Towards a Semantic Understanding of very High-Resolution Satellite Images: the Case of Major Disasters

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This dissertation is submitted for the degree of

Doctor of Philosophy

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Cheltenham, UK July 2022

To Adam and Myriam: my two beloved little ones, to my loving parents, to my husband, to my brother, and my twin sisters for their endless love, support, and the encouragement they have given me during the research and thesis writing periods…

Declaration

I hereby declare that, except where specific reference is made to the work of others in both text and references, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other University.

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July 2022

doi: 10.46289/KP51PK99

Abstract

The lack of knowledge on damage extent and damage level of affected areas following a major disaster impedes the delivery of the necessary support in guiding rescue teams on the ground, delimiting the extent and level of damaged buildings, spotting the best location for refugee camps, and selecting effective access roads. The increased accessibility of VHR satellite imagery offers new perspectives for the remote sensing and disaster management communities. RS technologies allow fast, effective, and accurate observations of the affected areas. However, these observations need to be rapidly inspected and interpreted to deliver the necessary support. The International Charter "Space and Major Disasters" is activated for this purpose to provide the rescue teams with ready damage maps prepared by means of manual processing and interpretation of satellite images by photo interpreters. A complex, lengthy, and demanding task, which is also subject to errors and subjectivity. Automatic/semiautomatic tools are good alternatives. Automatic processing offers the required prompt treatment intended in such critical situations, nonetheless, it generally presents a semantic gap drawback. The objective of this work is the incorporation of semantics into RS and GIS applications to express and represent expert knowledge in an automatic way. A global ontology that allows geographic and disaster-related knowledge representation, expressivity, and discovery is developed with expert knowledge in remote sensing, disasters, and geographic domains. The approach is based on (i) the conceptualisation of domain knowledge and information surrounding the context, (ii) the development of a global ontology including eight sub-ontologies representing the characteristics of the different related interdomains, (iii) the development of an ontology-based VHR satellite image classification technique based on GEOBIA, and (iv) the application of the ontology and the previous classification results for change detection and damage assessment. A case study on Haiti 2010 earthquake is demonstrated, and the strengths and limitations of the approach are discussed. The results validate the impact of the ontologies in the geographic, remote sensing, and disaster management fields.

Keywords*: Disaster response, ontology, semantics, knowledge-representation, remote sensing, major disasters.*

Acknowledgements

I am heartily grateful to my supervisor, Professor Kamal Bechkoum, for his insightful comments and invaluable advice, his unwavering support, guidance, and patience during my Ph.D. journey. Without his assistance, this work would not be accomplished.

I would also like to offer my regards to the following university staff: Professor Shujan Zhang, Dr. Phillipa Ward, James Lanciano-Newman, Natalie Morris, and Katy Borton for their assistance during my PhD research, and to my colleagues Djamel Eddine Machouk and Rédha Mohamed Sidoumou for their unwavering support.

Finally, I would like to express my gratitude to my viva's chair Dr. Hassan Chizari, and to the thesis examiners, Professor Marcello Trovati and Dr. Will Sayers, for the constructive comments and the extremely helpful recommendations they have provided for improving this thesis manuscript.

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List of Abbreviations

CD Change detection

CNN Convolutional Neural Network

CSV Comma Separated Values

DEM Digital Elevation Models

DL Deep Learning

DLs Description Logics

DSM Digital Surface Model

DTM Digital Terrain Model

DTs Decision Trees

EO Earth Observation

EMS European Macro-seismic Scale

FNEA Fractal Net Evolution Approach

GEOBIA Geographic Object-Based Image Analysis

GEO-MD Geographic Ontology for Major Disasters

GIS Geographic Information System

HBC-SEG Hard-Boundary Constrained Image Segmentation

KB Knowledge Base

KG Knowledge Graph

k-NN k Nearest Neighbour

KR Knowledge Representation

LiDAR Light Detection and Ranging

LULC Land Use and Land Cover

ML Machine Learning

MRS Multiresolution Segmentation

nDSM Normalized Digital Surface Model

NDVI Normalized Difference Vegetation Index

NDWI Normalized Difference Water Index

NIR Near-infrared

OBIA Object-Based Image Analysis

OWL Ontology Web Language

PCA Principal Component Analysis

RDF Resource Description Framework

RF Random Forests

RS Remote Sensing

SAR Synthetic Aperture Radar

SVM Support Vector Machine

SWRL Semantic Web Rule Language

UAV Unmanned Aerial Vehicles

VHR Very High Resolution

XML Extensible Markup Language

Chapter 1 Introduction

1.1 Background

Every year worldwide, millions of people are affected by both man-made and natural disasters. The impact of major disasters can be catastrophic. From the annihilation of infrastructures to the damage of prime agricultural lands, and the loss of important forests and wildlife habitats, major disasters can devastate entire regions in no time.

A first step towards dealing with major disasters is providing a relevant and current source of information that can help in understanding the situation and developing appropriate disaster management strategies.

In this respect, Remote Sensing (RS) technology provides data that can be used to extract, efficiently and promptly, information about land use. This is important because adequate information on different related aspects of the land must be available (and manageable) in order to make effective decisions. Land use and land cover are one such aspect, and knowledge about them is especially important for classification and change detection, as any change in land cover and land use can affect the global system.

1.1.1 Satellite remote sensing

Remote sensing can be defined as "*any process whereby information is gathered about an object, area, or phenomenon without being in contact with it. Our eyes are an excellent example of an RS device. We are able to gather information about our surroundings by gauging the amount and nature of the reflectance of visible light energy from some external source as it reflects off objects in our field of view*" (Eastman, 2001).

Technically, RS refers to information acquisition via satellite-mounted sensors that measure the intensity of radiation in a specific range of the electromagnetic spectrum (EMS) (Pettorelli et al., 2018). Satellite sensors can measure visible light as well as near-infrared radiation (e.g., multi-, and hyperspectral satellite imagery, Light

Detection and Ranging (LiDAR)), whereas others measure microwave radiation (e.g., Synthetic Aperture Radar (SAR)).

Remote sensors are generally characterised by their spatial, spectral, radiometric, and temporal resolutions:

- *Spatial resolution* is the measure of the smallest separable feature in the scene, it corresponds to the size of an individual pixel. The lower the spatial resolution is, the larger the size of the pixel is. The latter is generally expressed in meters (centimetres for very high resolution).
- *Spectral resolution* refers to scene information gathered by the sensor regarding the bandwidth and the sampling rate. The more colours are detected (a narrow bandwidth, e.g., 10 nm), the higher the spectral resolution. For example, a Panchromatic image contains only one band, a Colour image contains three bands (i.e., Red, Green, and Blue), a Multispectral image contains four bands (same as a colour image plus a NIR band), and finally, Hyperspectral images contain a large number of bands.
- *Radiometric resolution* is the capacity of the sensor to record the dynamic range or the degree of intensity of radiation. This difference in light intensity or contrast (grey values) of black and white imagery, is usually expressed in a bit number (e.g., a range of 8 to 16 bits). A higher radiometric resolution allows the detection of small differences in reflected objects' energy in the scene.
- *Temporal resolution* is the time interval between two consecutive images of the same area (i.e., geographic location) captured by a given sensor. Different sensors have different temporal resolutions which is determined by their orbits, which are usually measured in days (e.g., the temporal resolution of SENTINEL 2 is 10 days). The higher the temporal resolution, the shorter the time interval between two consecutive captured images of the same location.

The selection of the more appropriate RS data for specific use (e.g., disaster response) is possible by identifying the spatial, spectral, temporal, and radiometric requirements outlined above. The types of satellite sensors that can be used to support major disasters' response are many and varied, based on the spatial scale of the hazard and the appropriate data to use, very high spatial resolution data, for instance, is appropriate for targeting relatively small areas with a great deal of detail, where LiDAR data is more appropriate for elevation requirements.

1.1.2 Land cover and land use classification systems with remote sensing

Land cover is generally referred to as the physical, chemical, or biological categorisation of the terrestrial surface (e.g., grassland, forest, or concrete), whereas land use refers to the human purposes that are associated with that cover (e.g., raising cattle, recreation, or urban living) (Meyer and BL Turner, 1994). "Land use" and "land cover" may represent the exact same piece of vegetated land, but 'land use' carries connotations of function, organisation, and purpose, that 'land cover' does not (Couclelis, 2010).

Several classification systems have been designed for use with RS data and numerous approaches have explored land use and land cover (LULC) mapping from satellite imagery. Nevertheless, there is no ideal LULC classification, distinct perspectives exist in the classification process, which tends to be subjective (Anderson, 1976). Each classification is developed to fit the needs of a specific user, including the classification systems to be used with RS techniques, which are required to meet certain criteria.

Land cover classification from satellite images is done by grouping pixels representing objects in the imagery into classes, such as grassland, forests, and desert. This is commonly done using multispectral data and, more recently, hyperspectral data (Deshpande, 2017).

Classification can be done on individual pixels, generally extracted from low to medium resolution remote sensing images. Pixels are directly assigned into classes according to their spectral, textural, and spatial characteristics, or as an object-based process (Blascheke, 2010; Shimabukuro, 2015) commonly extracted from high to very-high-resolution satellite images.

Conversely, land use describes the economic, social, and regulatory factors of a region, which do not directly interfere with the land's physical and reflectance properties and therefore have a constrained link to RS (Cihlar and Jansen, 2001). Since RS data mainly represents the surface materials' spectral properties, they are more appropriate to describe the land cover. In short, RS technologies cannot directly measure the land use aspects. The latter requires further visual interpretation, advanced image processing, and spatial pattern analysis to infer land use from composite land-cover information and other auxiliary data (Cihlar and Jansen, 2001).

1.1.3 Knowledge representation and ontologies

"*There is no way to develop adequate computer understanding without providing the computer with extensive knowledge of the particular world with which it must deal*" (Schank and Abelson, 2013).

Knowledge representation (KR) (Davis et al., 1993) is one of the central concepts in artificial intelligence that studies the computer-based processing and formalisation of knowledge. KR focuses on designing computer representations and techniques of reasoning that allow the inference of new knowledge and conclusions from the knowledge captured about the world in a machine-interpretable form.

In remote sensing, expert knowledge is still very much required for image interpretation. Although satellite image processing can be achieved manually by human experts, which allows the highest semantics level, the tediousness of the process, the subjectivity of the result, and the required time needed to do manual labelling, make it less practical. Furthermore, the growing accessibility to VHR satellites made the analysis and interpretation of satellite images even more challenging, especially for particular situations such as disaster response where a set of image temporal sequences need to be promptly processed.

Expert interpretation of a satellite image observed scene produces semantics in remote-sensing data. To represent this knowledge, the provided domain experts' interpretation and understanding of the concepts of the predefined vocabulary is formalised using knowledge representation techniques. The latter has various forms; the most common techniques are based on semantic networks, rules, and logics (i.e., Ontologies).

In recent years, ontologies have become a good choice for knowledge representation in a range of computer science disciplines, including computer vision and remote sensing, for providing a conceptual yet computational model of a particular domain. Structural knowledge, like knowledge about the relationships between the objects and their connections to the low-level features apparent in the image data, can be represented efficiently by ontologies, with the additional benefit of reasoning about domain knowledge, similar to humans.

In philosophy, from where the word "ontology" was borrowed, we may refer to an ontology as a particular system of categories accounting for a certain vision of the world (Guarino, 1998). However, the ontology that we are referring to in this study, is the concept defined in Artificial Intelligence as "*a formal, explicit specification of a shared conceptualisation*" (Gruber, 1993), or as "*a formal representation of a set of concepts within a domain and the relationships between these concepts*" (Kohli et al., 2012).

A conceptualisation is an abstract, simplified view of the world with a specific purpose. The "world" here refers to a particular domain for which we explicitly gather the specific knowledge representing it, by defining the properties of the concepts of interest and the relationships that hold them together in a machine-understandable way.

To allow computer applications to communicate with each other and with end-users, ontologies offer a common vocabulary and meaning, plus a set of explicit assumptions regarding the intended meaning of the vocabulary words (Guarino, 1998). This set of assumptions usually takes the form of a logical theory (i.e., Description Logics) where terms correspond to unary or binary predicates, respectively called concepts and relations (Guarino, 1998). Furthermore, the fact that ontologies are based on DLs allows the use of DLs reasoners that can infer new knowledge from explicit descriptions.

1.2 Problem statement

Our environment is facing a growing number of major disasters such as floods, earthquakes, landslides, and wildfires. This situation prompted a number of organisations to devote more efforts to the disaster management field with the perspective of minimising loss and ensuring public safety.

RS technology has been widely used and is of great support to the disaster management field. The remote sensing and disaster management communities have been working together to establish effective and accurate techniques for disaster response and relief measures.

In a catastrophic event situation, pre- and post-disaster satellite images from affected areas must be rapidly analysed to guide rescue teams on the ground in establishing the extent of damaged areas, the best location of refugee camps, effective access roads, etc. Images must be chosen judiciously to allow the detection of objects of interest in the chosen application.

When a major disaster occurs, there is one foremost priority: saving as many lives as possible. Seeking and incorporating reliable data and disaster-related information, as soon as possible, is a key factor in developing effective decisions. The assimilation of RS data can provide valuable information, promote rescue operations, and assist teams on the ground in damage assessment (Bouyerbou et al., 2014).

However, satellite image visual analysis has become more complex and time-consuming given the image resolution. The use of human operators (photo-interpreters) to analyse, classify, and interpret images offers high-level semantics. Nevertheless, it is resource-hungry and often complex. In addition, human annotations are often subjective and ambiguous (Tamura and Yokoya, 1984, Chang and Hsu, 1992).

Since time is a key factor in this kind of critical situation, automatic or semiautomatic systems are strongly advocated, the so-called traditional pixel-based approaches. These techniques are mainly based on low-level features and spectral values and do not consider the spatial context. Automatic processing has the advantage of fast treatment, however, it generally presents a semantic gap handicap (Gudivada and Raghavan, 1995, Deserno et al., 2009). Geographic and remote sensing applications need to introduce semantics to express and represent expert knowledge.

Faced with these two major problems, a compromised solution exists: semantic classification or automatic annotation (Vailaya, 2000). This is a solution that delivers an automatic semantic description of the image with natural language vocabulary.

This research focuses on the exploitation of ontologies with GEOBIA in the case of major disasters. The goal of this research is to model and build an adapted solution that incorporates human-defined ontologies in bridging the gap between the findings of automated classification approaches and high-level semantics.

There are a few works related to this domain (Sowmya and Trinder, 2000, Datcu et al., 2003, Datcu and Seidel, 2003, Antunes et al., 2003, Gamanya et al., 2007). It remains important to invest more in the development of systems to provide a semantic classification of satellite images, thereby, facilitating their treatment, sharing, and exploitation.

The conception of effective image analysis systems necessitates knowledge about the underlying problem-solving processes (Benz et al., 2004a). The more knowledge we have about a given problem, the better we can represent this knowledge in a processing scheme, and the more effective the outcome product will be. One of the best-known and most powerful knowledge representation techniques is Ontologies. Ontologies have been widely used for different applications (e.g., medical fields, biology, education), and they are similarly gaining a growing interest in GIS and RS communities, allowing domain experts to integrate their knowledge into the interpretation process.

Geographic ontologies are becoming more prominent among domain ontologies. Considerable effort has been dedicated to this domain, and an increasing number of researchers are expressing interest in it, resulting in a growing number of research articles covering the topic.

Despite the significant number of developed geographic ontologies, there are many variations between their goals, constitutional elements, intended usage, and perceptions of the domain. Furthermore, none of them has been dedicated to major disasters in an effective way by integrating remote sensing data and the related interdisciplinary domains.

In this study, and in order to assist the photo-interprets in their work and smooth the relief process, a comprehensive geographic ontology for major disasters has been designed and developed, including a set of the following sub-ontologies: (i) Surface, (ii) Disaster, (iii) Damage, (iv) Imagery, (v) Sensor, and (vi) Spatial Location. And merged with two upper-level ontologies (i.e., GeoSPARQL and Time).

The specific ontology will be used for semantic classification, change detection, and damage assessment based on the methodology and the selective VHR multi-temporal remote sensing data.

1.3 Aims and objectives

This research focuses on ontology exploitation, as a knowledge representation technique, with GEOBIA in the case of major disasters. The aim of this work is to design and develop a new solution that bridges the gap between state-of-the-art classification and change detection techniques and high-level semantics based on expert-defined ontologies.

In working towards the above aims, the following objectives are identified:

1) Mapping, modelling, and implementing a global geographic ontology for major disasters including three main sub-ontologies (land use and land cover ontology, disaster ontology, and damage ontology) and a set of interdomain sub-ontologies.

2) Developing a novel optimised approach to ontology-based semantic classification of VHR satellite images, combining fuzzy-rule-based classification and ontology-based classification.
3) Applying, evaluating, and testing the proposed approach to satellite image semantic classification using multi-spatial (medium to very high spatial resolution) and multi-temporal (pre- and post-event) satellite imagery.
4) Assessing the eventual application of the proposed approach on damage assessment and change detection based on the previous results.

1.4 Thesis scope

In this dissertation, OBIA classification and change detection in the context of major disasters have been addressed, involving the following aspects of cognitive vision: knowledge representation, fuzzy logic, and recognition.

The scope of this thesis is to provide an exclusive geographic taxonomy related to major disasters and the resulting damage and to determine the efficiency of using a knowledge representation technique (i.e., ontologies), as an intermediate layer between domain knowledge and satellite image processing procedures for disaster response purposes. Although the developed ontology includes all types of major disasters supported by the international charter, this study has been validated only on earthquakes, specifically available data on Haiti's 2010 earthquake. The rescue process in disaster response will not be examined in depth in this study. Rather, it will show that knowledge representation techniques used along with remote sensing methodologies are a potential route toward efficient disaster response and require further investigation.

Satellite image classification results will be found for the study area using a knowledge-based technique. A post-classification change detection method will be performed on the classification results for change detection. Accordingly, multi-temporal VHR satellite imagery, LiDAR data, and GIS maps are used in the classification and damage identification. Different damage types and scales were included in the developed ontology. However, at the experimental level, damage assessment of the entire land cover elements in Haiti will not be discussed in-depth, only building damage level and extent are addressed due to the city's nature and the lack of ancillary data.

The next paragraphs briefly summarise the key ideas of the developed methods and how their presentations are organised within the various chapters of the thesis.

1.5 Thesis outline

In this manuscript, a set of hierarchical methods for knowledge acquisition and representation, object-based hierarchical classification, and change detection using multi-temporal and multi-resolution RS imagery is developed and experimentally validated with challenging imagery from the test site of Haiti. The thesis is organised into eight chapters.

Chapter 1 presents a brief background on RS data, LULC systems, knowledge representation, and ontologies. In addition to the general introduction to the related domain, the problem statement, aims and objectives, and thesis scope are emphasised here.

Chapter 2 summarises various approaches to satellite image analysis proposed in the literature with regard to major disasters. First, a variety of object-based image analysis (OBIA) approaches are reviewed. Then, satellite image classification approaches for major disasters are stressed by presenting several models used in the literature. A set of ontologies, with geographical and disaster response perspectives, is presented. Finally, key techniques for change detection and structural damage assessment are reviewed.

Chapter 3 describes our methodology for knowledge-based satellite image hierarchical classification and change detection using VHR satellite images. First, domain ontology development is presented. Then, a novel method for ontology-based hierarchical semantic classification is described. Finally, a post-classification CT method based on the previous classification results is proposed.

Chapter 4 describes the study area, namely Haiti's 2010 Port-au-Prince Earthquake, and the materials used in conducting the experiments.

Chapter 5 describes the specific aspects of the Geographic Ontology for Major Disasters' development, with a description of the methods used in building the ontology, a comparison to existing ontologies in literature is conducted, followed by a discussion.

Chapters 6 and 7 discuss the ontology-based VHR satellite image semantic classification, and earthquake building damage assessment using VHR optical imagery experimental results from the Haiti case study.

Chapter 8 sums up the main contributions of this work and discusses a few directions for further exploration. Conclusions on the proposed methods are drawn, along with comments on their possible relevance in the existing remote sensing solutions, and future possible enhancements of efficiency and reliability of the used methods are suggested.

Chapter 2 Satellite image analysis for major disasters

2.1 Introduction

Major disasters have emerged as an increasing worldwide concern. Natural and man-made disasters' frequency and magnitude have been rapidly increasing over recent years. In addition to the infrastructure damage and human life loss, the latter also has far-reaching implications for sustainable development through social, economic, and environmental impact (Novellino et al., 2019).

Although field-based tools and techniques offer straightforward outcomes, they often require a considerable workforce and effort to only cover a limited scale. Remote sensing technology, on the other hand, allows measurements over much larger spatial scales with minimum effort. For large-scale phenomena, such as major disasters, this is particularly appealing. Satellite data has been used to obtain information about major disasters across many spatial and temporal scales (Schumann et al., 2018).

Through active sensors and high-resolution optical images, RS technologies have demonstrated significant efficiencies in post-disaster damage quantification, recovery monitoring, and post-disaster rehabilitation and recovery progress (Eguchi et al., 2008).

This chapter introduces object-based image analysis and discusses different techniques existing in the literature. The chapter also discusses the use of RS data and techniques for major disasters. The role of ontologies is highlighted from a geographical and disaster response perspective. Finally, a review of the different change detection and damage assessment techniques found in the literature is given.

2.2 Geographic object-based image analysis (GEOBIA)

2.2.1 OBIA and GEOBIA

The concept of OBIA started gaining extensive attention within the GIS community around the 2000s, following the introduction of the first object-oriented mage analysis commercial software. Image objects illustrate “meaningful” entities or scene components that can be distinguished in an image (e.g., buildings, trees, cars) (Blaschke et al., 2014). Nevertheless, OBIA is based on earlier segmentation, edge detection, and classification methods that have been applied in RS image analysis for decades (Blaschke et al., 2008).

GEOBIA has been defined by (Hay and Castilla, 2008) as: “ *a subdiscipline of GIS devoted to developing automated methods to partition RS imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scales, so as to generate new geographic information in GIS-ready forma*t”.

GEOBIA initiates with the conventional segmentation concepts and then introduces the spectral and spatial concepts, and radiometric analyses, which are specific to the earth’s surface (in contrast with biological, medical, or astronomical aspects), to further develop the image objects (Blaschke et al., 2014). The introduction of GEOBIA has offered a new key bridge to spatial concepts applied in multi-scale satellite image analysis, and the connection between image objects and their radiometric characteristics (Blaschke et al., 2008). GEOBIA's overarching goal is to develop adequate theory, techniques, and tools for computer-assisted human interpretation of RS data.

As a result, GEOBIA scientific literature dramatically increased during the past decade. It is getting a large acceptance among RS researchers for various research topics (Clewley et al., 2014, Garcia-Pedrero et al., 2015, Kim et al., 2010, Powers et al., 2012). Both the advent of VHR imagery and the accessibility of powerful GIS and satellite image processing software allowed the growth of this new research area (see figure 2.1).

The proposed approaches are generally based on state-of-the-art segmentation techniques in addition to the incorporation of spatial analysis within feature extraction and image classification techniques. GEOBIA applications are broad, however, they typically include: (i) image segmentation, (ii) feature extraction, (iii) image classification, and (iv) change detection.

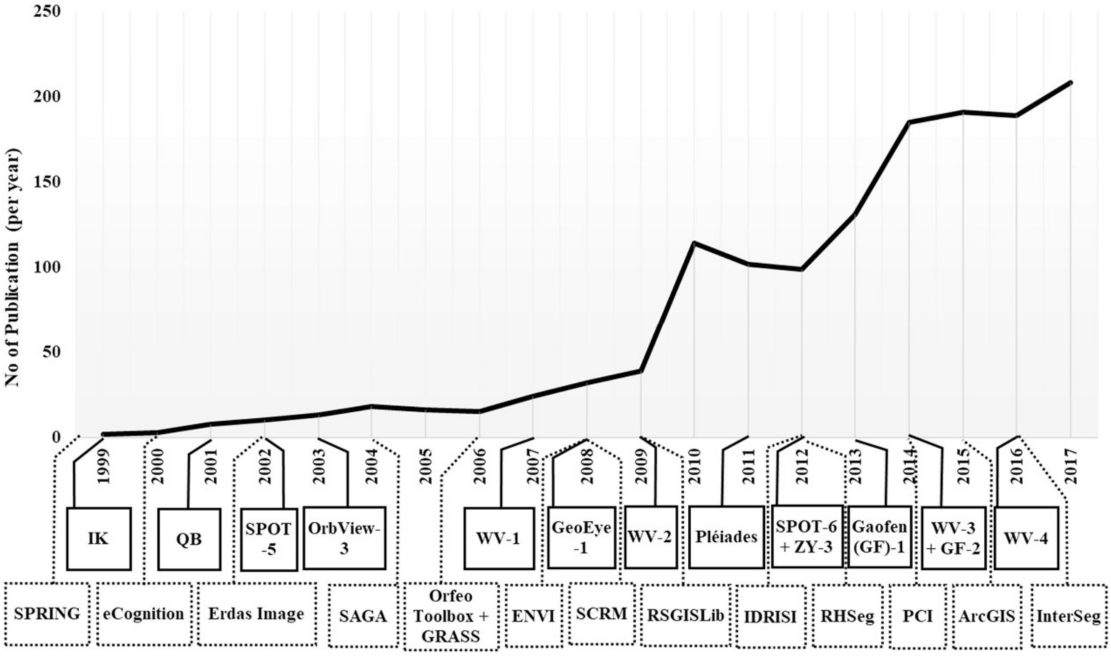


Figure 2.1. GEOBIA literature and related satellites and software (Hossain and Chen, 2019).

2.2.2 Segmentation

"*Segmentation is the splitting of an image into spatially continuous, disjoint, and homogeneous regions*" (Blaschke et al., 2004).

Image segmentation is a key step in the OBIA process as the resulting feature extraction and classification outcomes strongly depend on the image segmentation quality (Hossain and Chen, 2019).

There is a large range of segmentation techniques employed in pattern recognition and machine vision fields (Haralick and Shapiro, 1985, Beucher and Meyer, 1990, Shi and

Malik, 2000, Grady, 2006). However, they have limited use in the remote sensing domain as most of these algorithms were essentially designed for pattern analysis, medical imaging, and quality control of products, whereas the objective of RS imagery segmentation is the generation of spectrally homogeneous segments, which show the intrinsic dimensions/objects of the images (Blaschke et al., 2004).

Image-based object identification is generally approached in one of two ways: Edge-based or region-based segmentation. Theoretically, these are two different representations of the same object. Nevertheless, the region-based approaches may generate completely different segmentation results than the edge-based ones (Hossain and Chen, 2019).

First, edge detection techniques can be used to identify the objects' boundaries between the different image regions. The determination of the presence of an edge is performed by localising significant discontinuities in brightness or the variations of the grey level of the image. In general, edge-based segmentation consists of three steps (Jain et al., 1995): (a) filtering, (b) enhancement, and (c) detection.

Second, region-based techniques can be further categorised into: region growing, region merging, region splitting, or any combination of the three categories. Contrary to edge-based segmentation, region-based starts from the inside of an image object and develops by grouping similar components until a certain threshold is reached.

Another segmentation method, taking into account objects' spectral and textural properties, as well as their varying size and behaviour at various scale levels (Baatz, 2000). Multiresolution algorithm (MRS) is a well-established segmentation technique initiated along with the popular commercial application of eCognition software (Baatz, 2000). MRS is perhaps the most widespread image segmentation algorithm (Happ et al., 2010, Witharana and Civco, 2014, Tong et al., 2012).

MRS is a bottom-up, region-merging, algorithm based on the Fractal Net Evolution Approach (FNEA) (Baatz, 2000). MRS is based on three parameters: scale, compactness, and smoothness, where scale is the most significant parameter since it controls the average segment size in the segmentation (Wang and Li, 2014). MRS was selected as the best segmentation method according to a comparative study conducted by (Meinel and Neubert, 2004). Another study by (Kavzoglu and Tonbul, 2017) comparing the performance of the MRS algorithm and an edge-based technique watershed transform, when applied to very high-resolution imagery, found an estimated difference of 5% accuracy between the two methods.

Nevertheless, RS images contain ground objects of different sizes at different scales, which presents challenges for the perfect scale parameter. A poorly defined scale will produce either over or under-segmentation (Ming et al., 2012). A trial-and-error method is commonly used in order to determine the optimal scale (Hossain and Chen, 2019).

Furthermore, as an attempt to improve the performance of the MRS, numerous studies have been conducted. Optimisation typical schemes include automatic scale selection (Nikfar et al., 2012, Witharana and Civco, 2014, Zhou et al., 2017), and ancillary data sources integration (Smith and Morton, 2010, Anders et al., 2011, Sameen and Pradhan, 2017).

Meanwhile, different kinds of hybrid approaches (combining edge and region information), have also emerged (Chen et al., 2012, Mueller et al., 2004). Edge detection tends to be positionally precise but discontinuous edges may occur. On the other hand, the region-based might obtain closed ring segment boundaries but is not very precise (Wang and Li, 2014). The integration of both edge and region information may improve the segmentation accuracy.

In this direction, a two-stage merging technique was proposed by Wang and Li (Wang and Li, 2014). Where RS image edges are first detected by a Canny-Edge detector technique, and then primary segments are gradually merged into a larger segment, using the watershed segmentation technique, until the edge-controlled boundaries are reached. The authors claim higher segmentation accuracy, object primitive's boundary precision, and less dependence on the scale parameter. However, the method is not suitable for strongly textured images and requires additional computation time.

A hard-boundary constrained image segmentation (HBC-SEG) method was proposed by Wang and Wang (Wang and Wang, 2016). The authors claim that the method presents many advantages over MRS, particularly in region boundary precision. They further reduced the over-segmentation errors through a novel collinear and ipsilateral neighbourhood (IPSL-neighbourhood) model based on region and straight-line relationship modelling. However, the approach is only applicable to structures (e.g., buildings), and does not include other land cover classes (e.g., vegetation, water bodies).

Another direction in OBIA segmentation is the incorporation of advanced techniques such as semantic methods and supervised machine learning algorithms in segmentation, such as Support Vector Machine (Lizarazo, 2008, Saha et al., 2011), Markov Random Fields (Zheng et al., 2019, Krishnamachari and Chellappa, 1997), Convolutional Neural Networks (Sun and Wang, 2018, Wu et al., 2019), and deep learning (Kemker and Kanan, 2017, Kemker et al., 2018, Yuan et al., 2021, Yeung et al., 2022).

Although semantic algorithms are showing promising results, they are encountering several challenges (Hossain and Chen, 2019), notably the difficulty in:

- Defining appropriate features with semantic significance due to extensive texture in high-resolution images.
- Determining semantic rules in high scale and hierarchical images can distinguish objects at different scales.
- Reducing the semantic gap present due to spectral value similarities in different image objects (such as water and shadow).
- Optimising the required large training samples and the high proportion of parameters for tuning.

Another alternative is the incorporation of the knowledge derived from ancillary data (e.g., GIS maps, LiDAR), other sources, predefined rules, or already existing classification results, into the segmentation process (Ton et al., 1991). Knowledge-based approaches can significantly improve the segmentation results; however, they tend to be specific (e.g., roads extraction, buildings extraction), and require more user interaction.

2.2.3 Classification

The GEOBIA technique is increasingly replacing the traditional pixel-based method for LULC classification with high spatial resolution RS data. It remains the case, however, that a number of researchers opted for the combination of both methods (Aguirre-Gutiérrez et al., 2012, Belgiu and Csillik, 2018, Wang et al., 2004).

Image classification is one of the most image analysis areas to use OBIA techniques. A wide range of remote sensing literature claims that OBIA improves classification accuracy, compared to pixel-based techniques, particularly with the use of high spatial resolution imagery (Gao and Mas, 2008, Riggan Jr and Weih Jr, 2009, Juniati and Arrofiqoh, 2017).

GEOBIA has been well validated for the classification of high or medium-resolution images (Ma et al., 2017). Compared with pixel-based classification approaches, GEOBIA offers at least four new components that are not generally employed in pixel-based classification (Platt and Rapoza, 2008), namely: (i) the segmentation procedure, (ii) the nearest-neighbor classifier, (iii) the integration of expert knowledge, and (iv) the feature space optimisation.

Moreover, OBIA presents the possibility for satellite image classification to take advantage of spectral, spatial, textural, topographical, and contextual information.

The first step in OBIA, after performing any pre-processing of the RS imagery, is segmentation, where the images are first segmented into objects and subsequently classified into geographic categories.

After completing the segmentation step, the resulting objects are assigned to different classes either by:

- Specifying a process tree or by combining a set of if-then rules and statistical classifiers which is known as rule-based classification methods.
- Or using one of the existing classifiers/machine learning algorithms (i.e., supervised classification),

1) Rule-based classification methods:

Rule-based or knowledge-based classification methods generally follow a two-step workflow: 1) an initial segmentation and classification, 2) an iterative improvement of the initial segmentation and classification. The job for the second phase is based on a task-ontology that describes the key expert knowledge on image processing and can be saved and reapplied as an OBIA rule set (Ramakrishnan, 2017). The development of a well-defined rule set specifying the classes of interest and their corresponding properties is one of the important aspects of OBIA (Hofmann et al., 2011).

Rule-based classification is based on prior knowledge which can be re-applied to geographic objects classification (Belgiu et al., 2014). Rule-based methods have been widely used for OBIA due to their capability to adapt expert rules in their classifications (Bauer and Strauss, 2014, Gibril et al., 2017, Labib and Harris, 2018).

Rule-based classification offers the image analysts the opportunity to evaluate the characteristics of the image objects seamlessly and in detail (Belgiu et al., 2014), However, the more specifically and consistently RS data has to be analysed, the more complex are the methods and the rule sets (Ramakrishnan, 2017). The rule sets can group colour conditions, shape conditions, or context conditions. In order to achieve appropriate results for different image data, further manual intervention (e.g., editing single rules, adjusting object boundaries, or class assignments) may be necessary (Ramakrishnan, 2017).

Fuzzy rule-based classification methods follow the same workflow as rule-based techniques, though, the rule sets are defined as soft intervals, rather than a fixed crisp threshold. "*Fuzzy rules deal with uncertain, incomplete and/or vague information in order to steer or control processes or to assign objects to fuzzy sets*" (Hofmann et al., 2011).

In OBIA, a set of fuzzy rules is defined for each of the output classes using the features of image objects describing the specific class by the mean of membership functions. The latter specifies the possibility of an image object matching this class. The membership function defines the degree of membership μ ($0.0 < \mu > 1.0$) for each object based on the objects' values for a selected property (Hofmann et al., 2011).

With the emergence of OBIA, fuzzy rule-based classification techniques have been widely applied in a variety of RS applications (Jabari and Zhang, 2013, Sebari and He, 2013, Kalantar et al., 2017, Sameen and Pradhan, 2017).

On the other hand, hierarchical classification schemas are widely used (Eisank, 2010, Sellaouti et al., 2012, Gianinetto et al., 2014), since they give to reproduce the ontology representation of the classes' hierarchy and thus heighten the comprehensibility of the classification process and its results (Hofmann, 2016). Moreover, ontology-based classification has gained considerable interest in GEOBIA applications (Buccella et al., 2011, Kohli et al., 2012, Bouyerbou et al., 2014, Gu et al., 2017, Andrés et al., 2017). The incorporation of experts' knowledge in GEOBIA classification is becoming a new direction for implementing ontologies in remote sensing studies (Labib and Harris, 2018).

2) Supervised classification methods:

Several machine-learning classifiers such as SVM, k-Nearest Neighbour (k-NN), Decision Trees (DT), Random Forests (RFs), and Convolutional Neural Network (CNN), have been used for OBIA-supervised classification. The conventional k-NN and DT classifiers are still at the top of the most popular classifiers, according to extant studies on supervised object-based classification (Ma et al., 2017). This is mainly due to the widespread use of eCognition software, a commercial software dedicated to OBIA with the advantage of the rule set construction and k-NN and DT classification (Flanders et al., 2003, Nussbaum and Menz, 2008).

Recently, SVMs and RFs, two popular machine learning algorithms, have also shown remarkable performance in OBIA classification, and are attracting more and more attention among researcher papers (Tzotsos and Argialas, 2008, Li et al., 2010, Juel et al., 2015, Lebourgeois et al., 2017). For instance, Tzotsos et al. (Tzotsos and Argialas, 2008) proposed a support vector machine approach to evaluate SVMs' efficiency and potential for OBIA classification. The author applied an SVM approach for multi-class classification based on primitive image objects produced by the MRS algorithm. Spectral, texture, and shape features were selected as input features for the classification. Comparable results with the eCognition Nearest Neighbor algorithm were stated for small training and testing datasets.

Another promising classification technique that is attracting more and more attention in remote sensing and OBIA classification is Deep Learning (DL) (Zhang et al., 2019, Ma et al., 2019). The introduction of DL into supervised OBIA classification seems to be imperative in the future to examine, in-depth, the interactive effects between DL and OBIA in various aspects (Ma et al., 2017). In this regard, several works have been conducted using OBIA and deep learning for different applications as the latter becomes a popular approach in computer vision and remote-sensing areas (Feizizadeh et al., 2021, Bengoufa et al., 2021, Huang et al., 2020, Robson et al., 2020).

