Leveraging ontology for enhanced queries and analyses of urban point clouds

Matteo Codiglione, Raniero Beber, Fabio Remondino

3D Optical Metrology (3DOM) unit, Bruno Kessler Foundation (FBK), Trento, Italy
Email: (mcodiglione, rbeber, remondino)@fbk.eu - Web: https://3dom.fbk.eu

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ABSTRACT:
Point clouds are widely used in domains such as urban planning, heritage conservation, and forestry. They often present challenges related to processing, semantic enrichment, and querying due to their large size and complexity. This paper introduces a general ontology-based approach, embedded into a tool named 3Dont, that enhances the semantic structure and usability of point clouds across various fields. By representing the individual points of a clouds within an ontology, we enable easy access to dynamic, semantically rich, and highly queryable datasets that integrate multi-source and multi-temporal data. This methodology provides a spatially consistent and user-friendly representation, allowing for intuitive exploration and analysis through ontology-based queries. The approach facilitates data interoperability and high-level feature extraction, offering a versatile tool for diverse 3D data applications. A video showcasing the capabilities of the 3Dont tool is available at https://www.youtube.com/watch?v=Nvg2E755JNg.

1. INTRODUCTION

The management of large 3D datasets, such as point clouds, is often highly expensive in terms of processing time and needed hardware. In particular, when such datasets regard complex urban scenarios, they usually present significant large spatial dimensions and lack an efficient way to be explored and queried. Moreover, since such datasets should be an aid to the general picture of the "smart city", they should (1) be available for an efficient and intuitive semantic enrichment, (2) be explored with expressive and yet highly human readable queries and (3) be able to integrate different multi-source and multi-temporal data.
Those needs stem from the specific meanings of the smart city concept, where (1) the domain to be modelled is a dynamic city, perceived as composed by objects (i.e. houses, trees, etc.) rather than single points, (2) the data user can miss specific skills in managing complex 3D datasets and (3) the employed data are multi-sources and multi-temporal. It's worth to note that similar needs also apply for the heritage sector, with a decrease in the centrality of largeness issue balanced by an increase of the needed precision and detail.
A significant amount of urban 3D datasets comes in the form of point clouds (Zolanvari et al., 2019; Kölle et al., 2021; Han et al., 2024; Nex et al., 2024). Unstructured point clouds, enriched with colour or semantic information are a fundamental asset for urban planning, management and visualization. Semantically enriching point clouds (Zhang et al., 2019; Xie et al., 2020; Grilli et al., 2023; Bayrak et al., 2024) is the first necessary step in that direction, but we argued that a lot more could be done to address both a full exploitability and query explorability of such datasets. Ontology have seen some usage in the urban 3D data field (Falquet et al., 2009), but they have never been proposed in the spatially-consistent way that we are going to discuss in this paper.

1.1. Paper aims

In our previous work (Codiglione et al, 2024), we presented an intra-domain generalizable and spatially consistent ontology-based method to transform heritage point clouds from raw data into more useful and meaningful information.
In this work, we aim to extend the scope of this heritage-based ontology method to urban point cloud data, generalizing the approach for inter-domain applications and tackling the issues of object-level modelling, different data integration and multi-temporal analyses. The core idea is to offer a dynamic, semantically rich, easy to query and data-integrating alternative representation of an urban (but not only) point cloud in the form of a spatially consistent ontology, as well as to provide a tool - named 3Dont - to unitarily manage all those processes.

1.2. Novelties in 3D data management

The innovation we aim to bring in 3D data management is multifold. The first one leads to better 3D data inspection. A traditional standard tool for 3D data inspection allows a semantic inspection by selecting/activating a scalar-field and then fixing a certain range over its values. It is generally not possible to perform cross-inspections over more scalar-fields and it is not possible to perform syntactical queries. We aim to provide those possibilities in such a way that the dataset could be fully explored with queries which can map the logic structure of the questions the user needs to ask. The second innovation is the semantic enrichment of a geospatial dataset. At the present time most solutions rely on (i) machine learning approaches or (ii) manual annotations. These approaches have their upsides, but they both lack the possibility to link the semantic information contained in the dataset with expert domain knowledge (e.g. physical-chemical properties of materials). Moreover, machine learning solutions lack in explainability, while annotation-based solutions are time-consuming and subjective to operator expertise. Our ontology-based approach aims to tackle these issues, allowing for explainable, knowledge-based and automatic high-level features generation.

