THE USE OF OPENSTREETMAP AND GIS SOFTWARE TO IDENTIFY MASONRY BRIDGE IN A SPECIFIC REGION AND TO BUILD A DATABASE TO PRESERVING HISTORICAL STRUCTURES

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ABSTRACT

This research investigates the efficacy of OpenStreetMap (OSM) and Geographic Information Systems (GIS) for rapidly identifying and cataloging masonry bridges in specific regions integrating modern technology with historical data to enhance the mapping and preservation of these critical structures. The methodology developed is based on the use of OSM, Google Street View (GSV), and the Overpass API. It includes data extraction, processing, and validation through intrinsic and extrinsic quality measures, highlighting the robustness of masonry bridges, particularly in historical areas where traditional construction techniques prevail. The experimentation was carried out on an area of 1.225 km^2 in the province of Pescara (Italy). The results showed an accuracy rate of 74.35% in identifying bridge types from street-level images, despite the crowd-sourced nature of the data demonstrating the potential of combining open-access geospatial data with modern verification tools to support infrastructure mapping and preservation efforts, providing a comprehensive and cost-effective approach, especially in regions with deficient geospatial data.

Key-words: *OpenStreetMap, GIS, Masonry Bridges, Google Street View, Quality Assessment.*

1. INTRODUCTION

OpenStreetMap (OSM) is a user-generated platform that provides a detailed and editable map of the world, created and maintained by a community of volunteers and enthusiasts. The platform's extensive database includes a variety of geospatial data points such as roads, buildings, natural features, and critical infrastructure elements like bridges (Grinberger, 2022). The collaborative nature of OSM ensures that the data is continuously updated, making it a dynamic and valuable resource for researchers, urban planners, and policymakers. Given the resource-intensive nature and data volume of High-Definition Maps, recent research has turned towards OSM-based navigation methods. OSM offers a publicly accessible map that is easier to access and modify, requiring less storage while encompassing crucial road semantic information essential for global path planning. However, OSM suffers from lower geometric accuracy compared to proprietary maps. Haklay et al. (2010) noted an average 6-meter discrepancy between Ordnance Survey (OS) data and corresponding OSM locations across various London regions. While navigation methods based on OSM reduce map construction costs (Naik, 2019), the accuracy of Global Navigation Satellite System (GNSS) coordinates within OSM can be insufficient for precise navigation, posing risks. To mitigate this, researchers advocate for multi-sensor fusion to enhance accuracy in positioning, mapping, and environmental data acquisition. Zaman et al. (2013) proposed an outdoor navigation approach leveraging OSM, which integrated GNSS, IMU, and wheel encoder data to improve robot positioning relative to the map. However, this method primarily addresses robot positioning errors without fully addressing the accuracy limitations of OSM itself.

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Technical Geography is an emerging field within Geography that focuses on the integration of statistical methods and modern technologies. It plays a crucial role in supporting geo-information management and decision-making systems. With ongoing research and the growing number of applications in this field, it is expected that all branches of Geography will eventually adopt technical approaches and continue to evolve in this direction (Haidu, 2016).

Spatial data quality is a well-explored domain, governed by international standards that encompass various elements such as completeness, commission/omission errors, logical consistency, and spatial, temporal, and thematic accuracy. Over the past two decades, the concept of 'fitness-for-use' has emerged as a crucial yet subjective parameter of data quality, essential for numerous applications (Veregin, 1999). Evaluating the quality of OSM data remains a vibrant area of research for two primary reasons. Firstly, the volume of contributions to OSM is continually growing, with some European cities now extensively mapped. Secondly, the lack of standardized data production methods given that anyone can contribute necessitates evaluating how well Volunteered Geographic Information (VGI) reflects reality. Despite the presence of international standards such as ISO 19113 and ISO 19157, researchers generally employ two main strategies to assess OSM data quality: intrinsic and extrinsic measures (Barron et al., 2014). Intrinsic measures do not depend on a reference dataset; instead, they assess quality based on the development of a geographical object. This method is often favored due to the high costs or restrictive licenses associated with reference datasets. Researchers examine the data and its historical records to estimate quality. For instance, Haklay et al. (2010) validated 'Linus' Law' in the context of spatial accuracy, suggesting that spatial accuracy improves with the number of volunteers mapping an object or region. Another study used the ratio of buildings with a house number or name to the total number of buildings as a proxy for attribute completeness. However, as Barron et al. (2014) noted, absolute quality assessments require a high-quality reference dataset for comparison. Extrinsic measures assume the availability of reference datasets. Extensive research has compared OSM datasets with authoritative datasets, typically generated by legal entities and presumed to have superior quality. Recent studies advocate for combining intrinsic and extrinsic measures to mitigate the limitations inherent in each approach (Touya et al., 2017). Nicoară and Haidu (2011) conducted a study aimed at modeling the shortest path and closest facility problems for ambulances navigating a road network. They developed a system based on GIS technology, applying it to the city of Cluj-Napoca, Romania.

