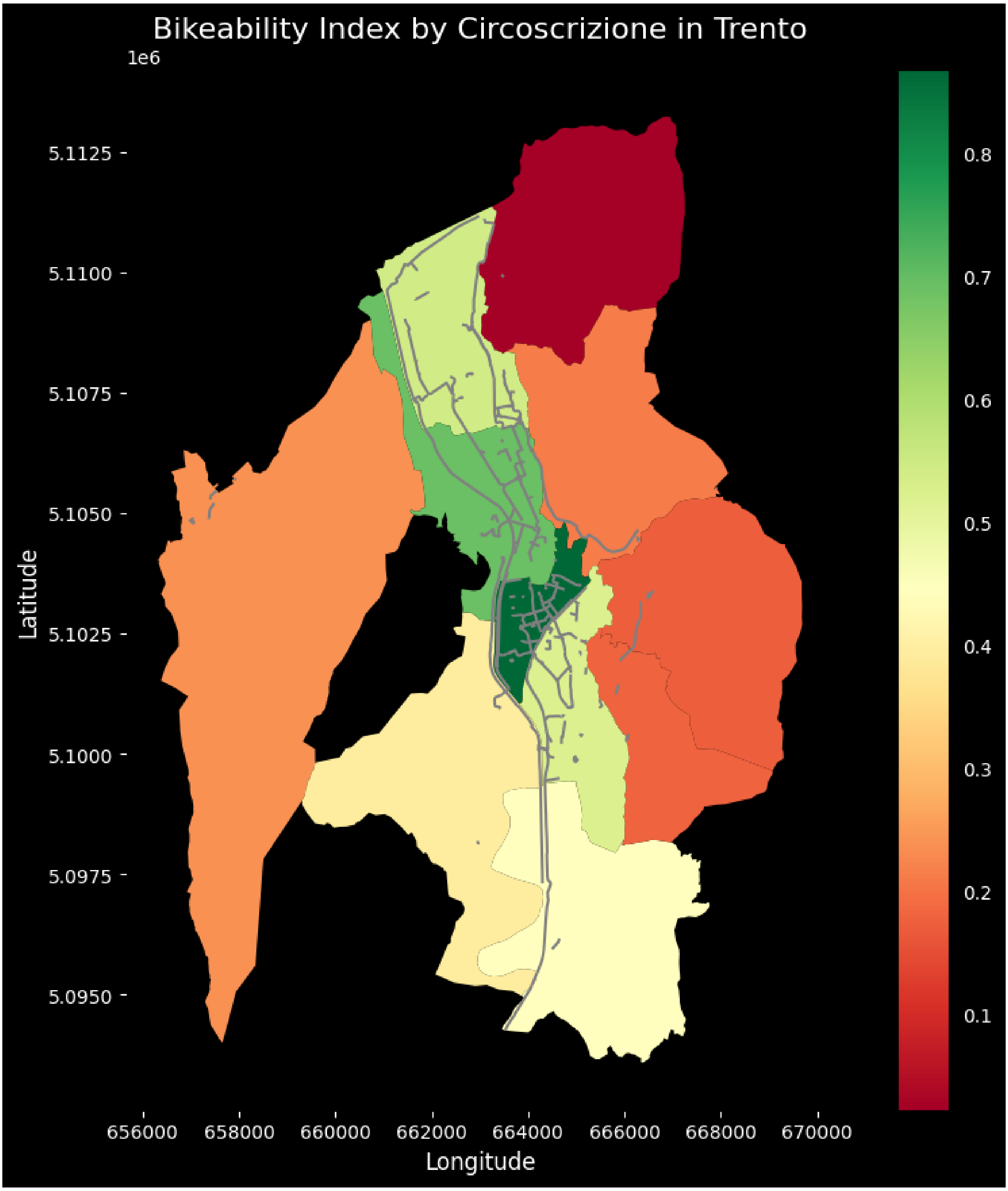


Figure 14: Bikability index for each district in Trento. As already mentioned, District 4 (Sardagna) is excluded from the analysis, as it has no bike lanes, making it impossible to calculate the index (or alternatively, it would be zero).