2. THE ONTOLOGICAL APPROACH

2.1. Ontology concept

Formal ontology, originally born as a branch of analytic philosophy, has found its applied usage in the project of semantic web and as a useful framework for organizing data with a knowledge-based approach (Grimm, 2009). Nowadays structured data sharing and semantic interoperability have become essential for advancing scientific research across various domains. RDF (Resource Description Framework) ontologies (W3, 2024) provide a robust framework for representing knowledge in a way that both humans and machines can interpret. An RDF ontology defines a set of concepts and their relationships within a particular domain, enabling consistent data annotation, integration, and reasoning (this is the case for the so-called "domain ontologies") or on a more general level, directly tackling the issue of data integration and interoperability (this is the case for "foundational ontologies"). By utilizing a subject-predicate-object model, RDF ontologies create a flexible yet formal structure for encoding complex information, facilitating seamless data exchange and analysis. Through the formal definition of classes, properties and constraints, the ontology offers a shared vocabulary that can be easily extended and reused across different research directions. Ontologies comprise:

a) a hierarchical tree of classes;
b) a set of properties and relationships;
c) a set of individuals with populate the classes and bear properties and relationships;
d) a set of inferential rules which aim to extend knowledge and check for inconsistency (Hmida et al, 2012).

2.2. Ontology-based approaches to 3D data

Flotyńsky and Walczak (Flotyński et al, 2017) reported a taxonomy of some existing ontology-based approaches to 3D data. Even if the article is now some years old, the classification scheme can still be considered representative. The first main subdivision lies between modelling-oriented approaches and representation-oriented approaches. The first category comprises approaches (Kalogerakis et al, 2006; De Floriani et al, 2007; Papaleo et al, 2007; Kapahnke et al, 2010) which utilizes ontologies with the aim of driving a 3D modelling activity. The approaches in the second category, to which our proposed method belongs, aim to provide a semantic representation of 3D data by leveraging an ontology as a part of their pipeline. This second category is then split into two branches. The first one regards the "concrete" approaches (Kalogerakis et al, 2006; Bille et al, 2004; Falcidieno et al, 2004; Albertoni et al, 2005), which work on extremely low-level geometrical features and focuses on the general domain of the 3D data in their generality. The second one, to which our method belongs, comprises the "conceptual" approaches (Pittarello et al, 2006; Otto, 2005; Gutierrez et al, 2007), which are more domain-specific and aim to higher-level features. Although different in terms of domains, our approach shares some peculiarities with Gutierrez et al. (2007). Both aim to extract higher-level features on the basis of lower-level ones, to obtain the latter by connecting domain knowledge to the 3D data and to use these features to directly enrich the 3D model. Main differences are the kind of concerned 3D data (we deal with point clouds),the way in which these data are handled (as a proper "ontology-based representation" for us, without intermediate external layers) the specific focus of the approaches (we aim to a representation able to sustain multi-source and multi-temporal data import) and the generalization possibilities (our approach is "generally specifiable", since our tool is able to manage different domain-specific ontologies).

3. METHODOLOGY

The ontological representation is developed within an ad hoc python tool - named 3Dont - which manages all the different processes (import of the point clouds and possible rasters layers, semantic rules application, object-based level generation, etc.). This tool automatically parses the selected ontology in order to recognize object-level structures and map classification scalar-field on ontology's set of classes. This feature grants a practical generality to our ontological approach to 3D data. This generality develops in two different layers: (i) the tool is able to manage different domain ontologies; (ii) every domain ontology can be populated with whichever dataset relates to the concerned domain. Moreover, the tool also grants the execution of external semantic inferential rules, which has been preferred over the traditionally employed reasoner-based SWRL (Semantic Web Rule Language) reasoning. This is due to the limiting aspects of OWA (Open World Assumption) which characterizes most of the traditional ontology's reasonings. We then rely on a Virtuoso Open Source Edition local server for indexing the elements of the ontological representation and for querying. Results can be visualized in any point cloud viewer, such as Cloud Compare (2024).