Bridges are pivotal components of transportation networks, enabling the passage over obstacles such as rivers, valleys, and other roadways. Their strategic importance in connecting regions, facilitating trade, and supporting emergency response efforts underscores the necessity of accurate mapping and identification. Traditional methods of mapping bridges often involve extensive field surveys and expensive remote sensing technologies. However, the advent of collaborative mapping platforms like OSM presents an innovative and cost-effective alternative.

OSM has become a vital resource in various fields due to its collaborative nature and open-access policy. Numerous studies have evaluated its data quality, application potential, and the dynamics of its contributor community. Borkowska et al. (2022) conducted an assessment of OSM as a geospatial open data source for monitoring Sustainable Development Goals (SDG) indicators, comparing it with national official data from a 1:10,000 scale topographic objects database. Salvucci and Salvati (2022) directed a study on Official Statistics, Building Censuses, and OSM Completeness in Italy providing a streamlined framework for assessing the coverage and completeness of settlement maps derived from the OSM database on a national scale, with potential applications in official statistics. Benjamin et al. (2021) explored the utilization of OSM collaborative maps over the past decade to support humanitarian efforts globally and address critical data deficiencies necessary for implementing major development frameworks such as the Sustainable Development Goals. Cerri et al. (2021) explored using OSM to build data for flood vulnerability modeling; in this latter case study the authors found that models outperformed simple stage-damage functions but often struggled outside their development areas. Klinkhardt et al. (2021) introduced a methodology for extracting points of interest (POIs) data from OSM for use in travel demand models. Jing et al. (2022) highlight OSM's utility in outdoor navigation due to its public availability and detailed road information. Xiang et al. (2024)

explored the sustainability of OSM by tracking individual editing behaviors from 2005 to 2021; this latter research investigated whether OSM can reliably provide its services in the long term, proposing an "inner cycle of career stages" to monitor sustainable status and applying critical mass theory to identify sustaining factors.

The proposed research focuses on assessing the quality of bridge attributes, comprehensively capturing their integrity and enabling an understanding of their fitness for accuracy purposes. This assessment follows frameworks and definitions established in the GIS science literature. Accuracy evaluates whether the value of an attribute is correct. Our approach to assessing accuracy involves using an external data source and concentrates on a subset of bridges, as it is not feasible to scale this method to the entire dataset. Additionally, the paper aims to develop an easily applicable method to analyze masonry bridges from OSM. The research provides a straightforward and efficient approach for identifying and evaluating masonry bridges, facilitating better data accuracy and usability for researchers and practitioners working with OSM data.

2. DATA AND METHOD

2.1. Study Area

Masonry arch bridges are part of Italy's infrastructure heritage and are often held up as examples for their consistency and resistance to the inexorable passage of time. This type of infrastructure also needs maintenance and checking even non-structural aspects can make a difference (Pepe et al., 2024). The study area covers the province of Pescara and is located in the Abruzzo region (Italy) and covers an area of about 1.225 km^2.

2.2. Method

This section will detail a generic step-by-step process that can be applied to various contexts. The method can be summarized in the following main steps: i) Data Collection, ii) Data Processing, iii) Data Validation, iv) Data Analysis, and v) Data Correction and Documentation.

