Mapping Post-Disaster Temporary Shelters Using Object-Oriented Image Analysis: Cases of the 2009 L'Aquila, Italy and 2010 Haiti Earthquakes

Nathan Christen Tift

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by

Nathan Christen Tift

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Thesis Assessment Board

Prof. Dr. Victor Jetten (Chair)
Dr. Jadu Dash (External examiner)
Dr. Norman Kerle (First supervisor)
Dr. Menno Straatsma (Second supervisor)

UNIVERSITY OF TWENTE.
ITC
FACULTY OF GEO-INFORMATION SCIENCE AND EARTH OBSERVATION

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Abstract

Earth observation (EO) data has become more and more abundant and accessible for use in responding to disasters. Traditional processing of these data to create useful products has been enhanced by new automation techniques and geocollaborative efforts. Object-oriented analysis (OOA) has increasingly been used in post-disaster and other situations to rapidly and efficiently extract features of interest from very-high resolution (VHR) satellite images and aerial photographs. OOA has been implemented to detect tents within established refugee camps, but determining the previously unknown locations of temporary shelters and camps set up after a disaster presents a different challenge. This thesis examines the needs of the disaster response community for information about temporary shelters and proposes a new method to aid in their detection based on OOA. An algorithm was developed using eCognition software by analyzing data collected after the 2009 earthquake near L'Aquila, Italy. An algorithm relying primarily on visible spectral bands and shape characteristics was shown to distinguish blue tents and locate most camps. The procedure was then tested on imagery acquired in two different areas of Haiti after the 2010 earthquake there. An assessment shows the method to be useful in distinguishing camps containing blue shelters as well as red shelters when a slight modification is made. The algorithm's accuracy, transferability, and usefulness for disaster responders are discussed.

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For educational and ethical reasons I must claim sole credit for this work. However I could not in good conscience fail to mention and thank a few of the people who have encouraged me along the way.

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Those thanks being said, if for any reason this work does not meet the reader's expectations, the aforementioned people should not be blamed.

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CNL	Cognition Network Language
DFD	*Deutsche Fernerkundungsdatenzentrum* (German Remote Sensing Data Center)
DLR	*Deutsche Luft- und Raumfahrt* (German National Aerospace Center)
DN	digital number
DPCN	*Dipartimento della Protezione Civile Nazionale* (Italian National Civil Protection Department)
EERI	Earthquake Engineering Research Institute
EO	Earth observation
EU	European Union
FSO	Feature Space Optimization
GEO-CAN	Global Earth Observation Catastrophe Assessment Network
GIS	geographic information systems
IAPSO	United Nations Inter-Agency Procurement Service
ICSMD	International Charter "Space and Major Disasters"
IDP	internally displaced person
JRC	Joint Research Center of the European Union
KIM	Knowledge-based Information Mining
MBGR	mean blue-green ratio
NGO	non-governmental organization
NOAA	United States National Oceanic and Atmospheric Administration
NDVI	Normalized Difference Vegetation Index
OCHA	United Nations Office for Coordination of Humanitarian Affairs
OOA	object-oriented analysis
RS	remote sensing
SERTIT	*Service Regional de Traitement d'Image et de Teledetection* (Regional Service of Image Processing and Remote Sensing)
UNDHA	United Nations Department of Humanitarian Affairs
UNOSAT	United Nations Institute for Training and Research Operational Satellite Applications Program
VHR	very high resolution
WMS	web mapping service
ZKI	*Zentrum für satellitengestützte Kriseninformation* (German Center for satellite-based Crisis Information)

1 Introduction

At 3:32 a.m. local time on April 6, 2009 a strong earthquake measuring 6.3 on the Richter scale shook the town of L'Aquila and the surrounding villages in the Abruzzo region of Italy. The quake left 300 dead, around 1 000 injured, and upwards of 48 000 homeless (DREF, 2009), Government relief agencies responded quickly, having learned from much maligned failures in previous disaster responses (Amendola et al., 2000). Tent camps sprang up the same day of the earthquake. The Italian president confidently reassured the victims his administration had control over situation. No outside help was needed, he said (Baldini, 2009)

Less than a year later on the other side of the world, an even more powerful 7.0 earthquake rocked much of the country of Haiti at 4:53 p.m. on January 12, 2010. The calamity claimed the lives of over 300 000 people and displaced another 1.3 million. Authorities were woefully unprepared for such an unprecedented disaster. Agencies and governments from around the world offered shelter and assistance, quickly converged on the scene in an extraordinary outpouring of humanitarian aid (DREF, 2010).

No one can predict the nature, location or magnitude of the next disaster (Johnson et al., 2006). A nation may be able to handle the recovery alone in a relatively orderly manner or it could require near worldwide coordination. Yet even the best handling of catastrophes can yield lessons in the cycle of disaster from readiness to rebuilding.

Effective response has long been recognized as a key part of mitigating the impact of disasters. To this end, relief organizations and response professionals have benefited greatly from recent advances in the field of geoinformatics. This tightening nexus of computers and geography has seen concurrent rapid improvements in earth observation technology and data processing techniques for disaster management (Rao et al., 2006). At the same time, a considerable amount and wide range of earth EO imagery products are now available to responding agencies in the immediate aftermath of disasters. Every year, more and more satellites are launched, increasing temporal resolution for every location on earth while providing better and better spatial and spectral resolution (Buehler and Kellenberger, 2007). Furthering these developments, the International Charter "Space and Major Disasters" (ICSMD) was put into place in 2000. This agreement encourages space agencies to share EO data. ICSMD can be triggered by member states, the United Nations, or the European Union (Ito, 2005). Since its initial inception, more and more agencies have agreed to participate and offer their data free of charge to aid in relief effort. The imagery has been utilized by an ever-growing and broad range of groups and organizations. From these data, geosciences professionals have created diverse products to aid in relief efforts, ultimately benefiting those directly affected by disasters (Voigt et al., 2005).