2.2.4 Conclusion

Segmentation is a key element of GEOBIA that plays an important role in the simplification of the representation of the satellite images into more meaningful image objects easier to analyse. With the emergence of high spatial resolution RS images, segmentation algorithms development is receiving increasing interest recently with a rapidly growing body of scientific literature. Nonetheless, the existing techniques have their strengths and drawbacks. Although edge-based methods tend to be simple and do not require much implementation effort, they overlook contextual information, for instance. On the other hand, the region-based methods give better results than the edge-based ones according to the literature, however, parameter optimisation remains challenging and still requires manual adjusting. When it comes to the hybrid methods, despite the promising results, these methods remain complicated and the lack of availability of a software package for their implementation adds to the complexity (Hossain and Chen, 2019).

OBIA approach is an improved image understanding philosophy. To pursue the human visual ability in detecting objects and object classes within an image, and to imitate this form of analysis within segmentation, it is important to follow the same path of ‘intuitive’ image understanding (Blaschke et al., 2004).

The next step following segmentation in image analysis is typically image classification. Classification is one of the image analysis areas that makes the most use of GEOBIA techniques. A wide variety of supervised classification options are available, and no single classification solution will always perform best considering all the performance factors.

Among the ML techniques, RF and SVM classifiers have shown significant classification performance. Deep learning is predicted to foster the development of supervised object-based classification techniques in the upcoming years (Ma et al., 2017).

However, ML and DL techniques, despite their complex programming concepts and extensive computing time, rely significantly on large and specific training and validation samples for image classification and accuracy assessment (Ghorbanzadeh et al., 2019). Moreover, supervised classification approaches lack the ability to integrate experts' knowledge into the classification procedure (Labib and Harris, 2018). To solve this issue, new emerging approaches attempt to integrate deep learning with rule-based techniques (Gu and Angelov, 2018, Gu and Angelov, 2019), and ontology-driven as the rule-based techniques seem to be more suitable for GEOBIA. Numerous studies are investigating semantic rule-based classification methods to improve image classification using experts' knowledge as a great potential to narrow the gap between image object classification and human interpretation (Labib and Harris, 2018).

In remote sensing science, ontology-based techniques are becoming a new direction for efficiently integrating remote sensing experts' knowledge. Ontology-based methods present the advantage of requiring no complex programming concepts or extensive computing time. Moreover, unlike ML and DL techniques, which operate as black boxes that can only be altered or extended by a programmer, ontology-based techniques allow the integration of experts' knowledge into the classification procedure. The latter is explicitly expressed as comprehensible, accurate, and self-contained statements modifiable by users, such as domain experts, with no computational background.

2.3 Remote Sensing for major disasters

The effectiveness and accuracy of RS technologies in assessing post-disaster damage, monitoring recovery, and preparedness and mitigation of major disasters, have been well demonstrated. The emergence of high-resolution open-source and commercially accessible satellite imagery and active sensors data has greatly contributed to this progress.

Remote sensing data can be used to alleviate major disasters impact in all four phases of disaster management (see figure 2.2): (i) risk analysis (mitigation) and preparedness, (ii) disaster monitoring, (iii) emergency relief (response), and (iv) reconstruction (recovery).

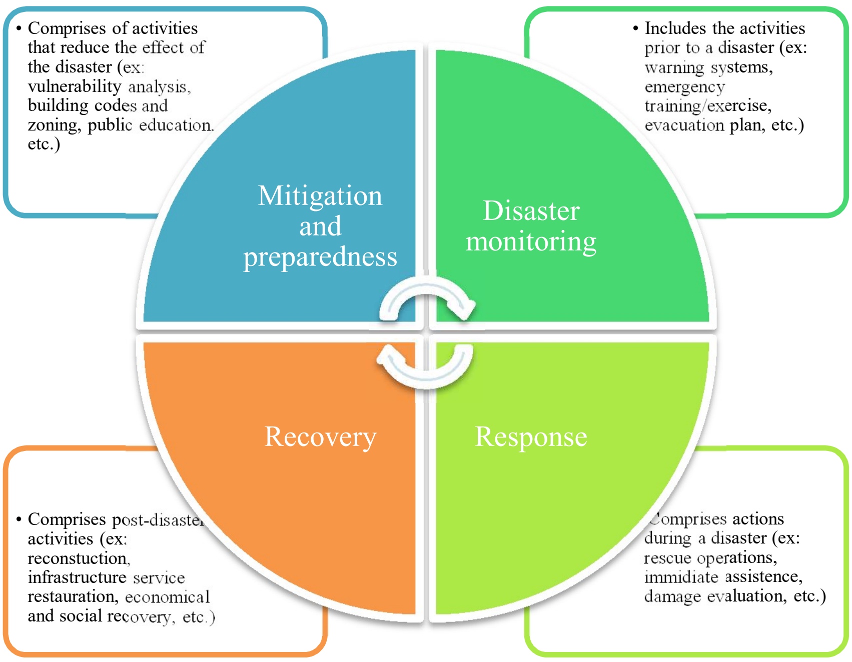


Figure 2.2. Disaster management cycle (Khan et al., 2008)

2.3.1 Disaster mitigation and preparedness

Earth Observations (EOs) can provide important multitemporal and spatial information as support to hazard planning and risk modelling. The historical information contained in the satellite imagery archives is compared to the new acquisitions to help select the highest risk regions and focus the effort on them, thus, optimising the preparations and the pre-positioning of the response assets (Petiteville et al., 2015). The introduction of RS data in disaster management implies that much larger geographic areas and a wider range of disasters can be addressed (Petiteville et al., 2015).

The phenomena underlying the hazards are rigorously modelled using the supplied EOs. The phenomena scale is sometimes too large to be supported by ground measurement only, and satellite and airborne observations can present the only data source for developing and validating adequate models (Chen et al., 2007).

Models built from GIS and RS data are powerful resources for wildfire mapping and characterising which can provide prompt and accurate outcomes supporting mitigation solutions in the best possible way. In this direction, many works have been conducted in wildfire and forest fire risk mapping using RS techniques (Chuvieco and Congalton, 1989, Chuvieco et al., 2010, Dlamini, 2011, Xu et al., 2016). For instance, Bhandary and Muller (Bhandary and Muller, 2009) analysed data processed from pre-fire and post-fire IKONOS images and other geo-referenced data using a logistic regression model to determine risk factors influencing a house's probability to burn from wildfire.

Landslide hazard mapping necessitates a thorough examination of previous occurrences in relation to the geo-environmental factors that caused them (Petiteville et al., 2015). Constant effort, regular updates, and the collection of observations over various sites are necessary for the maintenance of the hazard maps. This is made possible by the reliable and recurrent aspect of satellite acquisitions, which are combined with high-resolution airborne images, to help in smoothing the process (Petiteville et al., 2015). In the direction, remote sensing data are used for landslide (Metternicht et al., 2005, Pradhan and Youssef, 2010, Akgun et al., 2012) and flood risk analysis (Nawaz and Shafique, 2003, Demirkesen et al., 2007, Samarasinghea et al., 2010, Ahmad et al., 2013, Mojaddadi et al., 2017).

Topography information as well as Digital Elevation Models (DEM) produced from LiDAR and Satellite sensors are an important source that can discriminate inundation associated risks and support inundation risk modelling.

2.3.2 Disaster monitoring

A significant proportion of disasters (over 90% by some assessments) are related to hydrometeorological hazards (Petiteville et al., 2015). Moreover, the intensity and frequency of some of them are expected to increase with climate change and global warming. Therefore, meteorological, and environmental observations provided by satellites are important to enable extreme weather alerts over the world. Extreme weather forecasts allow the concerned authorities to prepare for the hazard and take early precautions.

Remote sensing data have been largely employed for flood monitoring either by monitoring rainfall (Toté et al., 2015), rivers (De Groeve, 2010), or coastal flood risk analysis using passive and active satellite imagery (Demirkesen et al., 2007). But also in other natural disaster monitoring, for example, Yamaguchi (Yamaguchi, 2012) presents the use of polarimetric SAR data for natural disaster monitoring (e.g. volcanic activity, snow accumulation, landslides, and tsunami effects caused by major earthquakes).

Furthermore, EOs can assist emergency agencies and firefighters by providing valuable information contributing to the identification of probable fire ignitions, in even the most remote zones, and reducing response time (Reddy et al., 2009, Badarinath et al., 2011, Petiteville et al., 2015). For instance, by estimating the required water status of vegetation to assess forest fire danger, which is related to the degree of vegetation dryness, Maki et al. (Maki et al., 2004) confirmed a relative relationship between leaf water status and the NDWI.

2.3.3 Post-disaster response and damage assessment

This phase requires the development and active delivery of suitable tools and products to support rescue teams and is perhaps the most to make use of RS data and EOs, in the disaster management cycle. Professionals are increasingly applying remote sensing techniques to quickly respond to major disasters and evaluate the occurred damage.

Remote Sensing systems provide rescue teams with the means to lift the “fog off disaster” (Voigt et al., 2016). Field surveys are one of the employed methods for response and damage assessment after a major disaster, however, given the large extent of the affected areas, the difficulty of access to certain regions, and the often limited and ambiguous collected ground truth information, EOs became a good alternative and a complementary source of essential information to overcome some of the filed investigations operational uncertainties that can obstruct the emergency response.

Moreover, RS technologies provide emergency responders with a situational overview normally challenging to get during certain circumstances. SAR sensors, for example, have the capacity to avoid clouds and weather-caused signal attenuation as well as day/night imaging capabilities and thus are ideal for remotely assessing the exact extent and severity of flood disasters in near real-time.

Unlike the previous disaster management phases, time is critical in disaster response. A review of RS-based emergency mapping from 2000 to 2014 (Voigt et al., 2016) reveals that in 2006, the average overall response time, from mobilisation to first product, decreased from ~4.5 days to ~2.5 days on average by 2014. This is mainly due to the increasing availability of earth observation satellite systems along with the developed remote sensing techniques, as well as to the special efforts and international collaborations dedicated to disaster response like the International Charter “Space and Major Disasters”[1].

The Charter is a partnership between the holders and operators of EO missions that delivers a satellite rapid tasking system for instant disaster response and offers RS data free of charge for authorised users following a major disaster. Following the

[1] https://disasterscharter.org/

UNISPACE III conference held in Vienna, Austria in July 1999, the European and French space agencies (ESA and CNES) started the International Charter, with the Canadian Space Agency (CSA) on 20 October 2000[2]. As of the start of 2021, the Charter was activated 700 times, and data, from 61 satellites, has been provided in response to cyclones, earthquakes, fires, floods, ocean waves, oil splits, landslides, volcanos, and other disasters in 127 countries.

Different disasters, each with their own characteristics, may require different categories of RS data. Generally, earthquakes can be identified on high-resolution satellite imagery with the visible and near-infrared spectral bands, whereas thermal infrared imagery is needed to capture the volcanic heat or to detect active wildfire.

Unlike meteorological and hydrological hazards, it is not yet possible to predict geological hazards (e.g., earthquakes), so the global coverage of satellites and their real-time availability makes them an exceptionally powerful tool for earthquake response managers (Petiteville et al., 2015).

After a major earthquake, infrastructures and the roads that enable access to them, are generally the two main objects of interest of emergency managers. VHR optical and SAR imagery showed the efficiency of their method in post-earthquake damage assessment (Chen et al., 2008, Brunner et al., 2010). This includes damage to buildings mainly, and damage to vital transport infrastructure (e.g., roads, bridges, and railways) based on before/after imagery. LiDAR (Li et al., 2008, Ural et al., 2011) and unmanned aerial vehicles (UAV) (Kakooei and Baleghi, 2017, Duarte et al., 2017, Adams et al., 2013) have also been used along with satellite imagery to improve the assessment results.

In the case of floods, radar imagery is usually used to produce rainfall and flood radar maps (Dadhich et al., 2019, Polcyn, 1987). Radar imagery has the capacity to avoid clouds and weather-caused signal attenuation as well as day/night imaging capabilities, which makes them a powerful source for remotely assessing the exact extent and severity of flood disasters in near real-time. Elevation data (i.e., DEM) are also

[2] Membership History - International Disasters Charter

employed to improve the delineation of the inundated zones, and to assess the submerged water depth (Psomiadis et al., 2019).

2.3.4 Disaster recovery

After a rushing, frantic disaster-response phase, a longer, more systematic recovery process begins. "*Recovery may be thought of as an attempt to bring a post-disaster situation to a level of acceptability*" (Quarantelli, 1999), involving the deployment of temporary humanitarian aid and logistics support while a more long-lasting recovery is planned and implemented (Petiteville et al., 2015).

Satellite imagery plays a critical role in the post-disaster phase. Products produced by the response observations (e.g., maps of the affected area, damage extent, number of damaged houses, etc.) and the post-disaster data acquisition, are not only employed to rescue people but also to develop a recovery strategy, claim damage process, quickly reimburse the victims, etc. the products delivered in the response phase can be utilised for disaster recovery and preparedness and for research and scientific work in the future.

In addition to the emergency observation data, RS data is also used to indicate different aspects of the recovery process. Brown (Brown et al., 2008), for instance, provides a number of post-disaster recovery indicators using satellite imagery, internet-based statistics, and advanced field survey procedures.

Satellite images also offer the possibility to visualise the recovery process over time. An example is Murao (Murao, 2005) who used Ikonos imagery to give a description of building reconstruction procedure after an earthquake, to monitor the recovery process, First, building footmarks were created and information regarding the key services, building type, and damage state were then attached to the corresponding polygons to identify them.

Compared to the response phase, recovery has got less interest in the literature regarding the use of remote sensing data.

2.3.5 Conclusion

Remote sensing data, including GIS, is becoming increasingly crucial in the disaster management cycle development. RS data integration has even become essential for the accomplishment of a number of operations. Although some of the satellite images are provided at no cost in the case of disaster response by some organisations, it is still not really the case for other EO data despite the important information they provide (e.g., SAR and LiDAR data). Furthermore, other disaster management phases (i.e., mitigation and preparedness, and recovery) are not getting enough attention. Open-source RS data is greatly desired in this domain to enable more scientific work and further research, and consequently, more outcomes.

Disaster response is one of the most sensitive and important phases in the disaster management cycle, and the most suitable domain for satellite images and other RS and GIS data. Despite the decent interest in literature and the good advancements compared to the past years, disaster response is still expected to improve its products, and enhance its results in terms of response time, consistency, validation of existing techniques, and the integration of experts' knowledge.

2.4 Ontologies – Geographical and disaster response perspective

2.4.1 Definitions and state of the art

An ontology is originally a philosophical and metaphysics terminology dealing with the nature of being. It was initially introduced in the Computer Science field by Gruber (Gruber, 1993) as " *an explicit specification of a conceptualization*". This definition was later refined by Feilmayr and Wöß (Feilmayr and Wöß, 2016) as: *"An ontology is a formal, explicit specification of a shared conceptualization that is characterized by high semantic expressiveness required for increased complexity."*

Ontologies define categories within a hierarchy, they generally consist of four components: (i) classes (i.e., objects), (ii) properties (i.e., attributes), (iii) instances (i.e., individuals), and (iv) axioms (i.e., assertions), and splits into three categories: upper ontologies, domain ontologies, and hybrid ontologies.

Domain ontologies, on the other hand, present concepts that are of interest within a specific domain or subject matter based on classical logic. "A *domain ontology provides an organized, customized, and aligned knowledge representation with a specific domain and/or user*" (Kolas et al., 2005).

Domain ontologies can be developed by different individuals following different methodologies and using different languages, they are often incompatible with each other within the same purpose. Moreover, with the growing spread of domain ontologies, and in order to establish a connection between them, upper-level ontologies have been developed to provide, domain-neutral, core ontological concepts.

Upper-level or foundation ontologies are models representing the common objects and relations generally shared and applied across various domain ontologies (e.g., measures, categories, time, and space). They usually define the most general categories through a core glossary that can be shared, integrated, and reused by different domain ontologies. Upper-level ontologies intend to create semantic interoperability of ontologies across multiple domains, facilitate domain ontologies' semantic integration, and guide the development of new ones. There is a variety of standardised upper-level ontologies including: Basic Formal Ontology (BFO), Descriptive Ontology for Linguistic and Cognitive Engineering (DOLCE), General Formal Ontology (GFO), OWL-Time, and Geo-SPARQL.

Among domain ontologies, geographic ontologies are receiving a growing proliferation, reflected in many research papers covering the subject area (Safia and Aicha, 2014, Buccella et al., 2011, Liu et al., 2010, Huang et al., 2007, Li et al., 2017). Geographic ontologies capture the knowledge of the geographic domain; they can, however, be linked to other domains or intended to fit a specific context (e.g., ecosystem, biomedical, disasters).

A variety of geographic ontologies have arisen in recent years. Given this, there are significant differences in their objectives, conceptualisation, and constitutional components, and several are directly derived from existing GIS, land use, or land cover systems (Bouyerbou et al., 2019). Furthermore, despite the high quantity of research articles on geographic ontologies, (Fonseca et al., 2002, Fonseca et al., 2003, Tomai and Kavouras, 2004), there was less literature on hazards and disasters.

A few disaster management applications made use of ontologies. Bernard et al. (Bernard et al., 2003) proposed the integration of well-defined ontology concepts, through disaster management (i.e., flooding) use case, for intelligent search, semantic translation, and semantic integration, where ontologies act as the basis for both search and translation. However, the use case reveals several semantic heterogeneity issues that need to be solved, the authors sketched an approach for addressing them with no further validation. In (Klien et al., 2006) the authors made use of ontologies to estimate potential storm damage in forests. Both ontology-based metadata and ontology-based search were for finding geographic information services related to hazard prevention. Semantic matchmaking by means of terminological reasoning and description logic, as a representation language, were used in the work. However, modules for spatial and temporal reasoning were not integrated, and the approach exposes a few limitations for geographic web service discovery.

Xu and Zlatanova (Xu and Zlatanova, 2007) developed a hybrid ontology architecture for emergency response and disaster management, the work remains theoretical, however, as the authors only perceived an ontology architecture without building it. Looking for real datasets and building the local ontologies remain perspectives.

Murgante et al. (Murgante et al., 2009) developed ontology in the risk prevention and disaster management domain (i.e., the field of seismic risk). However, the ontology presents a number of issues, as it does not integrate geographic information, was not converted into Ontology Web Language to verify its consistency, and was completed in the Italian language with English and French glossary. Finding matches among terms in three different languages may cause ambiguity.

In the same perspective, an ontology for transport infrastructure failures data diffusion and integration in case of natural hazards was developed by Roman et al. (Roman et al., 2017) under the name of InfraRisk. And a geospatial foundation adapted ontology for the representation of meteorological disaster systems was proposed by Zhong et al. (Zhong et al., 2017). The latter was designed to formally conceptualise the domain concepts and build relationships between them and was implemented at three levels: top-level, domain-level/task-level, and application-level. A case study of typhoon event prediction and evacuation decision was performed to evaluate and illustrate the ontology application.

Trucco et al. (Trucco et al., 2016) implemented two ontologies: (i) critical infrastructure systems ontology, and (ii) hazards and threats ontology. These ontologies are connected through vulnerability and (inter) dependency models to build a global critical infrastructure systems ontology to assist authorities and operators in risk assessment. The latter was further implemented into software to support the analyst in consulting the ontologies and generating a set of relevant disruption scenarios. However, it does not include policy, legal or regulatory regimes, economic systems, and trends of their complexity and difficulty to be properly implemented in an ontology. Another limitation is the ontology’s weak abilities in geo specification and description.

Alirezaie et al. (Alirezaie et al., 2017), developed a framework named SemCityMap to classify and augment satellite images with additional semantic information in order to allow queries about locating operational routes in a disaster situation (i.e., a flood simulation). The framework is based on existing upper-level ontologies in addition to the authors' newly developed ontology (OntoCity). The authors aim to transform satellite imagery data into an interactive map ready to be queried using CNN classifier. However, only the colour feature was considered. More advanced features of regions are required to enable automatic query of the classified regions (e.g., spatial relations, regions texture, etc.).

More recently in the context of flood disaster management and assessment, Potnis et al. developed a Flood Scene Ontology (FSO) for topological and directional knowledge mining in the context of flood disaster. The authors aim to bridge the spatial-contextual semantic gap in RS data understanding during a flood and enhance the automatic interpretation of flood-related RS imagery. Wu et al. (Wu et al., 2020) established an ontology-based data management framework for urban flood disasters. The framework processes collected multi-source data for flood disaster-related information retrieval.

Another direction in this area was exploring the potential of ontologies in the semantic web and web services. In a similar vein, Imran et al. (2015) reviewed over 10 hazard-related ontologies. And affirmed that disaster ontologies can be successfully combined with other ontologies describing social media concepts (e.g., users, tagging, sharing, and linking) to support disaster management mobile applications.

Grolinger et al. (Grolinger et al., 2013) proposed a Knowledge as a Service (KaaS) framework for disaster cloud data management (Disaster-CDM), using an ontology-based representation of simulation models, with the objectives of i) storing large amounts of disaster-related data from diverse sources, ii) facilitating search, and iii) supporting their interoperability and integration.

Jung and Chung (Jung and Chung, 2015) proposed an ontology-driven slope modelling for disaster management services (e.g., landslides). The proposed model represents context information necessary for disaster management service and uses disaster management inference rules to provide personalised service for users.

Qui et al. (Qiu et al., 2017) developed a flood disaster management system (FDMS): a platform providing comprehensive functional support for the flood disaster management process. An ontology-based linking approach was proposed to connect the environmental models with disaster-related data to support and increase the system autonomy during model choice and data retrieval tasks with a friendly graphic interface for a 3D visualisation of the integrated flood information. The platform helped in improving the interpretability of disaster data and the decision-making processes.

A Disaster Knowledge Graph (DisasterKG) based system was designed by Purohit et al. (Purohit et al., 2019), for querying disaster-related critical resources based on an extended ontology constructed from existing disaster domain standards. The authors made use of the ontology to unify the information from heterogeneous, open data sources (i.e., offline data or online data from Web sources) and demonstrate the approach's impact on improving decision-making in disaster management. However, the authors claim that the substantial human effort required for semantic information integration makes such an approach cost-effective and not very efficient by itself. The authors consider DL-based KG as a potential alternative.

2.4.2 Conclusion

Ontologies bring significant contributions to the geographic and disaster management domains, including knowledge representation, integration, and sharing within the geographic and disaster management communities and with other scientific communities. Ontologies allow data discovery and integration, image interpretation, and the management of disaster scenarios and workflows.

Ontologies have gained a good interest in literature. However, despite the application domain, most of the existing ontologies are semantically interoperable. Because each researcher had a unique perspective on the topic, the generated ontologies differed in goal and technique. Moreover, the majority of the research was centred on disaster and emergency management, overlooking the formal representation of the disasters, their properties, and relationships with other domains, and mostly concentrated on only one particular disaster/disaster category.

According to the literature, there are still noticeable drawbacks, and a number of issues have yet to be addressed. A global ontology that includes all major disaster categories and integrates geographical information and remote sensing data "does not exist" (Bouyerbou et al., 2019). Further work in such a sensitive area involving human lives should be pursued.

Whereas remote sensing applications are rapidly evolving mostly based on the "new" artificial intelligence (i.e., deep learning), the "old" artificial intelligence (e.g., AI based on mathematics and logic for knowledge representation) should be paid more attention to accompany the development of knowledge-driven approaches and facilitate the emergence of hybrid approaches (Arvor et al., 2019). In this regard, ontologies have not been used to their full potential in the domain and can contribute significantly more to the geographic, remote sensing, and disaster management communities by addressing the substantial conceptual and computational limitations of the traditional data-driven methodologies.

2.5 Change detection and structural damage assessment

Change detection is a technique for distinguishing the differences in the state of an object or phenomenon between two distinct observations (Lu et al., 2004). Change detection in earth observation is described as the use of multi-temporal satellite images to distinguish areas of land cover that have changed between periods. Satellite images should be collected by the same sensor, with the same resolution, and at the same acquisition time (Lillesand et al., 2004).

Change detection (CD) can be a challenging task as it is influenced by several factors, such as the spatial, spectral, and radiometric resolutions of the RS data, in addition to the thematic, temporal constraints, and atmospheric conditions (Jensen, 2005). Several change detection methods have been developed following the emergence of remote sensing data for diverse purposes. Comparative reviews of change detection methods are provided (Singh, 1989, Mas, 1999, Lu et al., 2004, Hussain et al., 2013).

Despite the large number of CD techniques introduced in the literature, and the novel methods that are still emerging, RS-based change detection analysis typically follows two approaches (Hussain et al., 2013): the traditional pixel-based change detection techniques, and the object-based change detection techniques.

Pixel-based CD techniques consider the image pixel as the basic unit of image analysis and change. They are mostly statistics-oriented and focus mainly on the spectral values, generally ignoring the spatial context. Object-based CD techniques, which are part of the OBIA/GEOBIA (described in part 2 of this chapter), were developed as an effort to get around the limitations of pixel-based techniques.

2.5.1 Pixel-based change detection techniques

These approaches can be categorised as pre-classification techniques because they are used on raw data. Several pixel-based CD methods were presented and reviewed in-depth, summarising functionalities, pros, and cons (Singh, 1989, Lu et al., 2004).

Pixel-based CD techniques mainly include algebraic and transformation-based comparisons. Pre-classification CD methods based on image algebra can be further divided into (Hussain et al., 2013): (a) image differencing, (b) image rationing, (c) image regression analysis, (d) vegetation index differencing, and (e) change vector analysis.

Whereas transformation techniques include: (a) principal component analysis (PCA), (b) Tasselled cap transformation, (c) Gramm-Schmidt, and (d) Chi-square transformations.

Pixel-based techniques are generally unsupervised and their primary objective is the use of a low-dimensional subspace to visualise, analyse, or compute the variations in sample distribution between the two dates (Munoz-Marı et al., 2009). Inspection of the involved spectral signatures can be used to investigate the aspect of changes observed in a suitably representative space (Munoz-Marı et al., 2009).

This type of CD technique is simple and can provide a high-level summary of impacts and recovery at a lower cost, however, they are unable to provide the complete change matrix, which includes detailed change statistics of specific features and changes between before and after an event (Lu et al., 2004). They only provide change/no-change (binary) information as an outcome. This change matrix is required in specific studies such as major disaster response and assessment, by assisting in the detailed identification of the location, form, and rate of disaster impacts and recovery (Hoque et al., 2017).

In literature, some of the earlier work employed a pixel-oriented change detection approach for damage assessment purposes (Yamazaki, 2001, Adams et al., 2004, Matsuoka et al., 2004). Yamazaki (Yamazaki, 2001) discussed the use of optical images for the pixel-oriented approach where the damage map is created by a purely pixel-based analysis between before and after damage images. The author proposes the use of proper thresholding of normalised pixel values to define two damage scales: slight damage and no damage to buildings were selected from the images to characterise the pixel value in the damaged areas and debates the potential use of colour indices and edge elements from aerial television images to identify a third scale: severely damaged buildings.

2.5.2 Object-based change detection techniques

Since images are usually segmented into regions or classes before any change detection technique is applied, object-based techniques are generally deemed as post-classification techniques. Image objects are the input units in OBIA described by richer information, such as texture, shape, neighbour spatial relationships, and auxiliary spatial data at various scales, allowing the spatial context to be exploited (Hussain et al., 2013). Only four multi-spectral and one panchromatic band are present in most extant VHR satellite images (Johansen et al., 2008), the integration of shape features, spatial, and contextual information becomes essential to enhance the classification results and hence the CD task.

Image segmentation is at the core of object-based change detection methods and various segmentation techniques are employed with varying results (see part 2 of this chapter), which allows the partition of the scene into meaningful objects and subsequently the selection and extraction of appropriate object features for further analysis and treatment (e.g., classification) of the satellite images. These images objects, in addition to the image classification results, will provide a basic unit for developing a change detection strategy (Hussain et al., 2013). According to Stow (Stow, 2010), object-based change detection can be further categorised into: (i) post-classification comparison, and (ii) multi-temporal image object analysis.

Post-classification change detection is one of the basic and commonly used CD approaches in natural disaster damage assessment and disaster recovery (Wang and Xu, 2010). Both pre- and post-event satellite images, as well as their corresponding classifications, are required to perform this technique. Multi-temporal images are initially classified independently, then classification results are compared, and change is reported.

This method enables detecting the changed area and identifying the type of change. However, the change detection accuracy strongly depends on the accuracy of each individual classification of the multi-temporal images, which means any error in the classification will automatically impact the change results.

Object-based approaches, in contrast to pixel-based approaches, are widely applied in the literature for damage assessment for several disaster categories (Fernandez Galarreta et al., 2015, Ramlal et al., 2018, Jiménez-Jiménez et al., 2020), especially earthquakes. For the latter, the areas of interest (i.e., buildings or roads) are first detected by means of segmentation and classification algorithms, and then change detection is performed. Bitelli (Bitelli et al., 2004) used object-based classification for earthquake damage assessment into three levels of damage using algorithms in e-Cognition and ERDAS software. The first operation performed in e-Cognition is the segmentation of post-event images, this is followed by a definition of objects of interest and damage analysis. Chesnel et al. (Chesnel et al., 2007) classified buildings into four damage grades using object-based assessment and correlation coefficients as features with two very high-resolution images and building footprints. Although 69 percent accuracy was attained, the requirement for correct building registration was highlighted.

2.5.3 Structural damage assessment scale

For disaster management, especially the response and emergency phase, damage assessment is considered a vital piece of information that allows the indication of the most affected zones and the dysfunction of paths and lifelines. Damage evaluation is also important in the immediate aftermath of an emergency, where a preliminary estimation of the overall damage is necessary to plan the recovery process rapidly (Serpico et al., 2012). Remote sensing data are important to promptly and reliably evaluate post-disaster changes and damages, especially for large extent areas where ground surveys are lengthy and challenging.

When a disaster occurs, there are several damages that could be considered, depending on the nature of the disaster, in the case of an earthquake, for example, damage can be stated as follow (Dell'Acqua and Gamba, 2012):

1) Damages to buildings and other built-up structures.
2) Damages to infrastructures (e.g., roads, highways, lifelines).
3) Secondary damages (e.g., landslides triggered by earthquakes, soil liquefaction).

For each of the above-mentioned damages, it is still necessary to distinguish between damage extent and damage level identification. Because the second and third categories are only partially covered by the application of the RS method, the first type (i.e., damage to buildings) accounts for the majority of work in the literature (Dell'Acqua and Gamba, 2012).

Structural damage extent identification can be performed by means of VHR satellite images, nevertheless, slight to moderate damages are not that obvious to detect, even with the use of VHR satellite imagery, as vertical data do not give complete information about the actual structures' condition.

Various organisations have developed a number of damage assessment evaluations for the damage scales (see Table 2.1). In addition to the widely used European Macroseismic Scale (EMS-98) definition (Grünthal, 1998), a chart was produced to describe the building damage patterns based on seismic vulnerability next in (Okada and Takai, 1999), and a damage scale combining Wind and Flood damages was proposed by Womble et al. (Womble et al., 2006).

Table 2.1. Example of existing damage scales (Bouyerbou et al., 2019)

Type	**Organisation**	**Class 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 Japan	5	Range 1	Negligible damage
			Range 2	Slight damage
			Range 3	Moderate damage
			Range 4	Major damage
			Range 5	Destruction
Wood frame buildings	Japan Prime Minister's Office	3		Moderate damage
				Heavy damage
				Major damage
Structure	WHO Damage Assessment Form	5	<25%	Minor structural damage
			>25%	Some structural damage
			>50%	Significant structural damage
			>75%	Major structural damage
			100%	Structure is unusable
Residential Construction	Womble, 2006	4	WF-1	Minor Damage
			WF-2	Moderate Damage
			WF-3	Severe Damage
			WF-4	Destruction

It is worth noting that the majority of these assessments only consider building damage, and in the best-case scenario, structural damage. Moreover, damage assessment may be well documented for several natural disasters (i.e., earthquakes), which is not necessarily the case for all major disasters where the resulting damage do not only affect people and structures but also forest and plant wealth, agriculture, environment, etc. (e.g., flood, forest fire, landslide). For instance, "damage assessment for flood risk is underdeveloped, especially compared to other risks" (Serpico et al., 2012). Few attempts have been made to regularly collect damage data, owing to the difficulty in

obtaining a complete picture of a flood event as it affects vast areas (Serpico et al., 2012).
Some efforts have been made in order to build an index system providing a thorough assessment of disaster damage (Fan et al., 2017). Fan et al. propose an index system for quantitative assessment of disaster physical damage using RS data in China that includes a damage scale of four categories: (a) buildings, (b) agricultural and structural sectors, (c) infrastructures, and (d) resources. Where three damage scales were defined for building damage (collapse, serious damage, moderate damage), and the same number for agricultural and structural sectors (affected, moderate loss, no harvest). However, the damage scale for the rest of the categories was not specified.

Natural disasters are the cause of death of about 60,000 people per year worldwide (according to statista.com). Earthquakes are major disasters that were reported for over 60% of the total natural disaster-related deaths from 2001 to 2011 (Dong and Shan, 2013). A risk that is expected to increase with the rapid global urbanisation.

Post-earthquake damage assessment is usually performed using a wide range of RS technologies and techniques such as optical satellite imagery, SAR, and LiDAR data, including GIS data as well. With the emergence of very high-resolution satellite imagery, the use of optical data becomes a more common and promising technique for earthquake damage assessment despite a few limitations (vertical view, unlike oblique view, dos not allow to evaluate of walls' condition). With the availability of pre- and post-event optical data, visual interpretation, spectral properties, and edge and textures are generally the most used for building damage detection (Ji et al., 2018).

Ehrlich et al. (Ehrlich et al., 2009) have discussed the potential of VHR satellite imagery, compared to SAR imagery, for post-earthquake damage assessment. The study showed that even on the highest resolution available SAR imagery, damage assessment accuracy was still low. Satellite images, with 0.5 m spatial resolution or better, were shown to be the more effective tool for damage assessment, yet insufficient to detect all damage grades.

Face with this problem, several researchers opted for the combination of different data sources. Nie et al. (Nie et al., 2016) developed a method that combines VHR images, statistics, and ground survey data to estimate the structures and types of damaged buildings caused by the China Lushan earthquake. First, manual interpretation of building damage rate and type with different structures of a small area is performed from VHR images and revised by ground survey data. Next, the corrected rates are assigned to the seismic intensity zones. Finally, damaged buildings' numbers and location in larger areas are estimated by combining rates in the seismic intensity areas and the statistical data.

Another potential solution is the use of ML algorithms to improve assessment accuracy. Cooner et al. (Cooner et al., 2016) evaluated the effectiveness of a number of ML algorithms in detecting earthquake damage caused by Haiti's 2010 earthquake. The algorithms' (i.e., feedforward Neural Networks, radial basis function Neural Networks, and Random Forests) efficacy was improved by providing 0.6 m multitemporal imagery, using texture features (dissimilarity and entropy), and structure features (Laplacian of Gaussian and rectangular fit) as inputs. Results from the study show that the ML algorithms can achieve nearly 90% accuracy using only panchromatic/pan-sharpened imagery as the single data source for both training and testing.

2.5.4 Conclusion

Damage assessment is an important task in the disaster management cycle. Results from disaster damage assessment provide core information and are at the basis of disaster relief, recovery, and reconstruction planning (Fan et al., 2017). RS technologies play a critical role in the process by providing essential and cost-effective information for change detection and damage assessment following a disaster. Researchers are showing more interest in exploring RS techniques for this purpose.

Despite the significant number of methods found in the literature, these methods present a number of limitations and are not always very efficient when it comes to lower damage scales and some complex damaged areas, which are not detectable by satellite imagery due to several parameters, such as the spatial resolution, off-nadir angle, shadow, and their incapacity to detect the elevation changes. Damage level assessment, indeed, is a much more challenging task compared to damage extent identification. This is mainly due to the level definitions used in disaster engineering, implying mostly ground-based evaluations and structural effects on some of the structure parts (e.g., walls) that are partially or totally invisible to nadir-looking sensors (Trianni and Gamba, 2008).

With the use of VHR satellite images, an increase in spatial resolution may allow a better characterisation of the damaged vs. undamaged class, however, it will not be very useful for identifying in-between damage levels, which require the assessment of the condition of the walls to be discriminated (Dell'Acqua and Gamba, 2012).

Oblique data and LiDAR data are good alternatives due to the useful information they can provide (oblique view from different angles and elevation information, respectively). However, they tend to be expensive and not usually available, especially for pre-disaster imagery. Data fusion of different data sources remains a good potential to improve the accuracy of the results.

Chapter 3 Knowledge-based satellite image hierarchical classification and change detection

3.1 Overall methodology

In this chapter, a methodology for OWL ontologies development is presented and employed as knowledge support to guide and reinforce hierarchical classification, change detection, and damage assessment. The approach lays on three axes: first the development of a set of ontologies to link major disasters with space, time, and the resulting damage. Second, the use of reasoning for automatic knowledge interpretation and semantic classification of RS data. And finally, the use of semantic reasoning and results of the semantic classification for post-classification change detection and rule-based damage assessment.

This approach (see figure 3.1) allows the representation of expert knowledge in a formal design and to further exploit it in an automatic and effective way for the research purpose.

The methodology is summarised in the following:

1) Capturing and formalising domain expert knowledge.
2) Mapping, modelling, and implementing a global geographic ontology for major disasters including three sub-ontologies: land use and land cover ontology, disaster ontology, and damage ontology, in addition to the formalisation of the remote sensing science and the enclosing contexts.
3) Performing DLs-based reasoning and implicit knowledge inference from the knowledge base for hierarchical semantic classification.
4) Performing an initial segmentation and classification of the multi-temporal images independently using a fuzzy-rule-based method followed by a semantic improvement of the initial segmentation and classification based on the previously developed ontology.
5) Comparing the previous classification results of the multi-temporal images and reporting change and its nature (change classification) for an attempt of damage assessment based on visual interpretation and ontology knowledge-driven logics.