The first step in this methodology is **Data Collection**, where the goal is to gather relevant geospatial data from a variety of sources. To begin, it is crucial to identify appropriate data sources. OpenStreetMap (OSM) serves as a primary resource due to its extensive, community-contributed geospatial data. Additional sources such as GSV or Overpass API can be leveraged for supplementary information. Tools like Geofabrik are particularly useful for obtaining region-specific OSM data extracts, while Overpass Turbo provides a powerful web-based interface for querying OSM data.
Once the data sources have been identified, the next task is to extract the relevant data. This involves downloading region-specific datasets, and ensuring that the correct geographic area and data layers (such as roads or bridges) are included. Overpass Turbo queries are then crafted to extract specific features of interest, like bridges or masonry structures, using appropriate tags such as highway=bridge or building=masonry. After extraction, the data must be prepared for analysis. This involves converting the data into compatible formats (e.g., GeoJSON or Shapefile) for use in Geographic Information System (GIS) software (Alcaras et al., 2023; Alfio et al., 2024), followed by a cleaning process to remove irrelevant features and focus on the study area.

The **Data Processing** phase involves isolating the relevant features from the collected data to facilitate detailed analysis. The first part of this step is data querying, where precise Overpass Turbo queries are employed to filter out the desired geospatial features from the dataset. These queries are designed to target specific characteristics, such as materials or structural types relevant to the study. Once the queries are executed, the resulting data is exported in formats suitable for further analysis.
In some cases, it may be necessary to enrich the dataset with additional attributes or by integrating data from other sources. This enrichment process can involve manually adding new attributes—such as the height, age, or structural type of a feature—or merging the dataset with other authoritative data sources.

Following data processing, the next step is **Data Validation**. This is a critical phase where the accuracy of the processed data is verified by cross-referencing it with authoritative sources. The first task is to identify and obtain these authoritative datasets, which may include government maps, official registries, or other reliable sources relevant to the study area. Using GIS software, the processed OSM data is overlaid with these authoritative datasets, and discrepancies in location, attributes, or completeness are meticulously checked. Field verification enhances data accuracy by involving site visits to physically check selected features, such as bridge materials or structures. Tools like GNSS devices or mobile mapping apps (e.g., OSMTracker) are used to collect field data, which is then compared with the dataset. Any discrepancies are corrected using GIS software or OSM editing tools like JOSM. If major errors are found, the data may need to be reprocessed to ensure reliability.

Once the data has been validated, the **Data Analysis** phase begins, where the dataset is thoroughly examined to draw meaningful insights. This process often starts with spatial analysis, which involves using GIS tools to perform operations like spatial joins, overlays, and proximity analyses. These techniques help reveal relationships between different features, such as the proximity of bridges to roads or rivers. Additionally, hotspot analysis can be employed to identify patterns or clusters within the data, such as areas with a high concentration of specific types of bridges.

The final step is **Data Correction and Documentation**. This step involves addressing any remaining discrepancies and making necessary adjustments to ensure accurate data representation. For OSM projects, corrections can be uploaded to improve community data quality. Documentation is crucial for transparency, requiring a detailed report on the methodology, tools used, challenges, and analysis results. This documentation, including maps and recommendations, should be shared with stakeholders or the public through publications, websites, or presentations, ensuring accessibility and usability for others. The methodology can be summarized as **(Fig.1)**:

