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RESEARCH ARTICLE

MethOSM: a methodology for computing composite indicators derived from OpenStreetMap data

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Abstract: The task of computing composite indicators to define and analyze complex social, economic, political, or environmental phenomena has traditionally been the exclusive competence of statistical offices. Nowadays, the availability of increasing volumes of data and the emergence of the open data movement have enabled individuals and businesses affordable access to all kinds of datasets that can be used as valuable input to compute indicators. OpenStreetMap (OSM) is a good example of this. It has been used as a baseline to compute indicators in areas where official data is scarce or difficult to access. Although the extraction and application of OSM data to compute indicators is an attractive proposition, this practice is by no means hassle-free. The use of OSM reveals a number of challenges that are usually addressed with ad-hoc and often overlapping solutions. In this context, this paper proposes *MethOSM*—a systematic methodology for computing indicators derived from OSM data. By applying *MethOSM*, the computation task is divided into four steps, with each step having a clear goal and a set of guidelines to apply. In this way, the methodology contributes to an effective and efficient use of OSM data for the purpose of computing indicators. To demonstrate its use, we apply *MethOSM* to a number of indicators used for real estate valuation of properties in Italy.

Keywords: composite indicators, indices, OpenStreetMap, OSM, methodology, data quality

1 Introduction

Composite indicators (also known as composite indices) are widely used by policy-makers, academics, media, and other interested parties as a tool to define and analyze complex social, economic, political, or environmental phenomena, that cannot be directly measured or easily defined. Composite indicators are formed by individual indicators, each of which quantifies one specific aspect of the phenomenon at study.

Traditionally, national and international statistical offices employ composite indicators for describing, comparing, and ranking various aspects of geographical areas related to sustainable development, progress of society, social welfare, poverty and social inequality, and provision of infrastructure. An overview of existing composite indicators measuring human progress and well-being is provided in [43]. Examples include the Human Development Index (HDI) and Multidimensional Poverty Index (MPI) proposed by United Nations [22], and almost a hundred other composite indicators proposed by individuals and research groups affiliated with international organizations, national governments, NGOs, civil societies, private consultancies, and universities.

Other disciplines use composite indicators for territorial analysis, with recent examples including the following. An overview of indicators and their usage in landscape research to measure landscape structure and processes is presented in [41], together with biodiversity and habitat analysis and evaluation of urban landscape patterns and road networks. The Sensitivity Index of Agricultural Land proposed in [26] is an example of usage of composite indicators to study processes of conversion from agricultural to urban land use. A comparative analysis of composite indicators and methodologies developed to measure the vulnerability, risk, or resilience of communities to disasters is provided in [7]. A terracing intensity index to identify terraced areas of agricultural significance is proposed in [1]. Composite measures of impact of social and ecological characteristics of territories on mosquito distribution are proposed in [16]. The usage of a composite social welfare index for Iran and Spain are presented in [23] and [44], respectively. A composite indicator for scientific and technological research excellence is proposed in [21].

Combining individual indicators into a composite measure that accurately reflects reality requires solid understanding of the phenomenon being measured. Meaningful selection of individual indicators for a composite indicator is a challenging task by itself, and it can be complicated by the absence of sources with relevant, up-to-date, and accurate data required for their computation. Indeed, due to the high costs and complexity associated with collection and procurement of data, official sources may provide outdated, scarce, or overly aggregated data. Moreover, getting access to official data sources can also be complicated due to administrative or legal restrictions.

In the attempt to address the common pitfalls of authoritative data sources, researchers started exploring sources of Volunteered Geographic Information (VGI) [18], free geographic information crowd-sourced through volunteer effort. Among those sources, OpenStreetMap (OSM)[1] has been recognized as "one of the most utilized, analyzed, and cited VGI-platforms, with an increasing popularity over the past few years" [32].

Several scientific disciplines consider OSM as a potential alternative or ancillary source to authoritative data [5] when computing composite indicators. For example, [38] demonstrates the use of OSM data to compute an Urban-Rural Index (URI) that measures urbanization processes. Another example of using OSM data to refine existing techniques in the

[1]https://www.openstreetmap.org

field of urban management and population mapping is presented in [6]. More recently, [27] studied the completeness of sidewalk information in OSM with the purpose of determining its fitness for use for routing and navigation application for people with limited mobility. Such examples indicate that OSM has a great potential to facilitate research in the underlying disciplines. OSM data is up-to-date, free, and has global coverage. In the absence or unavailability of similar data in official sources, OSM data can be an interesting alternative or ancillary source of data. Moreover, the rich semantic annotation and fine-grained spatial resolution of OSM data makes it beneficial for describing complex dynamic phenomena through composite indicators.

Although OSM presents itself as a valuable data source in this context, its user-generated nature means it suffers from data quality issues such as incompleteness, logical inconsistency, positional, temporal, and thematic inaccuracy [10, 12, 14, 19]. A wealth of literature is available where researchers address OSM data quality issues from different perspectives. One area of research is dedicated to assessment of OSM data quality by comparing it with authoritative data, such as data from National Mapping Agencies [4, 13, 19, 25, 42]. Other works not only analyze OSM data quality but also propose methodologies and software tools to enhance it (e.g., OSMatrix [35], OSM-based geocoding engine [2], OSM Inspector[2], KeepRight[3], MapRoulette[4], and MapDust[5]). Yet another area of research investigates the evolution of OSM across the world over time and proposes the use of historical analysis of OSM data editing to build data quality indicators [3,30,31,33].

Existing studies of OSM data quality can help identify and resolve potential issues with data quality when computing indicators from OSM data. However, no work currently exists to devise a systematic approach for extracting OSM data for the purpose of computing indicators, and for identifying common steps to compute OSM-derived indicators, while at the same time addressing issues with the quality of OSM data. Having it all together in the form of a systematic methodology would facilitate the underlying process, making the task of computing OSM-derived indicators more efficient and effective. In this paper, we propose such a methodology—*MethOSM*—for computing OSM-derived indicators and exemplify its applicability in computing indicators.

MethOSM's primary target audience are individuals interested in computing indicators using alternative geospatial data (OSM data in this particular case). Such individuals are typically generic data scientists, not necessarily geospatial data experts, and could benefit from the existence of methodological support in preparing the data for computation of the indicators.

The rest of the paper is organized as follows. Section 2 presents relevant related works. In Section 3 we provide a concrete example for computing OSM-derived indicators that our methodology is aimed to support and discuss various challenges in this context. In Section 4 we present and formalize *MethOSM*—our proposed methodology for computing indicators. We exemplify the use of *MethOSM* in Section 5 where we analyze each indicator in the driving example from Section 3 and show how the methodology applies to each of them. Section 6 discusses the applicability of *MethOSM* for computing a complex indicator for real estate property valuation in Italy as a way to validate *MethOSM* in a real business case. We conclude the paper in Section 7.

[2] Available online at http://tools.geofabrik.de/osmi.
[3] Available online at http://keepright.ipax.at.
[4] Available online at http://maproulette.org.
[5] Available online at http://www.mapdust.com.

