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# Geographic ontology for major disasters: methodology and implementation

Abstract: During a catastrophic event, the International Charter<sup>1</sup> "Space and Major Disasters" is regularly activated and provides the rescue teams damage maps prepared by a photo-interpreter team basing on pre and post-disaster satellite images. A satellite image manual processing must be accomplished in most cases to build these maps, a complex and demanding process. Given the importance of time in such critical situations, automatic or semiautomatic tools are highly recommended. Despite the quick treatment presented by automatic processing, it usually presents a semantic gap issue. Our aim is to express expert knowledge using a well-defined knowledge representation method: ontologies and make semantics explicit in geographic and remote sensing applications by taking the ontology advantages in knowledge representation, expression, and knowledge discovery. This research focuses on the design and implementation of a comprehensive geographic ontology in the case of major disasters, that we named GEO-MD, and illustrates its application in the case of Haiti 2010 earthquake. Results show how the ontology integration reduces the semantic gap and improves the automatic classification accuracy.

Keywords: Information retrieval, major disasters, ontology, ontology web language (OWL), reasoning, semantics.

#### 1. Introduction:

The world is facing a growing number of natural and artificial disasters and various organizations are making more effort in the disaster management field to bring new solutions for emergency response.

Rapid disaster-related information discovery and integration is a critical step for effective decisionmaking. The integration of geographic information can provide important knowledge relating to the disaster, smooth the progress of the relief operations, and provide better damage assessment.

In recent years, ontology has become one of the most important areas of interest in the geographic information science. Directly or indirectly, ontologies specify the composition, structure, and basic properties of the simplified worlds that our models represent and clarify the intended meanings of the terms we use [1].

Ontologies can be used for the identification and association of concepts related to a specific domain, their properties, and their relationships. The presentation of knowledge through ontologies is a solution to identify hidden knowledge and resolve semantic gap problems. Ontology has been recognized as an effective solution to overcome semantically related problems.

<sup>&</sup>lt;sup>1</sup> http://www.disasterscharter.org/

In this work, we design and build a geographic ontology for major disasters to perform semantic classification and damage assessment in the case of a major disaster.

The remainder of this paper is structured as follows. Backgrounds on geographic ontologies, land use, and land cover classification systems and related work are provided in Section 2. Methodology and ontology description are presented in Sections 3 and 4 respectively, followed by a discussion in Section 5. Section 6 presents an application on Haiti 2010 earthquake, and finally conclusion and indicators for future work are given in Section 7.

#### 2. Background and related work:

The term "Ontology" was employed with different denotations in a number of fields; it was originally derived from philosophy where an ontology is "a systematic account of Existence". Ontology was initially introduced in Artificial Intelligence field by Gruber [2] as "an explicit specification of a conceptualization". Uschold and Gruninger [3] gave further clarification about this conceptualization: "an ontology necessarily entails or embodies some sort of world view with respect to a given domain which is often conceived as a set of concepts, their definitions, and their inter-relationships; this is referred to as a conceptualization. Such a conceptualization may be implicit; the word `ontology' is sometimes used to refer to this implicit conceptualization. However, the more standard usage is that the ontology is an explicit account or representation of a conceptualization".

Alberts [4] brings in the notion of taxonomy in ontologies: "an ontology for a body of knowledge concerning a particular task or domain describes a taxonomy of concepts for that task or domain that define the semantic interpretation of the knowledge". Whereas Guarino [5] introduces the logical theory in ontologies: "an ontology is a logical theory that constrains the intended models of a logical language".

Given that ontologies must be as formal as possible, a logical formalism is often used to represent them, e.g. description logic (DL), thus enabling us to define rules of inference on a given domain yielding the discovery of implicit and hidden knowledge and allowing semantic representations about real-world knowledge.

Despite the philosophical nature of the term "ontology", and the theoretical definitions outlined above, Buccella [6] chooses to explain this expression by using a simple mathematical representation drawn from definitions proposed in the literature: *Definition.* An ontology  $\mathcal{O}$  is a 4-tuple { $\mathcal{C}, \mathcal{P}, \mathcal{I}, \mathcal{A}$ } in which  $\mathcal{C}$  is a set of classes,  $\mathcal{P}$  a set of properties,  $\mathcal{I}$  a set of instances, and  $\mathcal{A}$  a set of axioms. Classes represent the real-words entities or objects; properties accompany classes (i.e. as an attribute) or represent relations between classes (such as generalization/specialization, aggregations, compositions, etc.); instances denote the class individuals; and we specify by axioms additional constraints involving classes and/or properties.

Ontologies are often specialized and try to capture knowledge of a specific domain or subject matters, (e.g. biology, cars, animals, geography). According to Kolas et al. [7] domain ontology provides an organized, customized, and aligned knowledge representation with a specific domain and/or user.