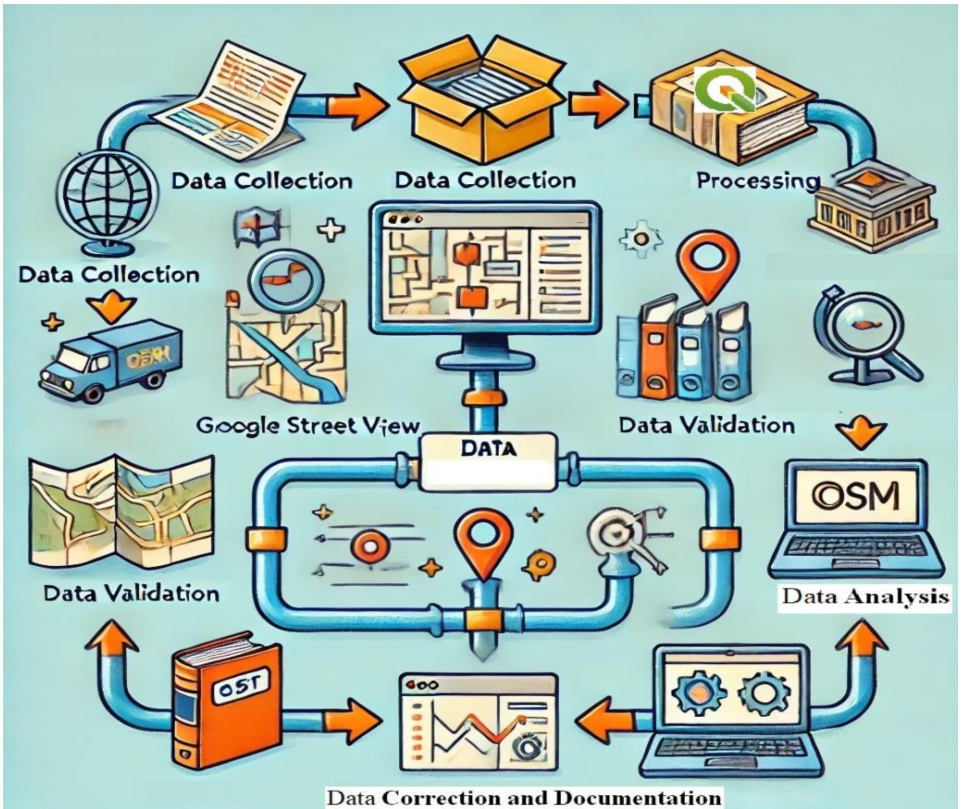

Fig. 1. Details of the Methodology Flow chart.

• Data Collection: Represent sources such as OpenStreetMap (OSM), Google Street View (GSV), and the Overpass API.

• Data Processing: Show the conversion of extracted data into formats for GIS software.

• Data Validation: Indicate cross-referencing with authoritative datasets.

• Data Analysis: Highlight GIS tools used for spatial joins and hotspot analysis.

• Data Correction and Documentation: Demonstrate uploading corrections to OSM and generating reports.

To evaluate the accuracy of the bridge classification method, the F1 Score was incorporated as a key metric. The F1 Score is a comprehensive measure that balances precision and recall, offering a nuanced understanding of the model's performance, particularly when handling imbalanced datasets. Precision quantifies the number of true identifications relative to the total instances identified as positive, while recall measures the number of true positives relative to the actual number of positives in the dataset. The precision (P) and recall (R) are defined as equations 1 and 2 (Alberg et al., 2004, Dewedar et al., 2024):

$$\mathrm{P} = \frac{TP}{(TP + FP)} \tag{1}$$

$$\mathrm{R} = \frac{TP}{(TP + FN)} \tag{2}$$

where *P* is Precision,
TP is True Positives
FP is False Positives,
R is Recall
FN is False Negatives.

The F1 Score (F1) is then calculated as the harmonic mean of precision and recall, using the formula (equation 3):

$$F1 = 2 \cdot \frac{P \times R}{P + R} \tag{3}$$

This metric provides a single value that accounts for both false positives and false negatives, ensuring a balanced evaluation of our model's performance. This is especially relevant in our context, where subjective interpretation and the inherent limitations of crowd-sourced data can lead to misclassifications. Employing the F1 Score in our methodology ensures a balanced evaluation, highlighting the effectiveness of our approach and identifying areas for further refinement. This metric not only validates the reliability of our classification but also guides improvements in integrating advanced imagery and enhancing the accuracy of our infrastructure mapping efforts.

3. CASE STUDY: (Identification of Masonry Bridges)

To download OSM data for a study area, such as Pescara, visit a site like Geofabrik, which provides regional OSM extracts. After downloading the relevant data from Geofabrik's Europe section, you can use the Overpass API to query specific map features, such as bridges. Bridges are categorized under the building tag in OSM. For easier interaction, Overpass Turbo, a web-based tool, can be used to run queries and visualize the results on a map for detailed analysis. To effectively process data with the Overpass API, it's crucial to understand the relevant map features **(Fig. 2)**.

```
/*
This has been generated by the overpass-turbo wizard.
The original search was:
“bridge=* in "Pescara"”
*/
[out:json][timeout:25];
// fetch area “Pescara” to search in
{{geocodeArea:Pescara}}->.searchArea;
// gather results
nwr["bridge"](area.searchArea);
// print results
out geom;
```

Fig. 2. Details of the Overpass Turbo interface displaying the query for bridges in the investigated region.