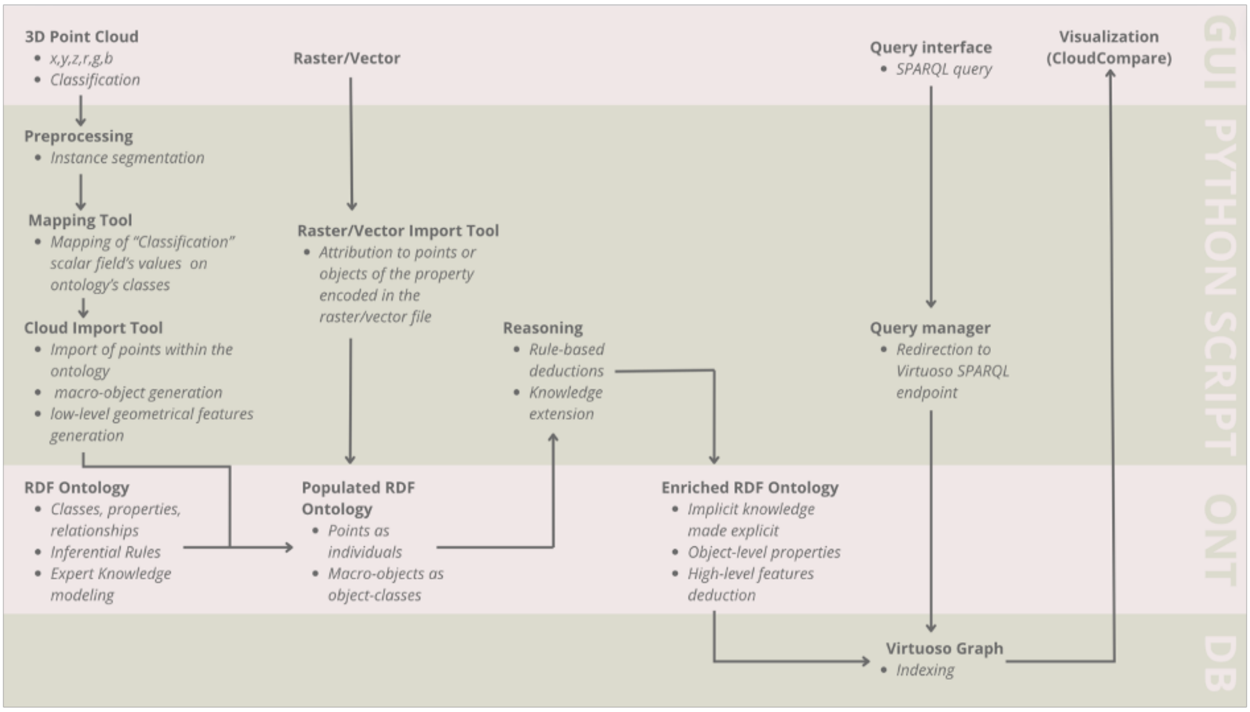

Figure 1. Schematization of the proposed ontology-based approach.

3.1. Structure of our domain ontologies

To be compatible with our approach and our 3Dont tool, domain ontologies have to be modelled according to a certain defined structure. We are not going to present every technical detail, but we will display the general structure.
The domain ontologies have four main class branches:

i. **Points**: a class whose subclasses contain points as individuals and represent the various classes of the ontologies. Every class is annotated with an ID number and a mereological tag, both useful for parsing and mapping. In this branch we would find, for example, "*Building_points*" as the superclass of "*Column_points*".
ii. **Macro-Objects**: a class whose subclasses contain individuals standing for the macro-objects and represent the various typologies to which macro-object can belong. In this branch we would not find "*Type_Building*" as the superclass of "*Type_Column*", but rather "*Type_Building_Part*", since, while a column point is also a building point, a column is definitely not a building. The IDs are present here too, allowing for identification of correspondences between the two branches.
iii. **Acquisitions**: this branch contains individuals standing for the single imported records of the various properties. It enables for metadata attribution to single acquisitions and therefore for multi-temporal analyses.
iv. **Predicates**: while some properties can assume a certain value over a numerical range (i.e. "temperature"), some others are better conceived as relations between individuals (i.e. "being made of"). The object predicates to which predicates can refer are modelled as individuals within this branch. We would here find individuals such as "marble". This allows for the attribution of properties (i.e. "solubility") to these predicates, enriching the implicit knowledge concerning them.