2 Related works

As our paper concerns methodological aspects for computing OSM-derived indicators, the literature review covers existing works related to computation of OSM-derived indices. While primarily we consider manuscripts where OSM data is used for territorial analysis, we also review studies of OSM data quality that compute indicators on top of OSM data to identify, measure, and address its quality issues.

OSM-derived indicators for territorial analysis. A methodology to quantify the urbanization process (i.e., population migration from rural to urban areas) is proposed in [38], where OSM data is used to complement remote sensing data. Two sub-indicators are computed, each of which encodes accessibility of urban infrastructure from urban areas in terms of travel times from/to the city centre. These sub-indicators are combined into an Urban-Rural Index (URI) that defines *accessibility of rural areas*. To calculate each sub-indicator, a process from downloading OSM lines to extracting road data to categorizing the roads into three categories that define their average velocity is proposed.

Using OSM data for land use and population mapping is studied in [6]. The hypothesis is that some types of points of interest can be correlated with a higher density of population. Specifically, this work determines points of high population density via places that were tagged on OSM as types potentially correlated with population density, such as schools, supermarkets, churches, and others. These points can be used to complement existing methods for areal interpolation of population estimates at building level.

The above mentioned works are closely related to ours in the sense that they utilize OSM data to compute territorial indicators and touch upon methodological aspects of using OSM data. They emphasize the importance of reproducible quantitative methods in the fields of urban development and human geography. Moreover, they show that OSM data is a crucial ancillary ingredient in such quantitative methods, especially in developing countries, where official sources are outdated and conventional satellite images lack proper resolution and miss important semantic annotations. What makes these works different from ours is that they focus on concrete domains (urban development and human geography, respectively) and the methodological aspects are considered in an ad-hoc manner, while our methodology is meant to be systematic and generalized to different domains. Their methods and the data quality issues they report (such as low data coverage, spatial and thematic inaccuracy of data on points of interest) are specific to urban development and human geography domains. In our methodology we consider a broader scope of OSM data quality issues and propose (and formalize) solution strategies that can potentially be applied to address issues mentioned in such works.

OSM-derived indicators to study OSM data quality issues. There are several works in the literature tackling OSM data quality issues. The majority of works reviewed in [5] identify OSM data quality issues and investigate methods for addressing them. OSM data quality in Portugal is analyzed in [15] by mapping OSM polygon features to the Corine Land Cover reference database. Through this mapping issues related to semantics and data heterogeneity are identified. A methodology to evaluate potential use of OSM data in Brazil as input to official spatial databases is proposed in [11]. This methodology allows for identification of rural and urban areas with incomplete data. A method to extract multi-lane roads from OSM urban road networks is proposed in [24]. This method is specifically tailored to deal with quality issues of VGI, such as duplicated lines that represent roads, tangles, broken roads, and singular angles. An urban network model that connects a private transport system (pedestrian, bicycle, car), a public transport system (rail, metro, tram, and bus), and a land use system is proposed in [17]. To address issues related to OSM data quality and consistency for this urban network model, a complex heuristic to process rich detailed description of street segments (duplicate features, overlapping segments, missing segments, closed segments representing areas, and others) is implemented. The more recent work in [39] reviewed data quality assessment methods in VGI, and touches also upon OSM data quality issues. An ontology of data quality measures is proposed in [28] and is applied using several examples of VGI, including OSM data. Finally, it is worth mentioning the software system described in [29], used to collect and process data about different aspects of OSM.

The above mentioned studies tackle OSM data quality issues to some extent. Some of them just identify the issues, others propose methods to overcome them. The work presented in [17] comes closest to the methodology described in this paper, as it defines specific heuristics to overcome OSM data quality issues. However, that work is different from ours as it describes procedures for a specific problem, building multi-modal urban network models, while our methodology is meant to take a broader perspective, be more generic and applied to different problems. In the next section we discuss in more details data quality challenges within the scope of *MethOSM* and do that also in relation to above mentioned related works.

3 Motivating example: mass transport and green area indicators in Turin

The aim of *MethOSM* is to assist in the computation of indicators derived from geographical data. To describe the proposed methodology, we present a concrete case study that illustrates the challenges of working with a specific source: OpenStreetMap (OSM). In this case study, we apply *MethOSM* to compute values for three indicators for the city of Turin in Italy. The results obtained through the use of *MethOSM* are utilized to produce choropleth visualizations that exemplify how these indicators can be used. The first two indicators are related to mass transportation, scoring areas of the city based on the proximity to public transport features: the number of nearby bus stops and the distance to the closest railway station, respectively. The third indicator is the green area coverage: the percentage of an area that is covered by vegetation.

These indicators are part of a more complex indicator used to objectively estimate the value of real estate properties in Italy.[6] Greater green area coverage and higher scores for mass transportation define areas with more valuable properties. OSM was chosen as an auxiliary source of contextual territorial information due to its availability, granular representation, rich semantic annotation, and global coverage. In Section 5 we discuss the computation of the three indicators for the city of Turin by applying *MethOSM* to each of the indicators.

To compute values for an indicator within a city, we split the city into smaller areas to which we will assign the scores. For the purpose of this paper, we use the standard census

[6]This indicator is discussed in more detail in Section 6.

partition[7]. According to this partition, Turin consists of nearly 4,000 census cells. We will take their geometries and use these alongside features in their surroundings to compute the indicators.

Next, we need to gather data about the surroundings that describe public transport features and green areas. We choose bus stops, railway stations, woods, parks, and gardens—data available and easily accessible in OSM using the Overpass API[8] and the query language it provides. We will apply *MethOSM* to analyze this data and transform it such that it can be used in the computation step that follows.

Finally, we have to decide how each indicator will be computed through a spatial relation between each census cell and its surroundings. In our example, the spatial relations include: *containment within a radius* to count the number of nearby bus stops, *minimum distance* to train stations, and *geometric intersection* of green areas on census cells. These spatial relations do not constitute an exhaustive list and are only referred here in relation to our chosen example.

Figure 1 depicts the process of computing the green area coverage indicator. The geometries of census cells in the city are obtained from the Italian statistical office. These constitute the *input set*. Next, we query OSM, our *contextual set*, for data describing the surroundings. We take only data about woods, parks, and gardens. These features are our *points of interest*, conveniently referred to as the *POI set*. Both the input and the POI sets are related through *geometric intersection* to compute the indicator for each census cell. Values for this indicator are used in Figure 1c, where cells with darker colours correspond to greater green area coverage.