Despite these strides, much of the potential heralded by technological progress and improvements in data-sharing practices remain unrealized. The informal nature of ICSMD has lead to an ad-hoc network of repositories that do not always effectively communicate or collaborate (Voigt et al., 2005). There has been a lack of effective sharing of both data and products between agencies that have diverging interests and perspectives ranging from technocentric, geographic, anthropocentric to ecocentric (Marincioni, 2007).

Soon after a disaster strikes, crisis responders require critical information such as the amount of people affected, areas impacted, and the amount of damage caused. Raw data need to be turned into useful products that can be presented to decision-makers in a way that allows them to easily interpret and understand this information (Kaiser et al., 2003). Broadly, there are three ways in which data have been gathered in efforts to produce these products: ground observation, manual examination of imagery, and automated analysis.

Ground-based emergency mapping services have been provided by non-government organizations (NGOs) like MapAction, which coordinates with large relief organizations including the Red Cross and Red Crescent. Mapping teams of two to eight people are dispatched within 24 hours of the onset of a disaster to take surveys of the affected area relying heavily on GPS data collection (MapAction, 2007). Though commenced quickly, such ground-based data collection activities are still limited to areas that are physically accessible. Maps from these data are often produced by the acquiring organization and quickly made available to responders.

Alternatively, the use of remotely-sensed data for the creation of information products following disasters has distinct advantages. Imagery can provide a visual representation of an entire affected area at a specific moment in time and be available within hours of an event. These images may provide a good overview, but crisis managers are often not skilled in analyzing them, preferring products that can be more easily interpreted (Buehler and Kellenberger, 2007). Informative maps and layers that can be color-coded and overlain demarcating features such as damaged areas, emergency shelters, and water sources are much more useful than raw images alone.

Not only is it useful for managers to have access to processed information such as thematic maps, it is also a requirement of ICSMD that data are used for such a purpose (Voigt et al., 2005). Geographic information systems (GIS) professionals and image analysts are usually tasked with bridging the gap between raw satellite data and useful information. Closing this gap can be difficult since producers must be knowledgeable about available data as well as cognizant of the product needs of the community. As increases in coverage area, time between capture, and spectra have accelerated, more data are now being produced than can be effectively processed (Shan, 2010). This illustrates the need to have a variety of effective procedures in place that can be initiated to quickly analyze these data, determine what is most useful, and create products.

Even when tasks are clear, manually processing large amounts of earth observation data can be incredibly time-consuming. Collaborative mapping infrastructure to rapidly create products have been proposed and initiated for recent disasters (al-Khudhairy, 2010, Brunner et al., 2009). Web mapping services (WMS) and digital globes such as Google Earth have allowed users to team up to tackle the processing of large amounts of spatial data, each working on a different area at the same time (Bevington et al., 2010). Although such methods are rapidly developing, the consistency and accuracy of products resulting from such "crowdsourcing" has been called into question (Goodchild and Glennon, 2010).

Automated detection has advantages over both traditional and more collaborative approaches. Though possibly not as accurate, such a method holds the promise of ensuring a level of consistency that is difficult to achieve using more subjective human interpretation (Benz et al., 2004). Automated methods can also process imagery for different locations and acquired at different times. Comparing data and products captured and produced before, during, and after a disaster can aid in the detection of changes. Furthermore, automated classification can serve a baseline for manual or collaborative efforts whose users can use the information to gain an initial idea of the areas warranting the most attention (Giada et al., 2003).

Though manifold GIS and image interpretation tasks could potentially be automated, crisis responders have shown particular interest in several areas where they believe automated solutions would prove the most useful for both producers and users. The crisis response team at Google indicated a strong interest among the relief community in the development of tools that automatically map floods, rubble, landslides and temporary shelters (Manolides, M., 2010, pers. comm., 3 Aug).

Research has already been undertaken to create methods to automatically detect flooded areas using synthetic aperture radar (Heremans et al., 2003). High-resolution imagery has also been used to detect flooded urban areas (Pesaresi et al., 2007). Automatic rubble detection has been carried out recently too, and shown promising results (JRC, 2010). Conspicuously absent from the literature are studies that pay specific attention to developing automated methods to detect temporary shelters in the immediate aftermath of a disaster.

Furthermore, automated dwelling-detection algorithms that have been developed have primarily focused on specific areas where structures are already known to exist. There is a need to evaluate the effectiveness of automatic post-disaster image analysis over a range of scenarios in order to characterize the robustness of such analyses. Therefore, a study comparing data, products, and algorithms from two separate study sites is called for.

Many of the studies devoted to establishing and improving automated feature recognition for both post-disaster situations and tent detection has relied on relatively new software employing object-oriented analysis (OOA). However, the knowledge gained in both these disciplines has not been applied to post-disaster shelter detection.

1.1 Research Problem

Knowing where people are in the aftermath of a disaster is of paramount importance. Disaster responders must be able to locate affected populations from the moment a disaster strikes, throughout the relief process, until there has been a full recovery (Lang et al., 2010). An immediate estimation of necessitous persons can help to assess a disaster's magnitude and extent (Kaiser et al., 2003). Like other required information, an on-the-ground enumeration of people, their locations, and their needs is preferred but not usually practicable, especially after large disasters in densely populated areas. Aerial imagery can be especially useful to quickly find people, not individually, but vicariously through their dwellings. If a disaster renders homes uninhabitable or unsafe, victims often construct shelters from tarpaulins, set up their own tents, or move into tents provided by various relief agencies. These structures have characteristics that make them readily identifiable on remotely sensed imagery, especially when they are grouped together or set up as separate camps. Knowledge of the location and area of these camps can help to establish rough estimates of the amount of people living in them.

Such rapid population estimates are also vital for relief organizations to make initial assessments and develop targeted plans to respond effectively (Adams, 2006). Moreover, locating temporary shelters over large areas quickly can help to ensure persons in need of aid are found and not inadvertently ignored (Wattegama et al., 2007). Over time, more detailed information may be required, the nature of which depends on the organization and phase of the relief operation (Telford, 1997). Some managers may want to know the exact number or size of tents while others care more about general locations or distance to potential hazards (Voigt et al., 2005). Still others are concerned with whether a camp is growing or shrinking (CDC, 2010). Many of these determinations have been made with the aid of remote sensing and GIS technologies. However, automated processes are not known to have been developed carry out such analyses.