Ontologies have not been used exclusively in the field of information system, but also in geographic information systems (GIS). Among domain ontologies, geographic ontologies are receiving increasing interest and are growing in significance [8], much effort has been devoted to this domain and more and more scientists, including geoscientists, are showing their interest in this area culminating in an increasing number of research papers that cover this subject [9-13].

Geographic ontologies represent mainly the geographic domain; however, they can be interrelated with other domains or designed according to some contexts (e.g. environment, demography, disasters). Several geographic ontologies have been developed in recent years. We can distinguish nevertheless, numerous differences in their purposes, constitutional elements (e.g. concepts, relations, axioms), and conceptualization, as some of them are directly designed from GIS, land use, or land cover systems.

Despite the large number of research papers relating to geographic ontologies, only a few recent publications addressed the hazard and disaster context.

Ontologies for disaster management were discussed in a few texts. Bernard et al. [14] present a use case from the area of disaster management (e.g. flooding); they propose the use of well-defined ontologies concepts for intelligent search, semantic translation, and semantic integration. Klien et al. [15] combined ontology-based metadata with an ontology-based search for finding geographic information services to estimate potential storm damage in forests. They focused their work on the mechanisms of semantic matchmaking by means of terminological reasoning and used description logic as a representation language. Xu and Zlatanova [16] present a hybrid ontology in risk prevention and disaster management domain, specifically in the field of seismic risk. Roman et al. [18] developed an ontology named InfraRisk to assist publishing and integration of data about transport infrastructure failures in case of natural hazard events. Zong et al. [19] proposed an ontology representation of meteorological disaster system. Trucco et al. [20]

developed a critical infrastructure systems ontology, and hazards and threats ontology, connected through vulnerability and interdependency models as a multi-dimensional hazards catalogue for critical infrastructure to support risk assessment, Alirezaie et al. [21] presented a framework named SemCityMap in which satellite images are classified and augmented with additional semantic information to enable queries about finding paths on a particular location in a disaster situation (simulation of flood) using existing ontologies and a developed ontology named OntoCity.

Another part of the work in this area was focused on the use of the semantic web and the web services [22-25]. Athanasis et al. [22] present a methodology for knowledge discovery in geographic portals based on the Semantic Web with an application in an experimental geoportal about natural disasters for the dissemination of geospatial information concerning wildfires and floods for the region of northern Aegean Archipelago (Greece). They exploit the Resource Description Framework (RDF) to describe the geoportal's information with ontology-based metadata. Babitski et al. [23] propose to support sensor discovery and fusion by semantically annotating sensor services with terms from a defined ontology called Geosensor Discovery Ontology (GDO). The GDO defines a terminology suitable for describing sensor observations and related entities in the context of disaster management.

Zhang et al. [24] propose a framework for automatic search of geospatial features using geospatial semantic web technologies and natural language interfaces with an ontology-based knowledge base to help emergency responders and disaster managers find needed geospatial information at the feature level. The prototype allows the emergency responders to query the ontology-based knowledge base using natural language. Chou et al. [25] focus on natural disasters and develop an ontology structure of elements identified from an inventory of Web pages drawn from natural disaster management websites for Web-based natural disaster management systems. The selected semi-structured data representation approaches are used to organize the resulting ontology structure which is further coded into a Web-based system allowing online access.

Despite the application domain, each author has a different view of the problem, and the use of the ontology varied both in the purpose and the techniques. Most of the studies were focused on the disaster and emergency management process, with a concentration on only a specific disaster. Literature shows that there are still visible limitations, and several issues have not been addressed. A global ontology that includes all major disasters categories with the integration of geographic information does not exist and further research in such a critical domain that involves saving human lives should be pursued.

#### 3. Methodology:

A list of techniques and approaches have been stated for ontologies developing [26]. We based ours partially on a conventional methodology of building ontologies [27] with a customization for more flexibility in this work.

#### 3.1 Purpose definition:

It is important to have a clear idea of the purpose for which the ontology will be built and its use. This has a direct impact on the domain, context, and vocabulary choices.

The main purpose of this work is to set a geographic vocabulary for major disasters context. The formal representation of the domain knowledge will be useful for automatic satellite images processing, to assist the photo-interpreters in their data treatments and accelerate the relief operations in a crisis situation. The ontology can be reused for semantic content representation of satellite images, for change detection, as well as for performing queries related to the emergency needs.

#### 3.2 Existing ontologies reusing:

Ontologies are designed to be used as a representation model due to their reusability capabilities. A number of standard and upper-level ontologies with a controlled vocabulary are available for reusing. For this work, we started developing our ontology from scratch, however, we came to update it eventually by merging two upper-level ontologies into it, namely GeoSPARQL and OWL-Time, for two important aspects in our work: space and time, and their general representation of these two properties.