Start by researching bridge-related tags on the OSM Wiki. These tags help identify and categorize bridges within the OSM data. A good resource for this information is the bridge tag page on the OSM Wiki. This page provides comprehensive details on how bridges are tagged in OSM, including examples and common usage patterns. Overpass Turbo wizard was used to generate a query to extract bridge data. Once pasted the script into the Overpass Turbo interface and then executed, it was possible to obtain data on tagged bridges **(Fig. 3)**.

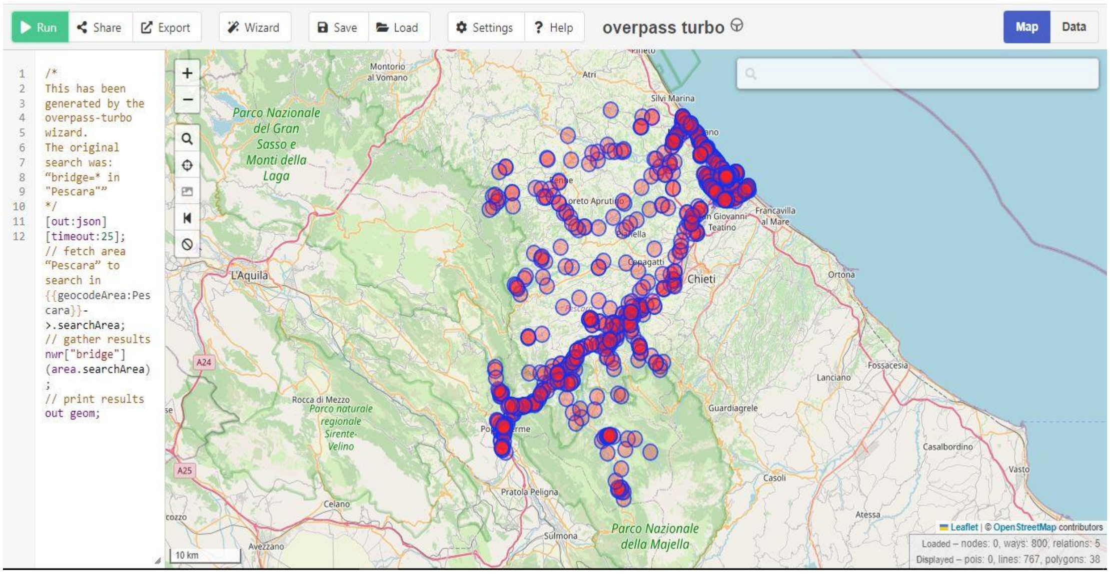

Fig. 3. Locations of bridges in the investigated region (multiple bridge locations marked with red circles outlined in blue).

Once the bridge data for the area under investigation has been exported (e.g. in GeoJSON format), a thorough analysis was performed to ensure the accuracy and completeness of the data. This analysis involved several steps:

a) **Data Loading and Initial Review**: Load the exported bridge data into GIS software (e.g., QGIS, ArcGIS) and review the data structure to ensure all necessary attributes are included. Use spatial queries to isolate bridge data and create a dedicated layer for further analysis.
b) **Data Comparison and Verification**: Obtain official GIS datasets for the Pescara region and perform a spatial join or overlay analysis to compare them with the OSM bridge data. Identify discrepancies and investigate inconsistencies through attribute comparison and satellite imagery integration.

c) **Manual Inspection and Data Correction**: Conduct a manual inspection of bridge locations using satellite imagery and OSM editing tools (e.g., JOSM). Verify the accuracy of bridge data, make necessary corrections, and document the process. Generate reports and maps to summarize the findings and share them with relevant stakeholders.