1.2 Research Objective

The aim of the research is to enhance the existing methodologies for locating and quantifying temporary shelters by applying object oriented analysis techniques to create an automated or semi-automated process. Important considerations include the ability for the method to be implemented quickly using data commonly available after a disaster as well as a sufficiency of robustness to be applied in multiple circumstances, locations, and timeframes.

1.2.1 General objective

To determine the effectiveness and robustness of object-based methods for detecting post-disaster temporary shelters and camps

Specific objectives

(1) To develop a method using object-oriented techniques to detect
    a. Individual temporary shelters
    b. Areas that contain temporary shelters (i.e. camps)
(2) To determine the usefulness of the method for each of two different situations
    a. 2009 L'Aquila earthquake
    b. 2010 Haiti earthquake.
(3) To evaluate the suitability of the method using
    a. Very high resolution (VHR) commercial satellite imagery
    b. High-resolution aerial photography
(4) To assess the overall accuracy and robustness of the method
(5) To determine what factors contribute to the accuracy of the method

1.3 Research Questions

(1) Is OOA a suitable technique for identifying
    a. Individual temporary shelters
    b. Boundaries of areas that contain temporary shelters (i.e. camps)
(2) How well can shelter areas be identified using imagery solely within the visible spectrum?
(3) What spectral ranges are ideal for accurate detection?
(4) How accurate is the analysis?
(5) Is the method useful to disaster managers?

1.4 Thesis Structure

The thesis first puts the problem into perspective by examining the literature and current situation within the spheres of disaster response and image analysis. The methods to address the problem are described as well as the software and data to be used. The accuracy of the results are then assessed and discussed, followed by conclusions and recommendations drawn from the research.

2 Context and Scope

This study is highly relevant to both the fields of disaster management and image analysis. It also touches on other disciplines. Therefore a discussion of where it might fit within these realms is warranted in order to contextualize the research and establish its scope.

2.1 Disaster Management

Since the primary beneficiaries of advancements in automated shelter detection are presumed to be disaster responders, it is important to understand where the mapping of shelters fits within the frameworks that exist in the disaster management discipline. Numerous categories, cycles, and continua have been described in the literature. A review of these models will be useful in establishing the scope of the research.

2.1.1 The Disaster Management Cycle

The idea of a disaster management cycle is often employed as a paradigm for studies in the field (Smith, 1996). Sometimes this notion simply separates the study of disaster into two parts: pre-disaster risk reduction and post disaster recovery (Seneviratne et al., 2010). However, four stages are typically delineated: response, recovery, mitigation, and preparedness (Figure 2-1).

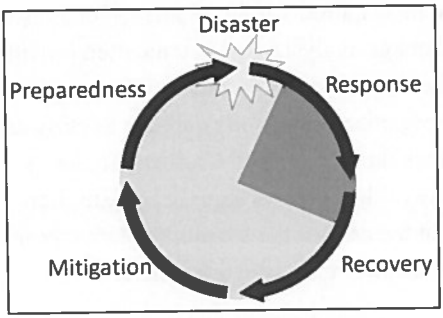

Figure 2-1: Disaster response cycle
Target time frame in dark gray
Source: Adapted from Alexander (2002)

These cyclical stages were first proposed by Haas et al.(1977) in an attempt to organize the findings of previous research and establish a framework for future work, claiming that "disaster recovery is ordered, knowable and predictable" (p. xxvi). Their division of disaster management into four overlapping periods or variations of them continue to be referenced in the literature (Abdalla and Li, 2010, al-Khudhairy, 2010).

Quarantelli (1982) questioned the simplicity of such defined cycles as applied to disaster response, favoring a less sequential way of looking at disaster response, especially with regards to housing. Later research has also called into question the usefulness of explicitly segmenting disaster response (Ganapati and Ganapati, 2009). This noted difficulty in drawing distinct lines within the customary divisions of cycles and stages in post-disaster situations should be considered when attempting to estimate the usability and timeframe for use of mapping products. Also meriting consideration in this discussion are the cultural, economic, and political differences between disaster situations that further complicate generalization with regard to disaster management (Johnson, 2007).

That being said, if the disaster management cycle paradigm is employed with regard to the need for maps showing the locations of shelters and camps, it would likely fall primarily in the first stage after a disaster (dark gray in Figure 2-1), often referred to as the response phase, This is the time period when shelters are being built, tents are being set up, and relief organizations are en route or on scene and developing strategies for proving aid.

Availability of imagery is also an issue at this stage. Though useful imagery is rarely available immediately, remotely-sensed data acquired within minutes after a disaster such as an earthquake can be useful for damage analysis, and is thus often provided. However, shelters are not likely to have been erected within this timeframe. If responding agencies arrive quickly, well-organized camps may appear as early as the same day as a disaster. A notable example is the Iranian Red Crescent Society's distribution of over 50 000 tents on the day of the 2003 earthquake in Bam, Iran (Ghafory-Ashtiany and Hosseini, 2008). In the case of the L'Aquila, planned camps are visible on imagery taken just a few hours after the earthquake there.

Knowledge of camp locations and extents is important throughout the rest of the response phase, as agencies try to monitor changes in camp size and ascertain which areas already contain tents provided by relief organizations. In addition to managing sheltering activities themselves, many other relief activities carried out in the first days and weeks can be aided by camp size and location estimation. These include planning food and water provisions and prioritization of medical response activities (Brown et al., 2001). Indeed, medical concerns are of very high priority for response organizations, ranging from treating injuries caused by the disasters to mental health concerns to preventing the outbreak and spread of disease (Noji, 2005).

A good understanding of camp areal extents is also helpful in the recovery phase. By this time, camp locations become more fixed as ground censuses are taken and agencies begin to share their data and come into closer coordination. It may also be necessary to identify areas that need to be relocated due to their vulnerability at the onset of weather events such as hurricanes or a rainy season (Voigt et al., 2005). Some camps are taken down or relocated. For this reason, change monitoring could be an important use for products derived from remote sensing. Unfortunately, image products that were previously obtainable through ICSMD may no longer be readily available. As efforts move from the recovery to the mitigation stage, the window for ICSMD data will most likely be closed. This lack of data availability in later stages of disaster is a noted shortcoming of ICSMD (Ito, 2005).