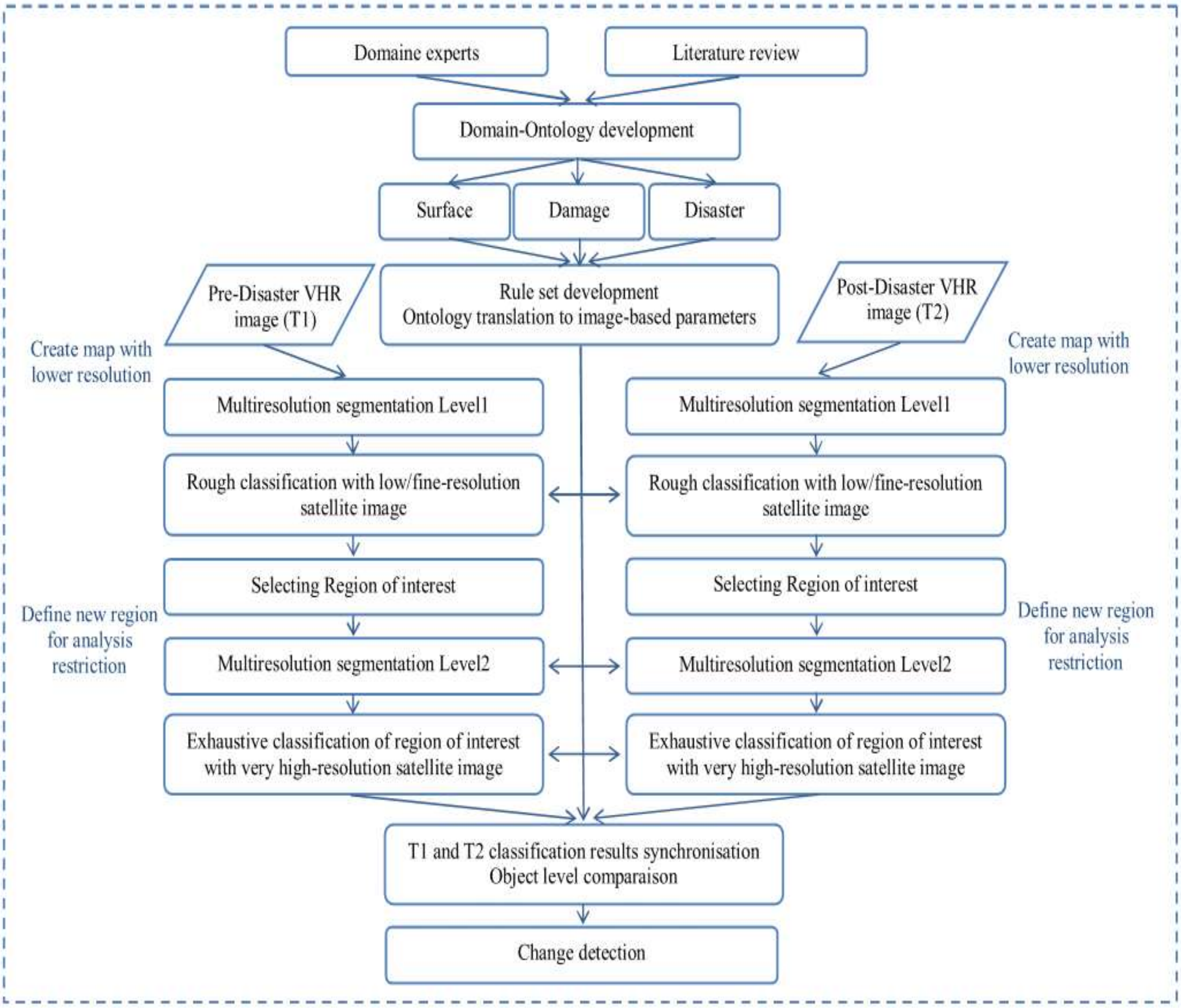


Figure 3.1. Methodology overview (Bouyerbou et al., 2014)

3.2 Domain ontology development

Several methodologies have been proposed in the literature for ontology development. In this work, the followed approach is partially based on a long-established methodology of ontologies development (Uschold and King, 1995) with customisation for better flexibility in ontology development.

3.2.1 Purpose definition

The first stage in developing an ontology is to have a clear and complete understanding of the ontology's purpose and prospective users. This will have a direct impact on the ontology domain, context, taxonomy, and the classes' choices. In this phase, the reason for which the ontology is built is identified, as well as its envisioned uses, and a set of possible intended users.

This work aims to the definition of a comprehensive geographic taxonomy in the context of major disasters. Domain knowledge and the related interdomains are represented along with a clear definition of the relationships linking them. The ontology will serve as a basis for several tasks including satellite image hierarchical classification and damage assessment, in order to assist the photo interpreters in their data analysis and to hasten the relief operations in crisis situations.
The ontology is shared and can be reused as a whole or as parts for semantic content representation of satellite images, change detection, as well as for performing queries related to emergency needs (Bouyerbou et al., 2019).

3.2.2 Knowledge acquisition

Effective ontology building requires a good understanding of the area of interest. Effective ontological analysis needs the acquisition of the domain concepts, their definitions, and an understanding of the kind of relationships that link them.
Ontological engineering is a demanding task that involves digging for the necessary domain knowledge. Generally, knowledge engineers are underprovided in specific

domain knowledge; on the other hand, domain experts lack the required technical expertise to develop a model of formalised knowledge (Bouyerbou et al., 2019). An effort of incorporating the two tasks is accomplished in this work.

Experts, books, articles, and further existing ontologies, used in conjunction with several techniques (i.e., formal, and informal texts analysis, brainstorming, and interviews), were the sources from which the domain knowledge was elicited and acquired.

Expert knowledge in this work was gathered through interviews and several meetings with different remote sensing experts and some of the international chart space and major disasters members (professors, doctors, Ph.D. candidates, and industry members) during an extensive six months internship in LIVIA[3][188] lab (Laboratory for Imagery Vision and Artificial Intelligence). The interviews with the experts helped in: (i) the identification of the key concepts and relationships between them regarding the domain of interest, (ii) refining the list of terms and their meanings, (iii) building concept classification trees, and (iv) compare them with the existing related literature.

The brainstorming technique was used during and after the interviews to produce all potentially relevant terms and their relations. An additional knowledge corpus analysis was performed to ensure adequate coverage.

In addition to that, numerous LULC standards-based ontologies, and related existing geographic ontologies found on the web, were examined. This section introduces three well-known land cover and land use systems (Bouyerbou et al., 2019):

(a) Corine Land Cover:

CO-ordination of INformation on the Environment is a European programme produced by the European Commission from 1985 to 1990 that established a catalogue of the land cover of 38 European countries, based on satellite image interpretation and supplementary data, in order to create the European environmental landscape. A first

[3] https://www.etsmtl.ca/Unites-de-recherche/LIVIA/accueil

edition was delivered in 1990 (Heymann, 1994), followed by two more versions in 2000 (Büttner et al., 2002) and 2006 (Aune-Lundberg and Strand, 2006) respectively. Corine is structured into three levels, with five classes in the first level, fifteen classes in the second, and forty-four classes in the third level. The OWL Corine land cover-based ontology [4] was downloaded and analysed for comparison with the ontology developed in this work (see Chapter 5).

(a) USGS:

The Anderson Land Use and Cover Classification System (Anderson, 1976) has been developed by The United States Geological Survey (USGS) for use with RS data. Developed to satisfy the demands of federal and state agencies by providing a four-level representation of LULC from distant sensors around the country. The first and second levels are generic, while the third and fourth levels are left open-ended so that other areas can develop more detailed land use classifications that are consistent with each other and the national system (Anderson, 1976). OWL USGS-based ontology [5] was downloaded and analysed for comparison with the ontology developed in this work (see Chapter 5).

(a) LBCS:

The American Planning Association created the Land-Based Classification Standards (LBCS) (Montenegro et al., 2012). LBCS is a comprehensive land use that provides a classification of urban space including five dimensions: activity, function, properties, site, and structure. The aim of LBCS is to provide semantic representations of geo-referenced spatial data. Montenegro et al. (Montenegro et al., 2012) present an LBCS-based OWL ontology, the latter was downloaded and analysed for comparison with the ontology developed in this work (see Chapter 5).

[4] http://harmonisa.uni-klu.ac.at/ontology/corine.owl
[5] cegis.usgs.gov/owl/USTopographic.owl

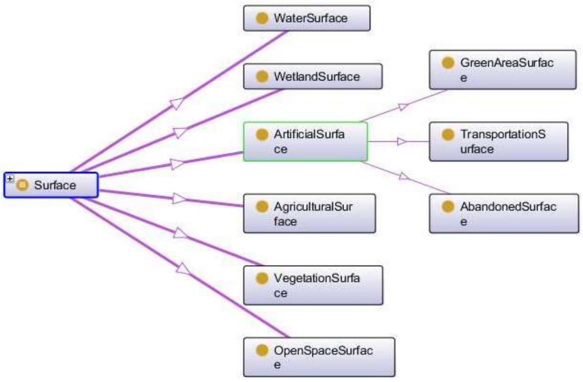
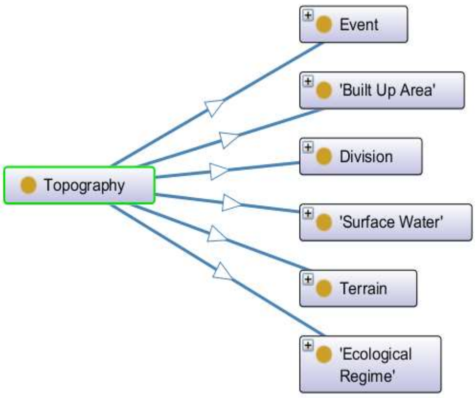
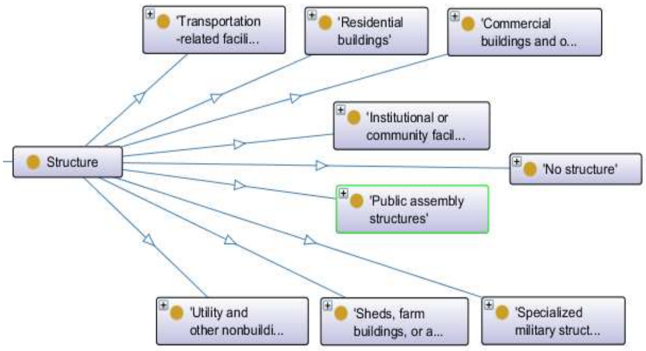


Figure 3.2. Part of Corine Ontology



(a)



(b)

Figure 3.3. (a) Part of USGS Ontology and (b) Part of LBCS Ontology

Although knowledge acquisition is an autonomous phase that is usually performed apart from the ontology design and implementation, most of the acquisitions are carried out either concurrently or following the purpose definition phase and tend to lessen with the progression of the ontology development process, however, knowledge acquisition should be rather carried out throughout the entire ontology life cycle to ensure its reliability.

3.2.3 Ontology building

Geographic ontologies provide a representation of geographic objects considering their nature, characteristics, and constraints. Geographic objects are dynamic, have a wide range of properties and values, and a have close connection to space and time. As a result, describing geographical concepts, their relationships, rules, and axioms necessarily involve a thorough examination of the semantics behind the geographical concept (Bouyerbou et al., 2019).

Three phases were performed to allow an effective ontology design and building:

A. Conceptualisation:

In this phase, domain knowledge acquired in the previous phase is structured in a conceptual model. The first step is to create a formal or semi-formal glossary using previously acquired knowledge and specifications expressed in natural language, as well as to collect all potentially useful domain knowledge. The glossary must include concepts, instances, verbs, and properties. Most of the ontology terms will be defined at this stage, nevertheless, some can still be identified/edited as the ontology construction process advances.
Concepts and verbs are further grouped to form the ontology concepts and their relationships. For related concepts with a specific hierarchy, a concepts classification tree is built.

B. Coding:

"*By coding, we mean explicit representation of the conceptualisation captured in the above stage in some formal language*" (Uschold and King, 1995). In knowledge engineering, several solutions for formal knowledge modelling and manipulation exist. We can find the Frames (Minsky, 1975), Conceptual Graphs (Sowa, 2008), and Description Logics (Baader et al., 2003). Those knowledge-based systems solutions have general common principles for knowledge representation and can be used for ontology modelling.

In this work, Description Logics (DL) have been employed for the coding phase, due to their wide use by the scientific community and by the W3C[6] standards, as DL are the formal fundaments of the OWL.

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[6] World Wide Web Consortium: www.w3.org

Table 3.1. Example of Description Logics syntax

Axiom	DL Syntax	Example
allValuesFrom	$\forall$	
someValuesFrom	$\exists$	
unionOf	$\cup$	
intersectionOf	$\cap$	
complementOf	$\neg$	
subClassOf	$C_1 \subseteq C_2$	Earthquake ⊆ NaturalDisaster
equivalentClasses	$C_1 \equiv C_2$	Temporal Entity ≡ Time interval
disjointClasses	$C_1 \subseteq \neg C_2$	land ⊆ ¬ sea/ocean
subPropertyOf	$P_1 \subseteq P_2$	Borders ⊆ TopologicalRelation
equivalentProperties	$P_1 \equiv P_2$	hasResident ≡ hasOccupent
inverseOf	$P_1 \equiv P_2^-$	after ≡ before^-
sameIndividualAs	$\{i_1\} \equiv \{i_2\}$	{Week} ≡ {7 days}
inverseIndividualFrom	$\{i_1\} \subseteq \neg\{i_2\}$	{Monday} ⊆ ¬ {Friday}
Range	$T \subseteq \forall P.C$	T ⊆ ∀ hasBegenning.TimeInstant
itypeC	$i : C$	Monday: Day

DL is a language family that corresponds to notational variants of the classical first-order logic. DL can be used to represent domain knowledge in a structured and comprehensive way. A domain representation in DL is performed through a knowledge base (K), which is constituted of a set of concepts (classes N_C), roles (properties N_P), and individuals (instances N_i) (see eq. 1). A knowledge base is a combination of two parts: a TBox T which represents the terminological part of the knowledge about the domain structure, and an ABox A which represents the assertional part or knowledge about a concrete situation (see eq. 2).

$$K = \langle N_C, N_P, N_i \rangle \qquad (1)$$

$$K = \langle T, A \rangle \qquad (2)$$

Where K is a knowledge base, N_C is a set of concepts C, N_P is a set of properties P, and N_i is a set of instances i.

The knowledge base K is the combination of the Tbox T and the Abox A.

Furthermore, to process the content of the modelled knowledge efficiently, the OWL Web Ontology Language was used in this work. OWL is an ontology language used to represent rich and complex knowledge, including complex relationships between classes, roles, and objects in a model similar to the one used in DLs (Flouris et al., 2005). OWL is recommended by W3C and is expected to play an important role in the future of the Semantic Web (Flouris et al., 2005).

C. Integrating existing ontologies:

One of the most interesting benefits of using ontologies is their reusability capabilities. Several standard and upper-level ontologies are shared and accessible for reuse. In this work, the developed ontology was initially built from scratch and eventually extended and updated by merging two upper-level ontologies into GEO-MD, namely GeoSPARQL and OWL-Time. The reason why this was judged imperative, is the need for integration of two important aspects: Space and Time, as well as their general representation of properties (Bouyerbou et al., 2019).

An upper-level ontology, also known as top-level ontology, is a high-level and domain-independent ontology, which generally contains generic, abstract, and universal concepts for the generality and expressiveness of a wide range of domains.

(a) GeoSPARQL[7]:

GeoSPARQL is a Semantic Web standard for representing and querying geospatial data. It defines terminology for RDF/OWL geospatial data representation and a query language for SPARQL geospatial data processing. GeoSPARQL includes top-level classes of spatial structures, a topology vocabulary for describing properties, and geometry components for data types (Perry and Herring, 2012).

(b) OWL-Time[8]:

OWL-Time is a temporal ontology that attempts to explain the temporal properties of real-world resources. The ontology offers a vocabulary for describing information

[7] http://schemas.opengis.net/geosparql/1.0/geosparql_vocab_all.rdf
[8] https://raw.githubusercontent.com/w3c/sdw/gh-pages/time/rdf/time.ttl

regarding topological relationships between instants and intervals, durations and temporal location, as well as date-time variables. (Hobbs and Pan, 2006).

In this work, a bottom-up approach was used to match the initially developed core domain ontology to the two upper-level ontologies. This approach represents more challenges compared to the top-down approach where top-level ontologies are used as a foundation for deriving concepts of the domain ontology and thus taking all the advantages of the knowledge already expressed in them.

Initially, a definite vocabulary was developed into the domain ontology (i.e., GEO-MD), and then the above-mentioned upper-level ontologies were integrated into GEO-MD to cover the spatial aspect of satellite images and the temporal aspect of a disaster situation. The three ontologies were aligned, and the necessary set of properties was established to connect the different classes of the ontologies (see figure 3.4).

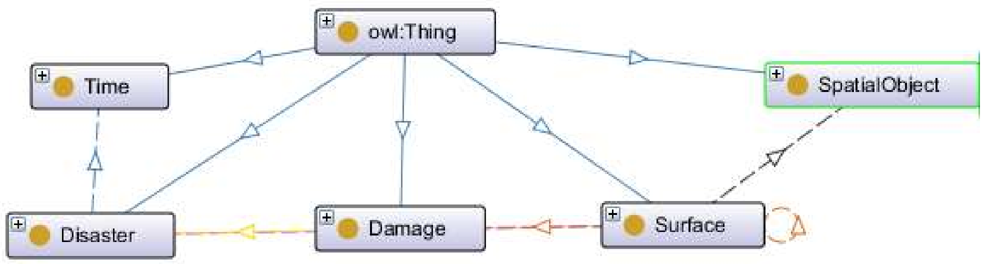


Figure 3.4. Ontologies alignment

3.2.4 Evaluation

Ontology evaluation is the "technical judgement of the ontologies, their associated software environment, and documentation with respect to a frame of reference" (Uschold and King, 1995). An ontology needs to be evaluated before being (re)used in final applications or aligning with other ontologies. Concept definition, taxonomy, and axioms should all be evaluated before any use to make it safer.

Ontology content should be evaluated throughout the life cycle of the ontology, and ontology development tools should aid in content evaluation during the ontology building process (Gómez-Pérez, 2004).

In this work, the first version of the ontology was initially created in 2013, and eventually evaluated and updated in 2020 using Protégé 5.5 tool and essential plugins.

3.3 Ontology-based hierarchical semantic classification

The complete classification task of this work involves a list of subtasks that must operate on image objects of different scales/levels. Scale is a critical aspect of image understanding. Scale in the RS domain is generally assumed based on pixel resolution; however, each object of interest may have its own scale. Some objects may appear at a certain scale and not at another, their occurrence/absence is often determined by the scale definition. Furthermore, the same objects can appear differently when the scale changes, consequently, the classification task is strongly related to the definition of the scale of interest (Benz et al., 2004b).

To perform the classification task at this level, first, lower-resolution maps are created from the original data (Fig 3.5 indicates the same area with different resolutions). This task is mainly performed to reduce the processing cost and accelerate the segmentation process. Multiresolution segmentation technique is applied to these low-resolution maps and an initial rule-based classification is performed to select the area of interest according to the disaster category using Surface Ontology first level (see figure 3.6).

Figure 3.5. Lower resolution map creation

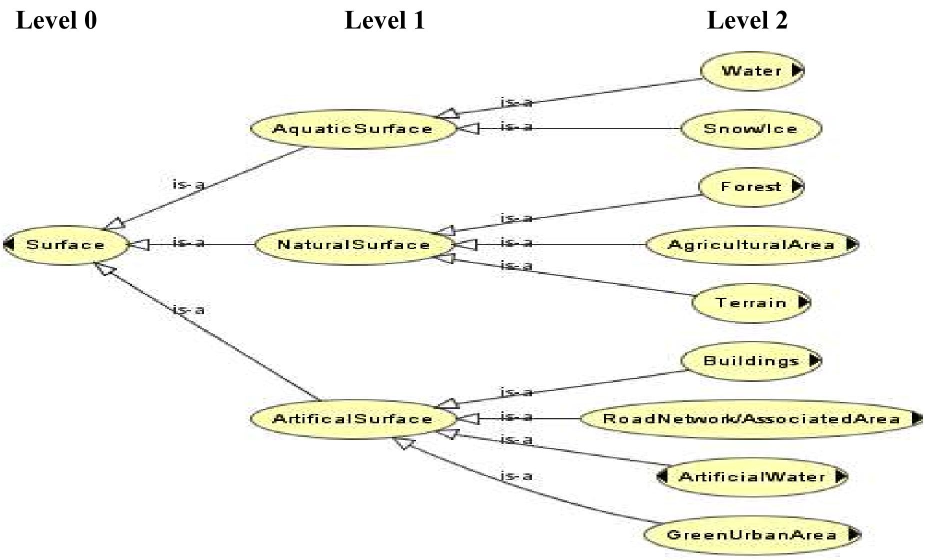


Figure 3.6. Surface Ontology levels and classes

3.3.1 Image segmentation

Contrary to the common, pixel-based approaches, where the image basic unit is single pixels, segmentation allows the first step toward image understanding which is finding meaningful image objects (segments) that give a close association between real-world objects and image objects.

After selecting the input satellite images. Several methods can be applied for segmenting where the target image is segmented into single image objects.

Object-based techniques split the satellite image into homogeneous image objects using segmentation techniques. The latter is the input for the object-based classification in the next step.

A segmentation technique that enables the extraction of image object primitives at different spatial resolutions is used in this work (i.e., Multiresolution Segmentation) which is available in the Trimble eCognition software.

MRS method is a bottom-up region-merging technique proposed by Baatz (Baatz, 2000), in which the "degree of fitting" h for a d-dimensional feature space f is defined as follows.

$$h = \sqrt{\sum_d (f_{1\mathrm{d}} - f_{2\mathrm{d}})^2} \qquad (3)$$

Where *h* represents the difference between two adjacent regions in an image, the lower this difference is, the closer the two regions are. The f_1 and f_2 are the feature space of the two image regions, respectively. The notation *f* is a general term for any object feature (e.g., texture features or spectral values), and *d* is the number of features in the feature space. Given a certain feature space, two image-objects are considered similar when they are close to each other in this feature space (i.e., a low *h* degree).

The standard deviation over the function segments in each dimension can be used to further standardise this distance:

$$h = \sqrt{\sum_d \left(\frac{f_{1\mathrm{d}} - f_{2\mathrm{d}}}{\sigma_{fd}}\right)^2} \qquad (4)$$

The MRS algorithm implemented in the eCognition software is an optimisation technique that minimises the average heterogeneity and maximises the respective homogeneity (i.e., a combination of local and global optimisation techniques) based on shape, compactness, and scale parameters (Trimble, 2011).

3.3.2 Multi-level classification

In this research, the employed method is an object-oriented fuzzy rule-based classification. Various resolution levels analysis is necessary to obtain the required results. All levels are linked (see fig. 6), this specific link is defined through the developed ontology, as well as the respective relations and axioms.

At level 1, main geographic Surface classes (Natural, Aquatic, and Artificial Surface) are extracted from the lower resolution multi-temporal maps created in the previous step using spectral characteristics such as Normalised Difference Vegetation Index (NDVI), Built-up Area Index (BAI), and Normalised Difference Water Index (NDWI), for classification. Moreover, spatial, temporal, and contextual information is subsequently used for refinement.

$$NDVI = \frac{\mathrm{NIR-RED}}{\mathrm{NIR+RED}} \tag{5}$$

$$NDWI = \frac{\mathrm{G-N}}{\mathrm{G+NIR}} \tag{6}$$

$$BAI = \frac{\mathrm{B-RED}}{\mathrm{B+RED}} \tag{7}$$

At level 2, the region of interest is selected according to the disaster type.
The disaster-affected regions are identified as regions of interest using ontology and knowledge inference, and the multi-temporal maps' resolution is increased to the original resolution (see figure 3.7).

Multiresolution segmentation is applied to the region of interest with new parameters, and a new rule set is created for a refined fuzzy ontology-based classification. The classification rule set differs from one region to another.

Different procedures are applied to different classified datasets instead of processing everything with the same algorithm. Thus, the results will be more appropriate for specific data (see figure 3.8).

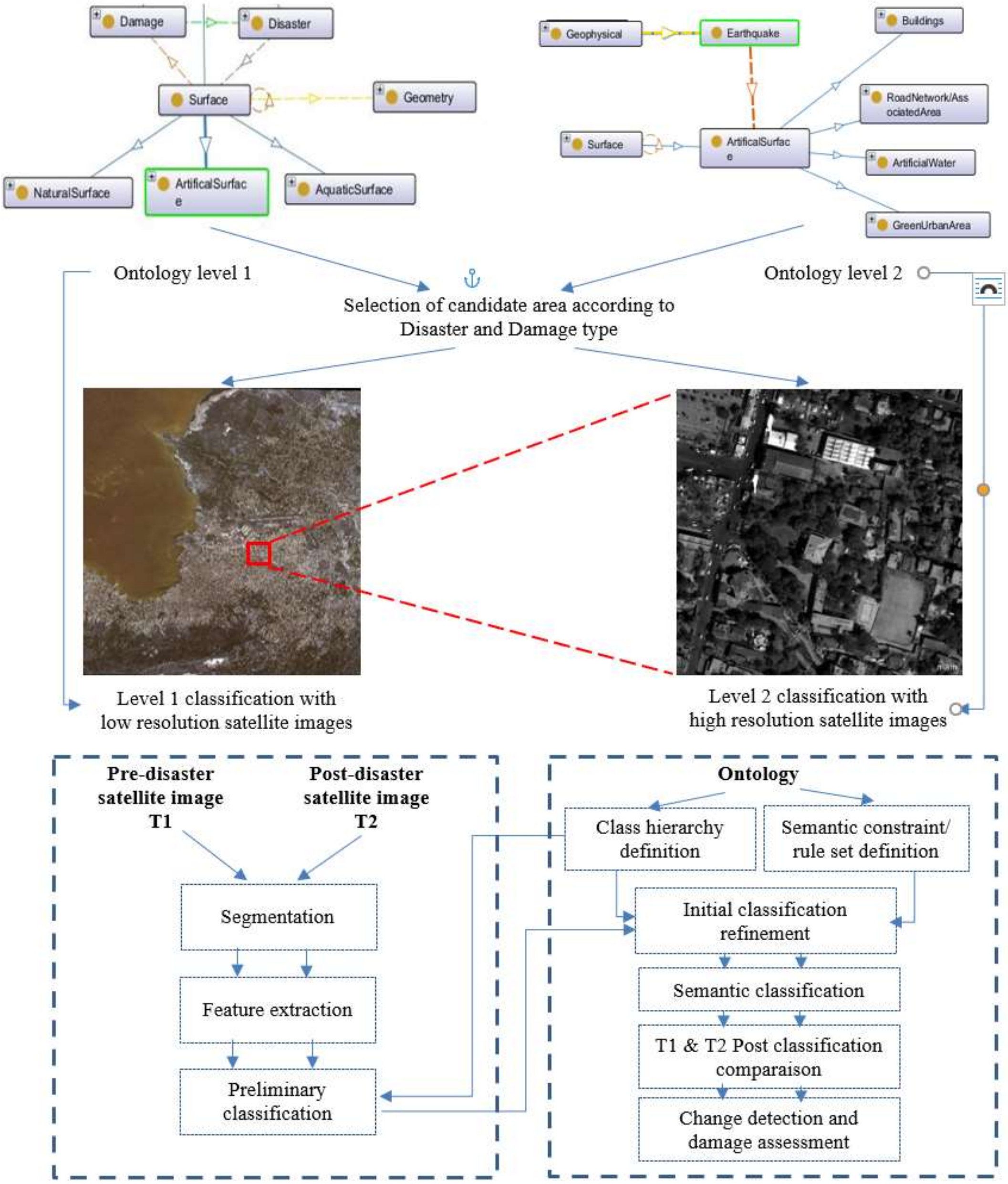


Figure 3.7. Classification methodology description (Bouyerbou et al., 2019)

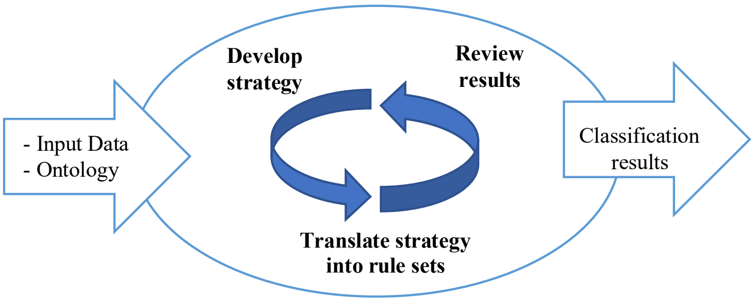


Figure 3.8. eCognition classification procedure

3.3.3 Accuracy assessment

Accuracy assessment is the process of verifying the classification's quality. Several errors can occur during the classification process (incorrect image registration, misinterpretation, class ambiguity, etc.) which can lead to insufficient results.

The accuracy of the classification outcomes was assessed using reference data generated from a visual interpretation of the test area satellite images and the existing expert manual interpretation maps.

The two error matrices of the rule-based initial classification and the ontology-based refined classification of the test area are subsequently compared, and results are reported.

3.4 Change detection and damage assessment

After multiresolution segmentation and supervised ontology-based fuzzy logic classification of the multi-temporal data (pre- and post-disaster satellite images), a comparison process of the previous results, where change is reported and classified (damage assessment), is performed at this level.

An object-oriented change detection approach and rule-based classification are used to complete the two-task process in this part. First, a post-classification comparison approach is performed for change detection. And second, change classification (damage assessment) using rule-based technique and the ontology knowledge-based inference.

One of the most fundamental changes detection techniques is the post-classification comparison approach which involves analysing spectral variations between two separately classified image dates to distinguish areas of change. (Al-Khudhairy et al., 2005). The classification results are compared not only in terms of spectral differences, but also in terms of shape, texture, and spatial information.

Post-classification comparison algorithm is applied with a conversion matrix as output. The conversion matrix shows the transformation from one class into another. Only the classes of interest are compared in this process (e.g., buildings in the case of an earthquake).

For change classification, the first results from the previous classification maps for pre- and post-disaster are used as thematic layers for a post-classification segmentation for the object-based change detection. When using a thematic layer for segmentation, the borders separating the involved classes do not undergo further segmentation.

After the two classes (change/no change) are selected. The second task consists of the classification of the detected change into predefined classes (damage severity) using rule-set classification and ontology inference. Following the segmentation, ontology-based damage axioms are translated into change detection rule sets to classify each object into one of the damage levels. For example, for structural damage, three levels were defined (collapse, severe damage, slight damage). The rules knowledge base is a typical decision tree.

First, a set of rules is initially created to reduce the classification errors from the two classification maps before performing the damage assessment and further classifying the changes into different levels of damage severity. Next, spectral characteristics, shape features, spatial, and contextual features are combined to create rules for damage assessment. The features and threshold values choice is determined by the ontology-driven expert knowledge, the literature, quantitative analyse, and trial and error approach.

The type of disaster highly influences the choice of the methods and the definition of the rule sets for the specific geographic object classification in the area of interest. The general flowchart is shown in figure 3.9. That will be further detailed for a specific disaster with a use-case in Chapter 7.

3.5 Conclusion

The general methodology followed in performing this research is described in this chapter. Three main approaches were introduced at this level, namely: (i) a domain ontology development approach, (ii) an ontology-based classification approach, and (iii) a change detection and damage assessment approach. The described approaches are general to the research subject. They will be further detailed in the following chapters with a specific disaster category, study area, and RS data, which are described in the following chapter, in addition to a set of materials used to perform this study.

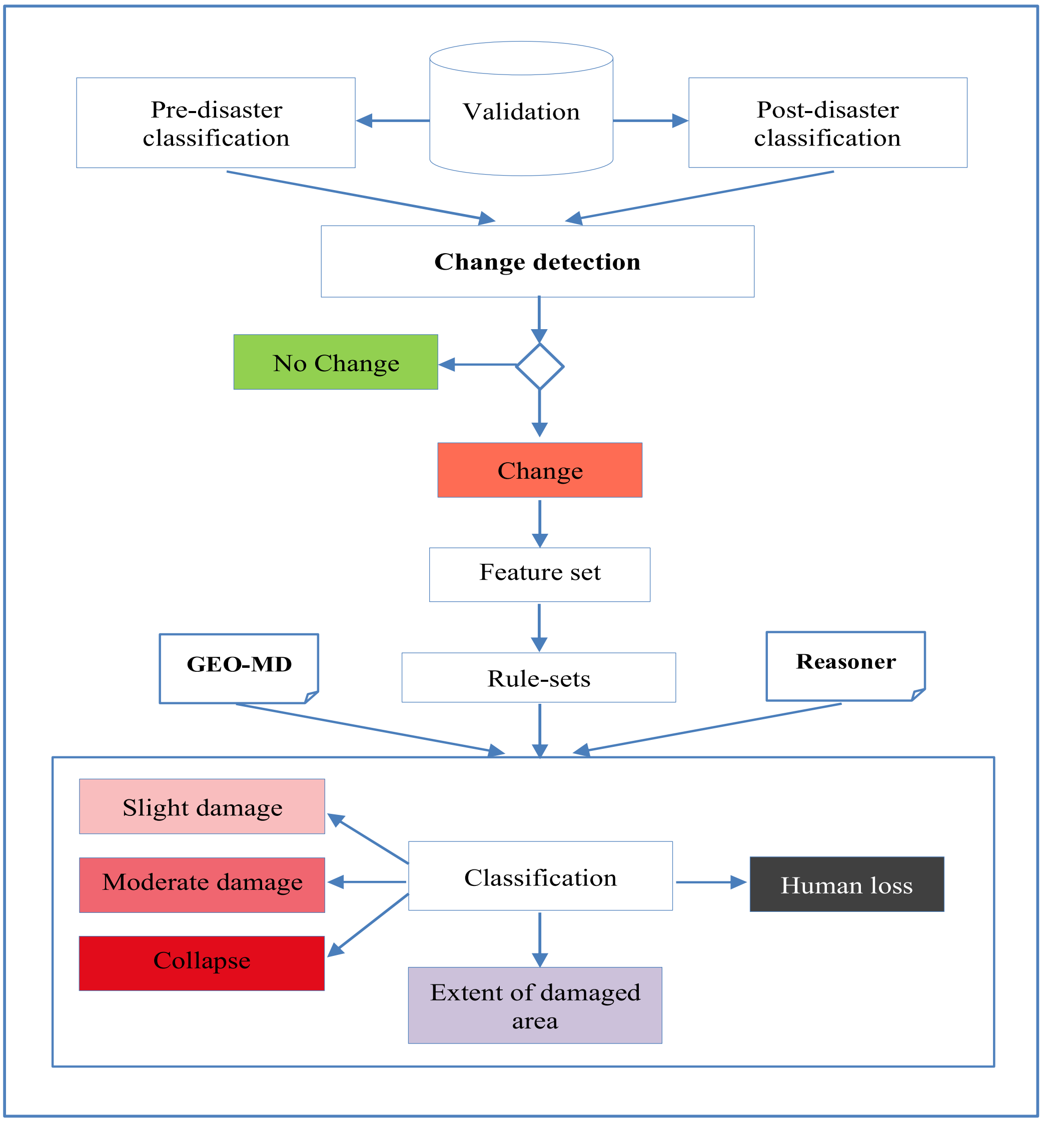


Figure 3.9. A flowchart of the change detection process

Chapter 4 Study area, data, and material

4.1 Haiti 2010 Port-au-Prince Earthquake

4.1.1 Study area

On the 12th of January 2010, a massive earthquake (figure 4.1), with a magnitude of 7 on the Richter scale, struck southern Haiti, wreaking havoc on the country's capital, Port-au-Prince. Authorities announced over 200,000 deaths, thousands of injuries, and 1.5 million people displaced. Over 30,000 structures were seriously affected, including over 1,300 schools and 50 healthcare facilities. The International Charter was triggered in the aftermath of the disaster for rapid mapping and damage assessment.

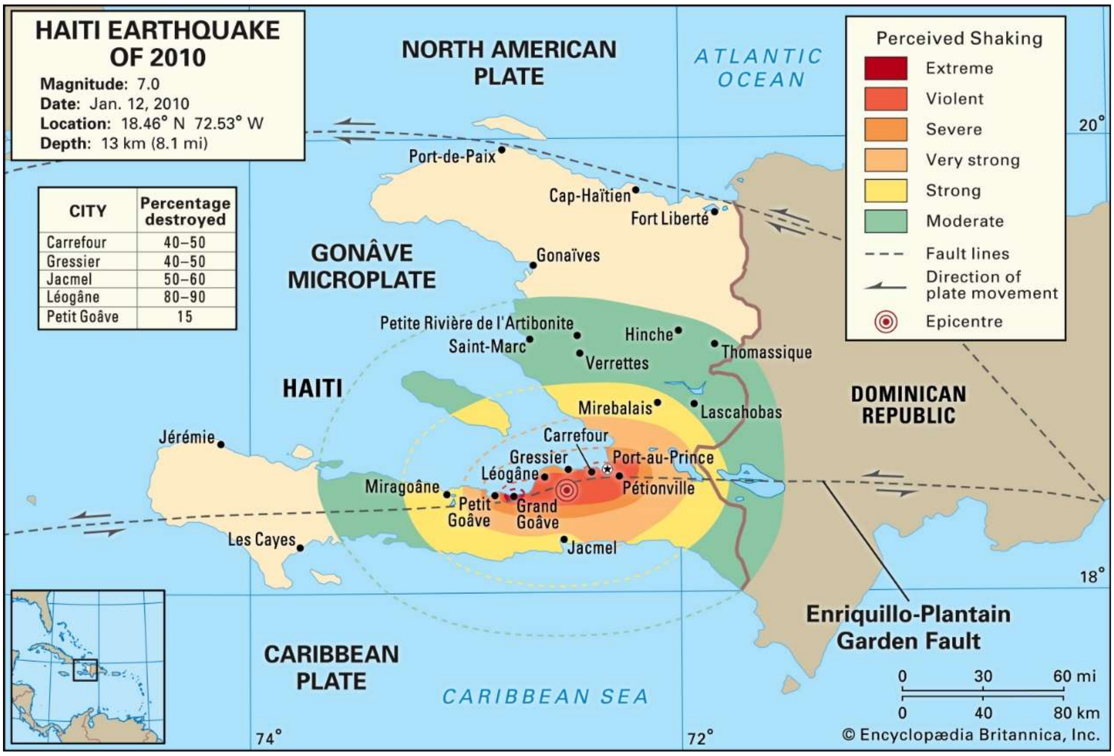


Figure 4.1. Shaking intensity and damage degree incurred by the Jan. 12, 2010, Haiti earthquake [9].