(a)
(b)
(c)

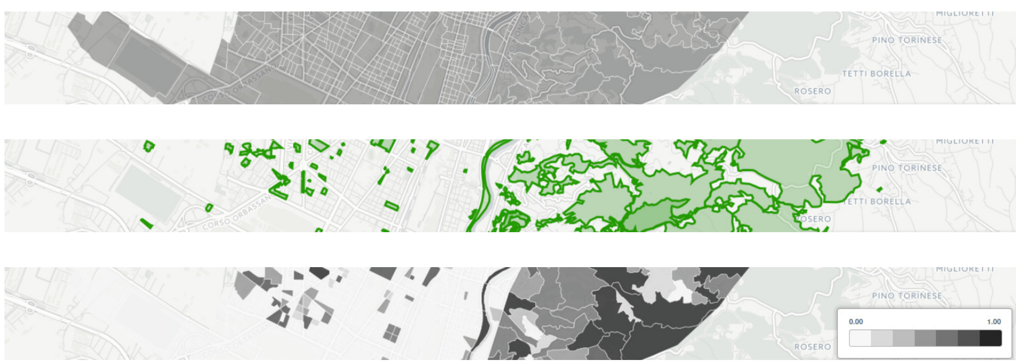

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Figure 1: Computing green area coverage for the city of Turin requires (a) the input set with the city's census cells and (b) a POI set with green area polygons to produce (c) a map using the coverage ratio as the colouring variable.

Although Figure 1 describes a seemingly straightforward process, we will see in the following sections that there are several challenges in extracting and using crowd-sourced geographical data such as OSM. These challenges arise from the analysis of the contextual dataset and can be classified as follows:

[7]Italian census cells: http://www.istat.it/it/archivio/sezione+di+censimento.
[8]https://wiki.openstreetmap.org/wiki/Overpass_API

- **Discrepancy of taxonomies.** This occurs when the alignment between the contextual features described in the indicator and the representation of these features in the dataset is not perfect. It may require iterating on query definitions until all needed features are retrieved. Our driving example uses OSM and requires us to get information about green areas. These are not directly represented in OSM as such. Instead, OSM uses the concepts of parks and gardens. To bridge the gap in this case, we use the Overpass API to retrieve a union of both sets.
- **Variations in coverage, specificity, and richness.** Data quality may vary from place to place, possibly requiring the use of very different queries depending on the annotation style used by the contributor. In OSM, some features are described only by name (e.g., the harbor in Bari uses the key-value pair *name="Bacino della Stazione Marittima"*) while in other cases features of the same type use more precise descriptions (e.g., the harbor of Sampierdarena also contains the key-value pair *harbour=yes*).
- **Duplicate entities.** Crowd-sourced databases, due to their very nature, can contain duplicate annotations about the same entity from different contributors. More often than not, there will be a need to deal with these repetitions before being able to compute the indicator. A specific case in OSM are schools that use the key-value pair *amenity=school* for individual entrances as well as for the area that represents the school.
- **Mixed representations for the same type of feature.** The contextual dataset contains more than one way of representing contextual features of the same type, in the same location. Depending on the spatial relation used, this may require that all the features are transformed to use the same representation. In our driving example, we find bus stops being represented both as nodes and as ways in OSM, and substitute those ways with their centroids to provide a uniform representation for the computation function.

These challenges in the context of OSM are discussed to various degrees in the related works on OSM data quality issues we mentioned in the previous section. While some works develop solutions to these challenges, many of them discuss the challenges and propose possible ways to resolve them as a future work. For example, [11] suggests that variations in coverage can be addressed by issuing specific calls and motivating volunteers for OSM data collection in areas where data coverage is scarce. A polygon-based method to resolve duplicated lines for the same road features is developed in [24]. This method is shown to be effective for extracting multi-lane roads from datasets with high level of detail but of a low quality (such as OSM), with further improvements being proposed the generalization of dual-line roads into single lines and simplification of complex junctions into single nodes. Discrepancy of taxonomies between OSM and the reference dataset Corine Land Cover is discussed in [15], where, as a possible solution to fix this issue, a trust mechanism is suggested for contributors of specific classifications to help decide if one class can be more reliable than the others, hence solving the conflict. [17] noticed that specificities in names of OSM keys and values have to be analyzed and taken into consideration when developing queries for OSM data, and similarly, duplicate entities and mixed representation for the same type of feature require individual study and human participation. Further, [17] proposed an automated procedure to address such issues with OSM data and produce a multi-modal urban network model representing a large region (while for building smaller network models, one should consider identifying and correcting any additional problems manually). Such specific strategies to address the above challenges are complementary to the methodology we propose in this paper, however when and how to perform the analysis of the contextual set regarding each one of the above mentioned challenges is part of *MethOSM* and will be detailed in the next section (while in Section 5 we perform this analysis for the specific case of our driving example).

4 *MethOSM*: a methodology for computing OSM-derived indicators

The computation of an indicator is achieved when a *scoring function* that realizes the semantics of the indicator is evaluated. The *MethOSM* approach assumes that these semantics are provided as an *informal description* which guides the analysis to identify certain elements. These elements are then used to define the scoring function and evaluate it. Figure 2 depicts the overall approach. Dark-coloured boxes to the left represent the *a priori knowledge* from which the rest of the elements in the figure are determined. The arrows show three flows of the analysis that allow for the determination of each element from elements to its left. The execution of the methodology is complete when the rightmost element o, that is, the *output value* of the scoring function, is determined.

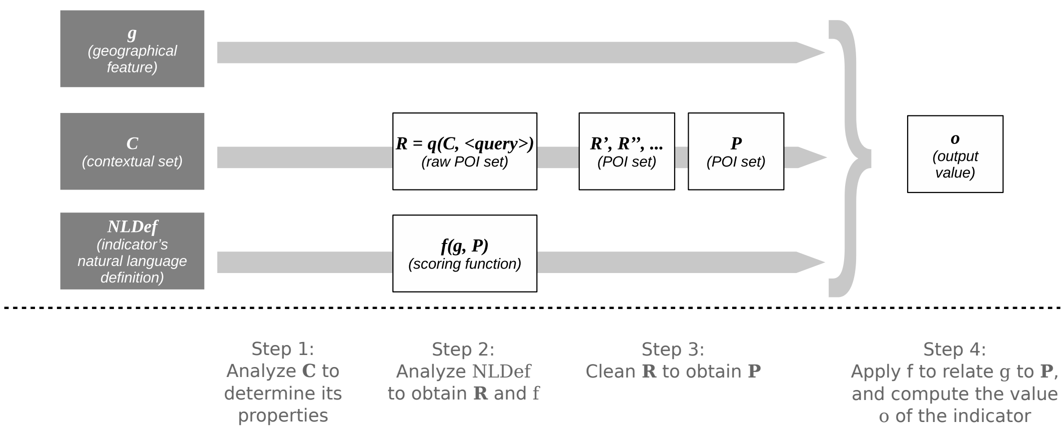


Figure 2: *MethOSM* approach for computing indicators: grey boxes denote input elements required by the approach while white boxes correspond to outputs resulting from the application of the approach.