2.1.2 The Housing Cycle

Often coincident with the disaster management cycle is a spectrum or cycle of housing transition (Figure 2-2). Sometimes this is seen as an activity and sometimes used to refer to physical structures (see section 0).

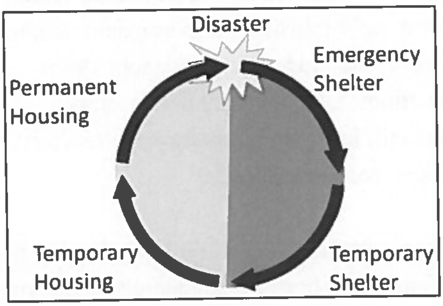

Figure 2-2: Housing cycle after a disaster
Source: Adapted from Alexander (2002) and Nigg et al. (2006)

Emergency shelters are often unplanned, uncomfortable structures intended to provide immediate, short term protection during a disaster and the immediate aftermath, with an anticipated occupancy of less than 24 hours. Sometimes they are simply gathering places where those seeking refuge have congregated for protection (Quarantelli, 1982). The shelters themselves may be of ad-hoc construction using tarpaulins and bedsheets or camping tents owned by evacuees. They could also be family tents specifically designed for the situation provided by local groups or early-arriving relief agencies. Though intended to be used only short-term, emergency shelters may be occupied much longer due to a lack of availability of alternatives or because families prefer to stay in them despite other options (Waugh, 2000).

Temporary shelters are meant to provide a longer term housing solution to those left homeless by disaster. They are differentiated from emergency shelters is that basic services such as water and sanitarian are usually available. Relief organizations are often involved in facilitating the establishment of temporary shelters which usually consist of family-sized tents. Aid organizations also supply accompanying amenities as well as organize shelters into communities or camps (Johnson et al., 2006). When these planned camps are well-organized and provisioned they have been highly effective in meeting the needs of the community. Some temporary planned camps have even been greatly underused in post-disaster situations with many units occupied for only short periods or not at all (Davis, 1977, Nigg et al., 2006).

The final two stages of the housing are much more situation-dependant. A transition from temporary shelters or tents to temporary housing may take place. Alternatively, the temporary housing stage may be bypassed in favor of an immediate transition to permanent housing. A primary impetus for a rapid transition to permanent solutions is fear that temporary post-disaster settlements may turn into permanent slums (Johnson et al., 2006). These fears are sometimes exaggerated but not entirely unfounded. Indeed, over 8 000 people were still living in temporary shelters ten years after the 1976 Fruili, Italy earthquakes (Johnson, 2007) .

Physically, both temporary housing and permanent housing differ considerably from both emergency and temporary shelters. Temporary housing is generally made of much sturdier materials such as steel or wood and expected to last three to five years (Sontag, 2010). Family dwelling units could take the form of prefabricated homes or moveable trailers (Nigg et al., 2006). Obviously at the permanent housing stage the structures are intended to be occupied indefinitely and thus built accordingly.

Whether temporary or permanent housing is constructed, a rapid method for detection has only been proposed for emergency and temporary shelters and these are therefore the target of the present research. Since the literature suggests strong physical differences between shelters and housing, this divergence provides a logical threshold for specifying the structures on which this thesis will focus. In other words, the intended focus is on both emergency and temporary structures but not temporary or permanent housing, as defined in the literature.

2.1.3 Stakeholders and Needs

While some needs can be looked at un a temporal manner, a deeper look at exactly which organizations need shelter data is helpful. Like the cycles, there is crossover, but trends exist. Largely, organizational needs can be seen as a spectrum from knowing the bare minimum to knowing detailed information about shelters (Table 2-1). The most pressing question knowing where shelters are can answer is "Where are the people?" Specific details are not as significant as a general idea. This is most important to immediate responders who are there to offer first air and supplies. As relief agencies arrive and assess the situation, they likely require more information as to the general extent of IDP camps. As camps are further organized and coordinated with other agencies, exact shelter numbers become important to agencies running the camps. Still other agencies have more specific concerns that may require specific information about the people living in the shelters including gender, age, or even details such as name and address.

Stakeholder	Example	Related activity	Needs
Immediate responders	Governments	Assess shelter needs	General location of IDPs
Relief organizations	Red Cross	Provide shelter	Specific locations of IDPs/camps
Camp managers	OCHA	Administer camps	Specific tent locations
Specific service providers	*Medicins sans frontiers*	Specific services	Population characteristics

Table 2-1: General needs of response organizations

2.2 Terminology

Sometimes many different words are used to describe the same thing. For example, IDP camp, spontaneous settlement, spontaneous camp, self-settled camp, unofficial camp, tent city, and tent village have all been used to refer to what is usually just a grouping of two or more temporary shelters. In this thesis, the term "camp" encompasses them all as well as other terms that may be used if the camp is more organized, such as official camp or planned camp. Other terms require explanation as well.

2.2.1 Disaster Victims, Refugees, and IDPs

Within the disaster literature, many terms are to describe those affected by disasters. Significant to this population are people whose houses were destroyed or rendered uninhabitable. Though sometimes used interchangeably, the terms "refugee", "IDP" (internally displaced person) and "disaster victim" have different connotations. The term "refugee" implies that a person has fled their home country and possesses a legal status that accords protection. "IDPs" are often defined by government agencies and relief organizations as people displaced from their homes but remaining within their own country (Barutciski, 1998).

2.2.2 Sheltering

The terms "shelter," sheltering," and "housing" are not always clearly defined within the disaster response community and the disaster literature. "Shelter" or "Sheltering" may refer to physical structures like tents, or to the action of protecting people from threats prior to or while they are happening such as moving them to hurricane shelters or bomb shelters. "Housing" may mean permanent homes to be constructed or re-constructed or simply temporary refuge victims may take in the houses of extended family in another town (Quarantelli, 1995). For the purposes of this thesis, the term "shelter" specifically denotes physical structures. The literature also refers to both "emergency shelter" and "temporary shelter" without clearly defining physical differences. Therefore, "temporary shelter" will used for the remainder of this thesis to denote both terms.