The structures between macro-objects are realized by mean of object relationships, while the data properties represent both the low-level and object-level numerical features.

3.2. The 3Dont pipeline

The proposed method relies on an ad-hoc python tool which manages the whole workflow and performs the following steps:

1. Modelling of a domain ontology using Protégé (Protégé, 2024) dedicated to a specific scenario (e.g. urban, heritage, forestry, etc.). This includes:
   - Definition of a hierarchical tree of classes (e.g. Surfaces, Objects, Immovable Objects, Movable Objects, etc.), a set of materials, relationships and properties;
   - Definition of a set of python external semantic inferential rules (e.g. rules for Flooding Risk Index or for macro-objects' average temperature calculation, etc.).
2. Pre-processing of the point cloud, i.e.:
   - Selection of the concerned domain ontology;
   - Mapping of the classification semantic information into the ontology's set of classes;
   - Point aggregation for each class in order to generate macro-objects instances (e.g. Building 1, Building 2, Tree 1, etc.).
3. Importing the point cloud within the ontology, i.e.:
   - Generation of a duplicate of the ontology which will be populated by the points of the point cloud;
   - Generation of an individual for each point and for each macro-object;
   - Institution of part-whole object relationships between such macro-objects, generating a mereological tree. (mereological = "concerning part-whole relationships");
   - Institution of object relationships between points and objects they belong to;
   - Application of geometrical inferential rules about macro-objects spatial relations and dimensions (e.g. Object A is on Object B);
   - Upload of the ontology within a local multi-functional database engine (Virtuoso Open Source Edition) provided by OpenLink Software.
4. Importing rasters within the ontology, i.e.:
   - Import of the raster-encoded values within the ontology, in the form of point-level property values or relationships with materials;
   - Application of the semantic inferential rules (1b) on the basis of the newly integrated data in order to generate high-level properties;
   - Upload of new data in the local Virtuoso quad-store.
5. Querying the ontology using two complementary approaches, i.e.:
   - Use a SPARQL-based query system:
   - Write a SPARQL query leveraging the ontology explicit vocabulary;
   - Execute the query on the local indexed Virtuoso quad-store;
   - Project the query results over the original point cloud using a scalar-field-like visualization;
   - Select a point-level property of the ontology (e.g. Temperature);
   - Use a certain value of the property to generate a point cloud with such values as a scalar-field;
   - Visualize the results e.g. within Cloud Compare.

The framework is realized ensuring that:

i. An ontology can be easily modified, e.g. adding new classes or properties, similarly to its rule file, e.g. including new inferential rules;
ii. For every available populated ontology, multiple rasters (with their encoded properties and semantic information) can be imported, linked to the point cloud and query;
iii. Raster data are imported considering their meaningful metadata (e.g. acquisition date) and a user-defined tag (useful for queries). This allows for multiple imports of the same property and multi-temporal analyses.

3.3. Evaluation datasets

We applied our methodology on three different datasets:

1. The USAGE dataset[1] (Beber et al., 2023) over the municipality of Ferrara (Italy) which comprises:
   - A LiDAR point cloud semantically enriched in 5 classes by FBK-3DOM research unit);
   - A RGB ortophoto;
   - Two summer thermal images, one acquired during day and one during night time;
   - A landcover raster layer with surface material information, derived from hyperspectral images.
2. The YTU3D dataset[2] (Bayrak et al., 2023) which comprises a classified (45 classes) UAV-based photogrammetric point cloud of the Yildiz Technical University (YTU) campus in Istanbul (Turkey).
3. The Temple of Neptune (Paestum, Italy) dataset which comprises a classified (10 classes) terrestrial and UAV photogrammetry point cloud of the Paestum's Temple (Grilli and Remondino, 2019).