The area of study is located in Port-au-Prince, Haiti (see figures 4.2 and 4.3). Haiti is regarded as one of the highest poverty rates nations in the world, with scarce economic and financial resources. Accordingly, the lack of resources impacts the disaster

[9] https://www.britannica.com/event/2010-Haiti-earthquake

management process and makes the rescue and relief efforts even more challenging, especially with extensive and considerable damages.

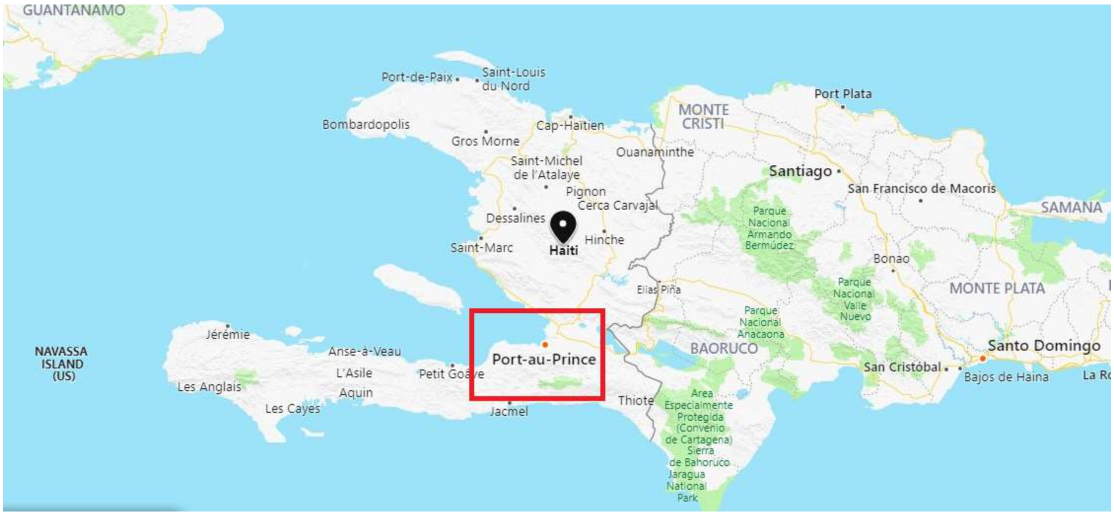


Figure 4.2. Port-au-Prince, Haiti. Study area retrieved from Bing map

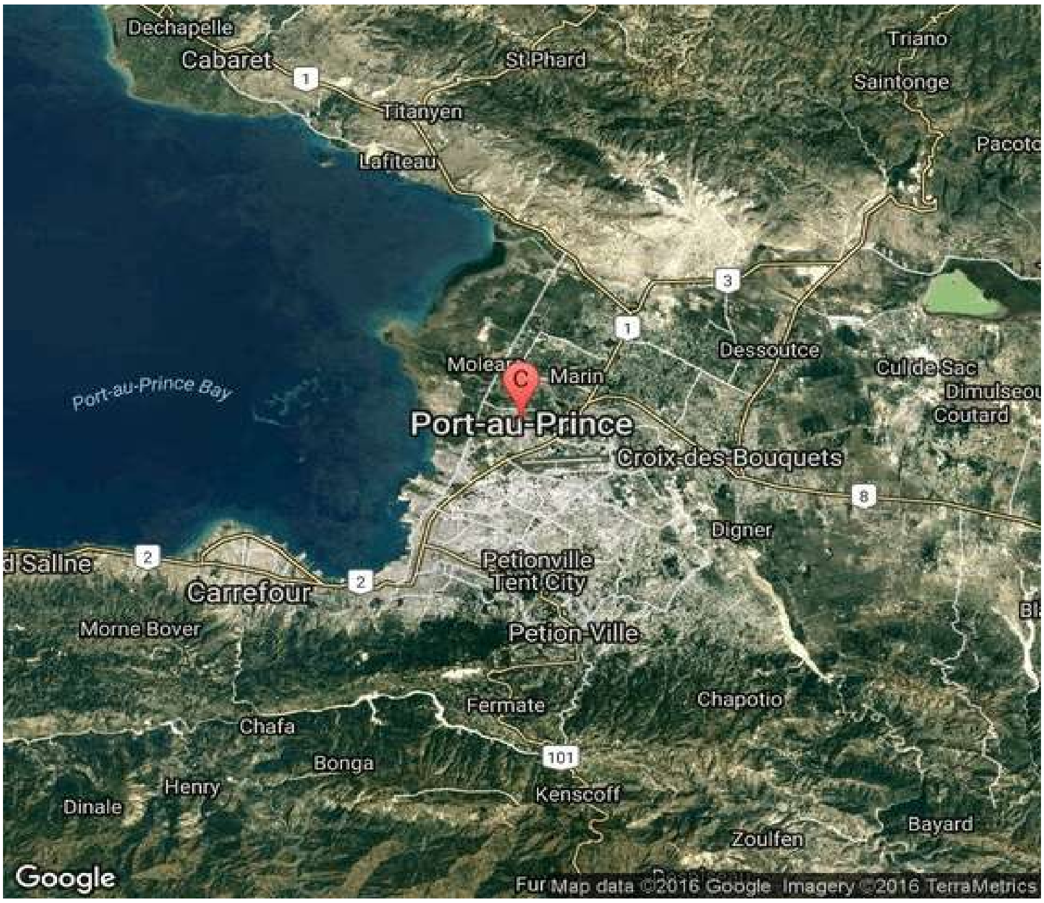


Figure 4.3. Port-au-Prince, Haiti. Study area retrieved from Google map.

4.1.2 Data

This section presents the datasets that were used to test the proposed approach and the efficacy of the developed ontology throughout the development of this research.

Various data from different sources were collected. This includes satellite images, LiDAR data, oblique aerial imagery, and manually annotated maps. Details are summarised in table 4.1.

Table 4.1. An overview of the data used for the study.

Source	**Resolution**	**Acquisition date**
QuickBird	2.4 m multispectral 0.6 m panchromatic	22 February 2009 15 January 2010
Leica ALS60	LiDAR 1 m UTM & WGS84	21/22 January 2010
Manual damage assessment maps: UNITAR/UNOSAT[10], DLR[11].	Auxiliary data	N/A
Building identification and preliminary damage surveys: PICTOMETRY Images[12]	High-resolution Oblique aerial imagery	January 2010

A. Optical imagery:

The QuickBird satellite, launched by DigitalGlobe in 2001, provides multi-spectral images with a spatial resolution of 2.4 meters and panchromatic images with the spatial resolution of 0.6 meters (see figure 4). A QuickBird multispectral image consists of 4 channels (4 spectral bands), namely, blue (450-520 nm), green (520-600 nm), red (630-690 nm), near-IR (760-900 nm). All images were pansharpened in the pre-processing stage.

[10] https://unitar.org/unosat/
[11] https://activations.zki.dlr.de/de/activations/items/ACT069.html
[12] http://haiti-patrimoine.org/

Figure 4.4. Haiti – Port-au-Prince: Quickbird panchromatic image (0.6 m)

B. LiDAR data:

The World Bank, ImageCat Inc., and RIT have publicly shared post-event Airborne LiDAR dataset collected between January 21 and January 27, 2010, in response to the January 12th Haiti earthquake. The data was collected by the Center for Imaging Science at Rochester Institute of Technology (RIT) and Kucera International on behalf of ImageCat, Inc., with funding from the World Bank's Global Facility for Disaster Recovery and Recovery (GFDRR). All data is in the public domain[13]. Elevation models derived from this data were also generated for usage in this study (see figure 4.5).

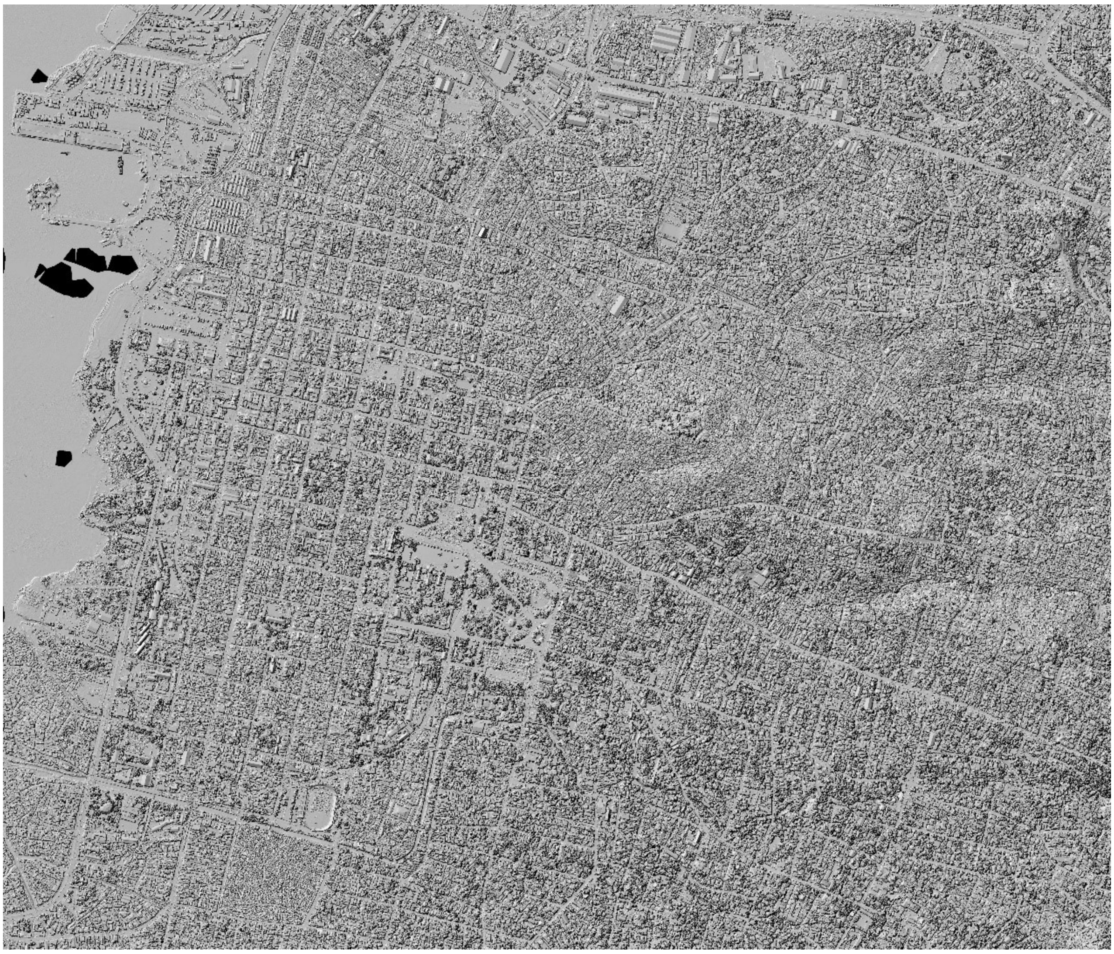


Figure 4.5. Haiti – Port-au-Prince : LiDAR DEM (Data Elevation Model) data.

[13] OpenTopography.org

C. Visual interpretation data:

Following the magnitude 7.0 Haiti earthquake, Haiti Government, with support from the international community and charters, has handled the emergency response operations. A number of experts and photo interpreters from different organisations have worked intensely to interpret the remotely sensed data manually and produce damage maps for disaster response and relief operations.

United Nations Institute for Training and Research (UNITAR), Operational Satellite Applications Programme (UNOSAT), the EC Joint Research Centre (JRC), and The World Bank worked jointly to provide remotely sensed-based damage assessments of buildings in the earthquake-affected area, using aerial photographs and satellite imagery. Scientists from the German Aerospace Center (Deutsches Zentrum für Luft- und Raumfahrt; DLR), under the umbrella of the International Charter on Space and Major Disasters, have also joined their efforts to achieve the same goal: geographic information analysis and satellite image derived mapping, damage interpretation, and preliminary damage assessments using available satellite imagery.

Figure 4.6. Haiti – Port-au-Prince : UNITAR/UNOSAT damage assessment sheet map example.

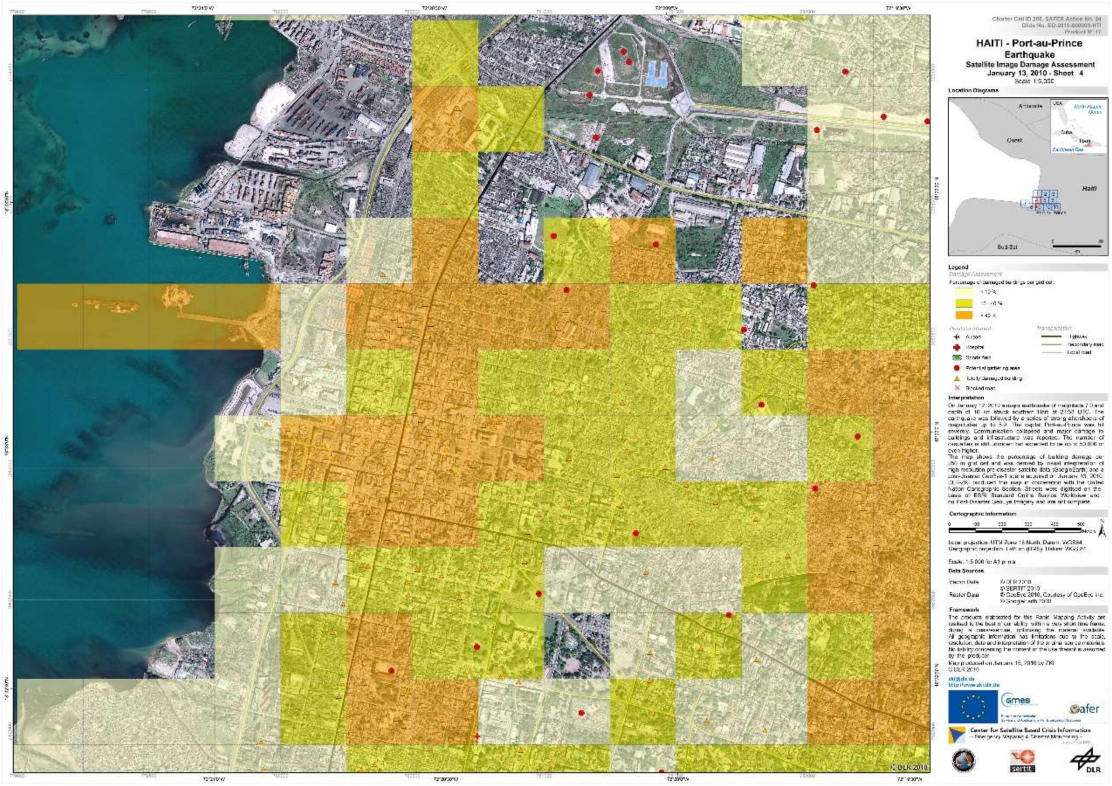


Figure 4.7. Haiti – Port-au-Prince: DLR damage assessment sheet map example as of 13 Jan 2010 (based on GeoEye satellite image)

UNITAR/UNOSAT performed the assessment on a point basis (see figure 4.6), using slightly different damage scales initially (EMS-98 reduced version). Whereas DLR performed the assessment on a block basis (see figure 4.7) using the EMS-98 reduced version of three damage scales.

D. Oblique aerial imagery:

In addition to the previously stated data, oblique aerial imagery, from manned aircraft and unmanned aerial vehicles (UAV), was made available by Pictometry, allowing the analysts to access detailed oblique views of the buildings. This data was highly valuable for validation of the joint assessment, as well as to better understand the limitations of images acquired at nadir.

Unlike optical satellite images, oblique images capture both roofs and façades with a very high spatial resolution, enabling a complete and accurate view of the buildings which provides additional information for damage assessment (Fernandez Galarreta et al., 2015). Figure 4.8 shows an example of the captured view (roofs and facades) of the damaged buildings.

Oblique aerial imagery was used to evaluate building damage, and remotely survey harder-to-reach areas. Oblique imagery allows a more rapid and detailed evaluation but remains less accurate compared to the field surveys regarding buildings' levels of detail.

Figure 4.8. Oblique aerial imagery showing roof and façade view of damaged buildings

4.2 Software tools

4.2.1 Protégé[14] 5.5

Protégé is an open-source framework with a suite of tools for designing, querying, visualising, and preserving ontologies, developed by the Stanford Centre for Biomedical Informatics Research at Stanford University's School of Medicine. Protégé offers a suitable environment for creating ontologies-based domain models and knowledge-based applications. Protégé supports a number of ontology languages such as RDF, XML, OWL, and OWL 2, and a set of OWL-DL-based reasoners such as Pellet and HermiT.

Protégé was used for the implementation of the ontology developed in this work, as well as for inference and reasoning tasks related to satellite image classification and damage assessment (see figure 4.9).

4.2.2 eCognition[15] 9.0

eCognition Definiens is a commercial software project initiated by the Munich Definiens Corporation, which was created by Nobel Laureate Gerd Binning in 1999 and has been in operation since then. eCognition is an OBIA software that can be used in all remote sensing applications providing a number of classification and segmentation algorithms.

It is also the first RS data analysis software based on target information to use a fuzzy classification algorithm backed by decision expert systems to overcome the limitations of conventional commercial RS software, which is typically based exclusively on spectral data (Xu et al., 2017). eCognition classification, in contrast to conventional pixel-based classification methods, is aimed at objects, allowing full use of object information, such as shape, texture, and level, as well as inter-class information (related

[14] https://protege.stanford.edu/

[15] https://geospatial.trimble.com/products-and-solutions/ecognition

features of neighbouring objects, sub-objects, and parent objects), significantly improving the automatic recognition accuracy of spatial resolution data (Zhang, 2018).

In this study, eCognition was used to process satellite images and LiDAR data, as well as to develop the segmentation and classification strategy (see figure 4.9).

4.3 ArcGIS[16] 10.7

ArcGIS is a commercial geographic data platform for GIS working with maps and geographic data, created by the Environmental Systems Research Institute (ESRI), Redlands, California, USA, and established in 1969 by Jack and Laura Dangermond.

ArcGIS is mainly used for creating, editing, and managing maps (with shapefile extension), but also for managing GIS databases, analysing geographic data, data fusion (e.g., satellite images, LiDAR, and a range of RS data), georeferencing, and for spatial analysis of vector and raster information.

The system offers an infrastructure for creating rich maps and geographic information data accessible as ArcGIS Online, ArcGIS Desktop, and ArcGIS Server.

In this work, ArcGIS was used for RS data fusion, processing, and visualisation of the shapefile classification results and the damage assessment maps (see figure 4.9).

[16] http://www.esri.com/software/arcgis

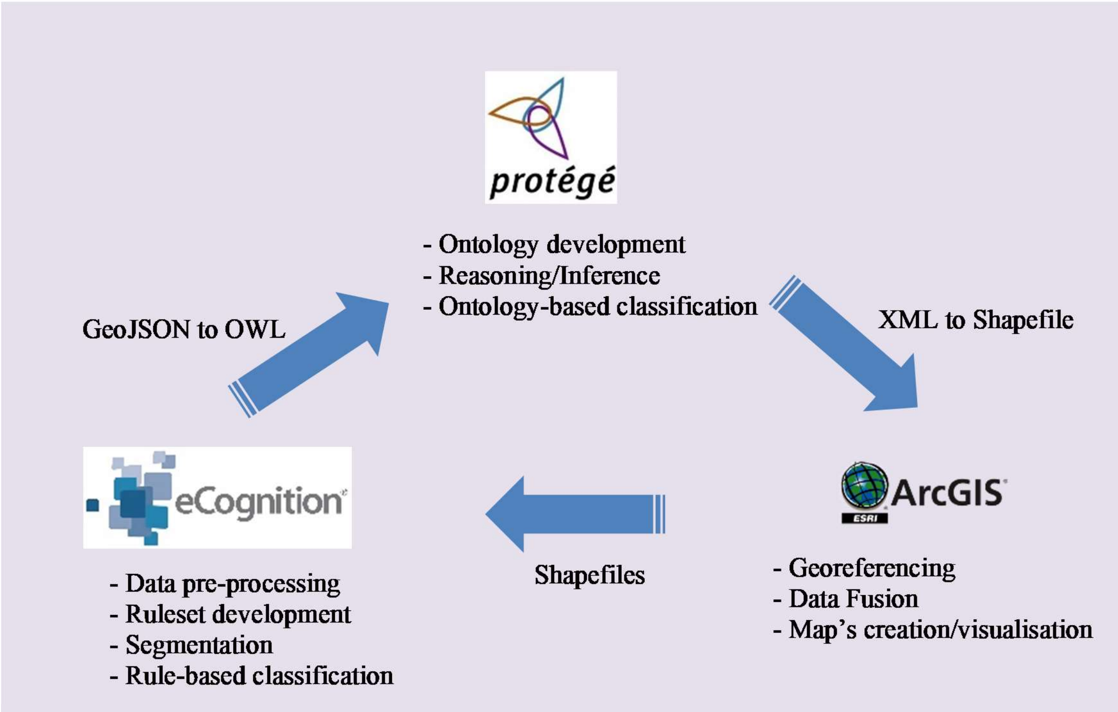


Figure 4.9 Software used in the study

Chapter 5 Geographic Ontology for Major Disasters Development

5.1 Introduction

This chapter represents the Geographic Ontology for Major Disasters (GEO-MD) that was developed as part of this work. The outcomes include the design and implementation of the sub-ontologies constituting GEO-MD along with their class hierarchy and relationships (object and data properties), ontology alignment with upper-level ontologies, semantic rules, and axioms. This chapter further evaluates the ontology and provides a comparison with existing related ontologies. The ontology was developed based on the methodology described in Chapter 3, section 2. Part of the chapter was published in (Bouyerbou et al., 2019).

5.2 GEO-MD Ontology

GEO-MD is an OWL geographic ontology for major disasters. The ontology was built using Protégé 5.5 framework and developed with OWL2-DL SROIQ(D), Pellet reasoner (Sirin et al., 2007). A tableaux-based Description Logic reasoner was used to verify ontology consistency and infer implicit relationships between established concepts. The choice of the reasoner was based on its ability to implement most of the state of the art optimisation techniques provided in the literature comprising (Sirin et al., 2007): Normalisation, Simplification, Absorption, Semantic Branching, Backjumping, Caching Satisfiability Status, Top-Bottom Search for Classification, and Model Merging.

Furthermore, SWRL (Semantic Web Rule Language) was employed to build semantic rules based on OWL concepts and properties assembled through inference elements.

5.2.1 Concepts

Domain ontologies are mostly drawn from a particular context. As a result, their concepts share a reliant understanding of the processed meaning.

Disaster and damage concepts involving space and time properties are included in the Major Disasters domain. A range of geographic concepts must be covered by geographic ontology. Furthermore, and for the main purpose of this research, which is understanding and interpreting remote sensing images in this context, Sensor, Imagery, and Spatial Location concepts were also incorporated into the ontology to get to the sought knowledge inference (see figure 5.1).

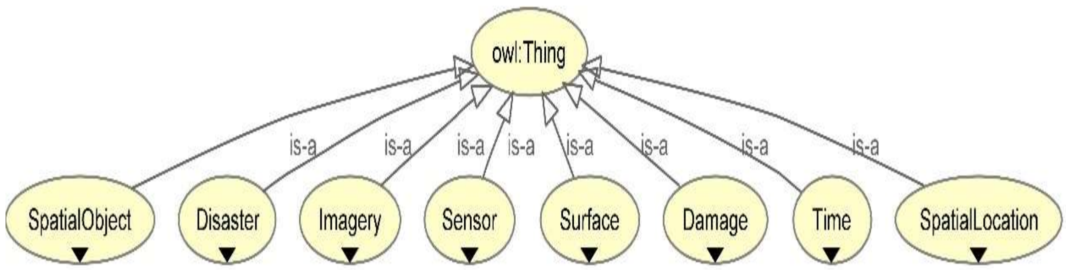


Figure 5.1. GEO-MD Sub-Ontologies

In what follows, classes of the three main defined sub-ontologies will be presented namely, (i) Surface area, (ii) Disaster, and (iii) Damage, in addition to: (iv) Sensor, (v) Imagery, and (vi) Spatial Location.

Extended concepts derived from merging two upper-level ontologies: GeoSPARQL ontology of geospatial data, and OWL-Time ontology of temporal concepts, are presented in subsequent sections.

A. Surface:

Surface primarily consists of five hierarchical levels of geographic concepts. It encompasses the majority of GEO-MD concepts. LULC classification systems, as well as a collection of spatial ontologies, were reviewed before establishing surface concepts. Some of the defined concepts were expanded/abstracted based on work requirements and study needs, where new concepts were created for the same purpose.

B. Disaster:

Disaster sub-ontology includes major disasters concepts. Disaster concepts were appropriately divided into two broad categories: Natural and Manmade Disasters.

Concepts in Natural Disasters were inspired in part by the natural disaster classification in (Below et al., 2009), whereas Manmade disaster was appended into three sub-classes: Accident, Oil split, and Power explosion (see figure 5.3).

A few other disaster categories were left out from this study because they are not covered by the International Charter "Space and Major Disasters" (e.g., terrorist attacks).

C. Damage:

The sub-ontology "Damage" refers to the effects of a disaster on the earth's surface. Different organisations have defined a number of damage assessment evaluations (see Chapter 2, section 4 for more details).

Since the existing damage scales mainly cover structural damage only (e.g., EMS-98 (Grünthal, 1998)), this sub-ontology included three distinct damage classes: (i) land cover damage, which covers damage to the ground surface, (ii) material damage, which comprises structural damage, and finally (iii) human loss. For Material damage, the evaluation described in (Center, 2000) was applied with an adjustment. The reason why EMS-98 was not adopted in this study lies behind the difficulty of separating damage classes within a satellite image for the reason that various parameters intervene in the classification process, and thus, its outcomes (e.g., satellite image spatial resolution, off-nadir angle, and shadow). As a result, damage classes have been grouped into three classes rather than five (see figure 5.4).

D. Imagery:

GEO-MD concepts were interconnected and extended to include more specific and informative terminology applicable to the RS domain, such as the fundamental concepts used by remote sensing experts to interpret satellite images.

In order to effectively represent the domain knowledge, as well as the qualitative and contextual knowledge, GEO-MD must describe, not only the real-world geographic concepts but also their corresponding geographic objects represented in remote sensing data. It was deemed necessary to include satellite images descriptions and build the essential relationships with the existing ontology classes.

The reasoning is performed afterward based on the different concepts, objects, and data properties to achieve the intended image interpretation.

Imagery sub-ontology describes the properties of remote sensing data. It includes four sub-classes: Satellite images, Aerial imagery, SAR, and LiDAR (see figure 5.5). The defined classes describe remote data the most commonly used for image interpretation and land use/land cover mapping.

E. Spatial Location:

Location is an important concept in geography. A spatial location of a geographic object is its exact place on Earth, often given in terms of latitude and longitude.

Spatial location sub-ontology classes describe the definitive reference for locating a geographic object. They have been further divided into two sub-classes: (i) Point location, which can be expressed in terms of latitude/longitude coordinates, and (ii) Region location, which can be expressed in terms of a street address, a city, country, or a range system (see figure 5.6).

F. Feature:

The sub-class Feature, which was initiated with no child nodes in the upper-level ontology GeoSPARQL, has been extended to cover a comprehensive set of image object features. The selection of the image object features was based on the processed features by eCognition software. The most relevant features, generally involved in LULC classification, were selected as new classes of the Feature concept (see figure 5.7).

G. Geometry:

Similarly, GeoSPARQL sub-class: Geometry was extended with a set of geometric types. A UML (Unified Modelling Language) object model for simple feature geometry was proposed in (Herring, 2011), this model was adopted with some minor modifications and translated into OWL classes to enrich the Geometry class hierarchy (see figure 5.8).

H. Time:

Time concepts consist of the class definitions aligned with OWL-Time ontology (Hobbs and Pan, 2006). Time is comprised of concepts that describe facts about topological relationships between instants and intervals and information about durations and temporal position.

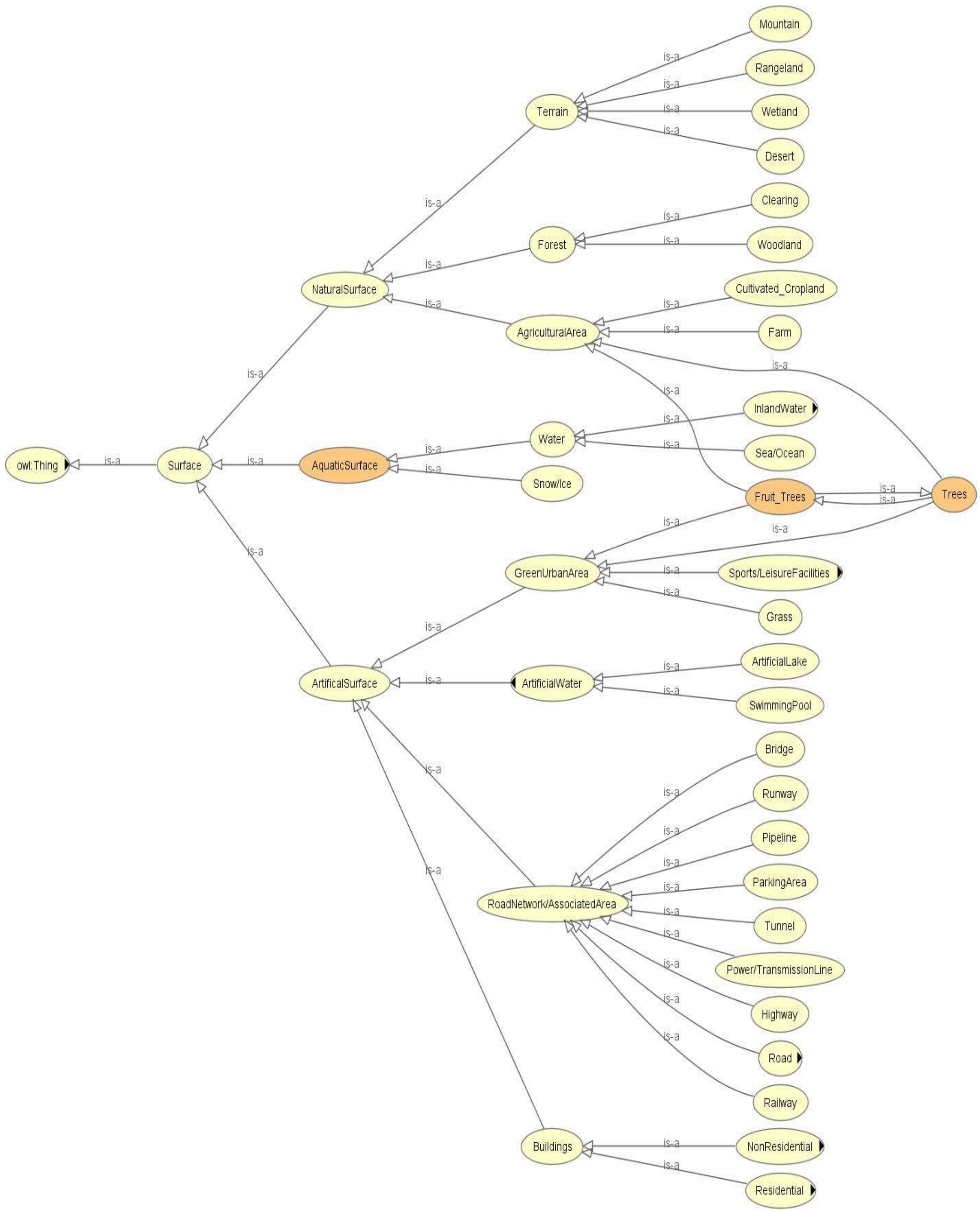


Figure 5.2. Surface class hierarchy

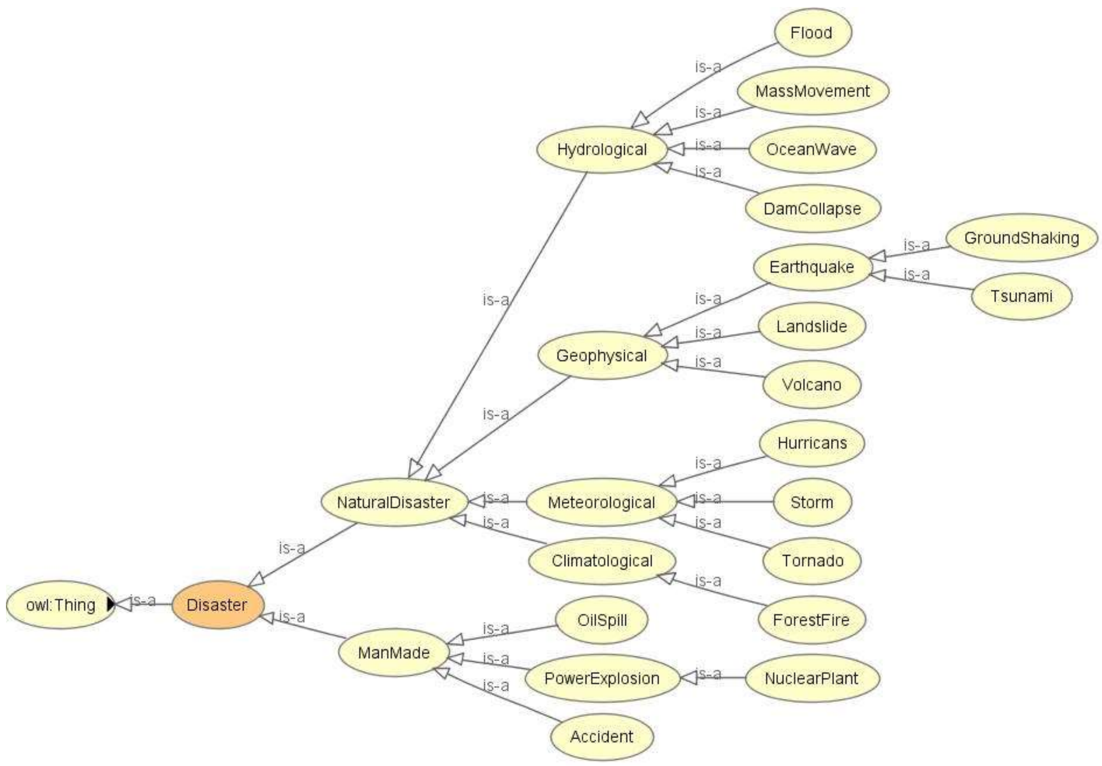


Figure 5.3. Disaster class hierarchy

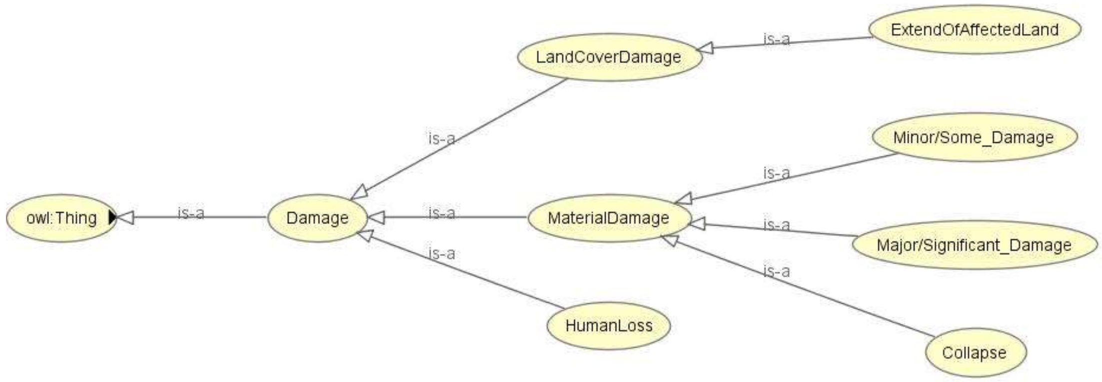


Figure 5.4. Damage class hierarchy

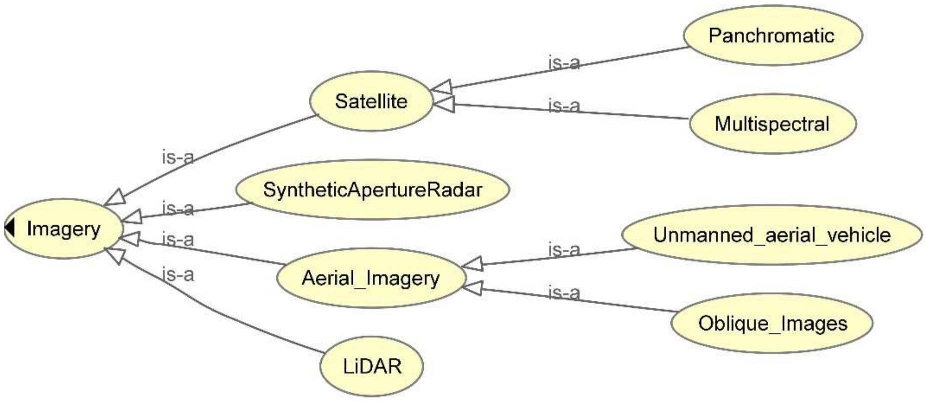


Figure 5.5. Imagery class hierarchy

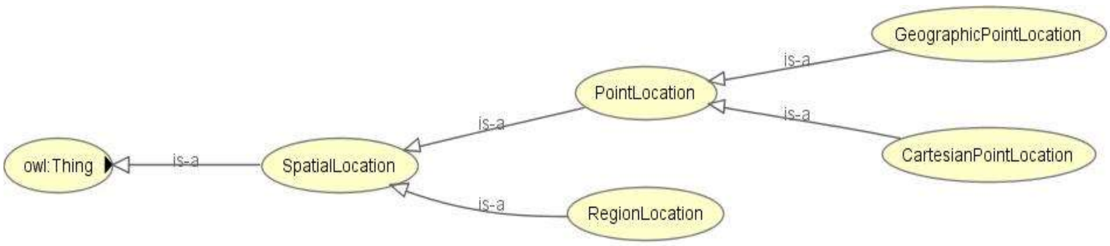


Figure 5.6. Spatial location class hierarchy

Figure 5.7. Feature concepts definition

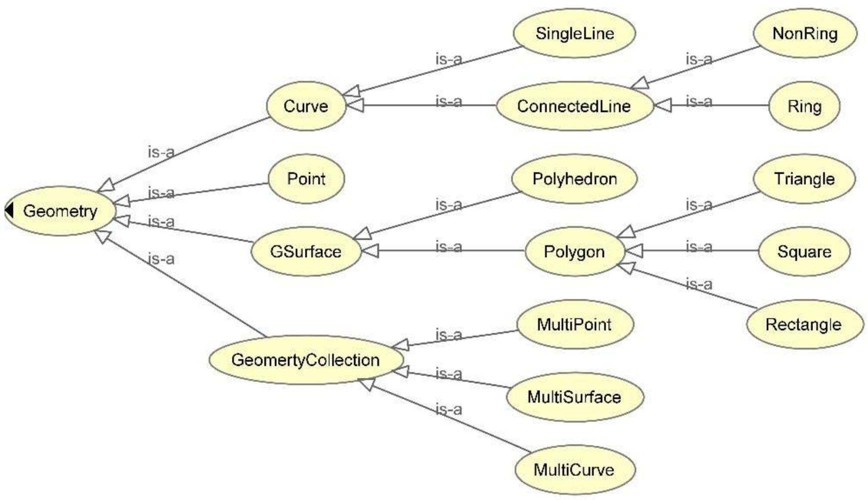


Figure 5.8. Geometry concepts definition

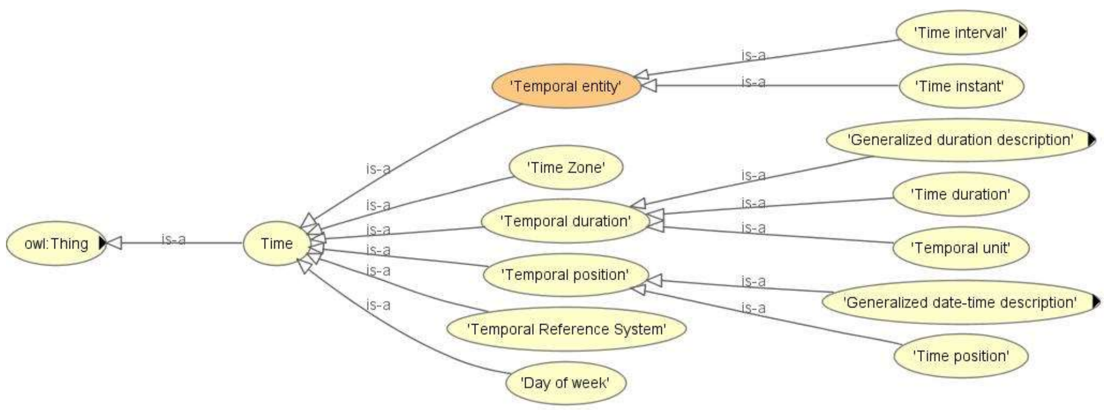


Figure 5.9. Time class hierarchy

5.2.2 Object and data properties

After the definition of the classes (objects) and class hierarchy, relationships between the different classes, and their qualitative description are defined. A list of relevant indicators, used by the domain experts to characterise and identify these objects, is also identified.