2.2.3 Shelters

A strict definition of what physically constitutes a temporary shelter is also lacking in peer-reviewed literature. However, aid organizations, government entities, and the

United Nations have included some descriptions in their publications. For example, the organization's Department of Humanitarian Affairs (UNDHA) defines shelter as

> "Physical protection requirements of disaster victims who no longer have access to normal habitation facilities. Immediate post-disaster needs are met by the use of tents. Alternatives may include polypropylene houses, plastic sheeting, geodesic domes and other similar types of temporary housing." (UNDHA, 1992)

2.2.3.1 Tents

Tents indeed seem to be a widely used form of temporary shelter. Several types of tents were used after both the Haiti and Italy earthquakes. Even though color, size, and shape characteristics can be ascertained by expert knowledge of the situation, terrestrial photographs, and even EO images, general characteristics can and should be gleaned from other sources.

A specific preferred tent color is not mentioned in the United Nation's "Guide to the Use and Logistics of Family Tents in Humanitarian Relief" (Ashmore, 2004). The manual only indicates inside and outside colors should be "appropriate," not camouflage, and take cultural and political sensibilities into account. The United Nation's Inter-Agency Procurement Service (IAPSO), in stipulating tent specifications to its suppliers requires only family tents be a "natural canvas color" (IAPSO, 2000). The same guide does stipulate these tents be 4 m × 4 m and square.

2.2.3.2 Tarpaulins

Tarpaulins often form the roof of improvised shelters. IAPSO dictates to suppliers plastic tarpaulins have a width of 4 m, a length of 5 or 6 m, and be green, white, grey, or blue. However, the United Nations Handbook for Emergencies specifies tarpaulins be blue (UNHCR, 2007). The dominance of blue materials may also be rooted in expectations and tradition. Whatever the origins, blue tents and tarpaulins have become universal icons of disaster response and humanitarian aid (Hailey, 2009).

2.3 Image Analysis

Though the present research is intended to be directly applicable to the disaster management community, the methods employed to solve the research problem draw on research from other fields. Many processes and frameworks have already been developed to better enable technological advances in a diverse range of fields to serve disaster managers. Some studies involving refugee camps share similar aims to disaster response. Image-based shelter detection can be further informed by research using highly-suitable methods not yet used in a shelter-detection context. A review of this literature will help to compare and contrast the present study with previous ones.

2.3.1 Disaster Response Mapping

An ever-growing number of quickly-created products are now been created for disaster responders, providing them with precise and up-to-date information. Recent literature related to disaster mapping products reveal three distinct themes: rapid mapping, collaborative mapping, and automated analysis.

2.3.1.1 Rapid Mapping

In the first stages of disaster situations, rapid spatial assessments are prized over detailed analysis (al-Khudhairy, 2010). Decision makes want information as soon as it becomes available in order to quickly allocate resources. The GIS community has responded to this priority by putting in place numerous systems to quickly acquire data, produce products, and deliver them to the response community. Though there are many organizations actively involved in making maps after disasters, a network of producers and users has coalesced in order to better coordinate these activities.

Before analyzing specific projects, a brief overview of the complicated organizational structure of the rapid mapping community will help put their activities into better context. One of the largest consortiums involved is the RESPOND alliance, funded by the European Space Agency (RESPOND, 2011). The prime contractor involved is Astrium GEO-Information Services (recently formed by the merger of Spot Image and Infoterra). Members of this alliance involved with mapping activities include the EU Joint Research Centre (JRC), The United Nations Institute for Training and Research Operational Satellite Applications Programme (UNOSAT), and the German national aerospace center DLR (*Deutsche Luft- und Raumfahrt*). Other contractors involved in rapid mapping activities range from the UK-based MapAction providing ground-collected data and products to the SERTIT (*Service Regional de Traitement d'Image et de Teledetection*) EO image processing center at the University of Strasbourg.

DLR is heavily involved in creating rapid-mapping products. Its satellite-based crisis Information center ZKI (*Zentrum für satellitengestützte Kriseninformation*), part of

Germany's remote sensing data center *Deutsche Fernerkundungsdatenzentrum* (DFD) create these crisis maps using data made available through the ICSMD. DLR-ZKI relies heavily on human analysis for rapidly interpreting EO data (Voigt et al., 2005). Depending predominantly on the work of experienced analysts, DLR-ZKI has been involved in rapidly providing response mapping products for tsunamis, fires, landslides, and earthquakes using visual interpretation.

SERTIT also provides rapid mapping services worldwide, boasting a continuously available professional mapping team that strives to produce and distribute maps within twelve hours of obtaining images. Originally conceived in 2001 for flood mapping, the agency's process chain has been adapted to serve managers in all types of disasters (Allenbach et al., 2005). In 2010, the SERTIT team used EO imagery to provide various maps including damage and impact assessments, locations of visible water surfaces, oil spills, as well as the observed locations of spontaneous gathering places (see Appendix A).

Though widely used by the disaster response community, shortcomings of the rapid mapping process currently in use have been pointed out. The usability of manually created mapping products depends on the experience and competence of trained analysts. When large amounts of data are involved such as airphotos and VHR satellite imagery, the staffing requirements for processing can be overwhelming, and may lead to inconsistent or subjective interpretation (al-Khudhairy, 2010).

To deal with these issues, several methods have been proposed. One example is the use of grid-based analysis. Broek et al. (2009) divided a large area affected by the 2005 Pakistan earthquake into 250 × 250-m grid cells. This allowed for a faster analysis of a large area. It also met user needs by enabling responders to focus on grids that were presumed to have incurred the most damage.

2.3.1.2 Collaborative Mapping

Building on the grid approach, collaborative mapping leverages Internet data sharing to allow agencies to work together on large scale mapping tasks. Brunner et al. (2009) proposed a novel method to distribute mapping tasks to multiple agencies using open-source standards and other tools such as Google Earth. A similar architecture was used in an initiative called Global Earth Observation Catastrophe Assessment Network (GEO-CAN). Funded by the World Bank and organized by ImageCat, Inc., the infrastructure allowed over 100 organizations including universities, government agencies and NGOs to collaboratively map damage caused by the 2010 Haiti earthquake. Assessment was carried out on 500 × 500-m subsets of high-resolution imagery (Bevington et al., 2010).