[1] https://github.com/3DOM-FBK/USAGE_Geospatial

[2] https://github.com/3DOM-FBK/ytu3d

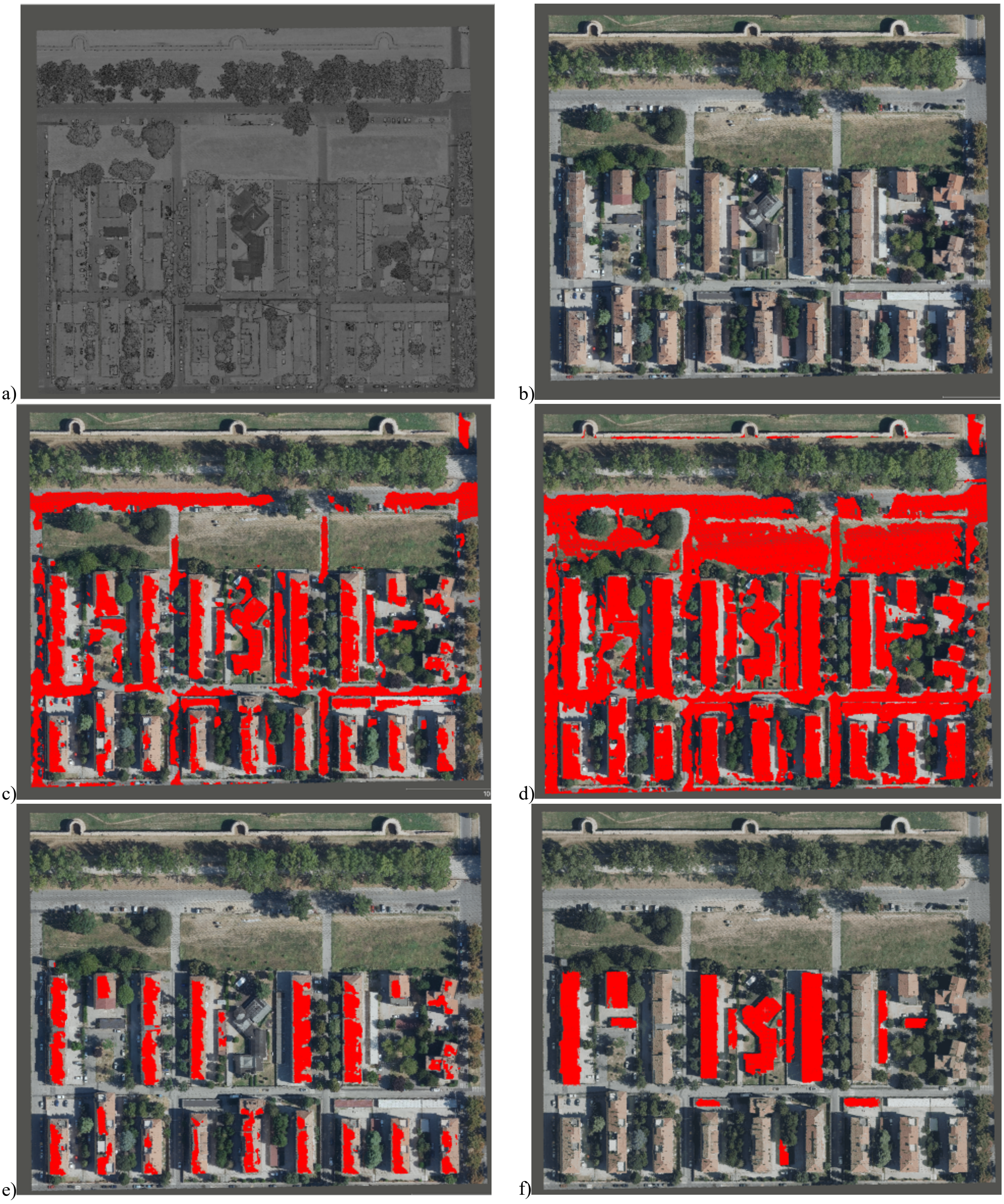

Figure 2. Ferrara dataset: Original (a) and RGB point cloud (b); Query results for points with day temperature greater than 50°C (c); Query results for points which temperature difference between day and night is greater than 20°C (d); Query results for point made of red tile, which are part of a building and which day temperature is greater that 50°C (e); Query results for building with an average day temperature greater than 50°C (f).