For this purpose, a set of object and data properties is defined to describe how classes can relate to each other, or to a datatype property that links individuals to their data values. Data properties are properties of a particular object/class, while object properties concentrate on relationships between two objects/classes.

A set of properties representing the spatial relations defined in RCC-8 (Region Connection Calculus) (Cohn et al., 1997) were integrated into GeoSPARCL (see figure 5.11). This work has specified a collection of semantic, contextual, spatial, geometrical, and morphological relations in addition to the temporal relations defined by Time ontology. The latter were defined in order to link: (i) the different sub-ontologies composing GEO-MD (see figure 5.12), and (ii) the different GEO-MD classes either within the same sub-ontology or not.

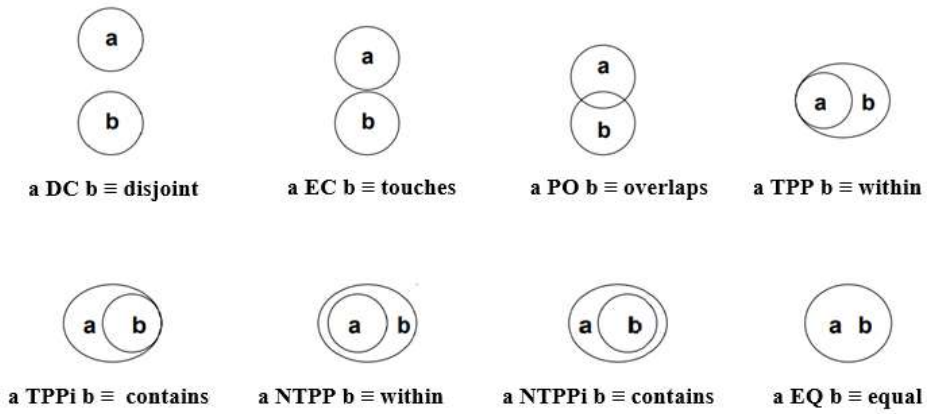
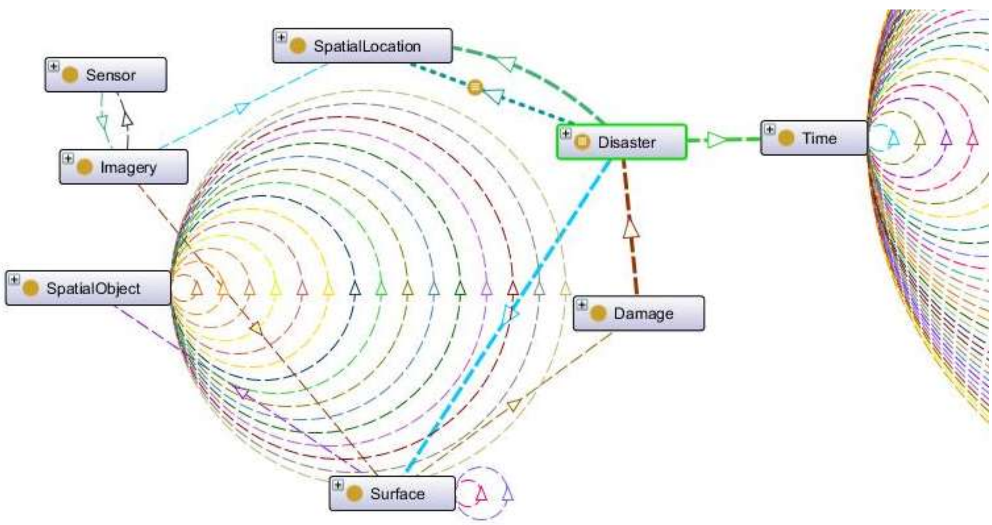


Figure 5.10**.** RCC-8 spatial relations.

Where DC: disconnected, EC: externally connected, PO: partially overlapping, TPP: tangential proper part, TPPi: tangential proper part inverse, nTTP: non-tangential proper part, EQ: equal, nTTPi: non-tangential proper part inverse, Figure adapted from (Cohn et al., 1997).



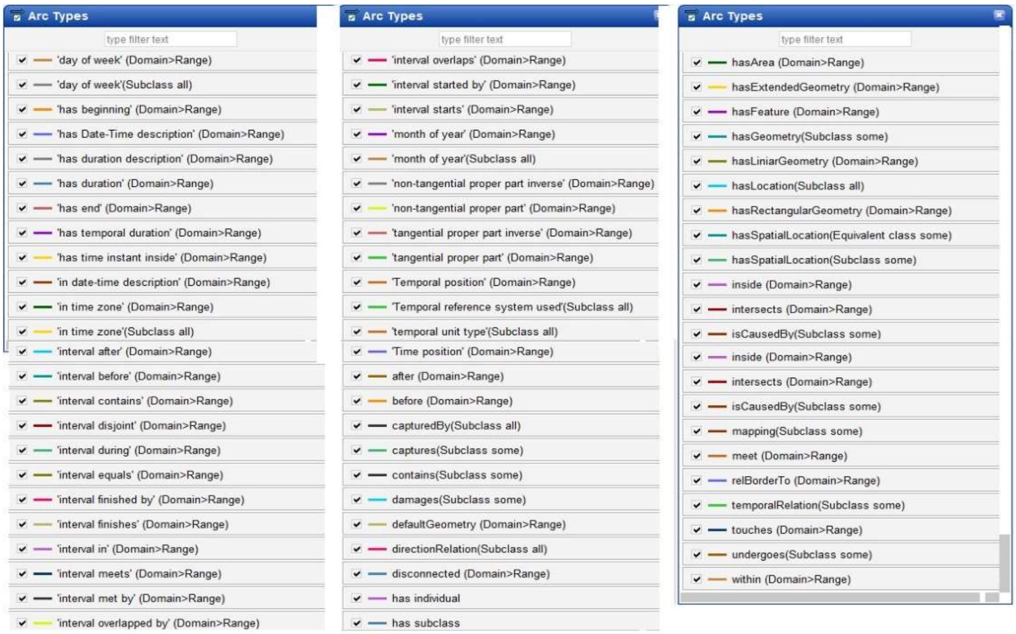


Figure 5.11. GEO-MD sub-ontologies and class linking

Table 5.1 shows an example of the established semantic, spatial, and temporal relations.

The complete list of object properties developed in this work to establish relations between the various individuals and help fasten individuals of the various classes together is shown in figure 5.12. An object property is defined in OWL as an instance of the OWL defined classes: owl:topObjectProperty.

Table 5.1. Example of GEO-MD relationships

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

Data properties, on the other hand, were defined based on: (i) the spectral, spatial, geometrical, shape, and texture features characterising geographic objects existing in a satellite image, and (ii) the temporal, location, and magnitude attributes characterising a major disaster and the resulting damage. Data properties are datatype specifications that connect the individuals to their data types and values in the ontology. In OWL, data property is defined as an instance of the defined OWL classes: owl:topDataProperty. The comprehensive data properties list defined in this work is shown in figure 5.13.

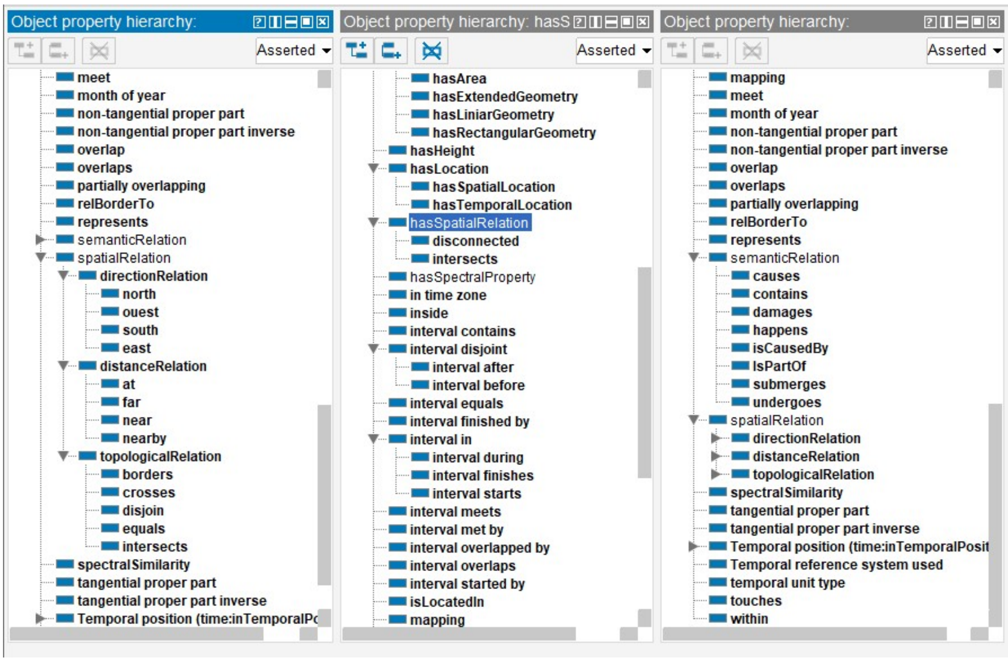


Figure 5.12. Object properties hierarchy

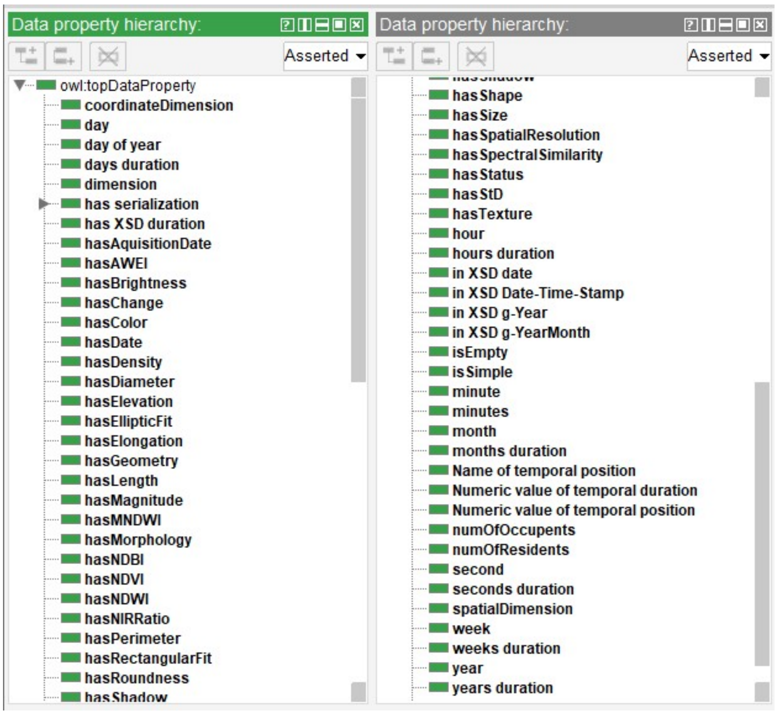


Figure 5.13. Data properties hierarchy

5.2.3 Axioms

Constraints on classes and attributes are essential and must be specified. First, constraints of the domain knowledge need to be well understood and underlined, axioms will then help in defining the valid conditions surrounding the specific domain and formally expressing them.

An OWL ontology comprises a set of axioms expressing clear logical statements regarding three forms of entities:: classes, individuals, and properties (Xiang et al., 2015). Axioms are essential for logical reasoning, hidden knowledge inference, and for completing specific problem-related queries since OWL ontologies are based on a logical formalism.

A set of axioms, implementing specific semantics, is defined in this ontology to establish logical relations among the ontology classes and annotations. The ontology axioms examples below are formatted using Protégé axioms syntax.

```
LandCoverDamage isCausedBy some
(Flood or ForestFire or MassMovement or OilSpill or PowerExplosion)
```

```
MaterialDamage isCausedBy some
(Accident or Earthquake or Landslide or OceanWave or PowerExplosion or
Storm or Volcano)
```

Or to specify some major disasters characteristics:

```
Tsunami (borders some Sea/Ocean) and (damages some ArtificalSurface)
and (hasMagnitude only float [> 0.0f, <= 10.0f])
and (hasMagnitude min 5 xsd:float)
```

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

5.2.4 Ontological rules

In this section, a set of semantic rules was developed using SWRL for performing a decision task: assigning concept instances to their corresponding domain and feature classes, in other words: for classification. In this part, the defined rules for assigning the Surface classes depend mainly on the Feature classes, but other ontology classes may also interfere in the reasoning and inference process.

To develop SWRL rules, domain knowledge needs to be extracted from the domain experts, visual interpretation keys (VIKs), and existing literature and then expressed in the specific SWRL syntax, and finally integrated into the ontology knowledge base.

Antecedent (body) and consequent (head) form the two sections of an SWRL rule. It is generally expressed as: antecedent → consequent. Where antecedents are conjunctions of atoms written $a_1 \wedge ... \wedge a_n$. An atom is composed of the predicates and the argument based on SWRL and OWL ontology, where predicates can be an OWL class, an object, or data property, and the argument can be OWL individuals, data value, and SWRL variable. Consequent is the acquired result of the combined satisfied antecedents.

An example of class attribution of vegetation, where two parameters are employed: NDVI and NIR ratio.

$$\text{NDVI} = \frac{mean\ NIR - mean\ Red}{mean\ NIR + mean\ red} \quad (8)$$

$$\text{NIR Ratio} = \frac{NIR}{NIR+R+G+B} \quad (9)$$

The related fuzzy rules for determining Green Urban Area and Trees respectively are:

If Surface and NDVI is high and NIR ratio is high then image object is Green Urban Area.

If Green Urban Area and relative border to Grass and relative border to Buildings and brightness is low and elevation is medium and roundness is high and has shadow true then object is Trees.

Where Low NDVI is < 0.1, Medium NDVI range from 0.2 to 0.5, and High NDVI range from 0.6 to 0.9. High NIR Ratio if equal or higher than 0.4.

The corresponding SWRL rules assembled through inference elements built by SWRL and Pellet reasoner are shown above.

Surface(?x) ^ hasNDVI(?x, ?ndvi) ^ swrlb:equal(?ndvi, "high") ^ hasNIRRatio(?x, ?nir) ^ swrlb:equal(?nir, "high")-> GreenUrbanArea(?x)

GreenUrbanArea(?x) ^ relBorderTo(?x, ?g) ^ Grass(?g) ^ relBorderTo(?x, ?b) ^ Buildings(?b) ^ hasBrightness(?x, ?brt) ^ swrlb:equal(?brt, "low”) ^ hasElevation(?x, ?elv) ^ swrlb:equal(?elv, "medium", "high") ^ hasRoundness(?x, ?rd) ^ swrlb:equal(?rd, "high”) ^ hasShadow(?x, true) -> Trees(?x)

In the same way, a more complex SWRL fuzzy rule example for assigning Buildings class is given below.

ArtificalSurface(?x) ^ relBorderTo(?x, ?g) ^ Grass(?g) ^ relBorderTo(?x, ?p) ^ ParkingArea(?p) ^ hasBrightness(?x, ?brt) ^ swrlb:equal(?brt, "high", "medium") ^ hasSize(?x, ?size) ^ swrlb:equal(?size, "medium") ^ hasElevation(?x, ?elv) ^ swrlb:equal(?elv, "high) ^ hasEllipticFit(?x, ?elF) ^ swrlb:equal(?elF, "high") ^ hasRectangularFit(?x, ?rec) ^ swrlb:equal(?rec, "high") ^ hasShadow(?x, true)

-> Buildings(?x)

5.2.5 Semantic queries

To express semantic queries, GEO-MD utilises OWL DL-query and SPARQL query. The queries can be written in natural language and subsequently formalised. Powerful queries can be performed since implicit knowledge can be identified in structured conceptual models through inference and knowledge reasoning using Pellet reasoner.

Figure 5.14 shows an example of a basic query for selecting residential buildings that have changed after a disaster. Furthermore, the given spatial and temporal rules can be used to reasoning about spatial and temporal relationships between objects in space as well as change over time. The reasoning rules can be used as inference rules to derive implicit spatial and temporal relations automatically.

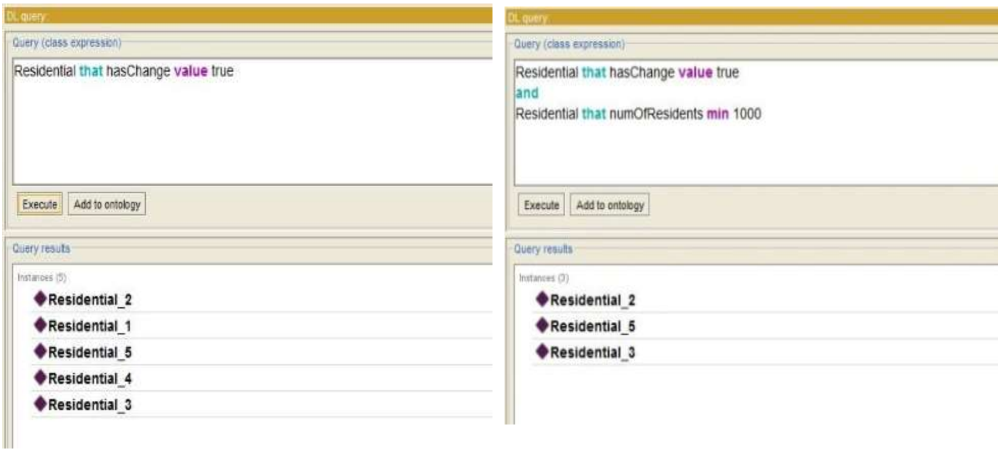


Figure 5.14. OWL DL Query example

5.3 Related ontologies

A literature review of existing ontologies was already presented in Chapter 2, section 3. The aim of this section is not theoretical, but rather technical, which is to compare GEO-MD to some existing OWL geographic ontologies shared online with open access to the OWL code source to compare their metrics with the developed ontology.

Despite the large number of research papers covering this field, a minor number provides access to the final resulting developed ontology, and some are still under development and only published part of the work, therefore, it will be difficult to give a concrete comparison based on the research article only.

A thorough search on the Web to identify relevant ontologies that did not appear in academic papers was performed. Ontologies designed originally for the geographic, disaster management, or related domains are included.

As result, a number of OWL, RDF, and XML ontologies were downloaded and metrics were extracted and compared to GEO-MD. The number of total collected ontologies was 45 (see figure 5.15). After investigating the collected ontologies, only 9 final typical ontologies were judged pertinent for further analysis. The selected ontologies are presented in the following.

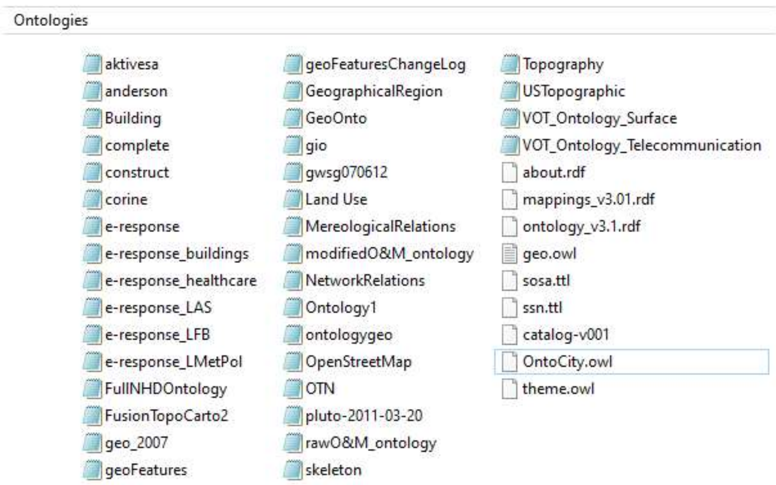


Figure 5.15. Preliminary collected ontologies

5.3.1 Corine

Corine has already been introduced in Chapter 3, section 2. The OWL Corine land cover-based ontology is reviewed in this section. Figure 5.16 represents part of Corine's corresponding ontology.

5.3.2 USGS

USGS has already been introduced in Chapter 3, section 2. The OWL USGS-based ontology is reviewed in this section. Part of the USGS corresponding ontology is shown in figure 5.17.

5.3.3 E-response

E-response is an OWL ontology for describing an emergency along with its response. The version reviewed in this part is the one created by Stephen Potter, in March-April 2006, with some concepts derived from the AKTiveSA ontology. E-response encompasses five categories: buildings, material, defects, and the related internal structures associated with some hazardous scenarios that may occur in buildings. Five related ontologies were created under E-response, the two first of them are used in the e-Response scenario for the CROSI Mapping System (CMS) to align input concepts to designated concepts related to the event in question (Kalfoglou and Hu, 2005):

- *e-Response Buildings:* Created by Yannis Kalfoglou (2006), a fabricated ontology for building defects, manufacturing materials, building types and any other building-related concepts.
- *e-Response Healthcare:* created by Kalfoglou and Hu (2006), a fabricated ontology using concepts derived from InfrastructureProducts, OpenGALEN, and some ad-hoc ones.

- *e-Response LAS:* this ontology describes the London Ambulance Service. It is used in the e-response demonstrator. Developed at AKT in Southampton by Yannis Kalfoglou.
- *e-Response LFB*: this ontology describes the London Fire Brigade data. Most of these data originate from the unofficial site of the London Fire Brigade[17], also from the official site of the London Fire Brigade[18], and from fire emergency services enthusiasts[19] [20].
- *E-Response LMetPol:* this ontology describes the London Metropolitan Police. It is used in the e-response demonstrator. Developed at AKT in Southampton by Yannis Kalfoglou.

5.3.4 AKTiveSA

The AKTiveSA Organisation ontology aims to highlight the importance of semantic and visualisation tools in improving situation sensitivity in a simulated humanitarian relief scenario, developed as part of the Data and Information Fusion Defence Technology Centre (DIF DTC) Phase I AKTiveSA project at the University of Southampton (Smart et al., 2007).

AKTiveSA conceptualises eight knowledge areas: (i) Geography, (ii) Transportation, (iii) Meteorology, (iv) Humanitarian aid, (v) Military, (vi) Equipment, (vii) Organizations, and (viii) Weapons.

5.3.5 OTN

OTN is an ontology for Transportation Systems derived from the GDF standard (Geographic Data Files) in OWL.

---

[17] http://www.lfbsite.com/features/types.html
[18] http://www.london-fire.gov.uk
[19] http://www.fire.org.uk/ranks/RANKs.htm
[20] http://www.firesafe.org.uk/html/fire&resc/ranks.htm

While GDF was designed primarily for data storage, it has evolved into a sophisticated ontology for transportation networks. GDF structures, nevertheless, are only described on paper, rather than using a formal ontology representation scheme (Lorenz et al., 2005). GDF is the European standard CEN/TC 278 and the international standard ISO/TC 204, mainly used for car navigation systems, however, it's applicable for location-based services as well, and for several other transport and traffic applications like fleet management, dispatch management, traffic analysis, traffic management, etc. (Lorenz et al., 2005).

As in GDF, OTN contains five different basic classes (Lorenz et al., 2005):

- Feature: comprises all the GDF features as OTN classes.
- Geometric: identifies the geometric forms of features.
- Composite Attributes: represent classes consisting of composing attributes.
- Relationship: defines the non-geometric relationships between features.
- Transfer Point: describes how to get from one object to another.

5.3.6 Theme

A number of ontologies were developed during the ICAN conference (International Coastal Atlas Network) by MIDA (the marine Irish digital atlas) with the intention of improving its performances by matching from several coastal atlases and allowing research in atlases.

For each Atlas, a corresponding ontology has been created. Each one of them defines the terms of five knowledge domains: discipline, theme, place, temporal, and stratum. The one reviewed in this part is the Theme.

Theme is a MIDA ontology for coastal erosion-related topics, created to display terms for existing or potential data.

5.3.7 OBOE

The Extensible Observation Ontology (OBOE) is a formal ontology that captures the semantics of scientific observation and measurement in general (Madin et al., 2007). OBOE forms a basis for incorporating comprehensive semantic annotations to scientific data, which develops the characteristic meaning of observational data. Observation context description (e.g., space and time), and inter-observational relationships clarification, such as dependency hierarchies and meaningful dimensions within the data, are among the many uses of the ontology (Madin et al., 2007).

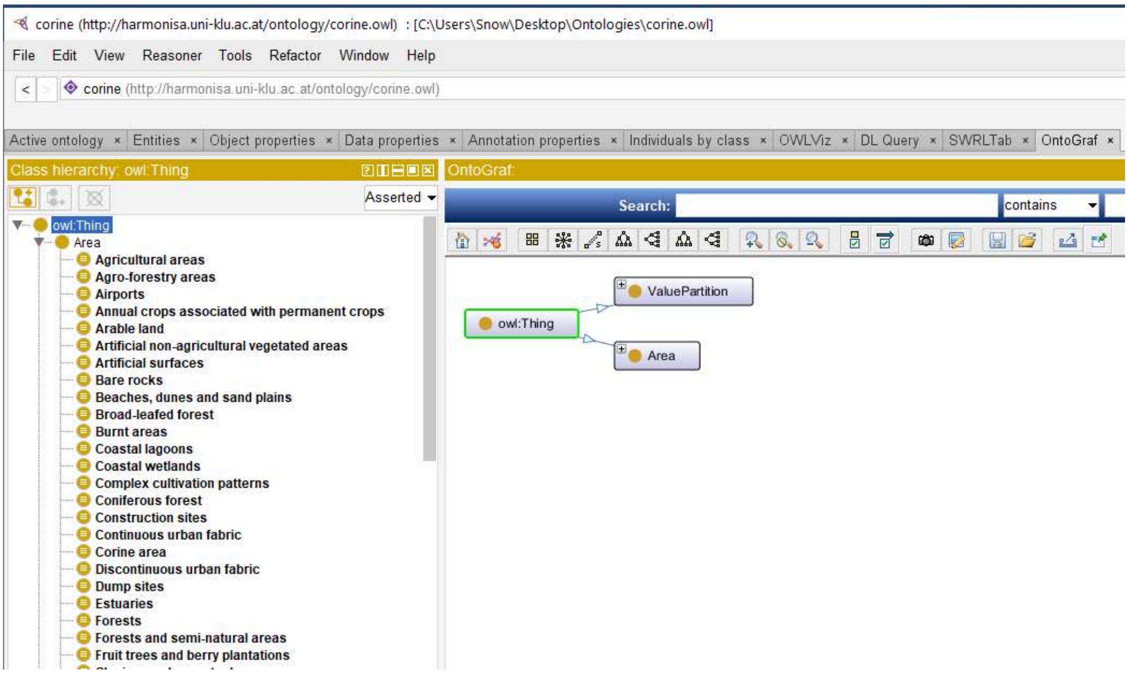


Figure 5.16. Part of Corine’s corresponding ontology

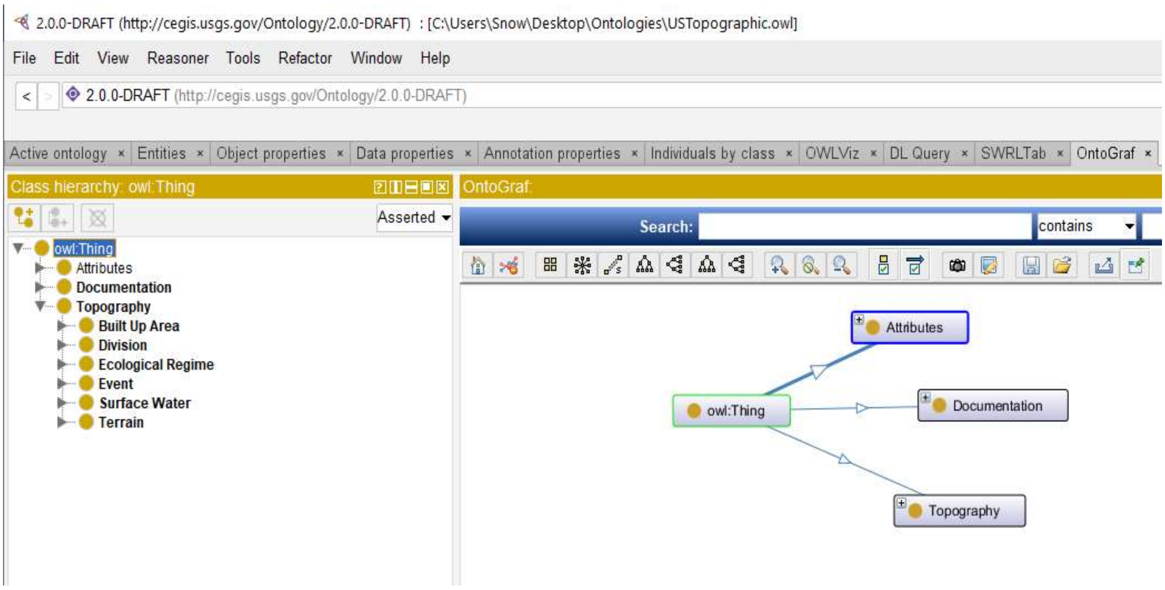


Figure 5.17. Part of the USGS corresponding ontology

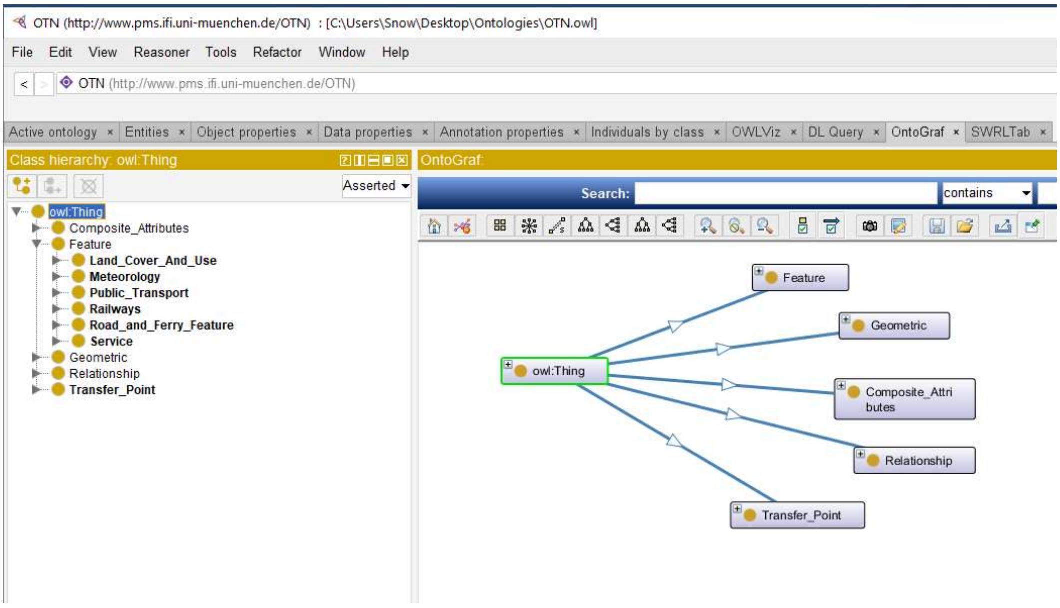


Figure 5.18. Part of OTN OWL ontology

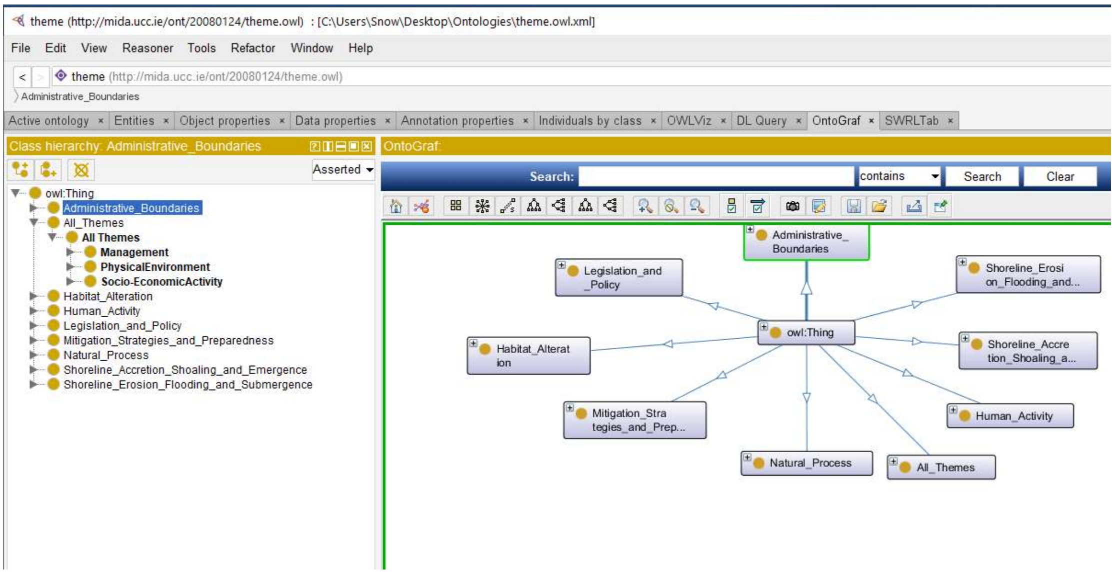


Figure 5.19. Part of Theme ontology

5.4 Discussion

Within the geographic domain, GEO-MD classes of the sub-ontology Surface were compared with the selected OWL geographic ontologies. There is an immediate difference in the terminology of the ontologies. A class definition may use different terminology to refer to the same geographic entity. An Agricultural object, for example, may have a different class name from one ontology to the next: Agricultural Surface in Corine, Agricultural land in USGS, and Agricultural area in GEO-MD (see table 5.2).