#### 3.3 Knowledge acquisition:

The first step in knowledge representation is domain concepts acquisition by conducting an effective ontological analysis of the area of interest.

Ontological engineering is not an easy task since it requires a deep understanding of the domain knowledge. Usually, knowledge engineers are deficient in specific domain knowledge; on the other hand, domain experts do not have the required technical expertise to develop a model of formalized knowledge. We attempt in this work to incorporate the two tasks in the context of geographical knowledge.

We have examined several land cover and land use based-ontologies, in addition to several existing geographic ontologies. This section describes three well-known land cover and land use systems with their corresponding ontologies.



Figure 1. Part of Corine Ontology

(a) Corine Land Cover:

CO-ordination of INformation on the Environment is a European program produced by the European Commission from 1985 to 1990 establishing an inventory of the land cover of 38 European countries to generate the European environmental landscape based on the interpretation of satellite images and auxiliary data. A first version was produced in 1990 [28], followed by two versions in 2000 [29] and 2006 [30] respectively. Corine is organized along three levels, with 5 classes in the first level, 15 classes in the second, and 44 classes in the third level. In this paper, we reviewed the OWL Corine land cover-based ontology <sup>2</sup> (see Figure 1).

#### (b) USGS

The Anderson Land Use and Cover Classification System [31] has been developed by The United States Geological Survey (USGS) for remote sensing data use. Initially developed to meet the needs of Federal and State agencies with four-levels of land use and land cover overview of remote sensor data throughout the country. The first and second levels are generalized whereas the third and fourth levels are left open-ended so that other regions can have flexibility in developing more detailed land use classifications in order to meet their particular needs nevertheless remain compatible with each other and the national system [31]. We reviewed the OWL USGS based ontology <sup>3</sup> (see Figure 2a).

<sup>&</sup>lt;sup>2</sup> http://harmonisa.uni-klu.ac.at/ontology/corine.owl

<sup>&</sup>lt;sup>3</sup> cegis.usgs.gov/owl/USTopographic.owl



Figure 2. (a) Part of USGS Ontology and (b) Part of LBCS Ontology

#### (c) LBCS

Land Based Classification Standards (LBCS) [32] is a detailed land use that was developed by the American Planning Association standard. LBCS offers a cutting-edge classification of urban space in five dimensions: activity, function, properties, site, and structure. LBCS has as purpose to provide semantic descriptions of geo-referenced spatial data. Montenegro et al. [32] present an OWL ontology based on the LBCS which we have analysed in this work (see Figure 2b).

#### 3.4 Analysis, conceptualization and knowledge formalization:

Modelling geographic ontologies should consider the nature of geographical objects which are subject to change, exhibit a variation of properties and values, and are basically tied to space and time. For this reason, the task of defining geographical concepts, relationships between them, and axioms, requires a comprehensive analysis of the semantics of what constitutes the geographical space.

Analysis of the existing land cover and land use systems, standards in the field, as well as several existing geographic ontologies, helped us to understand the semantics of concepts, relationships between them, and their properties, and allowed us to decide which concepts are most relevant to the context, with the relationships, properties, and axioms to define. This process can be quite a lengthy one, but it is essential for an effective ontology modelling.

Concepts, relationships, and axioms of the ontology are described and discussed in the following section.

#### 4. GEO-MD Ontology:

GEO-MD is an OWL geographic ontology with major disasters background. We built the ontology using Protégé 5.2 framework and developed with OWL-DL (Ontology Web Language Description Logics) where available reasoners can be used to check its consistency and deduct implicit relationships between the defined concepts.

# 4.1 Concepts:

Geographic ontology must cover a set of geographic concepts. Domain ontologies are often derived from a specific context, for this reason, their concepts share a dependent conceptualization of the processed context.

In our case, the geographic ontology addresses the context of major disasters. Ontology concepts should cover the geographic area with consideration to major disasters.

For this reason, we defined three sub-ontologies: (i) surface area, (ii) disaster, and (iii) damage. These are interconnected together with semantic, temporal and spatial relationships (Figure 3).

#### (a) Surface

Surface mainly includes geographic concepts, with five hierarchical levels; it represents the largest part of the ontology concepts. Concepts were defined after carefully analysing land cover and land use classification systems, in addition to a set of geographic ontologies. Some existing concepts were generalized/specialized according to our needs and their necessity for the subject matter, whereas new concepts were set.

#### (b) Disaster

Disaster includes major disasters concepts; we were inspired by the natural disaster classification in [33]. We appended to this three man-made disaster classes. Accordingly, disaster concepts were divided into two large major classes: Manmade and Natural disasters (see Table 1).

Some specific disaster categories have not been taken into account in this work since they are not included in the International Charter "Space and Major Disasters".