The a priori knowledge elements in Figure 2 are defined as follows:

- the geographical feature g for which the indicator will be computed,
- the contextual set **C** of all features that surround g, and
- the indicator's *natural language definition* (*NLDef*) that describes the indicator and states how **C** and g are related.[9]

[9]In order for the methodology to be applicable, *NLDef* needs to include details about the spatial relations used for computing the indicator. For example, to count the number of nearby bus stops, *NLDef* must also define what is meant by "nearby," e.g., "nearby" is defined as any Euclidean distance less than 500 meters.

The methodology guides the analysis of *NLDef* to select, clean, and transform elements in $\mathbf{C}$. This is done in order to define a set $\mathbf{P}$ of points of interest containing only the elements of $\mathbf{C}$ that are involved in the description of the indicator. In order to define $\mathbf{P}$, it may be necessary to perform a series of refining steps that operate on a *raw* subset of $\mathbf{C}$.

This raw subset is represented by $\mathbf{R}$, the *raw POI set*, and is defined by means of a query function q that selects some elements of $\mathbf{C}$. $\mathbf{R}$ is refined into $\mathbf{R}'$, $\mathbf{R}''$ and so on, performing tasks such as cleaning, deduplicating, and transforming to representations that are required by a *scoring function* f to determine the value of the indicator. Function f is defined from the relation described in *NLDef* between g and $\mathbf{C}$.

MethOSM performs this process of finding $\mathbf{P}$ and f from the informal description *NLDef* in a series of steps that are introduced below.

Step 1: analysis of the contextual set. Before attempting specific tasks related to a particular indicator, it is important to identify potential challenges that can arise from working with the contextual set. The analysis in terms of these challenges will guide decisions taken in steps further down the line for all tasks dealing with the contextual set. A typical set of challenges include:

- $\mathcal{A}$ **Discrepancy of taxonomies between the contextual set and the indicator definition.** A geographical indicator describes something about an entity in relation to its surroundings. To gather the input needed from these surroundings, the whole contextual set is queried to retrieve only features that are relevant according to the definition of the indicator. In some cases, there is a trivial translation of what is described in *NLDef* into queries to the contextual set. In most cases the alignment is not perfect: taxonomies are different and a non-trivial mapping is needed to reconcile these differences.
- $\mathcal{B}$ **Variations in coverage, specificity, and richness of annotations.** Contextual sets often present great variability in annotation quality. Sometimes this variability is seen by comparing one location to another for the same type of feature. Other times the differences are seen across types of features. In both cases, completeness, accuracy, and richness depend heavily on the community of annotators and the methodology employed.
- $\mathcal{C}$ **Duplicate entities.** The contextual set may contain duplicates (e.g., due to contributors repeatedly using tags on sub-entities rather than on the main entity—see Section 3 for a specific example). An analysis of the different cases of duplication must be performed to determine which strategies can be applied (e.g., deduplicate whenever there is an overlap or if features are closer than a certain distance).
- $\mathcal{D}$ **Mixed representations for the same type of feature.** Features in the contextual set can be described in many ways (e.g., sometimes as a point that describes roughly where the feature is located and some other times as a polygon describing its exact location and area). Depending on the spatial relation specified in the definition of the indicator, it will be necessary or desirable to reduce all features to the same representation type.

The challenges presented above are relevant in all scenarios where the contextual set contains noisy data. When we apply *MethOSM* to our driving example and to the choice of OSM as the contextual set for that particular case, we will explicitly recall these challenges as we find them.

At the end of Step 1 the properties of the contextual set are known and potential challenges are identified.

Step 2: analysis of the indicator's natural language definition. In this step, $NLDef$ is analyzed to determine two elements:

- A query q to produce a *raw POI set* $\mathbf{R}$. This query q will retrieve only the features in the contextual set $\mathbf{C}$ that are points of interest according to $NLDef$. The process of determining q is guided by the analysis performed in Step 1. It takes into account $\mathcal{A}$ and $\mathcal{B}$ to bridge any discrepancies and to minimize differences in coverage, specificity, and richness of annotations from location to location. The resulting raw set $\mathbf{R}$ is not yet ready to use. It possibly includes duplicates that need to be eliminated and heterogeneous representations that need to be harmonized.
- The scoring function f that will be applied to produce values for the indicator. This function f spatially relates g to points of interest in $\mathbf{P}$ and then uses these relations to produce a numerical description according to $NLDef$.

We define three scoring functions and three spatial relations to illustrate this step. This list is by no means exhaustive and is determined solely by the requirements of the indicators presented in Section 3 where we describe our driving example. Other kinds of indicators will require different scoring functions and spatial relations not listed here. The scoring functions of our driving example are defined in terms of spatial relations of containment, distance, and area intersection to compute the indicators by using g and $\mathbf{P}$ as input:

- **Count nearby.** Defined as:

$$countNearby(g, \mathbf{P}, d) = \left| \ \{p \mid p \in \mathbf{P} \ \wedge \ distance(g, p) \leq d\} \ \right| \tag{1}$$

  where $distance$ denotes the usual geographical distance and only the POIs $p \in \mathbf{P}$, contained within a circle defined using the distance d from g are selected. The count is the number of elements of the resulting set.

- **Closest distance.** Defined as:

$$closestDistance(g, \mathbf{P}) = \min_{\forall p \in \mathbf{P}} distance(g, p) \tag{2}$$

  where $closestDistance$ is the minimum distance from g to all the POIs $p \in \mathbf{P}$.

- **Shared to total ratio.** Defined as:

$$ratioSharedTotal(g, \mathbf{P}) = \frac{area(shared(g, \mathbf{P}))}{area(g)} \tag{3}$$

  where $area$ is defined in the usual way as the extent of a geographical surface. The $shared$ function is defined as:

$$shared(g, \mathbf{P}) = \bigsqcup_{j=1}^{n} g \sqcap p_j \qquad p_j \in \mathbf{P}, n = \left|\mathbf{P}\right| \tag{4}$$

  where $\sqcap$ denotes the intersection area and $\sqcup$ denotes the area resulting from the union between geographical surfaces. That is, $shared(g, \mathbf{P})$ is the union of the intersections found by comparing g to each one of the n elements $p_j \in \mathbf{P}$.

At the end of Step 2 we obtain the raw POI set $\mathbf{R}$ and the definition of f, the scoring function to compute the indicator for g.

Step 3: cleaning of the POI set. In order to apply the scoring function f, we need to transform the raw POI set $\mathbf{R}$ into the clean version $\mathbf{P}$. The analysis done in Step 1 should be used as guidance to achieve this.