4. RESULTS AND DISCUSSION

Visual results of the developed urban-based ontology method to query and visualized enriched point clouds are shown in Figure 2-3 (Ferrara dataset) and Figure 4 (YTU3D dataset). For Ferrara, results show the integration of multi-source and multi-temporal data, the high-level features generation and the object-level properties generation. For YTU3D, we obtained results regarding the object-level organization and the mereological structure generation.

Moreover, to show the robustness ad replicability of the proposed methodology, 3Dont has been applied to the Temple of Neptune dataset: Figure 5 shows visual results of queries related to single construction elements.

As pointed out, traditional ontology aims to tackle the issues of interoperability, data exchange and semantic description.

This is done or by broadly describing a specific domain (i.e. domain ontologies), therefore prioritizing the semantic description, or by specifying the general relationships and types of entities which characterize human comprehension of the world, and as such focusing on the interoperability issue (foundational ontologies). The presented approach utilizes ontologies in their domain-specific declination but aims to provide them with spatial consistency. We also saw that our approach can be classified as a "representation-oriented" and "conceptual" ontology-based approach to 3D data, but that it presents traits which make it different from approaches of the same branch. The core idea of our ontology-based approach is to consider the points of a point cloud as the individuals of an ontology. For each sector (heritage, urban, etc.), we model an empty ontology to be used as a schema and for each imported 3D point cloud we generate a point populated duplicate of such ontology. Such point populated ontology can be considered as an informed representation of the imported 3D point cloud. This representation is:

- *semantically conceptualized*, since the empty domain ontology is meant to model expert knowledge of the field (comprising semantic information, such as materials physical-chemical properties - Figure 3b - and a hierarchical structure of classes, which defines the reciprocal relations within different kinds of entities);
- *dynamic*, since it generates the object-based level on the basis of the point-based one - Figure 4 and 5 - and, moving from the low-level features, it produces some useful high-level ones (such as object-level properties or the ones we called "dispositional indexes" - see the flooding risk index in Figure 3d and the heating propension index in Figure 3c);
- *user-friendly*, since it can rely both on a scalar-field-like visualization tool (e.g. Figure 3) and on a SPARQL-based query system which can leverage the ontology well-defined structure and vocabulary (Figure 3 and 4);
- *homogeneous*, which means that data coming from different sources (i.e. RGB orthophotos, thermal images, hyperspectral-based material classification rasters, etc.) and from different times can be collected within the same 3D data ontological representation (e.g. Figure 2) - using points and macro-objects as referential joins and under the same property-based ontological structure, which allows for complex queries (see Figure 2e) and for multi-temporal analyses (Figure 2d).
- *explainable*, since every entity within the ontology (points, objects, properties, relationships) is explicitly defined, it can be inspected and the rules are accessible, modifiable and algorithmically generate high-level understandable features from low-level ones.

This last aspect is the main deviating point with respect to AI-based approaches. Moreover, our ontologies detach from the traditional ones as they describe a "world of points and objects in space and time", and the properties and relationships comprised in them aim to model attributes and relations of such points.