Furthermore, a close look into the current geographic ontologies reveals that, while referring to similar contexts, they often use different semantics given the differences in their meanings and purposes. Geographic ontology semantic definitions (e.g., properties, axioms) are rich sources of domain-specific scientific knowledge; they play a critical role in ontology semantics enrichment. Regarding the class number, an acceptable set of axioms and properties were defined to enrich GEO-MD: 1883 logical axioms, 108 entity properties, and 67 data properties were defined within 266 concepts, and they are prone to enrichment.

Some of the earlier presented ontologies have limited semantic definitions, and in some cases no definitions at all. For instance, within 272 concepts, only 33 object properties were defined in Corine, and no data property was defined, while FusionTopoCarto2 and Theme ontology has not set any properties (see Table 5.3). The existing geographic ontologies give very little or no importance to the semantic properties of the included concepts. Consequently, any kind of semantic distinction among concepts is only expressed by their definition.

Moreover, most of the previously presented ontologies are missing some important aspects of the intended role of ontologies. Although most of these ontologies are domain standards, their main focus was on terminology (class names), they seem to be missing the determination of relations among concepts, both in terms of semantic relations and semantic properties. This gap is the consequence of poorly-defined concepts hierarchies.

Table 5.2**.** Example of categories in geographic ontologies

GEO-MD	**Corine**	**USGS**
Buildings: Residential Commercial Industrial Facilities and services Transportation-related Construction site Educational Religious	Buildings: Housing Building Place of worship building Firm Building Service building Transportation building Construction Site Building Recreation building	Building: Church Hospital House Post office School Stadium Substation
Agricultural area	Agricultural surface	Agricultural land
Artificial surface	Artificial surface	Built up area
Aquatic surface	Water surface	Surface water
Forest	Forests	Forest

Table 5.3. Overview of geographic ontologies with metric comparison.

Name	File name	Organisation	Metrics							Domain/ Context
			DL	C	OP	DP	IC	A	LA	
Corine	http://harmonisa.uni-klu.ac.at/ontology/corine.owl	HarmonISA project	ALCF	272	33	0	0	1976	1009	Land Cover
USGS	cegis.usgs.gov/owl/USTopographic.owl	Usgs.gov	ALCH (D)	579	95	2	290	4413	1488	Land Use/Cover
E-response	http://e-response.org/ontology/e-response.owl	e-response.org	SHOIN (D)	1746	182	19	323	7011	4124	Emergency Response
GEO-MD	GEO-MD.owl	TCM project University of Gloucestershire	SROIQ (D)	263	112	67	37	3355	1921	Geographic / Major Disasters
Fusion-Topo-Carto2	http://geonto.lri.fr/ressources_fichiers/FusionTopoCarto2.owl	COGIT-IGN	AL	761	0	0	0	3576	783	Geographic objects
OTN	www.pms.ifi.lmu.de/rewerse-wga1/otn/OTN.owl	Ludwig-Maximilians University	ALCN (D)	180	36	75	0	1104	583	Transportation Network
Theme	http://mida.ucc.ie/ont/20080124/theme.owl	MIDA – the marine Irish digital atlas	AL	136	0	0	0	531	164	Coastal erosion
OntoCity	http://semrob-ontology.mpi.aass.oru.se/OntoCity.owl	Swedish Knowledge Foundation	SHQ (D)	51	30	11	0	769	181	Natural hazards
Aktivesa	http://users.ecs.soton.ac.uk/ar5/aktivesa/aktivesa.owl	Southampton University	SHOIN (D)	2256	166	19	359	9237	2829	Humanitarian aid
OBOE	http://data.bioontology.org/ontologies/OBOE/	University of California	SIQ (D)	292	24	7	0	1442	986	Measurement characteristics
DL: Description Logic expressivity, C: Class count, OP: Object property count, DP: Data property count, LA: Logical axiom count, SubA: Subclass of axioms count.										

5.5 Conclusion

This chapter represents the developed GEO-MD ontology with all its components. The ontology was developed as an effort to address the problem of semantics in geographic and remote sensing images by creating a global geographic ontology that provides a referential geographic vocabulary with fundamental semantic properties, axioms, and rules, in the context of major disasters.

The ontology consists of three main parts: Surface, Disaster, and Damage, aligned with two upper-level ontologies: GeoSPARQL and Time. GeoSPARQL has been further extended with new concepts to fully cover important aspects of remote sensing images: Features and Geometry. Furthermore, GEO-MD was extended with three more sub-ontologies: Sensors, Imagery, and Spatial location, to achieve the sought knowledge inference.

Ontologies provide a great opportunity to promote interdisciplinary research by better representing and managing scientific expertise (Arvor et al., 2019). Expert knowledge, indispensable to interpreting RS data, can be formally and explicitly represented by ontologies, contributing to reducing the gap between RS science and the application fields such as disaster management.

The essence of geographic ontologies is found, not only in their geographic characteristics, but also in their semantic and spatial relationships within the domains they are interfering with (e.g., disaster response), and the set of axioms that complement the defined concepts and relations in a well-developed ontology. By defining required restrictions, axioms aid in the clarification of concepts' meanings and the disambiguation of relationships between them. This was a crucial aspect in developing GEO-MD in order to reduce the complexity of the geographic concepts and their extensive interrelations.

Finally, GEO-MD was created to reflect expert knowledge in the geographic domain and the context of major disasters in a comprehensive, but representative way. Interdisciplinary science knowledge surrounding the domain was included, when it was deemed necessary, to meet the needs of the intended objective of this work.

Chapter 6 Ontology-based interpretation of VHR satellite images

6.1 Introduction

Satellite image interpretation is a complex task. Remote sensing experts spend much time, effort, and energy visually interpreting satellite images based on their knowledge and expertise in a given application domain. In this chapter, the previously presented ontology (Chapter 5), is integrated into the satellite image understanding process. A classification method is presented based on the ontology, purposely developed to capture the geographic domain knowledge and the surrounding interdomain knowledge.

The ontology usage (in whole or in parts) is expected to be applied in different use-cases. In the following, the ontology integration is illustrated with a case study in VHR satellite image classification in the city of Port-au-Prince, Haiti.

6.2 Methods

An ontology-based hierarchical GEOBIA approach, as detailed in Chapter 3 (section 3), was performed. The approach consists of three key steps: segmentation of the VHR satellite image into regions; region feature extraction; and classification of the regions into geographic objects. The purpose of the method is to match each region of the satellite image with the corresponding geographic concepts of the geographic ontology: Surface. These main three steps are further expanded into several tasks to achieve the desired results.

The methodology, described in Chapter 3 and illustrated in the workflow in figure 6.1 and detailed below, has been implemented for the city of Port-au-Prince's land cover classification.

6.2.1 Level 1 classification and selection of the Region of Interest

Processing and analysis of VHR satellite images are computationally expensive. This is due to the large texturally and spectrally rich image data, and thus, time-consuming, while disaster management applications require high-efficiency performance.

To address this issue, a down-sampled copy of the original dataset is created with a lower resolution (2.4 m) to perform an overview analysis and a first rough classification matching geographic regions with the first level of the Surface ontology classes.

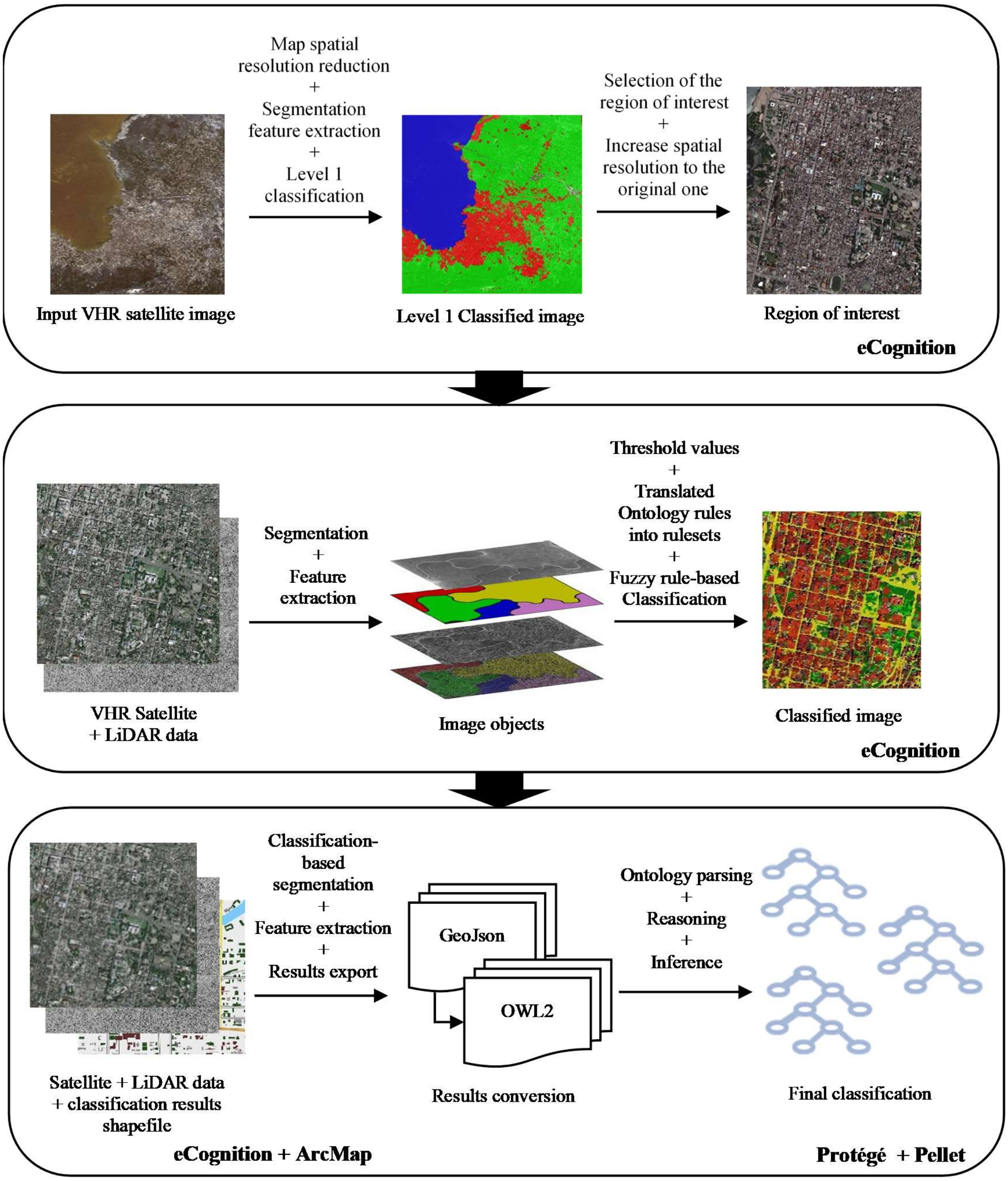


Figure 6.1. Workflow diagram of the presented method

Image analysis on a low-resolution map allows for faster and more effective processing. A multiresolution segmentation technique is applied to these low-resolution maps and an initial rule-based classification, translated from the ontology rules/knowledge base, is performed to select the area of interest. The latter is selected according to the disaster category using Surface Ontology's first level (Artificial Surface, Aquatic Surface, and Natural Surface).

eCognition Developer, Version 9 from Trimble, was used for the multi-scale image analysis, including the down-sampling, segmentation, feature extraction, and rule-based classification of the Quickbird satellite image.

The classification results will allow the identification of the regions of interest in the original dataset. The region of interest is selected according to the type of the disaster and the potential affected area/structures, which are specified with the ontology axioms through the well-defined relationships between the three ontologies: Disaster, Damage, and Surface.

In this use case, the relevent disaster is earthquakes. Artificial surface is selected as a region of interest for the next step of processing (see figure 6.2), where detailed image analysis is performed at a higher scale (0.6 m) to classify the image objects.

Figure 6.2. The relationship between Disaster and Surface ontologies to specify the Region of interest

6.2.2 Segmentation, and feature extraction

After selecting the datasets for the region of interest in the previous step, two distinct types of data are fused before moving to the next step: Quickbird satellite imagery (.tiff file) and LiDAR point cloud data (.las file). Fusion is performed at the feature level, where features can be extracted from both datasets. First, segmentation techniques are performed to segment the satellite image into objects. Next, features are extracted from each segmented image object.

eCognition Developer was used for the segmentation and feature extraction. Two segmentation techniques were carried out to segment the 0.6 m Quickbird satellite image: a two-round multiresolution segmentation refined by a spectral difference segmentation. Different spectral indices (e.g., NDVI, NDWI, BAI) were extracted from the Quickbird satellite image, and elevation and surface models (DEM and DSM) were extracted from the LiDAR data.

6.2.3 Feature selection

Feature selection is an important part of image processing that entails identifying all relevant features in order to achieve the best classification results.

In order to select relevant features, two questions can be asked: what type of features is important? And how many features are required? To answer these two questions, a number of feature-selection algorithms exist (Yu et al., 2002, Pal, 2006, Ghamisi and Benediktsson, 2014, Chen et al., 2016). However, prior knowledge can also be the basis of optimal object feature selection.

In this study, the selection of the most relevant and effective features from the previously extracted object features set was based on three factors: (i) the test region/dataset characteristics, (ii) prior knowledge, and (iii) the literature. The most informative descriptors were selected for the study following the four rules in (Gu et al., 2017), whereas the threshold conditions were defined based on a trial-and-error method.

Accordingly, forty-four features (e.g., brightness, NDVI, NDWI, mean, ratio, and area) were selected, conceptualised, and integrated into the SPARQL ontology under Feature class (see Chapter 5, section 2).

6.2.4 Ruleset generation and Fuzzy Rule-based classification

The rulesets are built from the knowledge base, and the fuzzy ontology rules are translated into decision rules to classify all objects into their potential classes. Fuzzy rules are ''if–then'' rules (if set of premises, then a consequence). For example:

If NIR ratio is high and NDVI is high

then the image object is going to be assigned to Vegetation.

The fuzzification step was already performed while creating the SWRL ontology rules (see Chapter 5), where three fuzzy sets are used to describe the selected features: "low", "medium", and "high", instead of crisp values. For example, NDVI is considered low if inferior to 0.2, medium if between 0.2 and 0.5, and high when superior to 0.5. A subsequent defuzzification is performed for the accuracy assessment where fuzzy results are translated back to a crisp value.

The output classes *C* (geographic categories) are selected from the Ontology classes. For a given *C* class, *R* rules are defined, where for each single class *c*, at least one rule *r* is defined. More rules are assessed for the more complex classes. For a given class *c,* r_c rules are defined:

$$R = \bigcup_{c=1}^{C} r_c \qquad (10)$$

After setting the consequent class set (a set of selected ontology classes), the rule arguments are defined using membership functions. In traditional classification methods, each image object will have an attribute equal to 1 or 0, respectively, expressing whether it belongs to a given class or not. Whereas fuzzy classification deals with the probability of an image object belonging to a given class, by applying fuzzy logic to membership functions with a membership value between 0 and 1, or by combining a set of conditions in a class description.

For assigning a membership, a number of fuzzy membership functions can be used, for instance: Trapezoidal, Gaussian, Triangular, or other standard functions. Appropriately, fuzzy logic operators can also be employed to combine the fuzzified features. In this study, Gaussian, Triangular, Fuzzy Large, and Fuzzy Small functions are used.

After the membership functions are defined for the previously selected features for each class, fuzzy logic is applied to combine the fuzzified features with logic operators. Fuzzy logic is able to assess the real world in its complexity and model imprecise human thinking much better than the simplified Boolean systems do (Benz et al., 2004b).

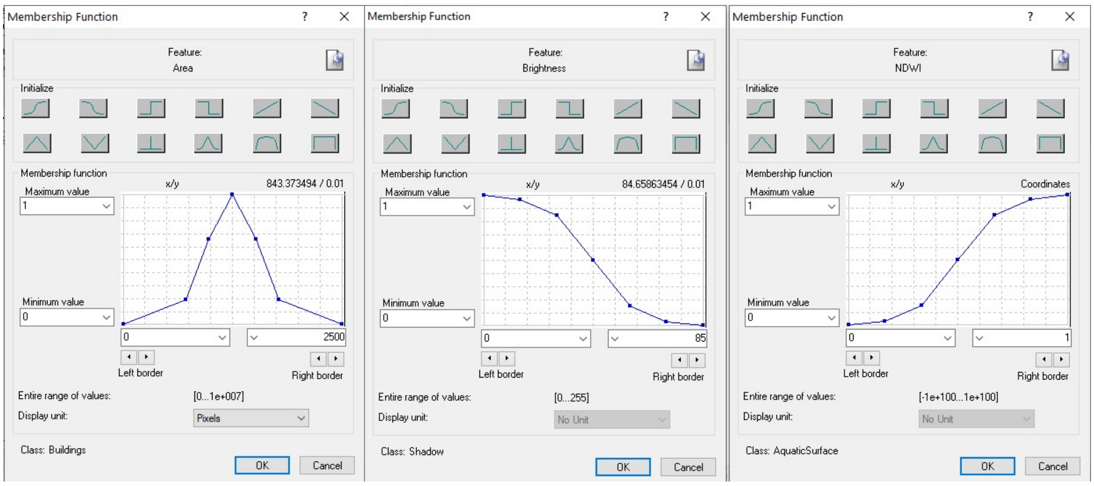


Figure 6.3. Fuzzy membership functions example with selected features for 3 classes: Buildings (Area), Shadow (brightness), and Aquatic Surface (NDWI)

Image objects are then assigned to classes based on their resulting membership degree values to a specific class *C*:

$$\mu_C(x) \in [0,1] \qquad (11)$$

Where, for a given image object x, $\mu_C(x)$ is the membership function of the class *C*. The higher $\mu_C(x)$ is (for the most possible class) the more likely x is assigned to *C*.

In this study, the eCognition software fuzzy inference system is used for the decision making and validation. The decision is more stable when the difference between the first and the second-highest membership values is relatively significant. An advanced classification validation is performed based on the above condition by calculating and visualising the classification stability.

Classification results are exported as a shapefile for data fusion in the next step.

The reasons why this initial classification is first carried out are: (i) to compare results with the next classification; and (ii) to reduce the ontology-based classification reasoning cost.

6.2.5 Classification-based segmentation and feature extraction

The initially performed segmentation was based on low-level information (i.e., pixels) and primary features (e.g., grey tone and shape), and since the classification accuracy strongly depends on the quality of the segmentation, the initial classification results were exported as a shapefile, analysed in a geographic information system (ArcMap), and used as high-level input for a second segmentation (i.e., classification-based segmentation), in order to get a more efficient and accurate object extraction with the intent of performing the final classification.

Classification-based segmentation is an enhanced segmentation based on existing classifications, generally applied in order to improve classification accuracy. New information and new knowledge are generated by this technique compared to the initial segmentation, which is more data-driven. The resulted knowledge and semantic differentiation can be beneficially used for subsequent analysis.

Previously performed fuzzy rule-based classification results, exported as shapefile by eCognition software and visualised and edited in ArcGIS software, are used as a thematic layer when performing a new segmentation of the VHR satellite image.

Features are then extracted out of segmented image objects from two data sources: satellite and LiDAR data (see figure 6.4).

In order to use the segmentation and feature extraction results for the next classification task (ontology-based), segmented objects have to be imported into Protégé, and because Protégé does not support shapefiles, the extracted features of the image objects must first be exported in GeoJSON format (Butler et al., 2008), and subsequently translated into OWL format and integrated into the ontology. Geographic JavaScript Object Notation (Geo-JSON) provides encoding capabilities for various geographic data structures, such as geometry, feature objects, or a set of features under an object collection of features.

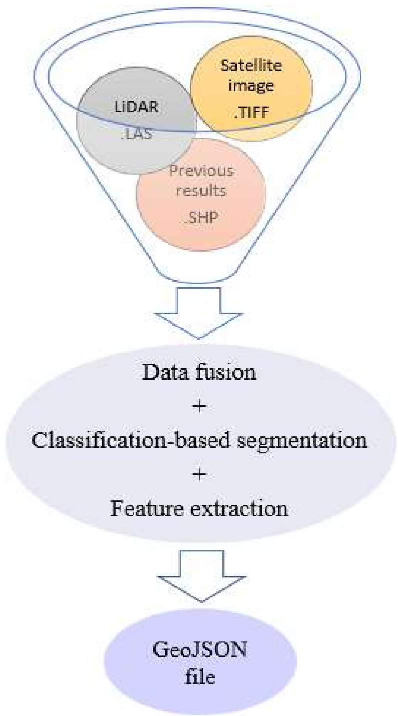


Figure 6.4. Data fusion workflow process for the segmentation and feature extraction

6.2.6 Ontology-based satellite image classification

The outcome of the previous task (i.e., image objects and their features) is the input of the ontology-based classification. The classification method consists of matching each image object with the ontology target concepts.

The segmentation and feature extraction results exported in the GeoJSON file are transformed into an intermediate format (e.g., XML, CSV) and then the denoted regions (image objects) are parsed into the OWL syntax to be finally merged into the ontology.

After the import of the regions and their features within the GeoJSON file, the objects are contained as individuals of the corresponding classes of the ontology. The ontology-based classification is performed by the inference engine after executing the SWRL rules based on the well-defined relations of the different ontology classes.

The expert-defined SWRL rules with the OWL-based knowledge base will decide which objects are a good match for which classes, by specifying the class description and constraints based on object and data properties. The Semantic Web Rule Language (SWRL) is a Protégé plugin for editing and executing rules with strong rule representation capabilities. The knowledge from the GEO-MD ontologies and the SWRL rules will be connected with a reasoner to generate inference results (see figure 5). The Pellet reasoner is responsible for the reasoning process (i.e., knowledge-based classification). Pellet is a sound and complete tableau OWL-DL reasoner with excellent performance and outstanding capabilities that employs description logics and makes use of the OWL 2 designed elements to perform the reasoning task. Pellet is coupled with a Datalog reasoner to implement the AL-Log framework for combining DLs with rules that allow OWL datatypes and SWRL built-ins in the antecedent of Datalog rules (Sirin et al., 2007).

SWRL semantic rules are evaluated and reasoned by the Pellet inference engine, and in the next step, segmented objects are assigned to their corresponding classes according to the feature characteristics and the membership degree values of the specific classes.

The classification results are exported to a shapefile format and visualised in ArcGIS software and can subsequently serve as a thematic layer for semantic segmentation (a classification-based segmentation). Finally, results are validated by comparison with ground truth data for accuracy assessment (see figure 6.5).

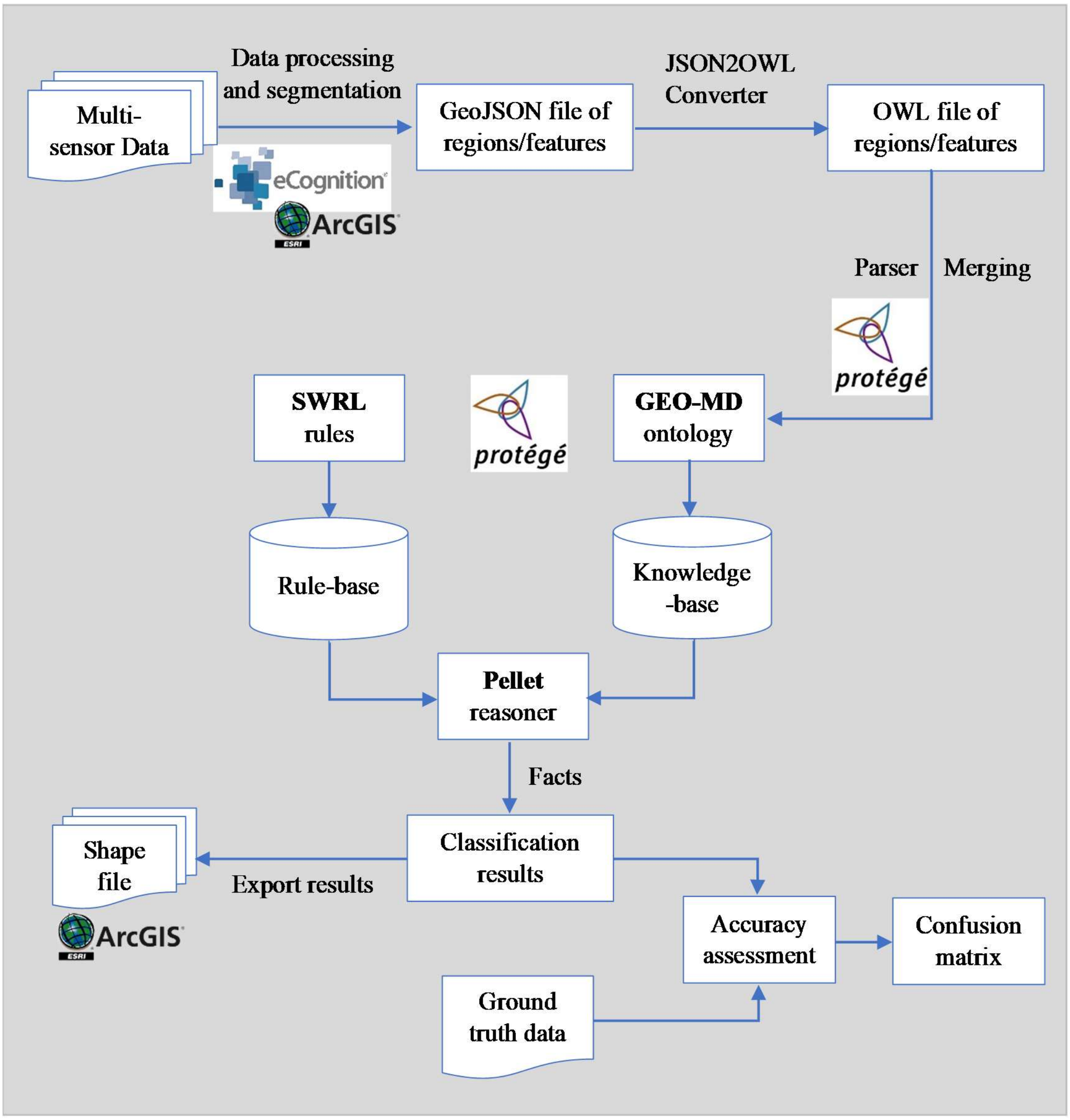


Figure 6.5. Workflow diagram of the ontology-based classification method

6.3 Experimental results

In contrast to data-driven approaches, which can be readily validated by computing statistical indices, the validation of knowledge-driven approaches is quite challenging (Andrés et al., 2017). The validation of ontology-based approaches is an open issue; it is not evident to compare the results with another ontology-based classification for three main reasons (Andrés et al., 2017): (i) the lack of similar ontologies; (ii) if one does exist, it will still produce similar results since the rules would be equivalent; and (iii) comparing results with another ontology-based approach, means comparing the quality of the knowledge put into the ontology with the knowledge of someone else, not the quality of the classification.

In order to evaluate the quality of the presented method, classification results were compared to ground truth data (data manually annotated by human experts). Two error matrices are generated for both the fuzzy rule-based classification method and the ontology-based classification method.

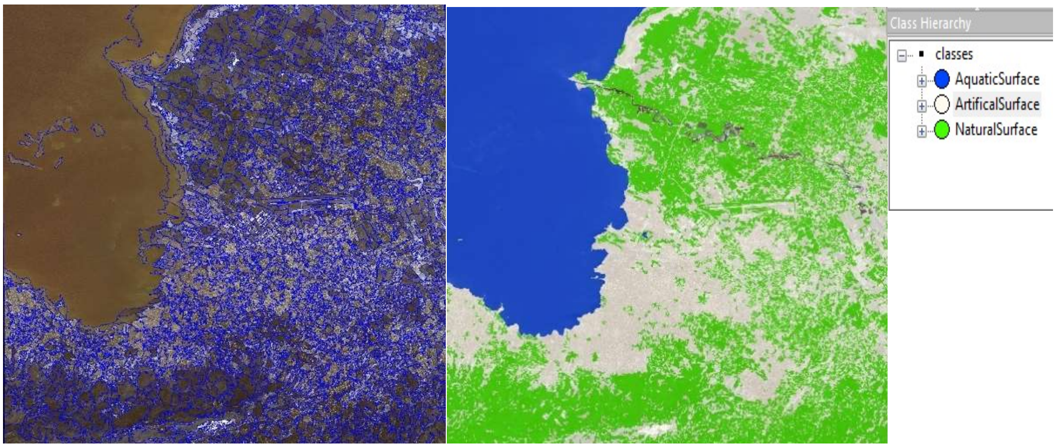


Figure 6.6. Level 1 segmentation and classification results.

Multiresolution segmentation results with scale 100, shape 0.2, and compactness 0.5 for the level 1 classification are shown in Figure 6.6. Level 1 segmentation and classification results. After the selection of the region of interest, and the increase of the spatial resolution to the original one (0.6 m), the second level classification segmentation process is performed with the first iteration of multiresolution segmentation with scale 20, shape 0.1, and compactness 0.5, followed by a second iteration with scale 50, shape 0.7, and compactness 0.7 (see figure 6.7) and refined by a spectral difference segmentation with a maximum spectral difference of 30 (figure 6.8).

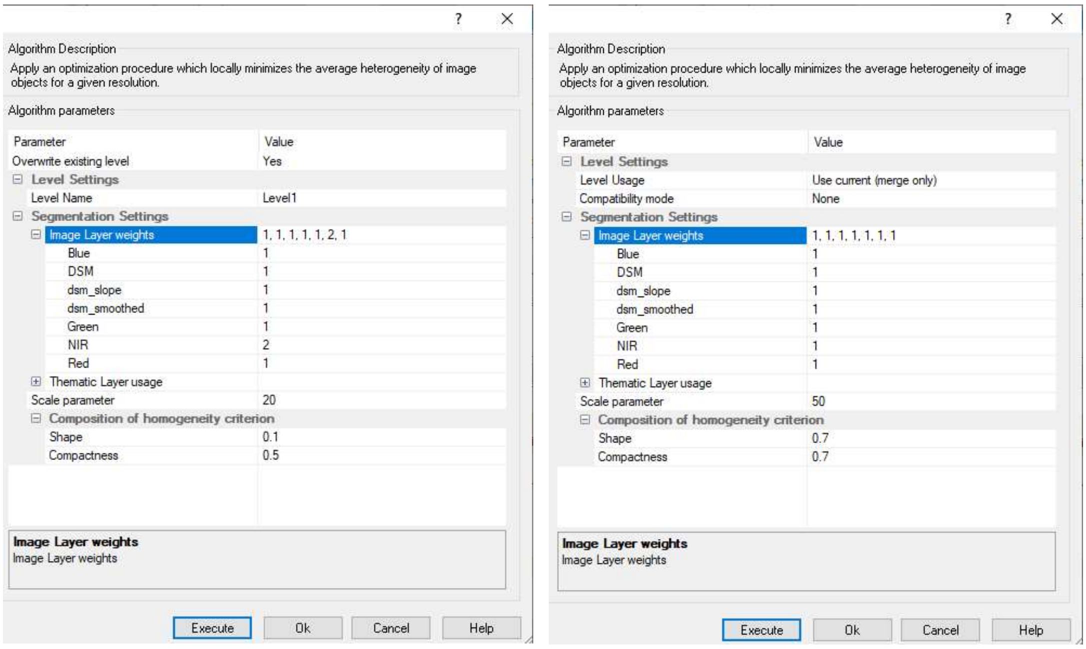


Figure 6.7. Multiresolution segmentation first and second iteration parameters.

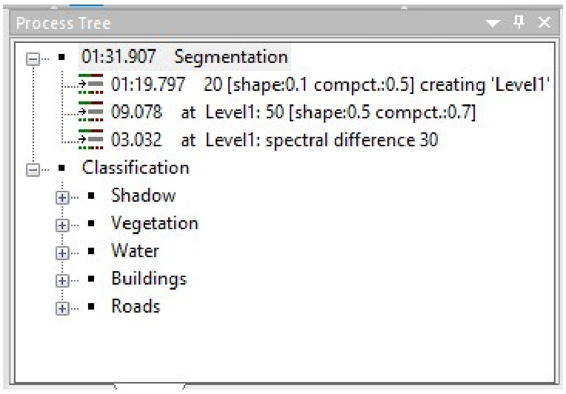


Figure 6.8. Process tree and the processing time for the segmentation workflow

28 637 image objects were generated out of the segmentation process and will be further classified into six classes for which a set of fuzzy rules is defined (see table 6.1). The decision rules were initially defined in the Ontology model and expressed in SWRL language (see figure 6.9), and then translated into the fuzzy-rule classification system. They were adapted to the dataset specification. For example, Buildings Area was initially specified as “Medium” but since part of the dataset contains slums, which are very small, closely packed housing units, the corresponding rule was adapted to include

this part as Buildings in the classification results. An example of the slums dataset and the corresponding classification results exported in shapefile is shown in figure 6.13.