In the case of our driving example, as a result of the analysis of $\mathbf{R}$ in light of challenge $\mathcal{C}$, we identify different cases of duplicate entities in $\mathbf{R}$ and the consequent need for deduplication in order to transform $\mathbf{R}$ into the clean version $\mathbf{P}$. We present the two deduplication strategies applied in our driving example:

- **Deduplication by intersection.** The elimination is done by detecting intersection areas between points of interest, preferring the more descriptive version over the less descriptive one.

$$\begin{aligned} dedupByIntersection(\mathbf{R}) &= \{r \mid r, q \in \mathbf{R} \ \wedge \ r \sqcap q = \emptyset\} \\ &\cup \{r \mid r, q \in \mathbf{R} \ \wedge \ r \neq q \ \wedge \ r \sqcap q \neq \emptyset \ \wedge \ isPolygon(r)\} \\ &\cup \{q \mid r, q \in \mathbf{R} \ \wedge \ r \neq q \ \wedge \ r \sqcap q \neq \emptyset \ \wedge \ \neg isPolygon(r)\} \end{aligned} \tag{5}$$

  where $\cup$ is the set union and $isPolygon$ is $true$ only when the element is a polygon. In this way, all $r \in \mathbf{R}$ are selected if there is no intersection. If there is an intersection, the polygon representation is preferred.

- **Deduplication by proximity.** The elimination is done by treating points of interest that are closer than a threshold as being the same entity.

$$\begin{aligned} dedupByProximity(\mathbf{R}, d) &= \{r \mid r, q \in \mathbf{R} \ \wedge \ distance(r, q) > d\} \\ &\cup \{r \mid r, q \in \mathbf{R} \ \wedge \ r \neq q \ \wedge \ distance(r, q) \leq d \ \wedge \ isPolygon(r)\} \\ &\cup \{q \mid r, q \in \mathbf{R} \ \wedge \ r \neq q \ \wedge \ distance(r, q) \leq d \ \wedge \ \neg isPolygon(r)\} \end{aligned} \tag{6}$$

  where d is the threshold distance to consider that there is proximity between two elements.

  In this way, all $r \in \mathbf{R}$ are selected if there is no proximity with q. If there is proximity, the polygon representation is preferred.

From $\mathcal{D}$ we identify different ways in which points of interest are represented in $\mathbf{R}$. Next, we assess the impact that these different representations have on the requirements of the scoring function f. There is a need to homogenize if not all the different representations can be used as input for f.

We use the dimensionality reduction strategy in our driving example. This strategy is applicable when the heterogeneity problem can be addressed by substituting complex representations for simpler ones. A concrete instance of dimensionality reduction is *reduction by centroid*, in which polygons are, as the name implies, substituted by their centroids. If f does not require areas, it can be applied after assessing the impact that the substitution will have. This impact will be negligible for features that cover small areas.

In other cases, there are features that simply lack the information necessary to be used as input. f requires a more complex representation and thus the only possible strategy is to discard those features.

The implementation of the strategies to tackle challenges $\mathcal{C}$ and $\mathcal{D}$ was achieved using PostgreSQL queries with functions provided by the PostGIS extension, although several current GIS toolkits should be up to the task.

At the end of Step 3 we obtain a clean POI set $\mathbf{P}$ that can be used to evaluate f.

Step 4: computation of the indicator. Once the scoring function f and the POI set $\mathbf{P}$ are known, we can compute the value of the indicator for g.

The process can be optimized if we establish a *horizon* for the contextual set $\mathbf{C}$, centred on g. This horizon establishes a *window* for querying $\mathbf{C}$, thus restricting the indicator to only describing phenomena inside the window defined by the horizon.

The horizon is selected in order to include all relevant features, assuming that there is a maximum distance beyond which there is no useful information for the computation. We propose the *bounding box* approach to define the horizon: the centroid of g is taken and the box is defined by transposing coordinates by a fixed distance in meters in all four cardinal points. We selected the bounding box approach due to its lightweight nature, although other approaches such as defining the horizon as a circumference of a certain radius from the centroid of g will produce the same results.

At the end of Step 4 we obtain the output o, that is, the value of the indicator for g.

Although we discussed scoring functions in Step 2 and cleaning strategies in Step 3, these are specific results of the application of the methodology in our driving example and for the case of OSM. Other datasets will present different situations and require different strategies that could require dataset-specific domain knowledge on the part of the data scientist. The goal of the methodology is to ease the task of defining the scoring function and of obtaining a suitable contextual set by analyzing the problem in the proposed four steps.

5 Exemplifying *MethOSM* for computing indicators

In Section 4 we presented *MethOSM* to compute indicators starting from an informal definition $NLDef$ of the indicator, a geographical feature g on which to compute the indicator and a contextual set $\mathbf{C}$ that describes the surroundings of g. In this section we show how we apply the methodology to our driving example, in order to compute each one of its indicators. The geographical feature g is the same in all cases: a polygon representing a census cell in the city of Turin. In the same way, OSM is the contextual set $\mathbf{C}$ shared among all indicators. We will query OSM to build our POI set $\mathbf{P}$. To this end, we will define queries using Overpass QL[10].

To apply *MethOSM*, first we describe Step 1 (the analysis of the contextual set) as this step is shared among all three indicators in our running example. Next, we perform the steps particular to each indicator in Subsections 5.1, 5.2 and 5.3, respectively.

Step 1: analysis of the contextual set. We analyze the challenges described in Section 4 in light of our driving example:

[10] http://wiki.openstreetmap.org/wiki/Overpass_API/Overpass_QL

$\mathcal{A}$ **Discrepancy of taxonomies between the contextual set and the indicator definition.** We find that in some cases there is a direct correspondence to a class of features in OSM (e.g., bus stops in OSM are represented with the *highway=bus_stop* key-value pair). In other cases there can be a partial correspondence which needs a more complex query. To query for railway stations we have to specifically filter out entrances to the subway network using *[railway=station][subway!=yes]*. Another example of partial correspondence occurs in the case of green areas: we have to issue a complex query that retrieves woods, parks, and gardens, represented as *([natural=wood]; [leisure=park]; [leisure=garden])*. This analysis is summarized in Table 1.

POI Type	**OverpassQL Query**
Bus stops	[highway=bus_stop]
Railway stations	[railway=station][subway!=yes]
Green areas	([natural=wood]; [leisure=park]; [leisure=garden])

Table 1: Mapping bus stops, railway stations, and green areas to Overpass QL queries.

$\mathcal{B}$ **Variations in coverage, specificity, and richness of annotations.** In the particular case of OSM, coverage can vary from city to city depending on region and size: bigger cities tend to have higher coverage in general while cities in the North of Italy present higher coverage than cities in the South. When analyzing specificity and richness for different types of features, we see that annotation provenance plays a decisive role. Official agencies have varied policies and spend resources differently; Italian municipal authorities do a good job annotating bus stops while annotation of harbor facilities is at best spotty.
Volunteer efforts often bridge the gap but they can be less rigorous. We found different approaches for annotating harbors (e.g., more specific *harbour=yes* versus less precise *name="Bacino della Stazione Marittima"*), often requiring a search for specific harbor names to get their locations instead of resorting to looking for the more suitable *key-value* combination.
Fortunately, for our driving example, which spans a relatively small area (i.e., the city of Turin), the quality of annotations for all types of points of interest is sufficiently adequate. In other cases a possible solution would require location-dependent queries. That is, there would be the need to specify custom queries attached to specific locations to supersede generic ones.