Begin The process of verifying and enhancing OSM bridge data begins by loading the extracted GeoJSON files into GIS software like QGIS or ArcGIS for visualization and analysis. After reviewing the data structure to ensure the inclusion of key attributes such as bridge type and material, spatial queries and filters are applied to isolate bridge data from other features. Next, official GIS datasets from local authorities are integrated through spatial joins or overlay analyses to compare the OSM bridge data and identify discrepancies. High-resolution satellite imagery is also overlaid for visual verification of bridge locations and attributes. Tools like JOSM are used for detailed inspection and corrections based on the findings. The verification process is meticulously documented, and reports are generated to highlight areas of accuracy and needed improvements. Finally, these findings are shared with the OSM community and local authorities to enhance the overall quality of the bridge data in the study area. Street-level imagery is also employed to manually inspect and verify bridge details, ensuring a high level of data accuracy.

4. RESULTS AND DISCUSSIONS

OSM mapping helps mappers develop a range of vital skills and expand their knowledge in various areas. These include deepening civic engagement, developing social identity, expanding geographic knowledge, enhancing spatial awareness, and increasing happiness and satisfaction. Remarkably, mappers retain most of these skills over the long term, regardless of their academic or professional backgrounds.

However, there remains significant scope for further investigation in this area. Ideally, this should be pursued through a longitudinal study with a larger and more diverse sample, as well as comparisons between different program designs. Such research would help fully understand the wide array of effects OSM mapping has on mappers and explore the potential to enhance positive outcomes through associated youth learning and leadership programs.

To design a balanced global sample, several 267 bridges were selected from OSM, focusing on those with existing attributes. The research aimed to inspect their street-level imagery using GSV. First, it was checked if GSV was available for the location and then determined if the bridge was visible (some might be obstructed by structures or vegetation). If the bridge was visible, a few visually verifiable attributes was inspected.

The analysis revealed that 74.35% of the sampled bridges are located in areas covered by GSV. Among these, a various types of bridge materials were identified: 6 bridges were constructed from steel, 7 from wood, and an impressive 150 from masonry, indicating the prevalence of masonry bridges in our sample. The classification process also identified 5 bridges using other unspecified materials. For bridges in OSM where the material type was available and could be inferred from the street-level imagery, it was achieved an accuracy of 74.35%.

This level of accuracy is noteworthy, particularly considering the crowd-sourced nature of the data on OSM. However, it is essential to acknowledge the inherent subjectivity in evaluating these values. The variability in user contributions and the diverse interpretations of bridge characteristics can impact the consistency and reliability of the data. Standardizing bridge identification and classification on a global scale remains a complex challenge due to these subjective elements. Despite these challenges, the relatively high accuracy of our findings underscores the potential of using crowd-sourced data for large-scale infrastructure analysis, while also highlighting the need for careful validation and standardization efforts to enhance data reliability and utility. Given these nuances and the fact that contributors might struggle with ambiguous cases (which do not significantly affect downstream analyses), the achieved accuracy is considered rather high.

After a thorough analysis of the bridges in Pescara, it was found that OpenStreetMap (OSM) represents bridges as either polygons or lines when opened with GIS software. To refine the results, a filter was applied in the attribute table to only include bridges longer than 50 meters. Initially, 267 bridges were analyzed after applying this filter, though this number was reduced by multiple iterations of filtering based on length. Additionally, many bridges initially represented by multiple lines **(Fig. 4 a)**, were consolidated into a single line. However, several discrepancies were observed, as described below.

- Incorrect Bridge Identifications: Some locations marked as bridges were, upon GSV inspection, identified as buildings **(Fig. 4 b)**. For instance, a building with a tunnel and parking ramp was labelled as a bridge.
- Vegetation and Forests: Numerous bridges were located in areas with dense vegetation or forests, making them invisible in GSV **(Fig. 4 c)**.
- Normal Roads Misidentified as Bridges: OSM occasionally misidentified regular roads as bridges, with no elevation difference discernible at ground level.
- Tunnels Misclassified as Bridges: Several tunnels were inaccurately classified as bridges.
- Footpaths and Small Paths: Footpaths, small pedestrian pathways, and bicycle paths were often erroneously tagged as bridges.