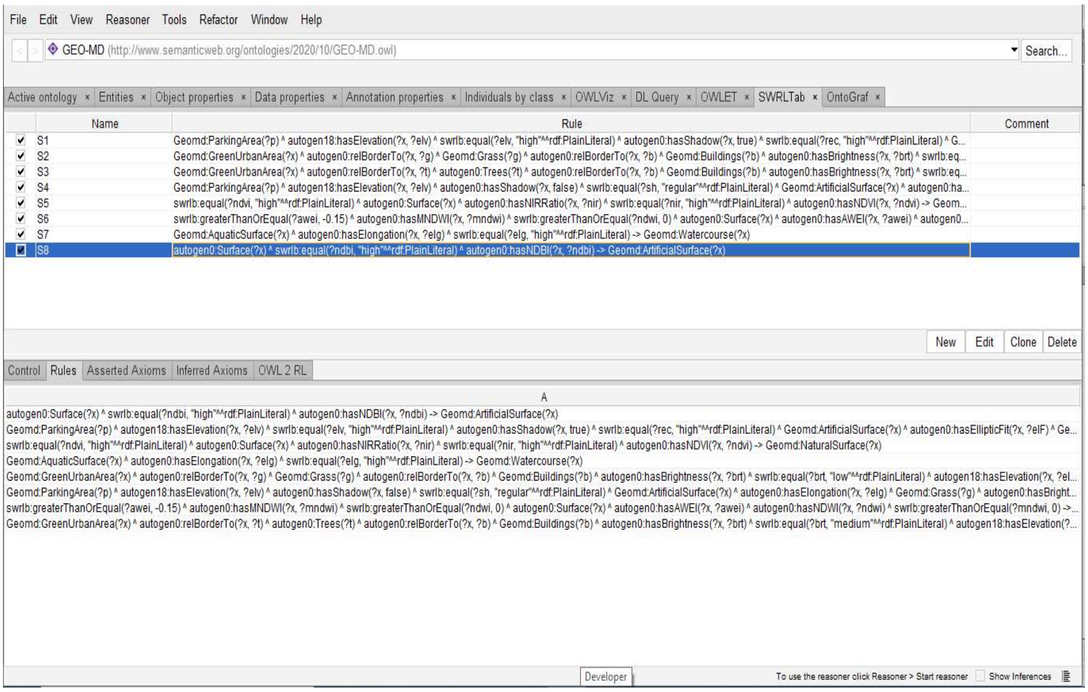


Figure 6.9. An example of the SWRL defined rules visualised in Protégé software

Table 6.1. Decision fuzzy rules of six classes

Class	**Fuzzy rules**
Buildings	RectangularFit (?x) is high ∩ meanDSM (?x) is (high, medium)f ∩ EllipticFit (?x) is high ∩ BorderTo Shadow (?x) ∩ Area (?x) is (small, medium) ∩ Brightness (?x) is high ∩ relBorderTo Grass (?x) ∩ relBorderTo Road Network (?x) -> Buildings (?x)
Road Network	Ellongation (?x) is high ∩ meanDSM (?x) is low ∩ StdDSM (?x) is low ∩ RectangularFit (?x) is (medium, high) ∩ Brightness (?x) is high ∩ Length/Width (?x) is low ∩ Asymmetry is high ∩ relBorderTo Grass (?x) ∩ relBorderTo Road Network (?x) ∪ relBorderTo Buildings (?x) -> RoadNetwork (?x)
Tree	NDVI (?x) is high ∩ meanDSM (?x) is medium ∩ NIRRatio (?x) is high ∩ Roundness (?x) is high ∩ Brightness (?x) is low ∩ BorderTo Shadow (?x) ∩ relBorderTo Grass (?x) ∪ relBorderTo Buildings (?x) -> Tree (?x)
Grass	NDVI (?x) is high ∩ meanDSM (?x) is low ∩ NIRRatio (?x) is high ∩ Brightness (?x) is medium ∩ relBorderTo Tree (?x) ∪ relBorderTo Buildings (?x) -> Grass (?x)
Water	NDWI (?x) is high ∩ meanDSM (?x) is low ∩ RectangularFit (?x) is low ∩ Brightness (?x) is low ∩ Length/Width (?x) is low GLCMHomogeneity is high -> Water (?x)
Shadow	Brightness (?x) is low ∩ meanDSM (?x) is low ∩ Density (?x) is low ∩ relBorderTo Tree (?x) ∪ relBorderTo Buildings (?x) -> Shadow (?x)

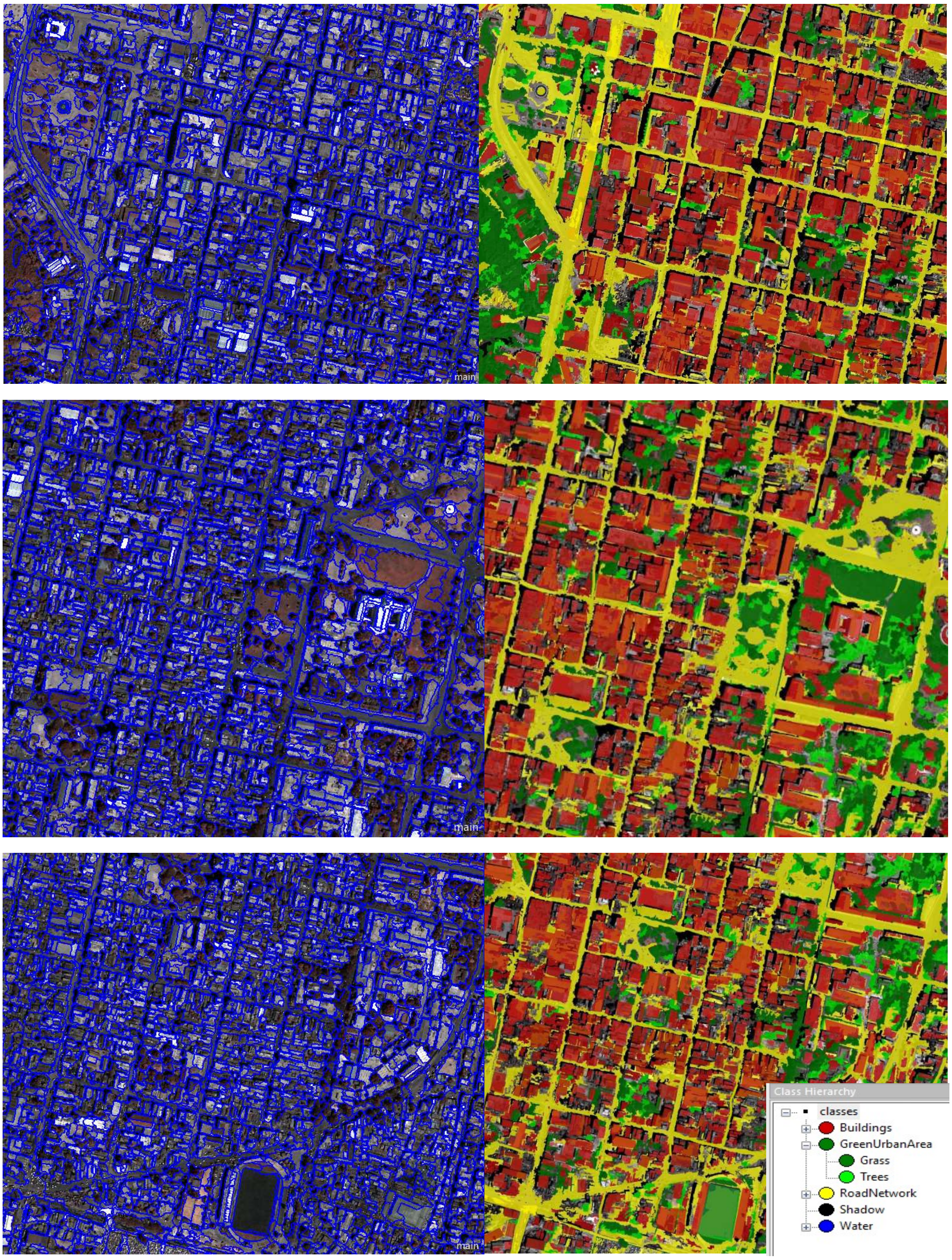
Table 6.2. Specification of the values range for different features in the fuzzy set.

Fuzzy set	**Low** (Smaller than or equal)	**Medium**	**High** (Larger than or equal)
Rectangular fit	0.2	< >	0.8
Elliptic Fit	0.2	< >	0.6
Roundness	0.2	< >	0.7
Brightness	85	< >	400
Mean DSM	50	< >	500
Std DSM	100	< >	200
NDWI	0	< >	0,5
NDVI	0	< >	0.6
Area (pxl)	100	< >	10 000
Border Length	150	< >	1000
Length	50	< >	200
Length/Width	1	< >	5
Asymmetry	0.2	< >	0.7
Compactness	1.5	< >	3
Density	1	< >	2
NIR Ratio	0	< >	0.2
Ratio	0	< >	2
Shape Index	2	< >	5

The range of the feature crisp values used for the specific fuzzy set is detailed in table 6.2. This range is specific to the test area characteristics and was defined throughout the satellite image processing with eCognition software.

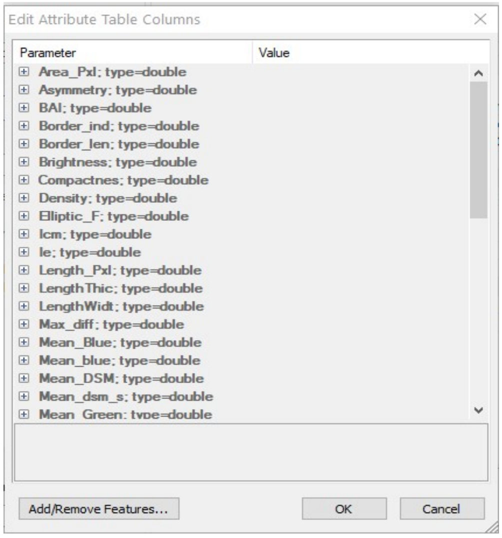
The level 2 segmentation and the fuzzy rule-based classification results are shown in figure 6.10.

11930 polygon objects and 44 selected features for each polygon (11 930 * 44) were generated as a result of the classification-based segmentation and exported in GeoJSON format to be integrated into GEO-MD (see figure 6.11). The generated GeoJSON file is first translated into XML format and then into OWL format. The image objects and their features are integrated as individuals into the extended SPARQL ontology, and each object is classified by the semantic rules in SWRL and validated by the Pellet reasoner for inference and decision making. Finally, the ontology-based semantic classification results, generated in OWL format, are translated into Shapefile format, and visualised in ArcGIS software. Results are shown in figures 6.12 and 6.13.



(a) (b)

Figure 6.10. Level two classification results, (a) show the segmentation results, and (b) the fuzzy-rule classification results of the dataset.



1	Area_Pxl	Asymmetry	BAI	Border_ind	Border_len	Brightness	Compactnes	Density	Elliptic_F
2	569	0.97781543...	0.024880...	3	426	235.9583598540...	5.237023963282608	0.5695748250146148	0
3	263	0.98598888...	-0.01519...	2.5	250	234.5398074152...	4.342505382215586	0.6068764236824418	0
4	274	0.87323311...	0.061459...	2.710526315789474	206	223.1443624705...	4.937688471303263	0.8906972205256634	0
5	301	0.88059826...	0.053647...	3.682926829268293	302	256.0447948874...	9.20161830728738	0.5912616735538493	0
6	191	0.23336633...	-0.11621...	1.6206896551724137	94	517.7025682539...	1.7865170826116583	2.0078173380000837	0.7277486910994764
7	126	0.97172793...	0.076259...	2.15625	138	242.7338408061...	3.5945639565102017	0.7576377572248664	0.0793650793650793
8	46	0.85207229...	-0.05839...	2.4705882352941178	84	470.1905622896...	4.829125534834709	0.7805589491466794	0
9	296	0.87036249...	0.038721...	2.4186046511627906	208	287.1295619333...	3.1749093009086087	1.1260949058587597	0.0472972972972974
10	913	0.94902647...	0.397055...	2.6538461538461537	414	131.6774308924...	3.078729933796931	0.9757831738292158	0
11	17691	0.43898002...	-0.09088...	3.747292418772563	2076	512.3301041284...	2.526792497252612	1.8166637468914997	0.3492736419648408
12	2600	0.94042579...	0.006435...	3.2113821138211383	790	324.3310580994...	3.0512031063681495	1.0820531944753091	0.1569230769230769
13	563	0.89001489...	-0.07153...	3.9649122807017543	452	461.7799234203...	6.361248371848235	0.6823474468196565	0
14	60	0.70529598...	0.259597...	1.3529411764705883	46	162.5803567588...	1.7841744995503297	1.523450191694421	0.6666666666666667
15	41	0.69491440...	0.546133...	1.2	36	131.6068214439...	1.4983332523509947	1.5583234326238238	0.9024390243902438
16	88	0.92536739...	-0.05829...	1.5833333333333333	76	316.1606850624...	2.0228426573510885	1.2225495709776288	0.5909090909090908
17	334	0.72691497...	-0.09973...	3.4871794871794872	272	443.6457425991...	4.347998173221	1.0807099832718525	0
18	157	0.72207346...	0.337535...	1.2857142857142858	72	186.7237940954...	1.5483151593934048	1.7256231235272874	0.7452229299363058
19	649	0.88671408...	-0.11992...	1.5081967213114753	184	610.1422576786...	1.691833590138675	1.5073161067805325	0.6856702619414483
20	635	0.80938734...	0.216294...	1.88135593220339	222	178.2727958500...	2.251200547910358	1.6300055079735645	0.6346456692913385
21	1453	0.53322651...	-0.10934...	1.875	300	611.1482854004...	1.5856847900894702	1.97902475871247	0.6324845147969718
22	129	0.94193848...	0.119035...	3	174	242.5824055634...	5.0336233176791945	0.7247991473382657	0
23	255	0.61865845...	-0.03162...	3.484848484848485	230	382.8704448886...	5.214385627643895	1.0573747886760732	0
24	185	0.74905419...	-0.07789...	2.7333333333333334	164	633.6461804157...	4.365660023286595	1.1078698726364098	0
25	187	0.56908884...	0.574295...	1.6206896551724137	94	108.5396533253...	2.280039153084567	1.6985450297047595	0.5294117647058822
26	194	0.95196699...	0.543826...	1.7837837837837838	132	149.9883989844...	2.7216494845360826	0.8219836009657886	0

Figure 6.11. The selected feature set for the segmented image objects exported in the GeoJSON file

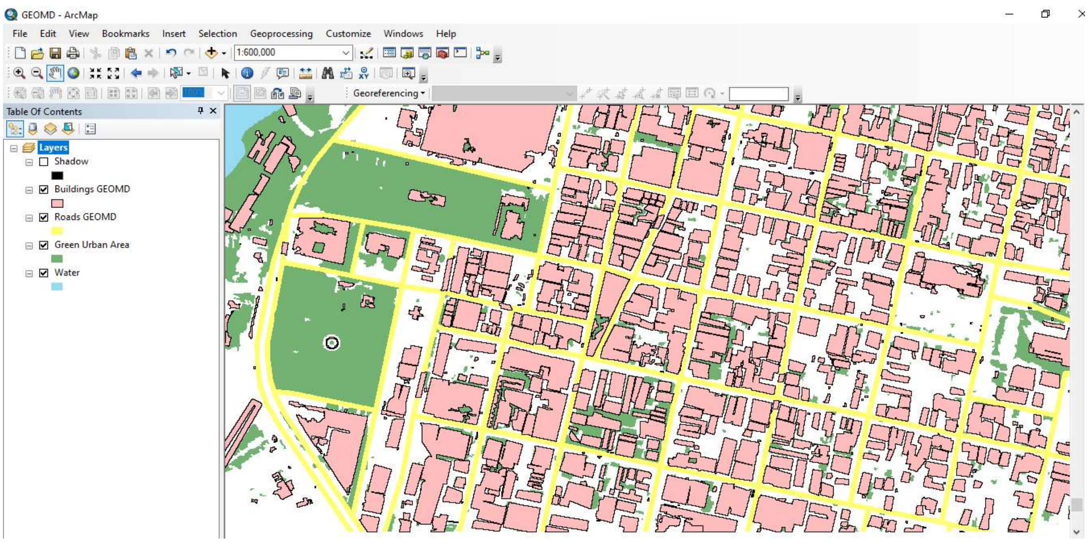


Figure 6.12. Ontology-based classification results in shapefile as visualised in ArcGIS software

Figure 6.13. Test area Quickbird satellite imagery and classification shapefile showing the slums region with miniscule buildings

An accuracy assessment was carried out by comparing the classification results with the ground truth data derived from the VHR satellite imagery visual interpretations, the oblique aerial imagery, and the existing GIS data layers of the test area.

The corresponding error matrices, with the producer's accuracy (PA) and the user's accuracy (UA) for each category, and overall accuracy are shown in tables 6.3 and 6.4, respectively. Overall Accuracy, PA (error of omission), and UA (error of commission) are estimated according to the following expressions:

$$UA = \frac{Number\ of\ correcly\ classified\ image\ objects\ for\ a\ category}{Total\ number\ of\ classified\ objects\ in\ that\ category} \quad (12)$$

$$PA = \frac{Number\ of\ correcly\ classified\ image\ objects\ for\ a\ category}{Total\ number\ of\ reference\ objects\ for\ that\ category} \quad (13)$$

$$OA = \frac{Total\ number\ of\ correcly\ classified\ image\ objects}{Total\ number\ of\ reference\ objects} \quad (14)$$

Table 6.3. Error matrix for the classified image by the fuzzy-rules classification method

	Ground Truth						Total	PA	UA
Class	**Buildings**	**RN**	**Water**	**Trees**	**Grass**	**Shadow**			
Buildings	5529	920	0	126	0	0	6275	0.82	0.88
RN	897	3578	0	0	37	62	4574	0.71	0.78
Water	0	0	1	0	0	0	1	1	1
Trees	240	0	0	873	78	0	1191	0.74	0.73
Grass	0	120	0	178	561	105	964	0.82	0.58
Shadow	45	142	0	0	0	782	969	0.82	0.80
Total	6711	4720	1	1177	676	949	**11124**		

Overall accuracy: 0.78 %

Table 6.4**.** Error matrix for the classified image by the ontology-based classification method

	Ground truth						Total	PA	UA
Class	**Buildings**	**RN**	**Water**	**Trees**	**Grass**	**Shadow**			
Buildings	6514	806	0	72	0	0	7192	0.97	0.80
RN	197	3804	0	0	0	0	4001	0.80	0.95
Water	0	0	1	0	0	0	1	1	1
Trees	0	0	0	920	78	0	998	0.78	0.92
Grass	0	110	0	185	598	26	919	0.88	0.65
Shadow	0	0	0	0	0	923	923	0.97	1
Total	6711	4720	1	1177	676	949	**12760**		

Overall accuracy: 0.88 %.

6.4 Discussion

Two rule-based classifications were performed using the same ruleset: a non-ontological fuzzy rule-based method, and an ontology-based method. The first classification was performed to improve the segmentation outcome and served as a classification-based segmentation input for the second classification. Thus, for the second method, fewer polygons of segmented images were generated, which improved the reasoner's performance because the reasoning time and computational cost may scientifically increase with the increase of the individual number to be classified with an ontology complex class definitions, axioms, and relations.

As previously stated, there is a direct correlation between the classification results and the quality of the segmentation in GEOBIA methods. Since the city of Port-au-Prince contains slum zones and anarchic constructions, some of the buildings were not correctly segmented and were merged with their neighbouring buildings due to their small Area (pixels). Therefore, (i) the multiresolution segmentation scale parameter was set to a smaller value (20), and (ii) the rules were rectified in a way to include smaller buildings in the classification. Comparable issues with the class Road Network are faced, where the image objects are sometimes over-segmented. Consequently, part of the semantic rules must be dedicated to the study area and consider the nature and characteristics of its geographic objects.

Moreover, classes with similar low-level features characteristics (e.g., Buildings and Road Network) can produce a drawback for the initial classification. To differentiate the two classes, further semantic, geographical, and class-related features might be introduced into the developed rules. Ontologies can help bridge the semantic gap between low-level features and high-level semantics considerably.

One of the main drawbacks of ontology-based approaches is the reasoner’s excessive processing time. Classifying a significant proportion of individuals using extensive class definitions can be a challenging task for reasoners since the processing time increases with the number of modelled concepts and individuals. This issue was minimised by using the results of the initial classification performed in this work in the ontology-based classification process. The number of polygon objects generated from the second segmentation process (i.e., 11 930 polygon objects) was cut in half compared to the first segmentation (i.e., 28 637 polygon objects), which was able to provide a significant performance boost of 58% in this case.

6.5 Conclusion

In this chapter, the previously presented ontology (Chapter 5) was employed to support the satellite image semantic classification at various scales and to tackle the semantics challenge in geographic and RS data.

The ontology-based classification added values comprise building bridges between different levels of understanding and inferring implicit knowledge through the existing reasoners. Additionally, the formulated knowledge by each of the GEO-MD composing ontologies can be shared, extended, and adapted to different geographic or disaster management applications.

The use of SWRL rules evaluated by the Pellet reasoner (Sirin et al., 2007) allows access to any class definition and generates rules in a machine and human understandable format that fit the purpose of different applications. Pellet allocates the imported image polygons to the defined classes' categories, where only individuals (i.e., image objects) satisfying the definition specified in the predefined SWRL rules will be returned.

Pellet employs a number of novel optimisations to improve reasoning performance. However, it is still relatively costly to allocate a large number of image polygons to the defined classes' categories in terms of computational and processing time. Since the latter may increase exponentially with respect to the modelled concepts and individuals number, an optimised approach was proposed in this chapter to reduce the number of the processed image objects by carrying out a fuzzy-rule-based classification followed by a classification-based segmentation using GEOBIA software (i.e., eCognition). Thus, fewer polygon objects will be imported into the Ontology framework (i.e., Protégé) as a result of the improved classification-based segmentation compared to traditional segmentation.

Using existing classification results to perform a classification-based segmentation helped in (i) reducing the number of the resulting segmented image objects and the feature space, and (ii) reducing the time and computational cost of the reasoner.

The ontology-based classification method presented in this chapter will be applied to the multi-temporal satellite images (both pre- and post-disaster imagery) to perform change detection and damage assessment in the next chapter.

Chapter 7 Earthquake structural damage assessment using VHR optical imagery and LiDAR data

7.1 Introduction

Earthquakes are one of the most catastrophic natural disasters, resulting in significant life losses and land damage each year. Immediately and properly identifying building damage following an earthquake, can help reduce morbidity and mortality and speed up rescue operations.

In this context, RS technology is identified as a practical tool for the rapid monitoring of damaged structures. Visual interpretation of the RS data to produce damage maps is usually completed by the photo interpreters through a time-consuming manual annotation of the satellite images and in-depth field examination. Damage assessment is an essential piece of information during the emergency phase that indicates the most damaged areas and connection lines' inoperability.

In this chapter, an automatic ontology-based change detection and structural damage assessment approach is presented and applied to a case study of Haiti, Port-au-Prince 2010 earthquake, to assist the photo-interpreters in their work and help in the emergency response phase.

7.2 Methods

A post-classification change detection technique followed by the classification of the detected change (damage assessment) is applied at this level. Both pre- and post-disaster satellite images as well as their corresponding classifications are required.

A top-down approach is followed. First, the pre- and post-disaster satellite images are classified using the method presented in the previous chapter (Chapter 6). The class Buildings' corresponding classification results, of both before and after the disaster, are exported as a shapefile and imported into the ontology (building image object and feature set).

A set of SWRL rules are defined to specify the criteria that should be applied to classify damage levels using reasoning functions. The rules are built based on a set of relevant features that have been selected due to their significance in building change detection. A similarity function is used to calculate the differences between the two classification shapefiles building-by-building (image objects and selected features).

The ontology and SWRL rules, defined via Protégé and SWRL editor, are stored in the knowledge base. Then, the rule engine and Pellet reasoner execute SWRL rules and generate new facts in the ontology management system.

A flowchart of the proposed method is presented in Figure 7.1.

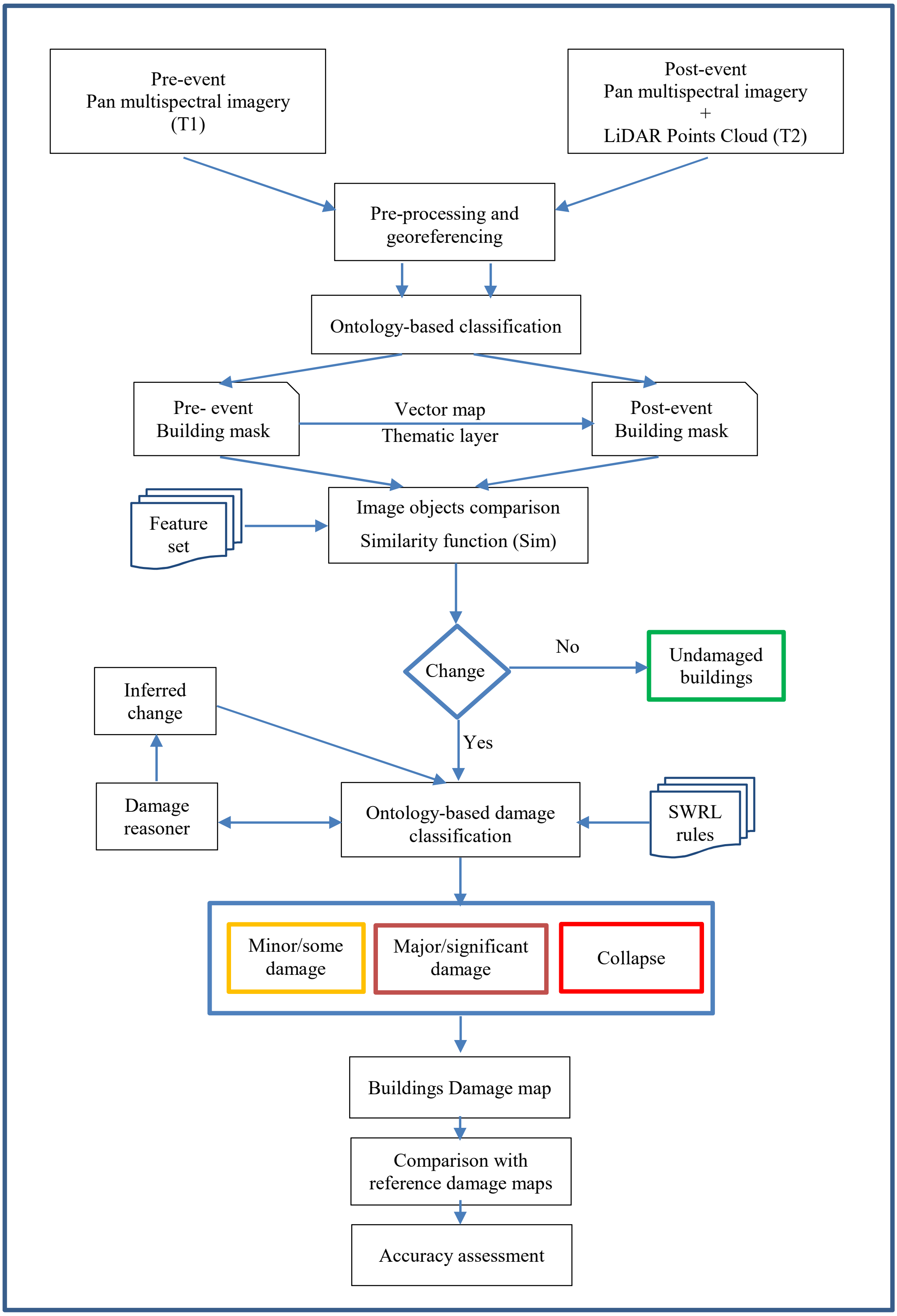


Figure 7.1 Overview of the proposed approach for building structural damage assessment

7.2.1 Building identification and extraction

In this study, the area of interest (i.e., buildings) is first detected by means of segmentation and classification algorithms, and then change detection is performed.

The process of building extraction is performed using the classification method presented in the previous chapter, and can be summarised in the following steps:

- Segmentation: this process was performed by using a sequence of three algorithms: (i) multi-resolution segmentation algorithm, (ii) spectral difference segmentation algorithm, and (iii) classification-based segmentation.
- Feature analysis: different spectral, geometrical, contextual, and spatial features are used for the classification of the segmented image objects and, eventually, for change detection. The feature space must remain significant for the classification and damage assessment tasks as both the eCognition rulesets and the SWRL rules are built based on it.
- Classification: the performed classification follows the methodology in Chapter 6. Fuzzy rule-based and ontology-based classification are employed to classify the segmented image objects into different selected classes based on the rulesets and the defined SWRL rules.
- Export: the classified objects are exported in a Shapefile format to ArcGIS for further processing and manipulation in a more appropriate geographic environment. They are next imported to the Protégé software for an ontology-based damage assessment. The imported image objects are translated into OWL format, where SWRL rules and Pellet reasoner will label the building class with "change" or "no change" and further assign the changed building objects into three damage classes: "minor damage", "major damage", and "collapsed".

Severely damaged or collapsed buildings may not be correctly classified as buildings in the post-disaster image, as the rules defined to detect buildings do not take into consideration the characteristics of a demolished or severely affected building. To ensure that no pre-existing building in the pre-disaster dataset is excluded from the post-disaster classification, the pre-disaster building shapefile is used as a thematic layer for a classification-based segmentation of the post-disaster image. All pre-disaster existing buildings are considered for the next step of post-classification comparison and damage assessment.

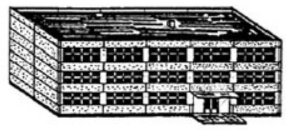
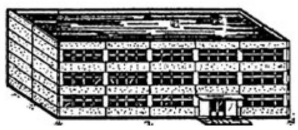
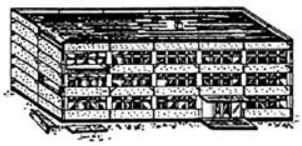
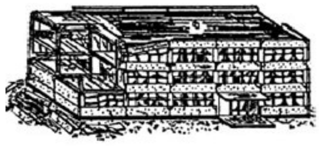
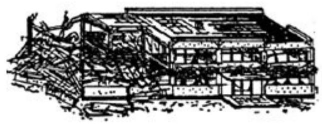
Furthermore, despite the relatively short period between the acquisition dates of the pre- and post-disaster satellite imagery (22 February 2009 and 15 January 2010 respectively), it is still possible for some building construction work to begin during this period. Buildings under construction, which do not appear in the pre-disaster imagery and that can be misclassified as damaged buildings in the post-disaster imagery, are not considered in this work. Only pre-existing buildings are evaluated in the damage assessment procedure to prevent any false negatives caused by the buildings under construction.

7.2.2 Implementation of damage levels

The EMS-98 (Grünthal, 1998) is by far the most widely used scale for both ground-based surveys and RS-based damage assessments of building structural damage. Although EMS-98 was basically made for in-field surveys as it mainly relies on the inspection of the walls and façades indicators, which can be challenging with the use of vertical remote sensing imagery, which basically relies on roof inspection (see figure 7.2). Furthermore, EMS-98 was developed to assess the damage to the entire structure, not only the section visible from a remote sensor's perspective (e.g., the roofs).

With VHR optical satellite imagery, better precision of the study area is provided. However, this does not improve the roof-based damage assessment. A vertical view allows a limited representation of the expressed damage, mainly based on the roof, which cannot be extrapolated for the whole building damage, and may lead to incorrect assessments, especially for the intermediary damage levels. Examples of cases where the roof is perfectly fine whereas the walls are completely destroyed, or even a collapsed roof with an intact façade and walls, are common.

Table 7.1: The five damage levels defined by the EMS-98 (Grünthal, 1998)

Masonry buildings	Reinforced buildings	Damage class
		Grad 1: negligible to slight damage
		Grad 2: moderate damage
		Grad 3: substantial to heavy damage
		Grad 4: very heavy damage
		Grad 5: total destruction/ collapse

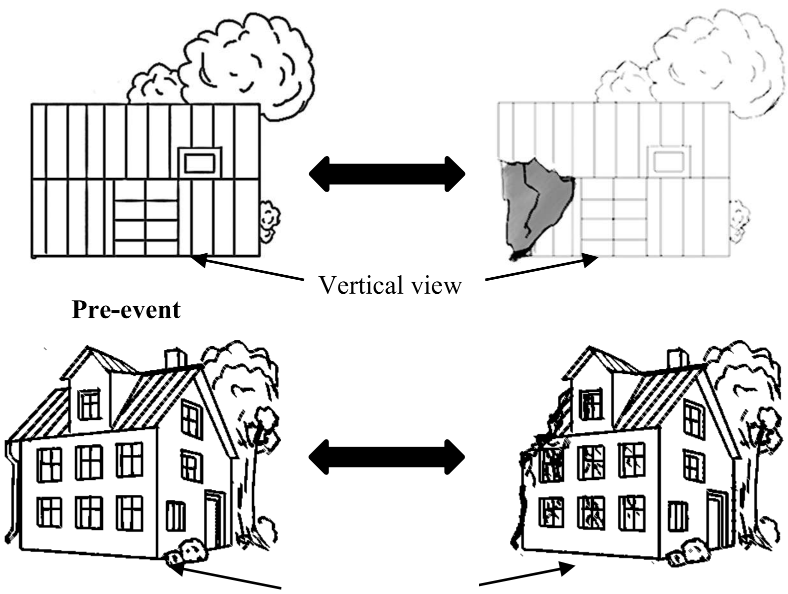


Figure 7.2 Illustration of the different possible views from where the damage can be studied.

Due to the conflicts in the intermediate damage levels and the limitations of VHR satellite imagery in detecting slight to medium damage, only three damage grades are considered in this work. The EMS-98 damage grads represented in table 7.1 were merged as follows: Grad 1 and 2 have been merged to represent the Minor/Some damage class, Grad 3 and 4 have been merged to represent the Major/Significant damage class, and the final grad, Collapse class, is the same as Grad 5 (see figures 7.3 and 7.4).

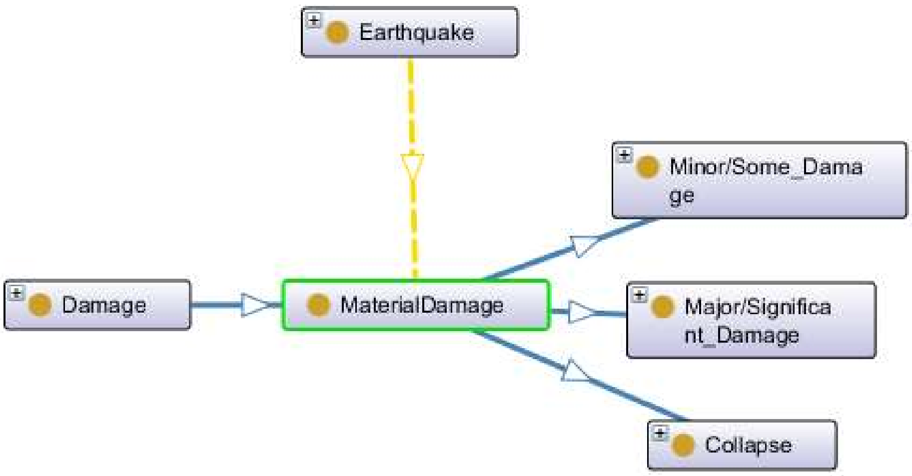


Figure 7.3 The ontology damage grad levels graph representation

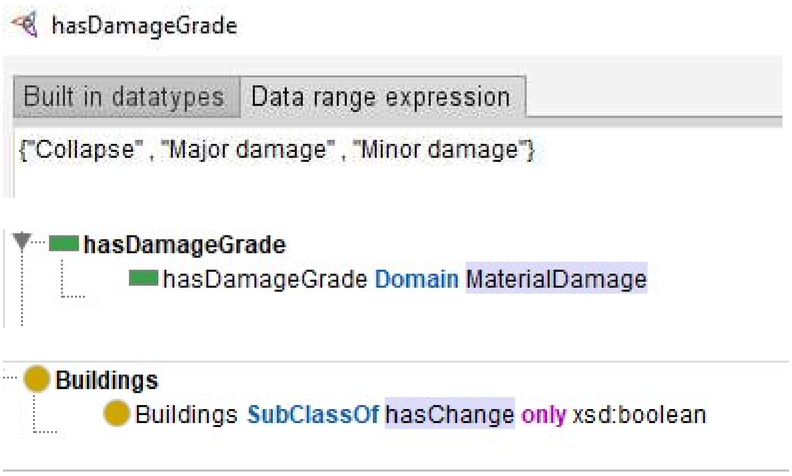


Figure 7.4 Damage grads data and object properties as defined in GEO-MD ontology

7.2.3 Damage-feature selection and extraction

Feature selection is an important stage in any classification-based change detection approach, since a different feature set may result in different classification results. As a result, any inconsistency in feature selection may result in unfavourable final results. The goal of the feature analysis step in change detection is to identify the most important features for distinguishing between changed and unchanged objects.

The selection of the feature set that can provide enough information for damage assessment is a challenging task. Damage features are usually difficult to select and reduce to a small number of parameters sufficient to represent an image object owing to their complexity and variability.

An extensive literature review was carried out to understand the relevant features essential to the damage assessment process and select them, including the study of the building damage protocol used in the visual damage assessment performed by the photo-interpreters of the project team of the Post-Disaster Needs Assessment (PDNA), the United Nation's UNITAR/UNOSAT unit, and the European Commission's Joint Research Centre of the study area (i.e., Haiti), for instance (Bevington et al., 2015): (i) increased brightness, (ii) rough or more variegated texture, (iii) offset roofs, and (iv) irregular shadow.

Common damage features include spectral, shape, size, and texture. Spectral features are acquired based on the reflectance of the incident electromagnetic wave of different objects in each band, including the spectral signal of objects in each band, brightness of objects, and maximum difference (Wang et al., 2018).

Textural features contain information on the coarseness, smoothness, and uniformity of image objects. They may be retrieved from a variety of groups, including Haralick, Gabor, Fractal, and first-order statistical features (Ranjbar et al., 2014).

In this study, 16 Haralick features, produced from grey level co-occurrence matrix (GLCM), and grey level co-occurrence vector (GLCV), were extracted from both pre- and post-event satellite imagery and post-event LiDAR data. This study also includes the mean-variance difference in the same geographical region of the pre- and post-event satellite images, as well as spatial characteristics in connection to neighbouring objects, such as the interaction between a building and its shadow.

Another existing procedure is the computation of a ratio between two images, like NDVI. This approach could provide good results if the images acquired before and after the events are quite close in time, but seasonal changes can induce false interpretations. Since the study area dataset has been acquired in the same season (22 February and 15 January), with a relatively small acquisition time interval (one year), the use of NDVI is deemed acceptable.

Five feature categories were selected to be used as comparison metrics between the pre- and post-event image objects. Table 7.3 summarised the feature set used in this work.

Table 7.2 Feature considered for building structural damage assessment.

Category	Parameter	
Geometry	Area Rectangular Fit Length/Width Ratio Asymmetry	
Shape	Perimeter/Area Ratio Shape Index Density Compactness	
Layer values	Brightness Max difference Standard derivation Skewness Mean Difference to neighbours NDVI Elevation	
Texture	GLCM Homogeneity GLCM Contrast GLCM Dissimilarity GLCM Entropy GLCM Ang. 2nd moment GLCM Mean GLCM StdDev GLCM correlation	GLCV Homogeneity GLCV Contrast GLCV Dissimilarity GLCV Entropy GLCV Ang. 2nd moment GLCV Mean GLCV StdDev GLCV correlation
Spatial relations	Relative Border to Shadow Relative Border to Debris (small irregular pieces with same spectral characteristics).	

The extracted features will be used as parameters in the defined SWRL rules and in calculating the similarity function between the pre- and post-event image objects building by building.

Generated features of the two dates of image objects are expressed as follow:

$$F = (f_1, f_2, \dots, f_n)^{T1} \qquad (15)$$

$$F = (f_1, f_2, \dots, f_n)^{T2} \qquad (16)$$

Where F is the set of the extracted features in different times T1 (pre-event) and T2 (post-event). And *n* is the number of the total features.

The change can be expressed by a linear combination of the features from the two dates. For each given image object *O*, represented by a feature space *F*, the similarity function *Sim* in (Wang and Chen, 2020) is calculated for each feature:

$$Sim\ (O_{T1}, O_{T2}) = 1 - \frac{|f_{T1} - f_{T2}|}{f_{max} - f_{min}} \qquad (17)$$

After calculating the similarity *Sim* of each feature, the overall similarity of the image objects representing the building class from the two dates is calculated according to the weight value w_f of each feature. The overall similarity of a case is a weighted sum of the similarities of features as follow:

$$Sim\ (O_{T1}, O_{T2}) = \frac{\sum_1^n w_f . Sim_f}{n} \qquad (18)$$

Where $Sim_f \in [0, 1]$ and $w_f \in [0, 1]$

The higher *Sim* the more similar $object_{T1}$ and $object_{T2}$ are and the less change is.

The lower Sim the less similar $object_{T1}$ and $object_{T2}$ are and the more change is.

Since this is a similarity function, the weight value w_f has an inverse relationship with the relevant damage features. Consequently, higher w_f values are accorded to the less relevant features for change detection and lower values are accorded to the more relevant features for change detection.

Since a thematical layer from pre-disaster building classification results is used for the post-disaster building classification to control the buildings' footprints, the image-objects boundaries of both images will be relatively similar. Geometrical and shape features are less relevant for change detection in this case (higher w_f value is accorded), whereas spectral, textural, and spatial features are more relevant (lower w_f value is accorded).