3.2 Walkability

To assess urban walkability, I adopted an approach inspired by Eemil Haapanen's study on Warsaw[3]. Using Trento's pedestrian network extracted from OSM, I first analyzed intersection density, based on the assumption that a dense urban fabric corresponds to higher walkability. Next, I conducted a city-wide routing analysis to evaluate pedestrian access to various urban amenities in Trento. Before proceeding with these analyses, however, I had to refine the pedestrian network by filtering out hiking trails and retaining only urban infrastructure, as detailed in the following section.

3.2.1 Elevation-Based Filtering of the Pedestrian Network

When extracting Trento's pedestrian network from OpenStreetMap, I selected pedestrian-accessible paths such as sidewalks, footpaths, and pedestrian streets. However, the obtained `walkways` dataset also includes mountain trails, which I aimed to exclude to focus on urban walkability. To estimate pathway elevations, I interpolated the geometry of each pedestrian edge and assigned an elevation value to its midpoint: I used a nearest-neighbor approach with a k-d tree built with `cKDTree` to retrieve the closest elevation value from the contour line data. The analysis (Figure 15) revealed that while most pedestrian pathways are located in urban areas (starting from 180 meters of altitude), some reach elevations up to 2170 meters (corresponding to the contour line near Monte Bondone's peak). Therefore, I filtered out all pathways above 600 meters: this threshold corresponds to Sardagna, the highest densely populated area in Trento, beyond which pedestrian infrastructure is sparse and primarily consists of hiking trails. After filtering, I reconstructed a new pedestrian network as a directed graph with preserved topology, which provides a refined representation of Trento's walkable infrastructure excluding high-altitude trails that do not contribute to urban walkability assessments (Figure 16).

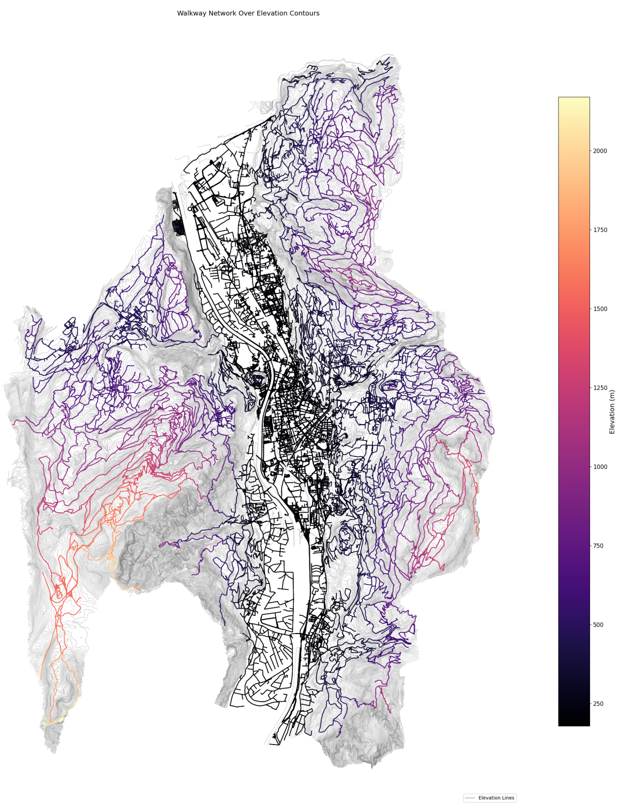


Figure 15: Trento's pedestrian network overlaid on contour lines. Edge colors indicate elevation, ranging from 180 meters (black) to 2170 meters (lighter shades).

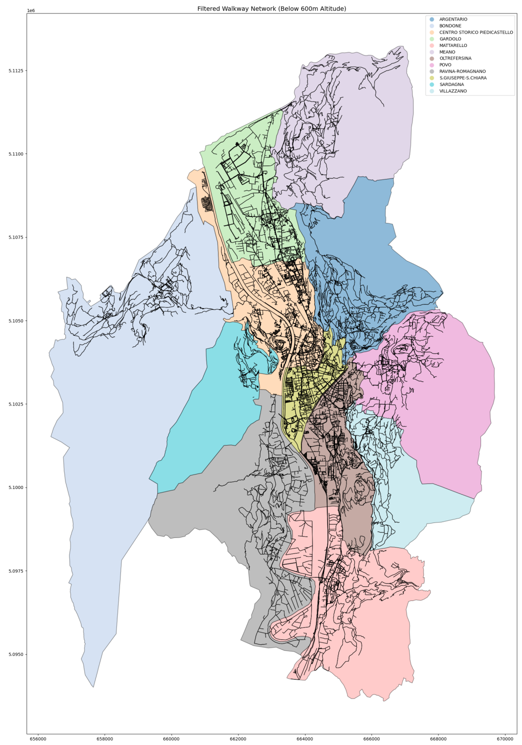


Figure 16: Trento's pedestrian network, filtered to retain only pathways below 600 meters in elevation, excluding hiking trails. The network is overlaid on Trento's districts, represented in different colors.