Figure 3. GEO-MD Sub-Ontologies Relations

Table 1. Disaster Concepts.

| Level 1          | Level 2         | Level 3       | Level 4        |
|------------------|-----------------|---------------|----------------|
| Manmade          | Accident        |               |                |
|                  | Oil split       |               |                |
|                  | Power explosion |               |                |
| Natural disaster | Geophysical     | Earthquake    | Ground shaking |
|                  |                 |               | Tsunami        |
|                  |                 | Landslide     |                |
|                  |                 | Volcano       |                |
|                  | Hydrological    | Flood         |                |
|                  |                 | Mass movement |                |
|                  |                 | Ocean wave    |                |
|                  | Climatological  | Forest fire   |                |
|                  | meteorological  | Storm         |                |
|                  |                 | Hurricane     |                |
|                  |                 |               |                |

#### (a) Damage

Damage contains concepts of damage following a disaster. Several damage-assessment evaluations have been defined by different organizations, table 2 summarizes five of the most knows building and structure damage assessment categories, a chart for describing the building damage patterns by seismic vulnerability was given in [34], and a combined wind and Flood (WF) damage scale was proposed by Womble et al. [35]. However, most of these assessments are only concerned with building damage, and in some cases, structural damage. This does not include damage caused by other types of disasters such as wildfire and oil spill, which do not cause necessarily damage to structures.

Thus, two damage classes were included in this sub-ontology: (i) Land cover damage, which covers damage to the ground cover, and (ii) Material damage, which includes structural damage. For the latter, we opted for the evaluation described in [36] with an adjustment.

Given the complexity of distinguishing damage classes within a satellite image due to several parameters that interfere in the classification process, and consequently, its results, such as satellite image spatial resolution, off-nadir angle, and shadow, we have clustered the damage classes into three classes instead of five (see Table 3).

| Table 2. | Example | of | existing | damage | scales |
|----------|---------|----|----------|--------|--------|
|          |         |    | 0        | 0      |        |

| Туре                     | Organisation                           | Class<br>N° | Damage scale | Meaning                     |
|--------------------------|--|-------------|--------------|-----------------------------|
| Masonry building         | EMS-98                                 | 5           | Grade 1      | Negligible to slight damage |
|                          |  |             | Grade 2      | Moderate damage             |
|                          |  |             | Grade3       | Substantial to heavy damage |
|                          |  |             | Grade 4      | Very heavy damage           |
|                          |  |             | Grade 5      | Destruction                 |
| RC building              | Architectural Institute of             | 5           | Range 1      | Negligible damage           |
|                          | Japan                                  |             | Range 2      | Slight damage               |
|                          |  |             | Range 3      | Moderate damage             |
|                          |  |             | Range 4      | Major damage                |
|                          |  |             | Range 5      | Destruction                 |
| Wood frame buildings     | Japan Prime Minister's                 | 3           |              | Moderate damage             |
|                          | Office                                 |             |              | Heavy damage                |
|                          |  |             |              | Major damage                |
| Structure                | WHO Damage<br>Assessment Form          | 5           | <25%         | Minor structural damage     |
|                          |  |             | >25%         | Some structural damage      |
|                          |  |             | >50%         | Significant structural      |
|                          |  |             | >75%         | damage                      |
|                          |  |             | 100%         | damaga                      |
|                          |  |             | 100%         | Structure is unusable       |
| Residential Construction | Womble, 2006                           | 4           | WF-1         | Minor Damage                |
|                          | ······································ |             | WF-2         | Moderate Damage             |
|                          |  |             | WF-3         | Severe Damage               |
|                          |  |             | WF-4         | Destruction                 |

# Table 3. Damage concept hierarchy

| Level 1           | Level 2                  |
|-------------------|--------------------------|
| Land cover damage | Extend of affected land  |
| Material damage   | Minor/Some damage        |
| -                 | Major/Significant damage |
|                   | Collapse                 |

#### 4.2 Merging upper level ontologies:

In addition to our defined ontology vocabulary, two upper level ontologies have been merged into GEO-MD to cover the spatial aspect of the satellite images and the temporal aspect of a disaster situation by reusing GeoSPARQL and OWL-Time respectively. The two ontologies have been merged into our ontology and a set of properties have been created to link the different classes (see figure 4).

# (a) GeoSPARQL

The GeoSPARQL standard supports representing and querying geospatial data on the Semantic Web. It defines a vocabulary for representing geospatial information in RDF/OWL, and a SPARQL query language for processing geospatial data.

The GeoSPARQL [37] contains several different components including top-level classes of spatial objects, a topology vocabulary defining properties, and a geometry components for data types.

#### (b) OWL-Time

OWL-Time is an OWL-2 DL ontology of temporal concepts, for describing the temporal properties of resources in the world. The ontology provides a vocabulary for expressing facts about topological relations among instants and intervals, together with information about durations, and about temporal position including date-time information [38].