$\mathcal{C}$ **Duplicate entities.** OSM is kept up-to-date by the combined effort of countless annotators. By their very nature, such crowd-sourced efforts are very decentralized and there is no easy way to avoid errors in the annotation task.
In some cases, the same entity is annotated several times by independent annotators. Consequently, some processing must be done to discard duplicates. In our driving example, some railway stations are mapped more than once, first as an area and again as a node, without a relation that links them. These cases can be systematically spotted as the distance between duplicates is zero or near-zero.

$\mathcal{D}$ **Different representations for the same type of feature.** Entities in the contextual set can be described in many ways. In the case of OSM, the same type of entity can be described as a point in one case, and as a polygon in another. This poses a problem if we require that features be of the same dimensionality in order to treat them uniformly across the entire computation of an indicator.

We deal with this situation when we count nearby bus stops for census cells within the city of Turin. In OSM, bus stops are often described using single points, although in some cases annotators have instead provided polygons that map the waiting area of these bus stops. These differences in dimensionality, when present, need to be taken into account before applying the spatial relation needed to compute an indicator.
A similar situation occurs also for railway stations and green areas. Some instances are thoroughly represented as polygons that give information about the area covered by the feature while other instances only give a general location as a point.

5.1 Number of nearby bus stops indicator

Step 2: analysis of the indicator's natural language definition. This indicator can be informally defined as:

$NLDef$: the number of nearby bus stops to each of the census cells in the city, where a bus stop is considered to be nearby if the distance between it and the cell is at most 500 meters.

An analysis of $NLDef$ determines the following:

- The raw POI set $\mathbf{R}$ is obtained by querying $\mathbf{C}$ (i.e., OSM, our contextual set) for bus stops, according to Table 1:

$$\mathbf{R} = q(\mathbf{C}) = overpass(\mathbf{C}, \text{``}highway = bus\_stop\text{''})$$

  where $overpass$ represents the query function in OverpassQL, $\mathbf{R}$ is the *possibly raw* set of features in the contextual set $\mathbf{C}$ that represent bus stops.

- The scoring function f that relates g with the POI set $\mathbf{P}$:

$$f = countNearby(g, \mathbf{P}, 500) \tag{7}$$

  where $countNearby$ is as defined in (1).

Step 3: cleaning of the POI set. In $\mathcal{C}$ we determined that $\mathbf{R}$ contains duplicate bus stops. To come up with a sensible cleaning strategy, we identified different cases of duplication:

- The bus stop being represented more than once with increasing degrees of complexity (i.e., as a point representing the general location of the bus stop, and as a polygon describing the exact waiting area for passengers);
- The feature being accidentally represented more than once due to contributor errors.

In the first case, the issue can be solved by applying $dedupByIntersection$ as defined in (5), discarding all points inside polygons:

$$\mathbf{R}' = dedupByIntersection(\mathbf{R})$$

where $\mathbf{R}'$ is the set resulting from the application of the strategy.

For the second case, *dedupByProximity* as defined in (6) will be enough to discard unwanted repetitions:

$$\mathbf{R}'' = dedupByProximity(\mathbf{R}', 3)$$

where 3 meters is the threshold distance we selected to assume that two features are the same and $\mathbf{R}''$ is the set resulting from the application of the strategy.

From $\mathcal{D}$ we know that our set of bus stops $\mathbf{R}''$ contains heterogeneous representations. Given the fact that the bus stops represented as polygons span a reduced area, we can substitute these polygons by their centroids with a negligible impact on accuracy:

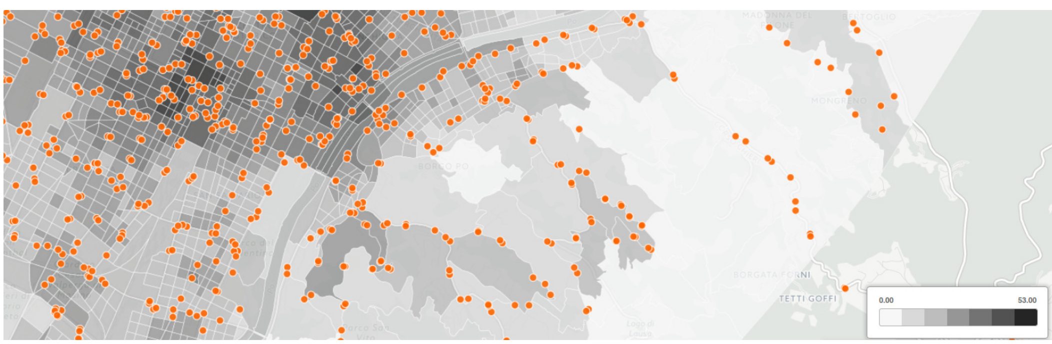
$$\mathbf{P} = reduceByCentroid(\mathbf{R}'')$$

where $\mathbf{P}$ is the clean, homogeneous set of points representing bus stops.

Step 4: computation of the indicator. Once $\mathbf{P}$ is determined, we are ready to find the output o for g by applying f as defined in (7):

$$o = countNearby(g, \mathbf{P}, 500)$$

Figure 3 shows a choropleth map of Turin census cells using the indicator as the colouring variable.



© OpenStreetMap contributors (http://www.openstreetmap.org/copyright) © Carto (https://carto.com/attributions)

Figure 3: Census cells by number of nearby ($d \leq 500m$) bus stops. Features representing bus stops are overlaid to provide reference.

5.2 Distance to the closest railway station indicator

Step 2: analysis of the indicator's natural language definition. This indicator can be informally defined as:

$NLDef$: the distance from the centroid of each census cell in the city to the closest railway station, where the distance is measured in meters.

An analysis of $NLDef$ determines the following:

- The raw POI set $\mathbf{R}$ is obtained by querying $\mathbf{C}$ for railway stations, according to Table 1:

$$\mathbf{R} = q(\mathbf{C}) = overpass(\mathbf{C}, \text{“}[railway = station][subway! = yes]\text{”})$$

  where $\mathbf{R}$ is the *possibly raw* set of features in the contextual set $\mathbf{C}$ that represent railway stations.

- The scoring function f that relates g with the POI set $\mathbf{P}$:

$$f = closestDistance(g, \mathbf{P}) \tag{8}$$

  where $closestDistance$ is as defined in (2).

Step 3: cleaning of the POI set. In $\mathcal{C}$ we determined that $\mathbf{R}$ contains more than one representation referring to the same railway station.

Unlike the case in Section 5.1, the impact of duplicates is negligible for finding the distance to the closest railway station in the city of Turin. This is due to (8) selecting the closest distance regardless of the number of times the same feature is represented.

From $\mathcal{D}$ we know that our set $\mathbf{R}$ of railway stations contains heterogeneous representations. After inspection, we determined that the centroids of railway stations are closer to where railway users need to reach to use the railway service than points in the perimeter of polygon representations. Through homogenization, we obtain more useful representations of each railway station:

$$\mathbf{P} = reduceByCentroid(\mathbf{R})$$

where $\mathbf{P}$ is the clean set of points representing railway stations and $reduceByCentroid$ is a function that finds the geometric centroid for each element in $\mathbf{R}$ to build $\mathbf{P}$.