3.2.2 Intersection Density

Starting from the filtered pedestrian network, I simplified it by merging all nodes within a five-meter radius into single intersection points and excluding dead ends. This process prevents real-world intersections from being split into multiple nodes when two paths merge at slightly different points in the graph. (Figure 17).

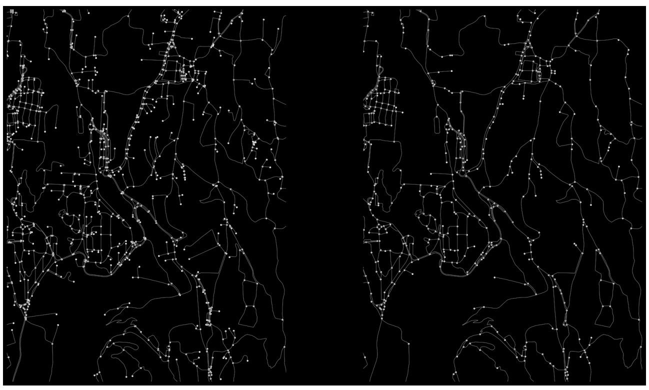


Figure 17: Comparison of the original (left) and simplified (right) pedestrian network. The simplification process merges nearby nodes into single intersections and removes dead ends, ensuring a more accurate representation of pedestrian connectivity.

Finally, I analyzed the spatial distribution of intersection density in Trento's pedestrian network using two different visualization techniques. First, I divided the area into hexagonal bins through Matplotlib's hexbin function, assigning each bin a color based on the number of intersections it contains (Figure 18). Next, I experimented with Seaborn's kernel density estimation

(KDE) plot, which highlights clusters of high intersection density offering a smoother, continuous representation (Figure 19).
Both visualizations immediately reveal that District 12 (Centro Storico - Piedicastello) has the highest intersection density in correspondence with the historical city center. Other districts with a dense pedestrian network include S. Giuseppe-S. Chiara (District 11), Oltrefersina (District 10), and Gardolo (District 1). Most of the remaining districts exhibit good intersection density in populated areas such as Sardagna (in District 4), Ravina (in District 5), Cadine (in District 3), Mattarello (in District 8), Meano (in District 2), Povo (in District 7), and Cognola (in District 6).