#### 4.3 Relations and properties:

We defined a set of semantic, spatial and temporal relationships in the ontology (see Table 4). We were inspired by the relationships defined in [39, 40], the representation in [41], and the metamodel in [42]. However, we only chose the relationships that we deemed relevant for this work, nevertheless, they remain subject to enrichment. We specified a set of semantic properties (see Table 5) in order to semantically enrich the ontology.



Figure 4. Ontologies class linking

# 4.4 Axioms:

It is important to specify constraints on classes and properties. To do this, we must first understand the constraints of the domain knowledge and formally express them. Since we use a logical formalism, the axioms will play an important role in logical reasoning, hidden knowledge inference, as well as performing problem-related queries.

A set of axioms were defined in this ontology.

For example, to specify land cover damage caused by a set of disasters:

LandCoverDamage isCausedBy some

(Flood or ForestFire or MassMovement or OilSpill or PowerExplosion)

Or to specify tsunami characteristics:

Tsunami (borders some Sea/Ocean) and (damages some ArtificalSurface) and (hasMagnitude only float [> 0.0f, <= 10.0f]).

#### And flood:

Flood SubClassOf (nearby Some InlandWater) and submerges some (ArtifialSurface or NaturalSurface)

Semantic Relations **Spatial Relations Temporal Relations** Topologic Direction Distance Relations Relations Relations isPartOf Borders Far North Before Causes, isCausedBy Crosses Near South After Contains Equals East During Nearby Damages, Happens West Intersects At Submerges, Undergoes

Table 4. Example of GEO-MD relations

Table 5. Example of GEO-MD semantic properties

Semantic properties hasChange, hasDate, hasMagnitude hasShape, hasSize, numOfOccupents, numOfResidents

| query:                                | DL query.  |
|---------------------------------------|--|
| luery (class expression)              | Query (class expression)   |
| Residential that hasChange value true | Residential that hasChange value true<br>and<br>Residential that numOfResidents min 1000 |
| Execute Add to ontology               | Execute Add to ontology  |
| Lucry results                         | Query results  |
| Portiontial 2                         | Instances (3)  |
| Pacidential 1                         | •Residential_2   |
|                                       | Residential_5  |
| Residential_5                         | Residential_3  |
| Residential_4                         |  |
| Residential_3                         |  |

Figure 5. Example of semantic queries

# 4.5 Semantic queries:

GEO-MD uses OWL DL-query and SPARQL query to express semantic queries; those can be initially expressed in natural language, and then translated to formal expressions.

With knowledge reasoning, implicit information can be detected in formal conceptual models for geographic and hazard domain objects and relations, thus powerful queries can be performed.

An example of simple queries for the selecting of the residential buildings that have changed is given in Figure 5. In addition, we can take advantage of the defined spatial and temporal rules for reasoning over spatial and temporal relations between objects in space and change over time. These reasoning rules can be used as the deduction rules for automatic derivation of implicit spatial and temporal relations.

GEO-MD USGS Corine **Buildings: Buildings**: Building: Residential Housing Building Church Commercial Place of worship building Hospital Industrial Firm Building House **Facilities and services** Service building Post office **Transportation-related** Transportation building School

Table 6. Example of categories in geographic ontologies

| Construction site  | Construction Site Building | Stadium           |  |
|--------------------|----------------------------|-------------------|--|
| Educational        | Recreation building        | Substation        |  |
| Religious          |                            |                   |  |
| Agricultural area  | Agricultural surface       | Agricultural land |  |
| Artificial surface | Artificial surface         | Built up area     |  |
| Aquatic surface    | Water surface              | Surface water     |  |
| Forest             | Forests                    | Forest            |  |
|                    |                            |                   |  |

# 5. Discussion:

The purpose of this paper was the design and building of a geographic ontology for major disasters. As the existing land use and land cover classification systems, and geographic ontologies did not fit our need, our aim was to develop a new ontology with sufficient representative concepts to cover the geographic ontology in the context of major disasters. Our ontology was compared with some existing geographic ontologies, we instantly notice a difference in the ontologies terminologies, a class can refer to the same object but uses different terms, for example an agricultural object has different class name from an ontology to another: Agricultural Surface in Corine, Agricultural land in USGS, and Agricultural area in GEO-MD (see table 6).