Step 4: computation of the indicator. Once $\mathbf{P}$ is determined, we are ready to find the output o for g by applying f as defined in (8):

$$o = closestDistance(g, \mathbf{P})$$

Figure 4 shows a choropleth map of Turin census cells using the indicator as the colouring variable.

5.3 Green area coverage indicator

Step 2: analysis of the indicator's natural language definition. This indicator can be informally defined as:

$NLDef$: the ratio of green area (parks, woods, gardens) to total census cell area.

An analysis of $NLDef$ determines the following:

- The raw POI set $\mathbf{R}$ is obtained by querying $\mathbf{C}$ for features that represent parks, woods and gardens. According to Table 1:

$$\mathbf{R} = q(\mathbf{C}) = overpass(\mathbf{C}, \text{“}([natural = wood]; [leisure = park]; [leisure = garden])\text{”})$$

Figure 4: Census cells by distance to the closest railway station. Railway station features are overlaid to provide reference.

where $\mathbf{R}$ is the *possibly raw* set of features in the contextual set $\mathbf{C}$ that represent green areas.

- The scoring function f that relates g with the POI set $\mathbf{P}$:

$$f = ratioSharedTotal(g, \mathbf{P}) \tag{9}$$

where $ratioSharedTotal$ is as defined in (3).

Step 3: cleaning of the POI set. In $\mathcal{C}$ we determined that $\mathbf{R}$ contains more than one representation referring to the same green area. Two cases were found:

- parks represented both as a polygon and as a point and
- parks annotated twice or more as polygons.

The first case is handled taking into account our analysis in $\mathcal{D}$; we cannot work with point representations to compute the green area coverage. We need to discard point representations:

$$\mathbf{R}' = discardPoints(\mathbf{R})$$

where $\mathbf{R}'$ is a set that contains only polygons.

The second case will be handled in the Step 4, since $ratioSharedTotal$ makes use of $shared$, as seen in (3). Note that $shared$ uses $\sqcup$, seen in (4), to compute the union between all green area polygons. This has a convenient side-effect: repeated green areas that overlap are taken into account just once. Consequently, $\mathbf{R}'$ is ready to be used as input for the scoring function:

$$\mathbf{P} = \mathbf{R}'$$

Step 4: computation of the indicator. Once $\mathbf{P}$ is determined, we are ready to find the output o for g by applying f as defined in (9):

$$o = rationSharedTotal(g, \mathbf{P})$$

Figure 5 shows a choropleth map of Turin census cells using the indicator as the colouring variable.

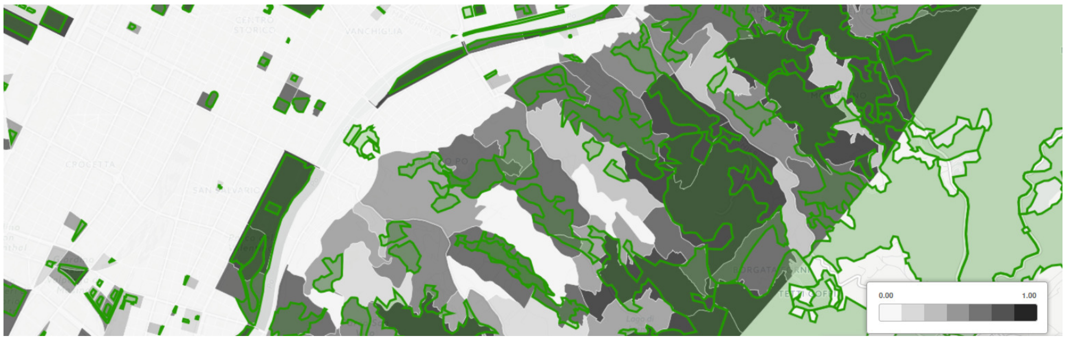


Figure 5: Census cells by ratio green area to total cell area. Green area polygons are overlaid to provide reference.

6 Discussions and validation of *MethOSM* for computing a complex indicator

In order to validate the proposed methodology in a larger setting, we used it for computing a complex indicator. The complex indicator describes a socio-economic phenomena—that of understanding how the value of real estate properties changes over time.

The indicators introduced in the previous sections were used to build the complex indicator used in an Automated Valuation Model (AVM) that estimates the value of real estate properties. In a nutshell, zones with higher scores for mass transportation and greater green area coverage presume to contain more valuable properties. This composite indicator was developed for Cerved, a credit scoring company in Italy[11], as part of Cerved's Cadastral Report Service (CCRS)[12] aiming to objectively estimate the value of real estate properties in Italy by using different types of datasets (open data / OSM, proprietary data, and third-party data). Valuation of real estate properties is a challenging task and requires accumulation and processing of different types of information about properties, including contextual information about their locations, such as economic and social trends, environmental conditions, proximity to the historical center, and concentration of managers' and shareholders' households [34], to name a few. This task is typically performed by expert evaluators who visually inspect the property. As such it is a long, expensive, and error-prone process which is mostly qualitative and based on implicit knowledge.

The objective of CCRS was to automate this task by building an AVM integrating composite indicators that could estimate values for real estate properties. Moreover, it was crucial for the service to be able to compute the indicator for the entire Italian territory.

[11] https://www.cerved.com

[12] More details about the CCRS business case can be found at https://blog.prodatamarket.eu/2015/06/cerved-in-the-prodatamarket-project.

OSM was chosen as a source of contextual territorial information. Starting from the exact location of a property, the property is mapped to the corresponding census cell and the related territorial scores. For each census cell, different indicators were computed based on the different sources available, in a hierarchical manner, following the *MethOSM* methodology, to arrive to an integrated final score used by the estimation algorithm (i.e., the real estate integrated score). These indicators computed per census cell were:

- *Social discomfort index (IDS)*: based on social and demographic variables from the ISTAT national census of 2011.
- *Real estate discomfort index (IDE)*: based on the state of conservation of properties from the ISTAT national census of 2011.
- *Social demographic score*: based on IDS and IDE.
- *Manager and Shareholder Concentration (MSHC) score*: based on Cerved official and proprietary data about the presence of managers and shareholders in the area.
- *People score*: based on the integration of MSHC and the Social demographic score.
- *Heavy Industrial Concentration (HIC) score*: based on Cerved official and proprietary data about the concentration of industries in certain NACE[13] categories.
- *Territory score*: based on HIC and other variables about territorial features. Among these territorial features, the following OSM-derived indicators were used: number of nearby bus stops, distance to the nearest railway station, green area coverage, total length of pedestrian paths in the vicinity, number of sites of historical relevance, number of nearby hotels and hotel-related features, ratio of land for industrial use to total cell area, and distance to the nearest coast (where applicable).
- *Real estate integrated score*: based on the integration of the People and Territory scores.