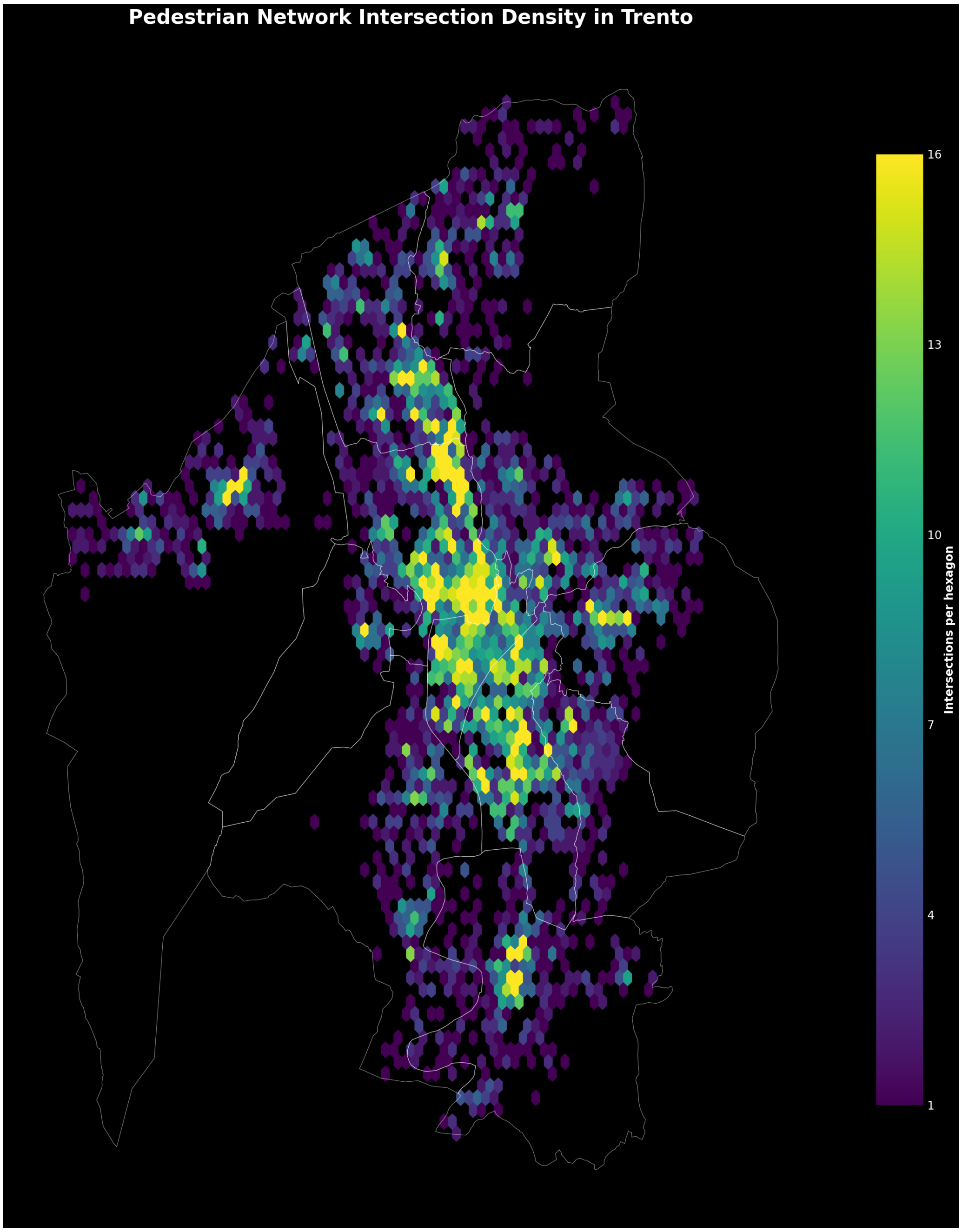


Figure 18: Hexagonal binning of intersection density in Trento's pedestrian network. The color scale represents the number of intersections per hexagon (from a minimum of 1 to a maximum of 16).