7.2.4 SWRL rules definition

To classify the damaged buildings into the abovementioned damage classes, a set of SWRL rules is created. The rulesets are built from the defined ontology, visual image interpretation, feature analysis, and semantics of the area. The fuzzy ontology rules are translated into decision rules to assign a damage status to Buildings instances. Fuzzy rules are ''if–then'' rules (if set of premises, then a consequence).

Defining the rules for each damage class is a complicated process since different factors, such as the nature of the building materials used in construction and the type of structure itself (e.g., masonry, reinforced, and slum), frequently impact the protocol for identifying the damaged building.

Moreover, despite the orthorectification of the post-event data, there are frequently misalignments between the pre- and post-event imagery. Only a supervised method (wherein human judgment could account for these inconsistencies) is suitable (Bevington et al., 2015). The use of SWRL rules presents an exceptional advantage in simulating expert-based assessment.

Both nadir imagery and LiDAR data were employed to define rules for recognising damage grades, including, building perimeters shifting, damaged buildings shadow and surrounding debris, and building elevation.

The SWRL rules are defined using the extracted features, similarity function, and a set of ontology concepts and properties. The rules were modified until a reasonable level of accuracy was achieved.

The similarity function *Sim* defined in the above section (equation (18)) has a range value: $Sim(Building_{T1}, Building_{T2}) \in \{0,1\}$

Where four fuzzy sets are used to describe the *Sim* function: “very low”, “low”, “medium”, and “high”.

- *If* Sim ($Building_{T1}$, $Building_{T2}$) is High & $Building_{T2}$-Shadow is **High** & $Building_{T2}$-Debris is **Low** *Then* (Damage level is ‘**Undamaged**’).
- *If* Sim ($Building_{T1}$, $Building_{T2}$) is Medium & $Building_{T2}$-Shadow is **Medium** & $Building_{T2}$-Debris is **Low** *Then* (Damage level is ‘**Minor-Damage**’).
- *If* Sim ($Building_{T1}$, $Building_{T2}$) is Low & $Building_{T2}$-Shadow is **Low** & $Building_{T2}$-Debris is **Medium** *Then* (Damage level is ‘**Major Damage**’).
- *If* *Sim* ($Building_{T1}$, $Building_{T2}$) is **Very low** & $Building_{T2}$-Shadow is **Low** & $Building_{T2}$-Debris is **High** & $Building_{T2}$-Elevation *is* **Low** *Then* (Damage level is ‘**Collapsed**’).

Collapsed buildings can also be detected based on post-earthquake LiDAR data solely by using existing elevation models.

Building elevation can be expressed by either:

- Digital Elevation Model (DEM) (Maune, 2007): which refers to the digital representation of the topography of the earth’s surface. The term DEM is used in a generic sense to represent: (i) any type of elevation data of the earth surface including terrain surface without any natural/artificial object on it (i.e., terrain model), (ii) actual surface with all types of natural/artificial objects on it (i.e., surface model), and (iii) absolute elevation from ground level (i.e., normalised surface model).
- Digital Surface Model (DSM): represents the first echo received by the laser for each laser pulse sent out, which can be thought of as elevation data directly acquired from remote sensing data. DSM indicates the height of the earth's actual surface, such as the tops of structures, trees, etc.
- Digital Terrain Model (DTM): refers to the digital representation of the actual terrain or bare ground elevation that contains elevations of natural terrain features such as barren ridge tops and river valleys. A DTM can be produced of DSM by applying appropriate techniques like filtering or mathematical morphology to remove elevations of vegetation and cultural features, such as buildings (Joshi, 2010).

- Normalised Digital Surface Model (nDSM): refers to the digital representation of the absolute elevation of the objects above ground level. nDSM is produced by subtracting the DTM from the DSM and is often used for identifying completely pancaked buildings in building damage assessment (Joshi, 2010).

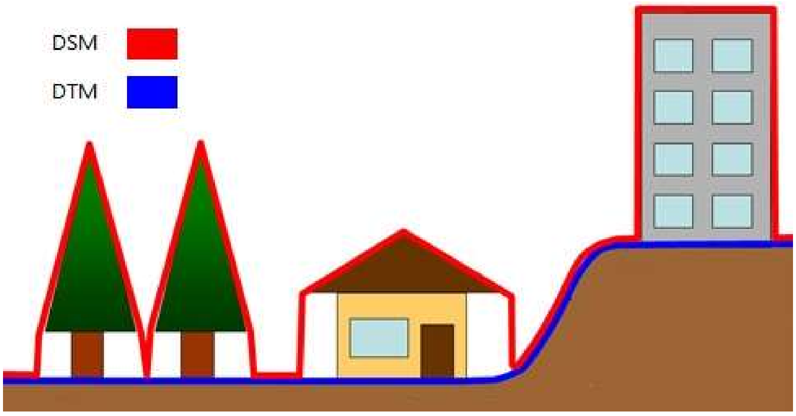


Figure 7.5 Difference between the two elevation models DSM and DTM.

Collapsed buildings detection can be performed either by using nDSM or by comparing the building elevation with the neighbouring road elevation, if they are similar, the building status is labelled as "collapsed".

Figure 7.6 SWRL rule for assigning building instance to status "Collapse"

All the rules are translated into SWRL format and stored in the knowledge-based reasoning task using Pellet reasoner.

7.3 Experimental results

In this part, an empirical evaluation of the proposed approach to assessing buildings damage is performed using optical and LiDAR data from the Port-au-Prince (Haiti 2010 earthquake). The 2010 Haiti earthquake caused significant and extensive devastation throughout the city of Port-au-Prince, with thousands of structures badly damaged or destroyed. However, the severity of the destruction varied significantly from one neighbourhood to another. The goal of this part is to produce the building damage map following a catastrophic event, as well as to discuss the particular advantages and weaknesses of the employed technique.

In order to verify the final result of the damage detection procedure, the UNITAR and UNOSAT geographic information analysis and satellite image derived damage map points belonging to the three damage classes (Grades 3, 4, and 5 of the EMS classification) were extracted for the validation sets through visual comparison. Figure 7.7 shows an example of a point-based building-by-building damage assessment. The maps were produced using computer-assisted visual interpretation of pre-earthquake satellite images and post-earthquake aerial photography.

Figure 7.7 Example of point-based building-by-building UNITAR/UNOSAT produced damage map

UNITAR/UNOSAT damage map description ((UNITAR); et al., 2010):

Region: Port-au-Prince

Satellite Data: WorldView-2

Imagery Dates: 19 Dec.2009 / 7-15 Jan. 2010

Resolution: 50cm

Copyright: DigitalGlobe

Aerial Photos: NOAA / Google & WB-IC-RIT

Imagery Dates: 18 Jan / 21 Jan / 22 Jan / 23 Jan 2010

Copyright: NOAA / Google / WB-IC-RIT data public domain

Source: USGS / ERDAS APOLLO WMS

Building Data: UNITAR/UNOSAT, Swisstopo and RSL-Zurich

Road & Urban Data: Open Street Map

Place Names: OCHA, Google Map Maker

Other Data: MINUSTAH, USGS, NGA

Elevation Data: ASTER GDEM

Source: METI & NASA 2009

Damage Analysis: UNITAR/UNOSAT

A comparison with field damage assessments of about 400 buildings in Port-au-Prince, conducted by Rathje et al. (Rathje et al., 2011), stated that the UNOSAT damage data, which were derived from visual interpretation of aerial photos and satellite imagery, included approximately 20% misclassifications. This large error is not surprising because it can be difficult to identify some features of significant damage from aerial imagery, besides the difficulty in identifying internal damage from RS imagery.

However, UNOSAT data were chosen as the truth data since they offered inclusive damage information for all structures in the study area.

Oblique imagery was additionally used for validation to complete the UNOSAT data. Since field damage assessments data was not available for this study, a visual interpretation of the available VHR oblique data was employed to confirm/negate a number of labelled buildings damage classes when deemed necessary (in some cases of uncertainty).

Buildings are first extracted by means of the segmentation and classification algorithms described in Chapter 6; two iterations of multiresolution segmentation with scale 20, shape 0.1 and compactness 0.5 and scale 50, shape 0.7 and compactness 0.7 respectively, and refined by a spectral difference segmentation with a maximum spectral difference of 30 (see figure 7.8). The initial corresponding classification results, as shown in figures 7.9 (c) and (d), demonstrate the differences in shape and size of the affected buildings, especially for collapsed buildings (example delineated in a red circle in figure 7.9).

However, as previously declared, by applying the same procedure for both pre- and post-event datasets, some of the buildings may not be correctly classified as the defined rulesets including shape and size features (e.g., area, rectangular fit, length/width ratio, shape index threshold conditions) explicitly conceived for undamaged building detection, do not take into consideration the characteristics of collapsed or severely altered buildings. For this reason, the pre-disaster building classification results shapefile is used as a thematic layer for a classification-based segmentation of the post-disaster image to control the segmentation results and assure that no pre-existing building in the pre-disaster dataset is excluded in the post-disaster classification.

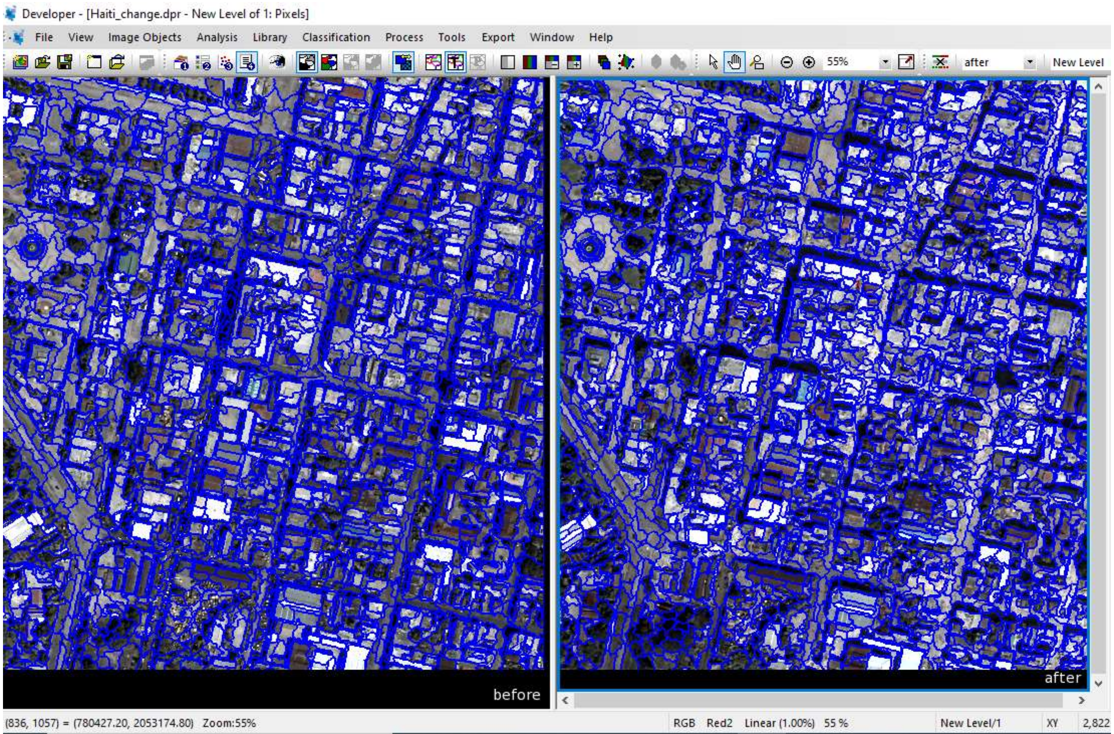


Figure 7.8 Segmentation results of both pre- and post-earthquake datasets.

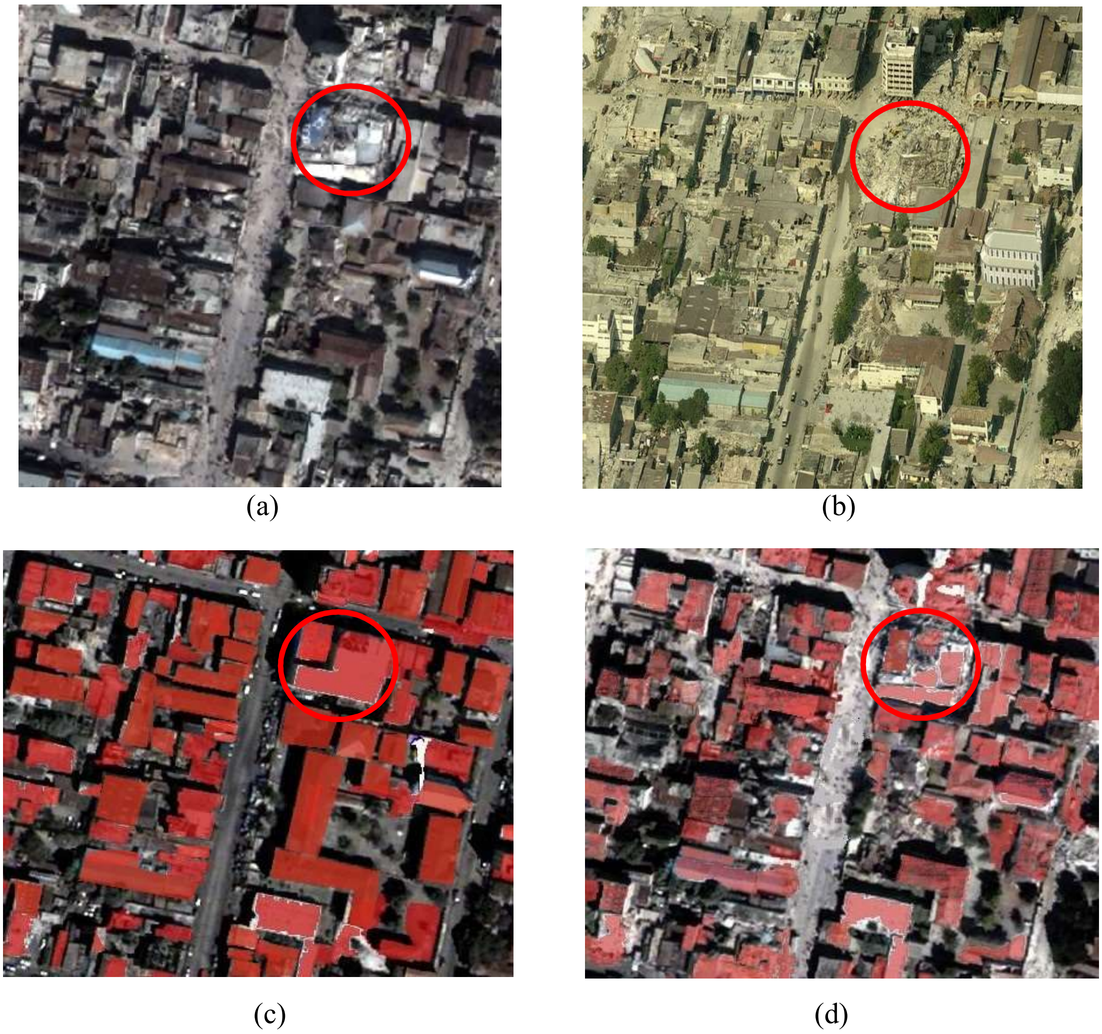


Figure 7.9 Selected test area from the Port-au-Prince datasets on pre- and post-event VHRS and oblique imagery; (a) post-event VHRS imagery, (b) post-event oblique aerial imagery, (c) pre-event buildings classification, and (d) post-event buildings classification.

For the post-classification change detection, only three classes from the previous classification results were considered: (i) Buildings, (ii) Roads, and (iii) Shadow. The "Buildings" class presents the main class in this study; however, Roads and Shadow from previous classification results were used for SWRL rules definition for building change detection due to their direct spatial relation with the class Buildings. An additional class "Debris" was exclusively considered and extracted using post-earthquake LiDAR data for the same purpose.

In order to identify the earthquake-induced damage, a test area of the city of Port-au-Prince was selected for damage assessment (see figure 7.10). Both VHRS imagery and LiDAR data (figure 7.11 - 7.12) are fused following the methodology described above.

The classification task was performed using eCognition 9.1, Protégé 5.5, and Pellet reasoner, while ArcMap 10.7 was used for georeferencing and map creation and visualisation.

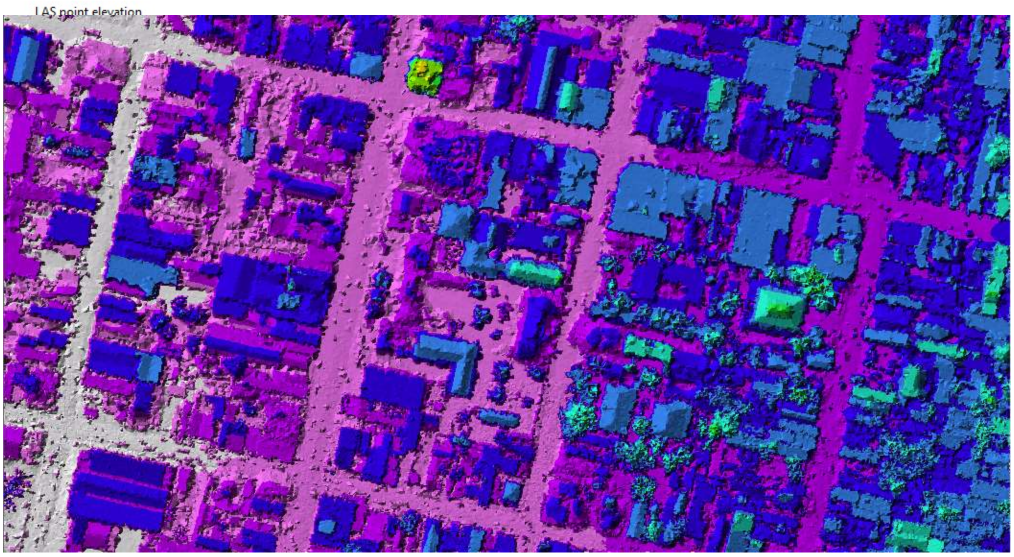


Figure 7.10 LAS (LASer) points elevation (point cloud data)

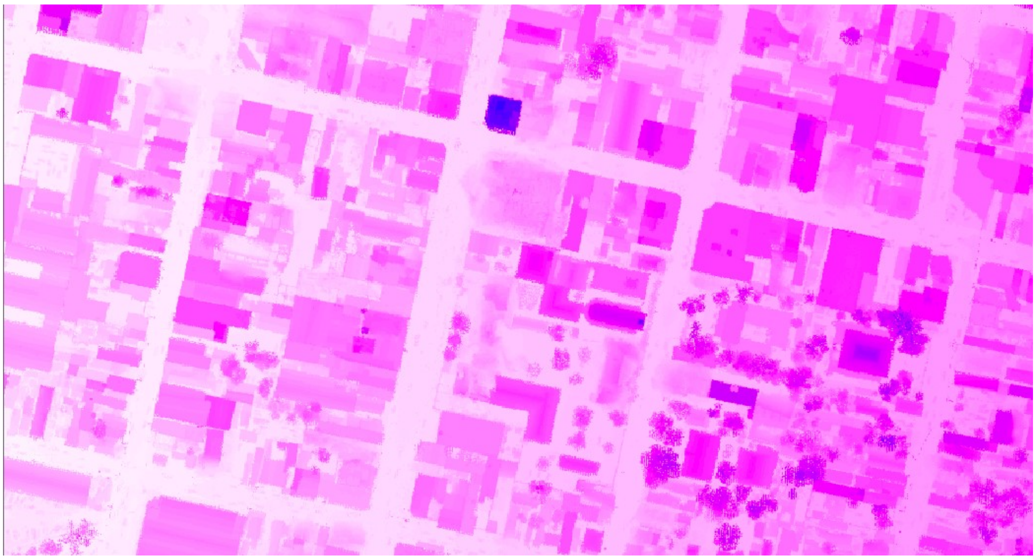


Figure 7.11 Digital Elevation model (DEM)

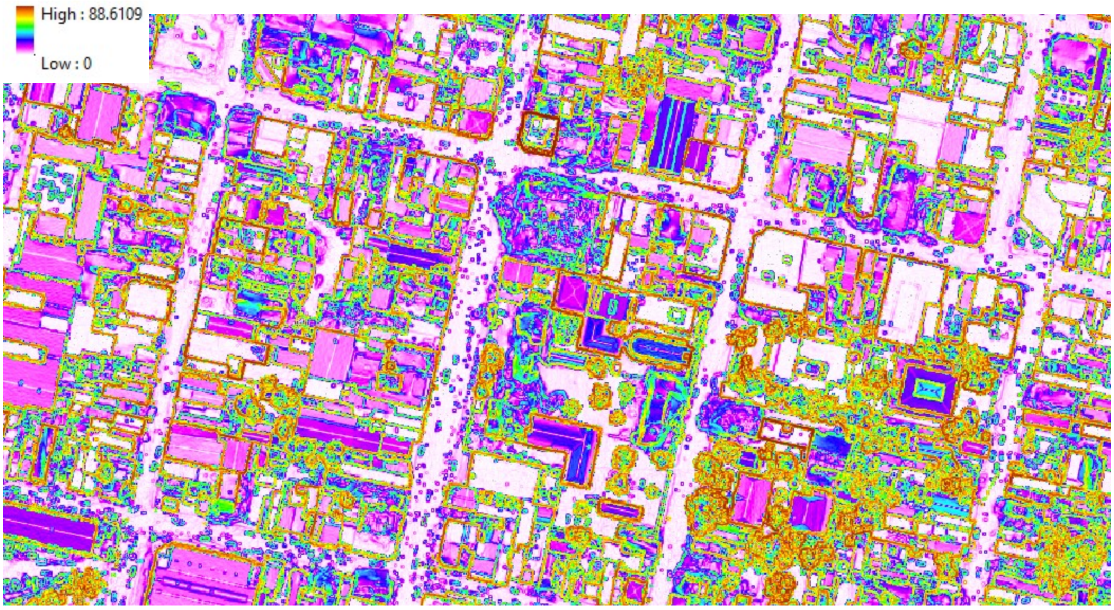
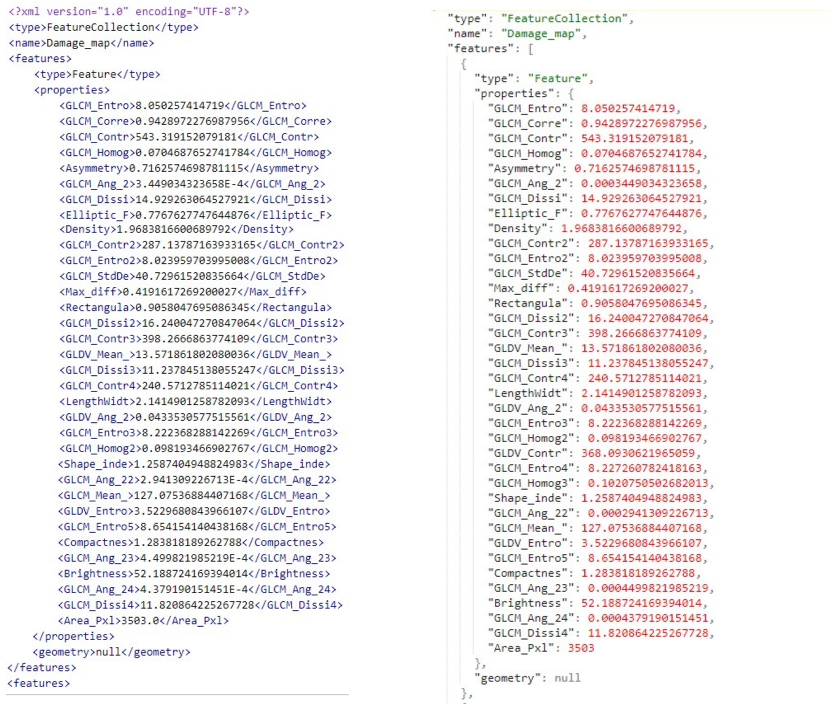


Figure 7.12 Contour and slope derivation of LiDAR data

The damage classification results (i.e., image objects and feature set) were extracted, exported, and translated into the appropriate format (e.g., GeoJSON, XML) for integration and visualisation in ArcGIS (shapefiles). Figure 7.13 shows part of the exported results.



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    "properties": {
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      "GLCM_Homog": 0.0704687652741784,
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Figure 7.13 Part of the exported results (image objects and feature set) in GeoJson and XML format

The proposed method's final damage map of the test region is presented.

Figure 7.14 displays the generated damage map of the given area, visualised in ArcMap 10.7, using the best experiments with the highest accuracy.

Figure 7.14 Generated damage map shapefiles of the selected area visualised in ArcMap

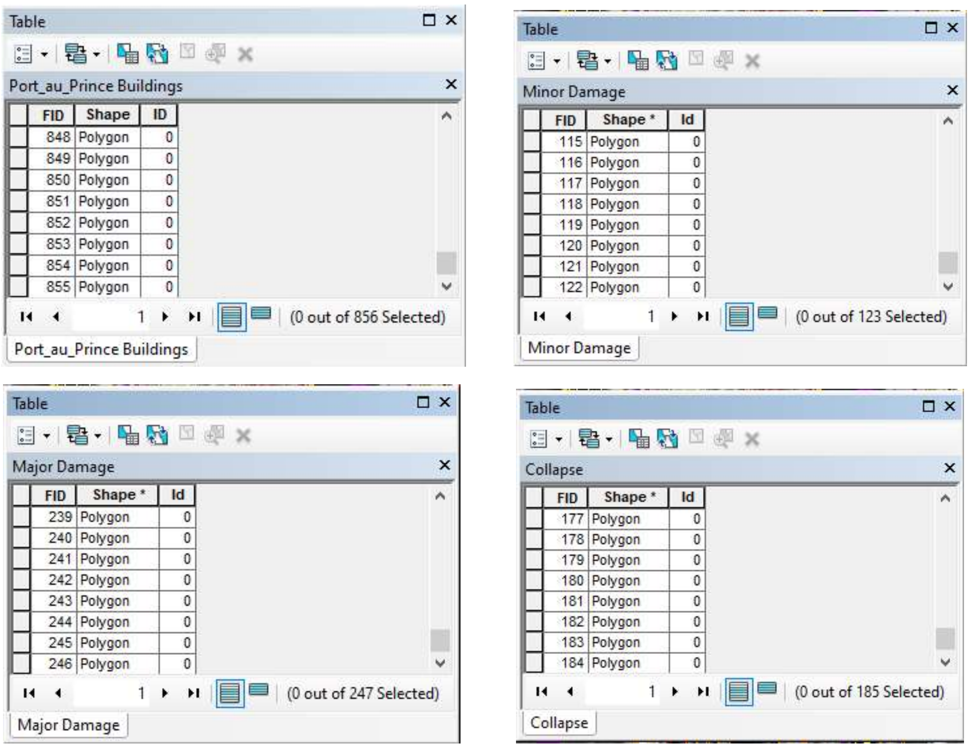

Figure 7.15 Building polygons attributes of the three damage classes.

Amongst 856 extracted buildings from the test area. 185 buildings were classified collapsed, 247 labelled with major damage, and 123 labelled with minor damage (see figure 7.15).

Table 7.3 below shows the accuracy of the proposed method over the Port-au-Prince area, as measured by ground-truth buildings.

Table 7.3 Error matrix for the damage classes with the ontology-based approach

	Ground truth						
Class	***Undamaged Building***	***Minor Damage***	***Major Damage***	***Collapse***	Total	PA	UA
Undamaged Building	255	42	0	0	301	0.93	0.84
Minor Damage	16	95	19	0	123	0.62	0.77
Major Damage	0	14	211	17	247	0.87	0.85
Collapse	0	0	11	174	185	0.91	0.94
Total	273	151	241	191	**735**		

Overall accuracy: 0.85%

7.4 Discussion

When opting for a post-classification-based CD technique, it is worth noting that the accuracy of the change detection will strongly depend on the accuracy of each individual classification of multi-temporal images. An error in the classification has a direct effect on the results of the changes. Any errors in the input maps are transferred straight to the change map.

Acquiring ground truth based on field observation is the best way to assess a method. However, due to the unavailability of this data for this study, the available visual interpretation of the study area was used. In this case, the obtained test data were quantitatively verified to determine the overall accuracy in order to evaluate the classification results. Comparing the results to ground-truth data (visual interpretation) revealed that the above-presented method achieved robust and acceptable results. Although the employed ground-truth data was declared not 100% accurate as it contains some errors due to the visual interpretation limits since it is based on vertical remote sensing data and roof-based assessment only, the proposed method achieved close results to the human-based interpretation as it follows an analogous reasoning process.

The class “Collapse” achieved the highest accuracy over the damage classes (0.91 producer accuracy, and 0.94 user accuracy). This is mainly due to the integration of LiDAR data, which offers the advantage of elevation information about the collapsed building. On the other hand, lower damage grades were the most difficult to identify even with the use of both pre- and post-event imagery. As a result, the identification rate of damaged buildings with lower damage classes was less accurate than those with higher damage grades.

It is also noticeable that when spectral and spatial characteristics are integrated, the detection rate is much higher than when spectral information is used alone.

7.5 Conclusion

A knowledge-based approach to detecting damage building from pre- and post-event satellite imagery and post-event LiDAR data is proposed in this chapter.The proposed method begins by classifying pre- and post-event satellite imagery using the method presented in Chapter 6. Buildings are extracted from post-event data using the pre-event vector map. Similarity function along with a set of SWRL rules are used to categorise the extracted buildings into changed/non-changed and further classify the changed buildings into three damage scales (i.e., minor damage, major damage, and collapse). The knowledge-based developed method allowed the detection of three damaged grades with good accuracy even in a complex urban area like the city of Port-au-Prince, which presents a variety of building categories with broad differences in type and size.

Building damage assessment is challenged by a variety of factors, including imagery type, spatial image resolution, viewing angle, comprehension of damage characteristics, and subjectivity.

One of the most critical phases in the response and recovery process is the creation of damage assessment maps. Supervised approaches tend to be robust. However, a large amount of training data is required as a prerequisite to precisely model the feature distribution of information classes and get accurate results by using machine-learning methods.

Case-based reasoning, on the other hand, can automatically recognise objects with no training datasets needed. This factor can significantly reduce processing time, a key aspect of disaster management.

Furthermore, SWRL was used to express rules as well as logic in a human comprehensive way, with easy interpretation. The rules can be managed and applied separately, and can be updated and reused for a new case.

Chapter 8 General Conclusion

8.1 Remainder of objectives

The present thesis focuses on the development of a global geographic ontology and a novel semantic interpretation technique of satellite images collected over the same geographical area at different times (i.e., before and after a major disaster) based on the proposed ontology. The objectives of the thesis are as follows:

1) Formal context: Proposal of a global ontology modelling the content of satellite images, major disasters, and damage, and considering its specificities (sensors, space, time, and constraints) and related domain knowledge.
2) Functional context: Proposal of a methodology for satellite image classification guided by the proposed ontology allowing reasoning, change detection, and damage assessment from the multitemporal satellite image classification results.
3) Application context: Application of the proposed methodology for the classification and structural damage assessment following the Haiti 2010 earthquake.

8.2 Conclusion

This work presents an attempt to overcome the semantics challenge in geographic and RS data. To aid in the semantic classification of satellite images at various scales, as well as to assist in change detection and damage assessment following a major disaster, a global geographic ontology delivering a referential geographic vocabulary, and an inclusive taxonomy in the context of major disasters was developed.

In this dissertation, three different problems are addressed. First, building a domain ontology from scratch to address the previously underlined needs. Second, seeking effective classification methods for VHR satellite images based on the developed ontology. And finally, assessing structural damage following a major disaster based on the preceding classification results. Three problematical aspects, domain ontology development, knowledge-based classification, and damage assessment, are investigated. In this concluding chapter, previous efforts are first summarised. Subsequently, future research directions are proposed.

For the first purpose of this work (Chapter 5), a geographic ontology for major disasters (GEO-MD) is proposed, developed, and validated. GEO-MD consists of three core sub-ontologies: Surface, Disaster, and Damage, and three secondary sub-ontologies: Sensors, Imagery, and Spatial Location, to fully cover the associated interdomains. Additionally, GEO-MD is aligned with two upper-level ontologies: GeoSPARQL and Time. GeoSPARQL was further extended with new concepts to fully incorporate the important aspects of remote sensing data: Features and Geometry.

For the second purpose of this work (Chapter 6), a knowledge-based classification method is adapted with an added value in building the bridges between different levels of knowledge and inferring implicit knowledge through the existing reasoners. Two rule-based classification approaches are presented at this level: a non-ontological fuzzy rule-based method and an ontology-based method. This first classification serves two purposes: (i) to improve the segmentation results and (ii) to serve as a classification-based segmentation input for the second classification. A well-known drawback of reasoners is that their computational cost increases with the increase of instance numbers. By using an initial classification, fewer polygons of segmented images are generated as input for the classification process, which will considerably improve the performance of the reasoner in terms of reasoning time and computational cost. Furthermore, the customised application of SWRL rules evaluated by existing reasoners will allow access to any class definition and generate rules in a machine- and human-understandable format that fit the purpose of various applications.

For the third purpose of this work (Chapter 7), a knowledge-based approach is proposed to detect damage building from pre- and post-event satellite imagery and post-event

LiDAR data based on the previous classification results. A similarity function, along with a set of SWRL rules, is used to assess building damage. The knowledge-based developed method allowed the detection of three damage grades (i.e., minor damage, major damage, and collapse) with good accuracy even in a complex urban area like the city of Port-au-Prince, which presents a variety of building categories with broad different types and sizes.

In principle, any supervised classifier can be used for this scheme. Supervised approaches tend to be robust. However, a large amount of training data is required as a prerequisite to precisely model the feature distribution of information classes and get accurate results by using machine-learning methods. The reason why case-based reasoning was ideal for this research, is its ability to automatically recognise objects with no training datasets. This specific characteristic can considerably reduce the processing time, a crucial factor for disaster management.

Experiments on Haiti earthquakes using multispectral very high-resolution satellite images and LiDAR data demonstrate how the incorporation of the ontology enhances the classification results and lessens the semantic gap between low-level features and high-level ontology-driven semantics. Moreover, the presented method proved its effectiveness in building structural damage assessment, which was comparable with expert visual interpretation. Experimental results confirmed that the proposed methods were able to provide both accurate classification and damage maps.

8.3 Future research

This thesis investigates and proposes a global ontology that represents expert knowledge in a formal and explicit way, contributing to knowledge sharing and integration and and reducing the gap between RS science and application fields such as disaster management.

Several contributions made by this work, particularly efforts to develop a sharable knowledge base representing expert knowledge in the field, are critical to interpreting RS data and laying the groundwork for a broader range of applications. Furthermore, the way the challenges of this work have been addressed can direct researchers towards better approaches for successfully addressing similar challenges. A list of potential directions for future research is discussed below.

Development of an exclusive semantic classification and damage assessment platform

The ontology-based system was not integrated on an inclusive platform in this work. Different commercial and opensource software (e.g., eCognition, ArcMap, Protégé) were used separately to perform the required experiments to validate the study. Sometimes the outcome of the processing in one software was not compatible with the other (e.g., OWL, GeoJSON, shapefile, XML) and needed translation before processing in the second software. The development of an inclusive platform including all the tasks (pre-processing, segmentation, classification, and damage assessment) would considerably simplify the job of the end-user.

Automation of the classification parameter selection

While the proposed system strives to automate every element of satellite image classification and damage assessment, there are a few aspects that still require additional manual monitoring (e.g., segmentation perimeter choice, threshold conditions definition, etc.). All of this creates additional challenges that need to be addressed in future work.

Optimisation of the segmentation parameters

The problem of image segmentation is well-known and several techniques have been proposed to overcome it. A disadvantage of such techniques is their parameterisation, which needs to be meticulously optimised based on the problem at hand. The optimisation of these parameters leads to obstacles in their use in an unsupervised manner, as sub-optimal parameterisation can lead to over and under-segmentation problems. The performance of the ontology-based classification and building detection processes is heavily dependent on the quality of the segmentation. Parameter tuning is required for the algorithms to run correctly with different types of image datasets. The introduction of accurate, robust, and unsupervised image segmentation techniques for the problem of object detection and extraction is necessary.

Validation of the proposed methods on additional use cases

Testing GEO-MD in different disaster categories (e.g., floods, wildfires, and hurricanes), and for different test areas around the globe to fully estimate its purpose should be addressed in future work. A first version of the ontology was released in (Bouyerbou et al., 2019) to serve as a geographical vocabulary source in the context of disasters for various geographic and disaster management purposes. It can be used in whole or in parts for further research work.

Exploration of hybrid approaches incorporating knowledge-driven techniques and ML/DL algorithms

One of the main strengths of formal ontologies in the field of remote sensing is their ability to, not only address the complexities of satellite image interpretation of geographic concepts, but also efficiently incorporate knowledge from other fields of application. As a result, formal ontologies make it easier to share and reuse formalised RS expert knowledge with the rest of the scientific community, including experts from other domains. On the other hand, ontologies do not significantly enhance the OBIA process in terms of classification accuracy (Arvor et al., 2019), which might be viewed as a drawback given that classification accuracy may be a priority within the RS community. In this regard, emerging ML, and DL techniques, in particular, have shown robust results and extremely high classification accuracy. The incorporation of an ontology-based classification approach with ML algorithms may deliver outstanding results, in both explicit intra-domain and interdomain experts' knowledge integration, sharing and re-use, and classification accuracy.

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