(a) (b) (c)

Fig. 4. Some examples of errors in bridge recognition: Bridge on Google Maps but has 2 lines that were identified twice at OSM (a), Detection of a Bridge Over a Triangular Architectural Structure (b), bridge was located with dense vegetation (c).

Overall, the study highlights the need for meticulous review and verification of bridge data in OSM to ensure accuracy and reliability. The results underscore the complexities and challenges of using crowd-sourced data for precise applications like infrastructure mapping.

The widespread presence of masonry bridges in Italy's historic regions highlights the nation's dedication to preserving its architectural heritage. Many of these bridges are protected as cultural heritage sites, attracting global attention for their historical and aesthetic value. Constructed using local stone and traditional techniques, they reflect a deep connection to regional resources (Crisan et al., 2024). The ongoing maintenance and restoration of these bridges are crucial to ensuring their functionality within modern infrastructure while preserving their historical significance. In this study, five masonry bridges, comprising 2.5% of the 200 sampled, were identified using GSV imagery, showcasing the blend of modern technology with historical preservation efforts.

This F1 Score of approximately 0.666 reflects the model's balanced accuracy in classifying masonry bridges. While this score is relatively high, indicating a good level of precision and recall, it also highlights areas for improvement, particularly in minimizing false positives and false negatives. The integration of advanced imagery and more robust validation techniques could further enhance the accuracy of our classification method, thereby improving the F1 Score and the overall reliability of the data. For instance, of the 200 bridges analyzed, the precision achieved was 0.625, recall 0.714 and F1 Score 0.666.

After setting up the QGIS environment, the OSM Downloader plugin was used to download relevant OSM data for the area of interest. The data, including roads, buildings, natural features, and bridges, was loaded into QGIS. Bridges were filtered using attributes like “bridge=yes” and refined further by isolating masonry bridges with tags such as “bridge = masonry.” A new point or polygon layer was created to represent these masonry bridges, with an attribute table that included fields for ID, Name, Material (Masonry), Condition, Year Built, OSM ID, and Photo. Images of the bridges were linked to the dataset through a Photo field or the built-in attachment feature in QGIS, allowing pop-ups to display detailed information and images.

The masonry bridges were visually symbolized with custom icons or styles, distinguishing them from other bridge types. The completed database was integrated with broader OSM data in QGIS for advanced spatial analysis and map creation. It was then exported to formats like Shapefile or GeoJSON for sharing or further analysis. To make the data accessible, it could be published on a web map using plugins like QGIS2Web. This approach allowed for a visually rich and interactive spatial database, enhancing applications in academic research and heritage management. For instance, a masonry bridge named "Contrada San Clemente" was identified in the spatial database, and its attributes (ID: way/48998350, material: Masonry, structure: One Arc) were linked to a photo for better visualization and context **(Fig. 5)**. The photo of the 'Contrada San Clemente' bridge was linked to the spatial database, allowing its current state to be compared with historical records from the last century, enabling a detailed assessment of structural changes over time and ensuring the data remains up-to-date.