| Name                       | File name                         | Organization                         | Metrics       |      |     |    |      |      | Domain/<br>Context                      |
|----------------------------|-----------------------------------|--------------------------------------|---------------|------|-----|----|------|------|---|
|                            |                                   |                                      | DL            | С    | OP  | DP | LA   | SubA |   |
| Corine                     | Corine.owl                        | HarmonISA<br>project                 | ALCF          | 272  | 33  | 0  | 1009 | 269  | Land Cover                              |
| USGS                       | USTopografic.owl                  | Usgs.gov                             | ALCH<br>(D)   | 579  | 95  | 2  | 1488 | 612  | Land<br>Use/Cover                       |
| LBCS                       | LBCS.owl                          | planning.org                         | ALCHOF<br>(D) | 985  | 6   | 3  | 3013 | 1033 | Land Use                                |
| E-<br>response             | e-response.owl <sup>5</sup>       | e-response.org                       | SHOIN<br>(D)  | 1746 | 182 | 19 | 4124 | 2147 | Emergency<br>Response                   |
| GEO-MD                     | GEO-MD.owl                        | TCM project                          | SHIQ (D)      | 169  | 88  | 11 | 265  | 189  | Land<br>use/cover<br>Major<br>Disasters |
| DLR<br>Ontology            | dlrOntology.owl <sup>6</sup>      | German<br>Aerospace<br>Center (DLR)  | ALHI (D)      | 54   | 12  | 15 | 78   | 46   | Earth Virtual<br>Observatory            |
| Fusion-<br>Topo-<br>Carto2 | FusionTopoCarto2.owl <sup>7</sup> | COGIT-IGN                            | AL            | 761  | 0   | 0  | 783  | 783  | Geographic objects                      |
| OTN                        | OTN.owl <sup>8</sup>              | Ludwig-<br>Maximilians<br>University | ALCN<br>(D)   | 180  | 36  | 75 | 583  | 299  | Transportation<br>Network               |
| FTT                        | FTT-v01.owl <sup>9</sup>          | Muenster<br>university               | AL            | 1262 | 0   | 0  | 1287 | 1287 | Geography                               |

Table 7. Overview of geographic ontologies with metric comparison<sup>4</sup>

DL: Description Logic expressivity, C: Class count, OP: Object property count, DP: Data property count, LA: Logical axiom count, SubA: Subclass of axioms count, EqA: Equivalent classes axioms count, DisA: Disjoint class axioms count.

<sup>&</sup>lt;sup>4</sup> Metrics were extracted using Protégé 5.2

<sup>&</sup>lt;sup>5</sup> http://e-response.org/ontology/e-response.owl

<sup>&</sup>lt;sup>6</sup> http://www.earthobservatory.eu/ontologies/dlrOntology.owl

<sup>&</sup>lt;sup>7</sup> http://geonto.lri.fr/ressources\_fichiers/FusionTopoCarto2.owl

<sup>&</sup>lt;sup>8</sup> www.pms.ifi.lmu.de/rewerse-wga1/otn/OTN.owl

<sup>&</sup>lt;sup>9</sup> http://ifgi.uni- muenster.de/~janowicz/downloads/FTT-v01.owl

Moreover, a close examination of the existing geographic ontologies shows that even though they seem to refer to similar categories, they often use different semantics due to their different contexts and purposes. Semantic definitions of geographic ontologies (e.g., properties, axioms) are rich sources of scientific knowledge of a domain; they play a very important role regarding ontology semantics enrichment. We attempted to define an acceptable set of properties and axioms regarding the class numbers. For 169 defined concepts, 88 object properties and 11 data properties were defined, and they are subject to enrichment.

Some existing ontologies contain a few or no semantic definitions, for example in Corine, within 272 concepts, only 33 object properties were defined, and no data property was defined, while FusionTopoCarto2 and FTT have not set any properties (see Table 7). This may be due to their initial purpose and their target use.

Nevertheless, the specificity of geographic ontology does not lie only in their geographic features, it lies overall in their semantic and spatial relationships, which was an important aspect in developing GEO-MD, in addition to the temporal relationships to cover change in time in a disaster situation which is one of the main outcomes of this research.

#### 6. Application on Haiti 2010 earthquake:

#### 6.1 Target area and data used:

A severe earthquake with a magnitude of 7 hit the southern Haiti on January 12, 2010 leaving devastating impact on Port-au-Prince, the capital of the country. The authorities reported over 200,000 casualties, thousands injured and around 1.5 million left homeless. Over 30,000 buildings were severely damaged, more than 1,300 schools, and 50 health care facilities were destroyed. Following the disaster, the International Charter was activated for rapid mapping and damage analysis.

The test site is located in Port-au-Prince, Haiti. We employed pre-disaster QuickBird pansharpened and multispectral data with 60 cm and 2.4 m resolution (Red, Green, Blue and near-infrared bands) respectively, which were acquired in February 22, 2009, and post-disaster pansharpened 60 cm resolution, multispectral 2.4 m (acquisition date January 15, 2010), and Lidar 1 m (acquisition date January 22, 2010), experimentations were performed using Protégé 5.2 and eCognition Developer 9 software.