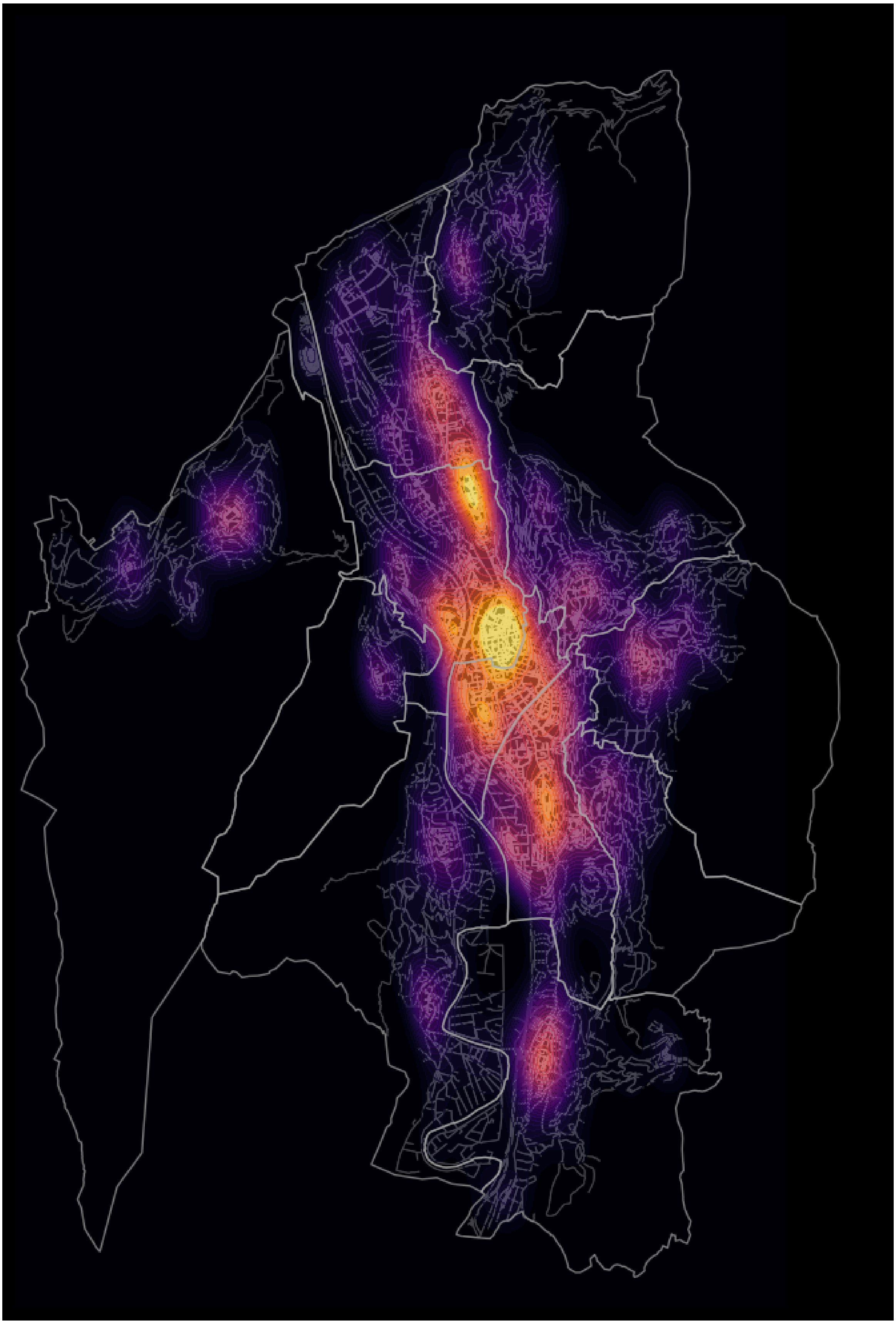


Figure 19: KDE plot of pedestrian intersections in Trento. Brighter areas indicate higher intersection density, overlaid on the pathway network and district boundaries.

3.2.3 Access to Sociable Places

While intersection density provides one measure of walkability, it can be complemented by analyzing pedestrian access to sociable places, such as cafés, restaurants, and shops. To achieve this, I extracted the relevant points of interest from OpenStreetMap; then, I prepared the street network for routing and calculated travel times from each network node to its 10 nearest POIs, considering only those reachable within a 15-minute walk. For simplicity, I assumed a uniform walking speed of 4.5 km/h for all edges. The results highlight spatial variations in accessibility across Trento (Figure 20).