Though the effort was judged by many to be a success, subsequent assessments of this unprecedented geo-collaborative effort revealed several issues with the approach (Eguchi et al., 2010). A report produced by ImageCat in conjunction with the Earthquake Engineering Research Institute (EERI) concluded the method lacked rigorous quality control standards for both the data and analysis. Consistency was also an issue since some volunteers were more skilled at image interpretation than others. There were also problems due to a lack of sufficient bandwidth to transfer such large amounts of data over the Internet (ImageCat and Earthquake Engineering Research Institute (EERI), 2010).

2.3.1.3 Automated Mapping

A growing number of methods have been proposed and implemented that attempt to automate post-disaster mapping. The European Space Agency (ESA) has been developing a computer application known as KIM (Knowledge-based Information Mining) that automatically analyzes and classifies images with limited user input. The system first spits an image into segments based on predefined spectral and textural criteria. A user then assigns labels to segments of interest and the system uses this information to identify similar features within the entire image (Molch, 2008). This semi-automated system has been used to quickly map damage for many disasters, including the 2010 Haiti Earthquake (JRC, 2010).

A similar approach that uses image segmentation is gaining popularity in many fields using the eCognition software suite. This OOA-based software developed by Definiens was originally used for medical image processing but has been increasingly been utilized to solve geographic problems in the analysis of EO imagery (Johansen et al., 2010). In fact, eCognition is now separate from the medical imaging software and is designed solely for geospatial uses.

A true OOA approach is more flexible and powerful than information mining approaches such as KIM in that it supports contextual analysis designed to mimic human image interpretation. Rather than focusing on pixels and pixel values, that basic units of OOA are image objects which are the result of image segmentation. This type of analysis relies heavily on the processing power of computers which has increased significantly in recent years (Benz et al., 2004). Nevertheless processing large datasets can still be very time-consuming, and thus its usefulness for rapid-mapping in post-disaster situations has been questioned among disaster management researchers (Voigt et al., 2007).

OOA is seen by others to have much potential. It has been applied to post-disaster mapping projects related to flooding, damage assessment, landslide detection, and oil spills (Blaschke, 2010). OOA solutions can also be combined with other approaches to improve results. For example, a framework developed by Heremans et al. (2003) employed automated methods to detect flooded areas using OOA bolstered by volunteered geographic information from water managers using an Internet interface.

2.3.2 Humanitarian Response Mapping

Many of the same organizations that supply rapidly produced maps to the disaster response community also provide in support of humanitarian operations that do not fit within the traditional disaster management cycle. In fact, Voigt et al. (2005) pointed out a blurring of the line between disaster response and long-term humanitarian aid efforts when it comes to providing users with mapping products. Indeed, ICSMD can be activated for providing data to support response to events ranging from natural disasters to epidemiological outbreaks to armed conflict.

While disaster response facilitates the needs of people affected by rapid-onset emergencies, the term complex emergency (CE) is often used to describe situations addressed in a slightly different way. CE response usually involves long-term or ongoing humanitarian aid to those affected by enduring internal or external violent conflicts (Keen, 2008). Though differences abound, a conspicuous similarity between responses to CEs and disasters is the coordination of camps comprised of tents provided by relief agencies.

Though literature specifically devoted to the detection of tents and camps in post-disaster situations is scarce, there have been many studies devoted to quantifying spatial information regarding refugee or IDP camps set up in response to CEs. Much of the research has focused on developing sophisticated statistical techniques for extrapolating camp populations based on its areal extent or the number of tents contained within (Brown et al., 2001, Grais et al., 2006). Population-oriented studies have relied on ground-based measurements of camp area by either walking around the camp's perimeter with a GPS or recording odometer readings in a vehicle. However, promising automated and semi-automated methods have also been developed to locate tents and camp areas using EO image processing tools such mathematical morphology and OOA (Laneve et al., 2006).

Perhaps the most significant development toward full automation of tent detection was presented by Giada et al. (2003). In their study, semi-automated processes were created to count individual tents within Lukole refugee camp, Tanzania using VHR satellite imagery. Pixel-based analysis and OOA methods were compared. The former had 10-15% error rate, while that of the latter was less than 3%, both at a 95% confidence level.

In Lukole, the individual tents had similar spectral reflectance and size characteristics, limiting the suitability of the detection method for use in other situations. However, Lang et al. (2010) applied a similar methodology to a refugee camp study area in Zam Zam, Darfur that contained more complex mix of dwellings and surrounding features. Round huts with low reflectance and much more reflective white tents were extracted and mapped in a scene that also contained fences with low reflectivity. The authors note, however, that the scene in Zam Zam, like Lukole, generally has a background that has spectral characteristics that clearly distinguish it from anthropogenic features.

Insight from these studies could prove to be a useful resource for the establishment of similar techniques for detecting temporary shelters and camps in the immediate aftermath of a disaster. However, numerous and important differences exist. While the refugee camp studies were concerned with determining the area and number of tents within camps, the locations of the camps were already known. What is more, the methods did not seek to find new camps, which is a primary goal of the present study. Furthermore, both the Lukole and Zam Zam studies focused exclusively on refugee camps existing in developing countries having relatively homogenous environmental aspects. Factors that might influence detection in other parts of the globe were not analyzed, such as terrain, land cover, vegetation, climate, and even cultural and socioeconomic conditions.

2.4 Section Summary

An analysis of the literature and appraisal of the current posture of the disaster response field reveals a natural timeframe and niche within current operations where a new shelter mapping automation tool would fit. A novel method could improve the capabilities of organizations and structures to quickly disseminate new or improved shelter mapping products to disaster responders. Following the trajectory of other automated rapid-mapping products, an OOA algorithm could help to solve some of the shortcoming identified with manual mapping and geo-collaboration.