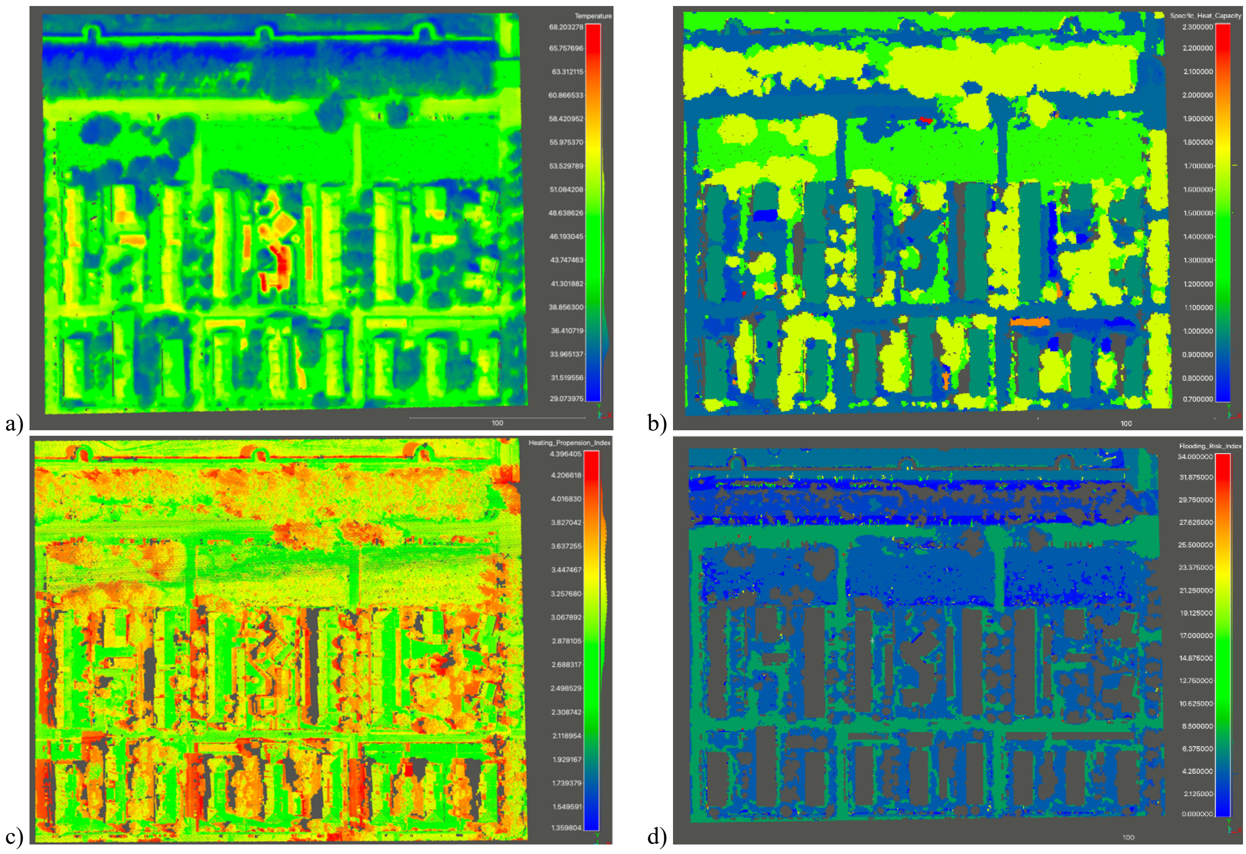

Figure 3. Ferrara dataset: Scalar-field-like view of thermal acquisition during day (a); Scalar-field-like view of specific heat capacity (b); Scalar-field-like view of Heating Propension Index (c); Scalar-field-like view of Flooding Risk Index (d).

Figure 4. YTU3D dataset: Query results for movable objects (a); Query results for buildings (b); Query results for building number 1 (c); Query results for building number 2 (d); query result for the roof of building number 1 (e); Query results for the roof pipelines on the roof of building number 1 (f).

5. CONCLUSIONS AND FURTHER RESEARCH

The paper presented the general features and some initial results of 3Dont, an ontology-based tool to organize, query and visualize semantically enriched and integrated geospatial data. In a nutshell, the core strengths of the proposed method are:

- the high human readability of data and the high controllability of the rules which generate the high-level features;
- the low-level expert knowledge that can be represented within the ontology, both in the form of materials' physical-chemical properties and in the form of explicit relationships between classes;
- the high conceptual richness that can be expressed in the queries and the ease to visualize the results;
- the possibility to utilize the ontology-based representation as a "collector" of heterogeneous data coming from different sources;
- the highly intuitive way in which points are organized in simple or nested macro-objects, which can provide a support for likewise intuitive queries.
- the high generality of the approach, which can be applied to all sort of 3D data as long a dedicated domain ontology is available.