#### 6.2 Methodology:

The methodology for this application is illustrated in figure 6. A hierarchical classification is performed together with the Surface ontology levels. First, the satellite images resolution is reduced for rapid processing (2.4 m), and a rough classification is performed after a multiresolution segmentation using Surface level 1 categories (artificial surface, aquatic surface, and natural surface). Figure 7 shows segmentation results with scale 100, shape 0.2, and compactness 0.5 and classification results.

The candidate area is then selected according to the disaster type and the potentially affected area based on the ontology semantic representation, Artificial Surface in this case has been emphasised.

The region of interest resolution is restored to the original resolution (0.6 m) and an initial classification is performed using Surface level 2 categories for both pre and post disaster satellite images after performing a multiresolution segmentation with scale 100, shape 0.5 and compactness 0.5, followed by a spectral difference segmentation with a maximum spectral difference of 30. Only low-level features are employed for the initial classification, the employed features are summarized in table 8 on the feature set.

The threshold conditions for the extracted features are specific to the data set and have been selected using a trial/error method. Built-up Area Index (BAI) which is calculated in equation (1) is used to extract Buildings and Road Network in addition to brightness and a set of shape and extent features.

$$BAI = \frac{mean Blue - mean Red}{mean Blue + mean Red}$$
(1)

Normalized Difference Vegetation Index (NDVI) in the following formula (2), and brightness have been employed to extract the Green Urban Area (Trees and Grass).

$$NDVI = \frac{mean NIR - mean Red}{mean NIR + mean red}$$
(2)

And finally, the brightness component I to extract shadow area, and Ratio b\_nir using the blue and near infrared bands to enhance its details are shown in the following formulas:

$$I = \frac{mean \, Red + mean \, Green + mean \, Blue}{3} \tag{3}$$

$$\begin{array}{l} \text{Mean Ratio}_{B_{NIR}=} & \frac{mean Blue - mean NIR}{mean Blue + mean NIR} \end{array}$$
(4)



Figure 6. Classification methodology description

The initial classification is refined based on the ontology constraints and defined semantics. Five classes are included in the semantic rule constraints for this study, the corresponding semantic rules were developed according to the test area and data set characteristics, literature, and priori knowledge, they are summarized in table 8.

At level 3, the two semantic classifications of pre and post disaster images using the same parameters are compared, and an object-based change detection is performed. Damage assessment can be accomplished at this level.

# 6.3 Results and discussion:

The level 2 initial classification results are shown in figure (8a), while the ontology-based classification results are shown in (8b). An accuracy assessment was carried out for the two classifications at this level, the corresponding error matrixes of the two methods for the test area are shown in table.

The error matrixes show how the ontology semantic rule set improved the initial classification where the overall accuracy of the ontology-based classification was 89.4 (see table 9b) compared with 67.9 for the initial classification (see table 9a).

Classes with similar low-level features characteristics produced the most drawback for the initial classification, especially the two classes Buildings and Road Network as the area of interest is an Artificial Surface, this has been improved with the ontology by adding more semantic, spatial, and class-related features to differentiate the two classes, the use of ontology significantly reduced the semantic gap between low-level features and high-level semantics.



Figure 7. Level 1 segmentation and classification results

| Table 8. Features and | semantic rule set | of 5 | classes |
|-----------------------|-------------------|------|---------|
|-----------------------|-------------------|------|---------|

| Class        | Feature set                            | Semantic rule set  |
|--------------|--|--|
| Buildings    | BAI>0                                  | Regular $\cap$ Light $\cap$ High $\cap$ Adjacent to Road             |
|              | Mean brightness > 150                  | Network $\cap$ Rel. Border to Shadow                                 |
|              | Rectangular Fit $> 0.7$                |  |
| Road Network | BAI>0                                  | Regular $\cap$ Long $\cap$ Strip $\cap$ Low $\cap$ Light $\cap$ Rel. |
|              | Mean brightness > 150                  | Border to Tree   |
|              | Length $(pxl) > 50$                    |  |
|              | Length/width $(pxl) > 3$               |  |
|              | Asymmetry > 0.8                        |  |
| Tree         | NDVI > 0.2                             | $Dark \cap Round \cap High \cap Adjacent to Grass \cap Rel.$         |
|              | Mean brightness < 150                  | Border to Shadow   |
|              | Roundness > 0.6                        |  |
| Grass        | NDVI $> 0.2$ , Mean brightness $< 200$ | Relatively light $\cap$ low $\cap$ Adjacent to Tree $\cap$           |
|              |  | Adjacent to Buildings  |
| Shadow       | Mean Brightness < 85                   | Dark $\cap$ Low $\cap$ Rel. Border to Buildings $\cap$ Rel.          |
|              | 70 < I < 190                           | Border to Tree   |
|              | Mean Ratio $_{B_NIR} > 0.21$           |  |