Studies focusing on refugee camps have shown that under optimal conditions, structures such as tents can be detected and counted. Applying this method to count temporary shelters may provide useful information to disaster responders, but it may be more important to know the general locations of those in need with enough accuracy to find them.

3 Materials and Methods

Since it has shown success in other disciplines related to the mapping of tents, OOA was chosen to be tested in this study using eCognition software. The primary study site is located in the Abruzzo region of Italy, near L'Aquila. A subset of the area was used as a training site for developing the method. The method was then applied to the entire study area and the results were analyzed. To evaluate its robustness, the method was then tested on a different study site in Haiti.

The general procedure is:

(1) Identify suitable study sites and data
(2) Determine training site
(3) Develop and refine algorithm for training site
(4) Execute algorithm over entire study site
(5) Apply algorithm to another study site
(6) Analyze results and refine method

3.1 Implementation of OOA

As discussed in section two, OOA has been increasingly used in EO image analysis and employed in some disaster management contexts. Several aspects of OOA make it highly suitable for this investigation. The ability to distinguish objects at multiple levels is important (Benz et al., 2004). Much like individual trees make up a forest, individual shelters make up a camp. OOA allows individual shelters to be segmented into objects based on their unique spectral characteristics and further categorized into camps by defining hierarchical rules using a bottom-up approach (Taubenböck et al., 2010). OOA also allows for a top-down approach in which large areas of interest are first analyzed from which smaller areas of interest can be identified. Both approaches can be combined in one OOA algorithm, as they are in this study.

3.2 Software

The first commercially available and most widely-used software employing OOA is Trimble's eCognition, which was used to develop the shelter detection algorithm. Components of ESRI's ArcGIS were employed in the accuracy assessment.

3.2.1 eCognition

eCognition Developer 8.64 software was used on an x86-64 personal computer running the 64-bit version of Windows 7 operation system. The shelter detection algorithm was developed as a "rule set" in cognition network language (CNL).

3.2.2 ArcMap

ArcMap, part of the ArcGIS suite of software, was used to create camp polygons based on the eCognition tent points output. It was also used for the accuracy assessment. The software was chosen because it has the capability to create convex hulls from points. It also allows for eCognition results to be displayed on top of the original images as well as WMS layers.

3.3 Study Sites

The two study sites were chosen because of their many differences and also the different circumstances of the disasters occurring there. Italy is an industrialized and relatively wealthy country while Haiti is developing and extremely poor. Though the L'Aquila quake was quite strong and left many homeless, the situation was much more severe in Haiti. And while international aid organizations poured into Haiti to help after the disaster, the Italian government refused any offers of help.

L'Aquila shelters were generally well organized into camp clusters with uniform family tents. This is more or less a model temporary sheltering response by the Italian government from a disaster management perspective. For this reason, the Italian camps were used in the initial development of the shelter-detection algorithm. The shelters in Haiti were less ideal, comprised of a mix of shelter types and not always set up in clearly definable camps. This situation allowed for a test of the effectiveness of the method in a more challenging environment and the opportunity to determine which parts of the algorithm were the most robust and which components may require situational modification.

3.3.1 L'Aquila, Abruzzo, Italy

The Italian study site is defined by the area of a VHR QuickBird image slightly east of central L'Aquila acquired 8 April 2009, two days after the earthquake. The image covers approximately 19 km². Several camps can be clearly identified. The image was obtained from Planetek, an Italian DigitalGlobe distributer. The product is a four-band pan-sharpened image with 60 cm spatial resolution. Radiometric, sensor, and geometric corrections were applied by the supplier as well as projection to the UTM zone 33N coordinate system.

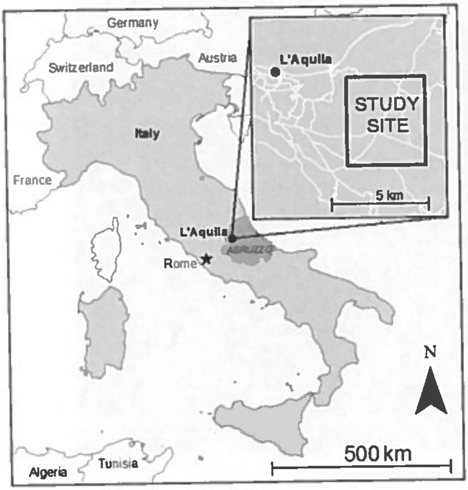

Figure 3-2: Primary study site near L'Aquila, Italy
Sources: ESRI, OpenStreetMap

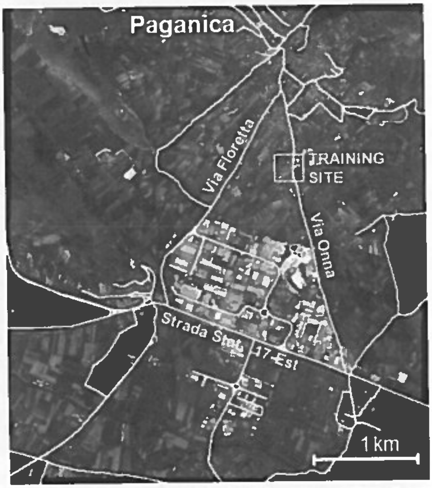

Figure 3-1: QuickBird image of Italy study site showing training site
Sources: DigitalGlobe, OpenStreetMap

3.3.1.1 Training Area Subset

A training site was chosen in an area known to contain tents set up by the Italian civil protection department *Dipartimento della Protezione Civile Nazionale* (DPCN). The area is approximately seven ha located about 1 km south of the village of Paganica and five km east of L'Aquila (Figure 3-3: Tent camp subset of QuickBird image
© DigitalGlobe). This site was ideal for initial analysis of camps and shelters since it contained many tents set up on gravel and grass surfaces in several configurations and orientations. There were also many distinguishable features nearby such as paved areas, cars, buildings, fallow fields, and a dining tent.