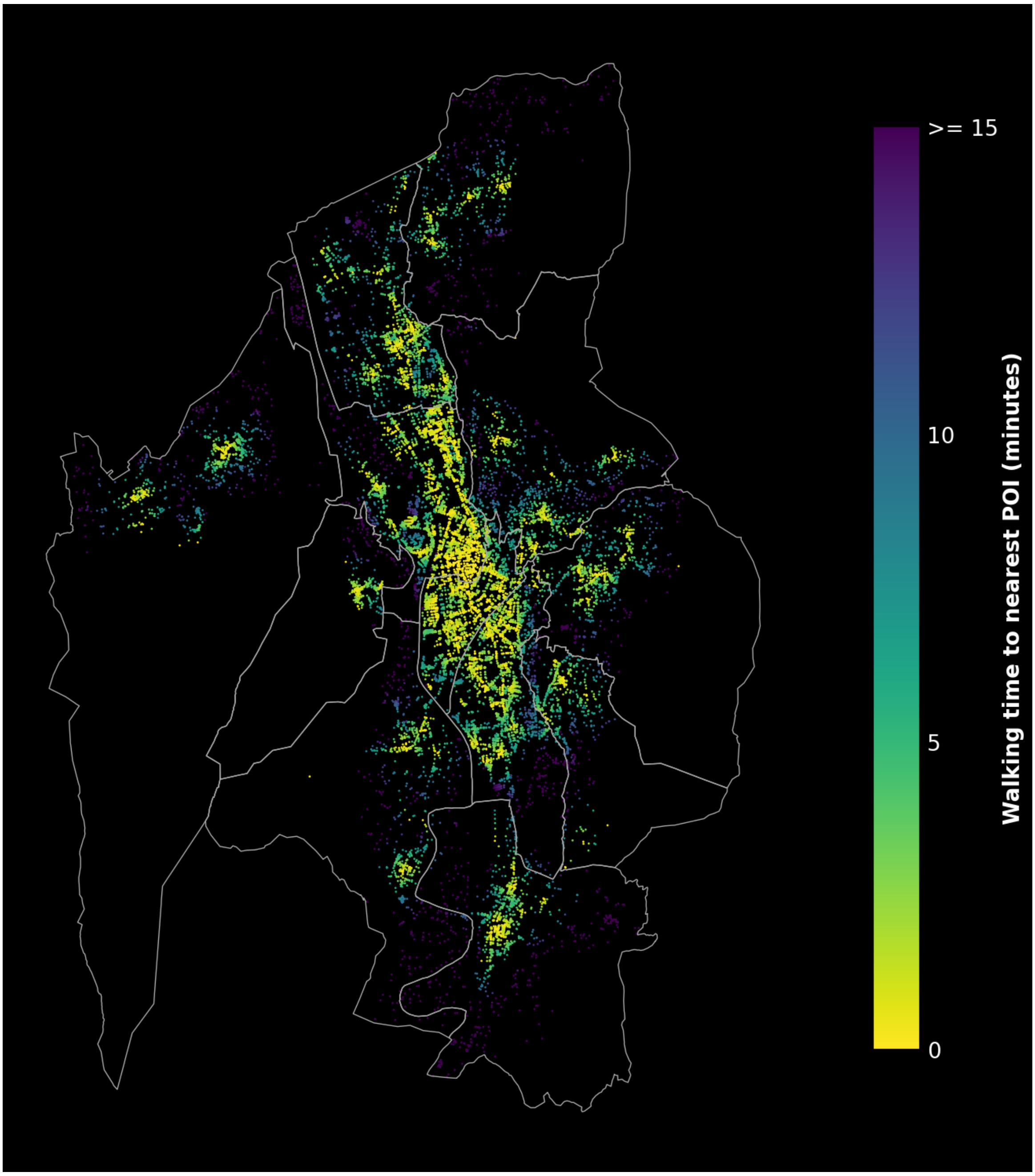


Figure 20: Walking time to the nearest POI. For each district, the color gradient distinguishes areas with high accessibility from those where amenities require a longer walk.

As a final step, I analyzed areas with high concentrations of amenities by comparing walking times to the 1st, 5th, and 10th nearest points of interest. This approach distinguishes between areas with a single nearby amenity and those surrounded by many: if a location ranks highly for the nearest POI but much lower for the 10th, it must be relatively isolated from a broader set of amenities; conversely, if its rank remains high across all measures, it indicates a dense and well-connected amenity network. To provide a clearer overview, I used Matplotlib's hexbin plots, averaging travel times within each hexagonal bin. The results, shown in Figure 21, reveal that while short walking times to the nearest POI are present in various areas across all districts, only Districts 12 and 11 exhibit low travel times to the 10th nearest POI: in District 12, these short travel times are concentrated within a single zone corresponding to the historical city center, whereas in District 11 they are more dispersed, covering almost its entire surface.