(a)

Figure 8. Level two classification results of the two methods

| Table 9.   | Error | matrixes | of th | he two  | methods |
|------------|-------|----------|-------|---------|---------|
| 1 4010 / . |       | mannes   | 01 11 | 10 0000 | memous  |

|           | Buildings | Road<br>Network | Trees | Grass | Shadow |
|-----------|-----------|-----------------|-------|-------|--------|
| Buildings | 4753      | 3067            | 0     | 0     | 0      |
| Road      | 1152      | 2859            | 0     | 0     | 0      |
| Network   |           |                 |       |       |        |
| Trees     | 0         | 0               | 647   | 115   | 0      |
| Grass     | 0         | 0               | 226   | 452   | 0      |
| Shadow    | 0         | 0               | 0     | 0     | 968    |

# Overall accuracy=67.9%

(a)

|           | Buildings | Road<br>Network | Trees | Grass | Shadow |
|-----------|-----------|-----------------|-------|-------|--------|
| Buildings | 6514      | 1306            | 0     | 0     | 0      |
| Road      | 197       | 3814            | 0     | 0     | 0      |
| Network   |           |                 |       |       |        |
| Trees     | 0         | 0               | 762   | 0     | 0      |
| Grass     | 0         | 0               | 0     | 678   | 0      |
| Shadow    | 0         | 0               | 0     | 0     | 968    |
|           |           |                 |       |       |        |

#### **Overall accuracy= 89.4%**

(b)

We selected a smaller area with only building mask (see figure 9) for a change detection task and applied the same ontology-based classification on pre and post disaster satellite image.

Using no elevation model, 695 buildings have been detected on the pre-disaster, while only 458 buildings have been detected on the post-disaster same area, which means the collapse of 237 according to the classification. A profounder object-level comparison for each object of Buildings class can be performed for a damage assessment. However, due to the nature of buildings in Haiti, which are not well structured, and the complexity of the task, we could not perform a full damage assessment of the area in this work. As our objective was to represent the ontology and show its general application on a disaster situation, change detection and damage assessment will be subject for future work.



Figure 9. Buildings classification before and after the earthquake

## 7. Conclusion:

In this work, we attempted to resolve the problem of semantics in geographic and remote sensing data, by developing a global geographic ontology that provides a referential geographic vocabulary and an inclusive taxonomy in the context of major disasters and assist the semantic classification of satellite images at various scales.

The ontology consists of three parts: surface, disaster, and damage which are jointly interconnected with semantic, temporal and spatial relationships for semantic reasoning and inference. The first sub-ontology "Surface" includes geographical concepts with five hierarchical levels, that can represent satellite imagery with multi-resolution and at different scales. Each level gives a complementary content description of the satellite image according to our need. Surface concepts were defined after a careful analysis of the existing land use and land cover classification systems (i.e Corine, USGS, LBCS), in addition to a set of geographic ontologies. The second sub-ontology "Disaster" includes the totality of the disasters included in International Charter. The concepts were further divided into two main classes: Manmade and Natural. Finally, the third sub-ontology "Damage" includes the concepts of damage following a disaster with two sub-classes: Land cover damage, which covers damage to the ground cover, and Material damage, which includes structural damage. The interaction between the three sub-ontologies and the semantic reasoning will highly guide the specific use of ontology like reducing the area of interest in the satellite image for a semantic classification.

We attempted in this work to design the OWL ontology in a straightforward, yet representative way regarding the geographic domain and the major disasters context. On one hand, it is important that the ontology concepts are semantically rich and sufficient to describe the geographical area, on the other hand, the ontology has been primarily designed to describe the content of satellite images, the concepts of the ontology will play the role of classes, a large number of classes may create complexity for an automatic process.

Relationships are an integral part of an ontology, they serve to define the relationship between the concepts of ontology, we have defined in this work a set of semantic relations, but also spatial relationships, considering the quality of the treated area where the notion of space is very important, and temporal relations given that the spatial objects are subject to change particularly in disaster context, where changes are very important. In addition, we enriched the domain ontology with semantic definitions (e.g., properties, functions, axioms).

A demonstration of the ontology practice with experiments on Haiti earthquakes using multispectral very high-resolution satellite images shows how the integration of the ontology improved the classification results and reduced the semantic gap between low-level features and high-level ontology-driven semantics.

The ontology will be shared and serve as a geographical vocabulary basis in context of disaster for other purposes, it can be used in whole or as parts.

For future work, and as well as improving the ontology in terms of a comprehensive domain representation, we will be looking for its applications into other areas. Of particular interest is the ontology-based semantic annotation of satellite images [43], change detection, and response to queries related to emergency needs, such as the location of hospitals compared to affected areas, detecting operational roads, and location of the highest priority areas (schools, residential buildings, etc).

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