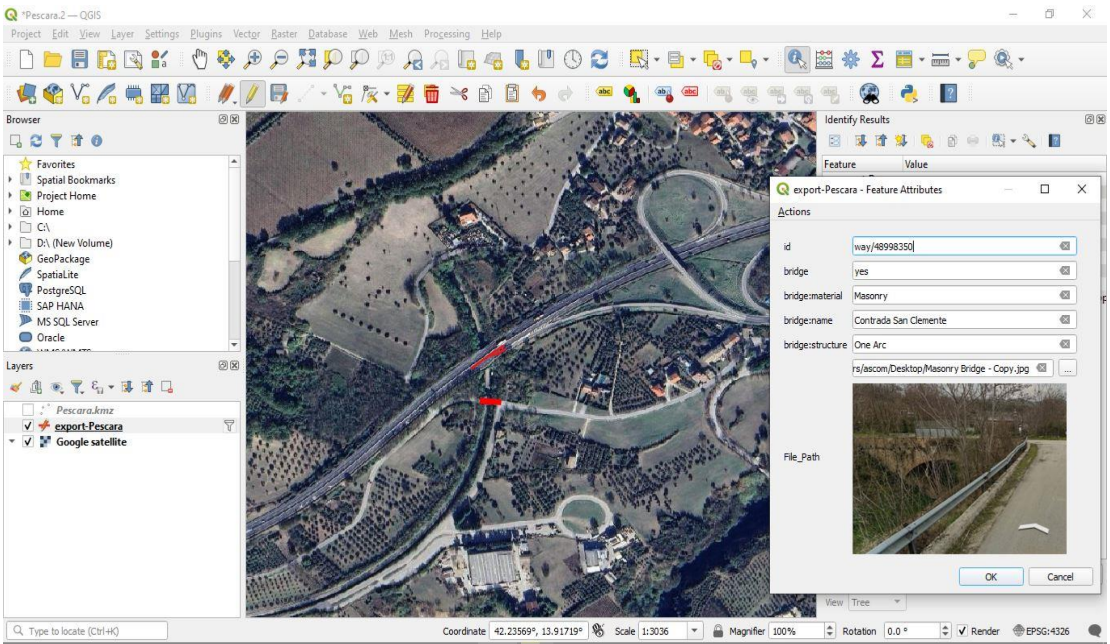

Fig. 5. Integration of Bridge Attributes with Visual Data in QGIS.

5. CONCLUSIONS

This study systematically analyzes the completeness of OpenStreetMap for 267 bridges in the case study. The focus was exclusively on bridges due to their relevance for applications such as urban planning and civil engineering. Data collection and management were carried out using QGIS with a visual comparison approach. Geospatial building information sourced from OSM, including both geometric and descriptive attributes, has gained a foothold in multiple domains across the built environment, thanks to its liberal license, growth in the completeness of the building stock mapped, and increasing awareness of this crowd-sourced platform of geospatial data.

This paper aimed to showcase the viability of using OpenStreetMap for bridge identification. By leveraging OSM's comprehensive and continually updated geospatial data, researchers and planners can obtain accurate bridge information more efficiently than traditional methods. The implications of this research extend beyond bridge identification, offering insights into the broader applications of collaborative mapping platforms in infrastructure management and urban planning. Currently, due to the lack of automated methods for acquiring essential parameters and the need for manual steps in certain aspects of conflation, the bridge identification cannot be considered a fully automated, one-click solution. Instead, this study highlights the importance of active user involvement in reviewing results step-by-step, leveraging the capabilities of both QGIS and JOSM toolsets to achieve optimal outcomes. Users are encouraged to undertake a Tasking Manager validation project after importing the data to ensure accuracy.

The main limitations of the method include its inability to handle multi-level roads such as overpasses, the frequent lack of accurate information on OSM street levels, and the uncertainty regarding the presence of bridges. Future iterations of the plugin could address these limitations by integrating satellite and/or terrestrial imagery. Plans also include extending the plugin's functionality to make it easily integrable as a QGIS processing provider algorithm with additional features such as drawing missing intersections and access points.

Another valuable lesson from this study is that comprehensively measuring the accuracy and correctness of OSM tag values by comparing them to street view imagery of real bridges is impractical and unscalable. However, the large and well-balanced sample of bridges used in this study provides a strong indication of the general accuracy of the data and highlights variations across different regions. Quantifying the accuracy of text-based tag values is also challenging as it is highly subjective and influenced by personal knowledge and opinions.

Scaling spatial data quality assessments and conducting them across multiple countries with diverse architectures and morphologies remains a significant challenge. Nevertheless, this study aims to advance this research area and set the stage for future work. As new buildings and bridges are continuously mapped and existing ones updated with additional information, the findings of this study will remain relevant for several years, as many of the identified advantages, trends, and challenges are likely to persist.

In addition to the findings discussed, the database obtained from OSM can be customized to meet specific research needs. By developing custom queries, relevant features like specific types of masonry bridges can be extracted and additional attributes such as construction materials or historical significance can be included. Integrating external data sources and validating against authoritative datasets can enhance the database's accuracy. This flexibility allows researchers to address unique project requirements and broadens the applicability of OSM data in fields like infrastructure management and cultural heritage preservation.

Finally, this approach is particularly useful in regions where there is a lack of geospatial information, such as the absence of numerical cartographies or thematic maps.

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