For the *Territory score*, in addition to the three indicators computed in Section 5, *MethOSM* was used to guide the analysis for the five other indicators mentioned above. In the following list we discuss some of the peculiarities of the application of *MethOSM*, compared to the indicators discussed in Section 5:

- **Total length of pedestrian paths in the vicinity.** After a preliminary analysis, it was determined that the best alignment with the intended definition of pedestrian path was produced by the query that retrieved features tagged with at least one of *highway=pedestrian, highway=footway, highway=cicleway* and *highway=steps*. To clean the raw POI set **R**, we eliminated all features that were single points or polygons, leaving only lines. The scoring function selected all paths within a radius of 1000 meters from the centroid of the census cell.
- **Number of sites of historical relevance.** After a preliminary analysis, it was determined that the relevant tags were *tourism=museum, historic=ruins, historic=yes, historic=castle and historic=building*. The annotation on the area representation was preferred for overlapping annotations. The reasoning for the scoring function was similar to the case described in Section 5.1 for "number of nearby stops."
- **Number of nearby hotels and hotel-related features.** In this case, we determined that the relevant OSM tags were *tourism=hotel, tourism=hostel* and *tourism=guest_house*. The deduplication strategy chosen was the same as in the previous case.

[13]EC NACE: http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary: Statistical_classification_of_economic_activities_in_the_European_Community_(NACE)

- **Ratio of land for industrial use to total cell area.** Here the OSM taxonomy is well aligned with the intended meaning of industrial land use. Polygon representations tagged with *landuse=industrial* were retrieved and used in a scoring function similar to the case described in Section 5.3 for "green area coverage."
- **Distance to the nearest coast.** In this case there is a good alignment between the OSM *natural=coastline* and the concept of coast required by the indicator. The POI set obtained by issuing the query contained only open paths that represented lines. Consequently, no further transformations were required. The scoring function was analogous to the case described in Section 5.2 for "distance to the closest railway station."

MethOSM was successfully employed to compute the OSM-derived indicators for the whole of Italy: more than 400,000 census cells in 7,978 municipalities and 20 regions, including rural areas, villages, towns, and cities in the following configurations: coastal, inland, and mountain. The reason for computing the OSM-derived indicators in different configurations and weighting them differently in the final composite indicator was to take into account variations in availability and quality of the data in various areas. In order to measure the quality of the resulting indicator, one has to compare it to a "golden standard." In our case of the indicator estimating the value of real estate properties the only way to check how good it is was to compare it to a corresponding indicator calculated based on historical data on real estate transactions (data available from the Italian government, though not open data), i.e., the "golden standard." The computed indicator closely followed the "golden standard," meaning that the employed data and method were sound for this particular problem. This required the computation of the OSM-derived indicators in different configurations as mentioned above, and adjusting their weights in the final composite indicator till a close enough match to the "golden standard" was obtained. *MethOSM* played a key role in guiding the process for harmonizing the complex process of dealing with OSM data for computing the various indicators, making the overall task of computing OSM-derived indicators efficient and effective. Indicators from this business case were made available as Linked Data in [40] through the DataGraft platform[14] [36, 37].

The applicability of this complex indicator to another country depends on several factors. First, for computing the scores that use proprietary data (e.g., data about presence of managers and shareholders in a given area), similar data would need to be obtained for that country. Typically this is commercial data and not open. Further, the structure of this proprietary data would need to be similar to the one used for computing the indicator for Italy, likely requiring some transformations. Second, for the OSM-derived indicators several aspects would need to be take into consideration. For example, cultural differences may result in concepts such as *nearby* being defined differently. Additionally, the alignment work for OSM to match the intended meaning contained in the natural language definition of the indicator may produce different results depending on the annotation methodologies used from location to location. Consequently, also the deduplication strategies may need adjustments to reflect this fact.

[14]https://datagraft.io

7 Conclusions and outlook

With the availability of increasing volumes of data, new opportunities are opened for the development of various composite indicators to define and analyze complex social, economic, political, or environmental phenomena. The emergence of open data is especially relevant as it has enabled individuals and businesses the access to affordable data on top of which interesting indicators can be computed. An example of such an open dataset is OSM which has been used as a baseline dataset for computing indicators, for example, in areas where official data did not exist, or simply because OSM data is freely available and can be easily accessed. Previous work on computing indicators derived from OSM has shown a number of challenges in extracting and using data for computing indicators, with ad-hoc, often overlapping solutions being developed to address the challenges. In this context, this paper proposed (and formalized) *MethOSM*—a systematic methodology for computing indicators derived from OSM data, with the aim of supporting individuals with a clear set of steps and help them identify a set of issues that need to be addressed for an effective and efficient computation. To that end, we exemplified the successful use of the proposed methodology on a number of indicators that use OSM as the contextual source, and validated the methodology for computing a complex indicator in a real business case for estimating the value of real estate properties using OSM data.

We consider the methodology proposed in this paper generic in the sense that it can be used with other contextual datasets. To this end, we plan to investigate the use of *MethOSM* with contextual datasets other than OSM such as the Italian Car Fleet Database[15] to describe fleet configurations by municipality and region and the Atoka Company Database[16] to model phenomena related to economic activity throughout Italy. The study of these contextual datasets will add to the list of challenges introduced in Step 1 in the current version of *MethOSM*. With a more exhaustive list, it should be possible to introduce a more systematic approach to the analysis of the contextual dataset. The study of other well-known reference datasets should result in the identification of a set of cleaning and deduplication strategies and a description of the conditions in which each strategy can be applied. Additionally, an analysis of the different representations and spatial units in use could result in extensions to *MethOSM* that deal with these differences in an automatic or semi-automatic way. Moreover, the application of *MethOSM* to compute new types of indicators will most likely add to the scoring function types now present in Step 2. The next iteration of *MethOSM* will introduce *feature selectors* and *feature evaluators* to further describe the process of transforming natural language definitions into scoring functions. Future work can include the use of OSM to compute indicators based on more complex distance algorithms such as walking distance, driving distance, and commuting distance. Comparison of *MethOSM* results against a dataset of commuting times in metropolitan areas could open an interesting avenue for performance evaluation. Another avenue for potential future work could be related to biases (e.g., socio-political) introduced in OSM data during its production and how such biases could be taken into account in *MethOSM*. On one hand, we foresee certain improvements of the data extraction procedures. As demonstrated in [20] positional accuracy of OSM data increases with the amount of contributors who worked on a given spatial unit of OSM. It is worth exploring whether this and possibly other intrinsic data properties could be used to improve data extraction and data cleansing procedures of our

[15] https://www.dati.gov.it/dataset/parco-circolante-dei-veicoli
[16] https://atoka.io

methodology. On the other hand, fundamental studies on the imprint of social inequalities and digital divide on VGI question consistency and utility of VGI as a category [8, 9]. It is important to incorporate data about demographics of the OSM contributors into our extraction procedures, so that the users of the methodology can decide whether and how to utilize such data.

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