A demo of the developed methodology is available in this video: https://www.youtube.com/watch?v=Nvg2E755JNg

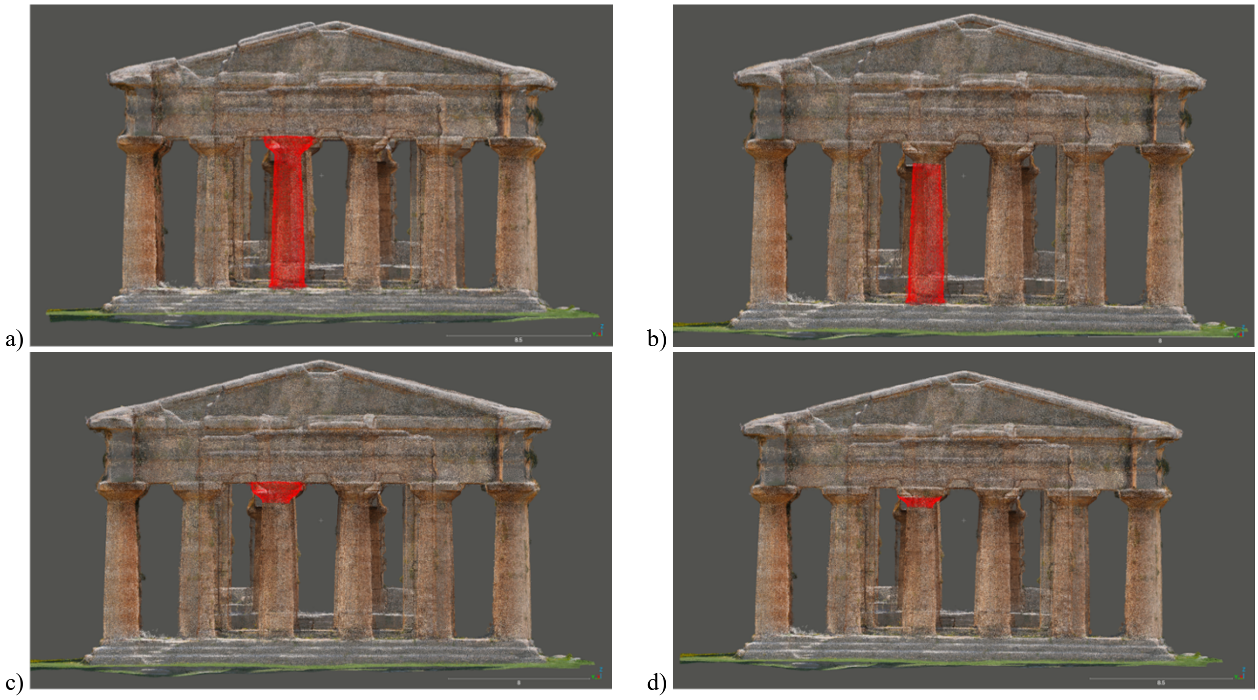

Figure 5: Query results on the Neptune Temple dataset for column number 49 (a), shaft of column number 49 (b), capital of column number 49 (c); and echinus of the capital of the column number 49 (d).

The presented methodology is a proof-of-concept research work, it does not undermine its technological validity. In particular, what should be brought forth as future work is:

- more complete domain ontologies, collaborating with domain experts, to reach further generalizations;
- a wider range of inferential rules;
- an implementation of an LLM-based query system to allow users to inspect the dataset with natural language queries which get automatically translated into SPARQL queries;
- the implementation of machine learning-based method to generate missing low-level features, particularly for cases where few raw data are available;
- a dedicated visualization tool able to read and write directly on the populated ontology, making possible visual inspection (both for point and object-level information) and manual annotation of the ontology-encoded point cloud.

Nevertheless, the method has no structural limits neither in which properties get addressed by the rules nor in how the rules are actually written.

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