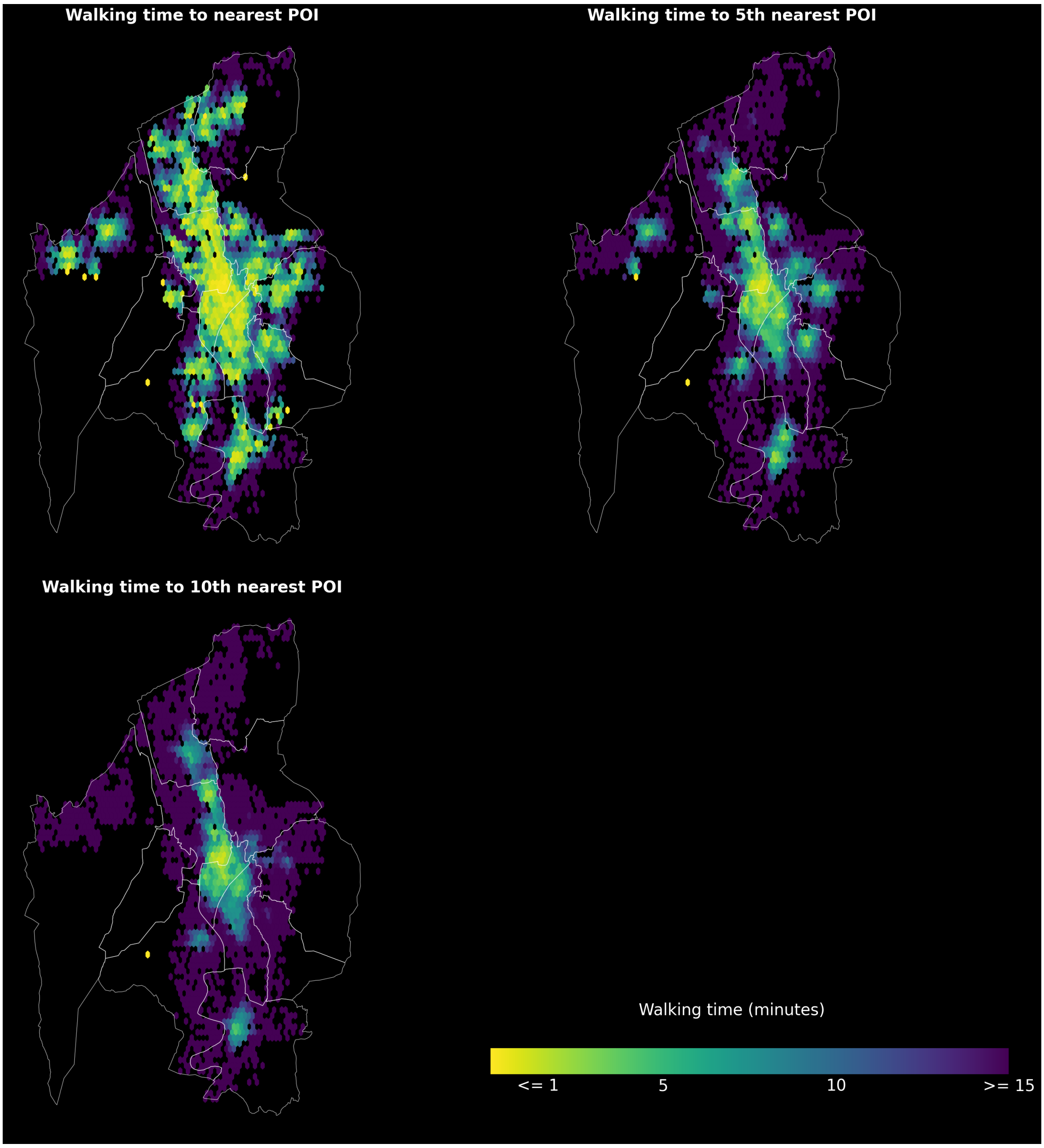


Figure 21: Comparison of walking times to the 1st, 5th, and 10th nearest POI, highlighting areas with high concentrations of amenities.

4 Conclusions

Both the bikeability and walkability analyses converge on the conclusion that the most bike- and pedestrian-friendly districts in Trento are Centro Storico - Piedicastello (District 12) and San Giuseppe - Santa Chiara (District 11). District 12 benefits from the highest intersection density, particularly in the historical city center, where short walking travel times to sociable places are concentrated. District 11, on the other hand, maintains a consistently high pathway intersection density across almost its entire surface; additionally, it features a high concentration of points of interest and bike parking spots, along with excellent bike lane coverage. Overall, the charts, visualizations, and proposed indicators provide insights for all twelve districts in Trento, highlighting their strengths and weaknesses in relation to active mobility.

Naturally, the analysis has limitations. Data extracted from OpenStreetMap, for example, may contain inaccuracies or gaps, as OSM tags are not always standardized, and individual mappers may use uncommon attributes. Additionally, the bikeability index could be further refined by incorporating additional indicators—such as speed limits and motor vehicle frequency near bike lanes—while the walkability analysis could benefit from considering different types of urban features based on the specific needs of various demographic groups: for instance, by identifying areas that are more or less walkable for seniors, families with children, or individuals with mobility impairments.

Despite the limitations, I believe that this study represents a valuable first step in assessing walkability and bikeability in Trento. The findings already point to key areas for improvement, such as targeted infrastructure investments to expand bike lanes in underserved areas and increase bike parking availability. Future research could refine these analyses by integrating real-world pedestrian and cycling flow data, further supporting efforts to enhance active mobility and make Trento an even more vibrant and sustainable city for all.

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