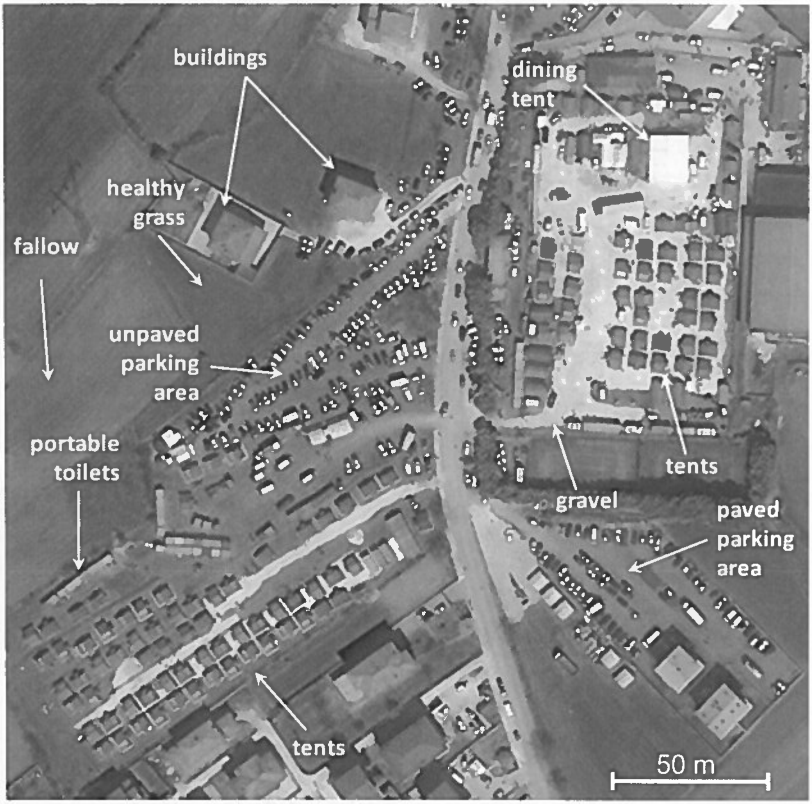

Figure 3-3: Tent camp subset of QuickBird image
© DigitalGlobe

3.3.1.2 Validation Data

Validation data was available via WMS. The *Geoportale Nazionale* (National Geoportal) of the *Ministero dell`Ambiente* (Italian Ministry of the Environment) provided a public WMS layer of high-resolution aerial imagery acquired on 6, 7, and 8 April 2009 by DPCN (Figure 3-4). Detailed metadata for the layers or their sources could not be obtained, but they appear to be derived from true-color images with a spatial resolution of about 25 cm.

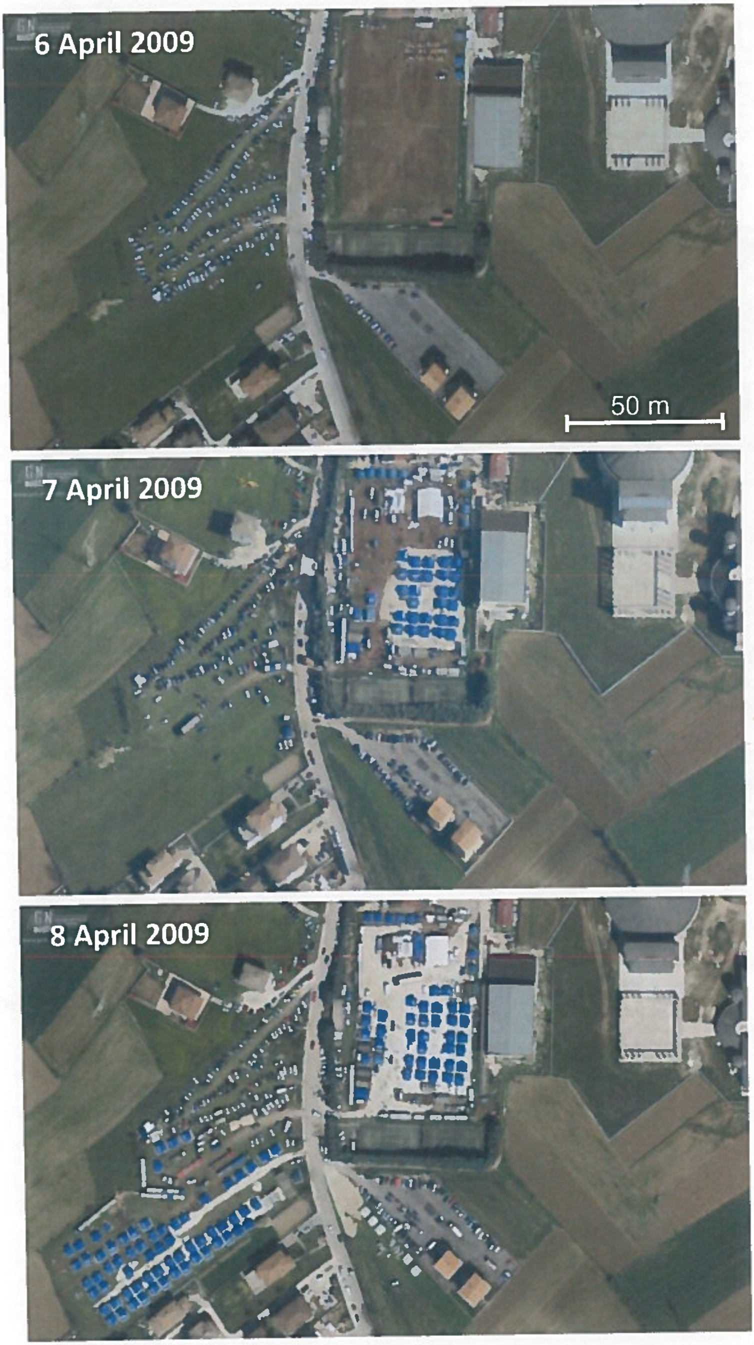

Figure 3-4: Screenshots of WMS services for training area
Source: DPCN

Individual tent locations were obtained via a private WMS layer hosted by DPCN. The name of the tent layer on the WMS indicates the date 10 April 2009, but it is unclear as to what part of the data creation/dissemination process this refers. However, the placement of the tents strongly suggests the layer was created by visual interpretation of the 8 April aerial photograph (Figure 3-5).

Figure 3-5: Tent WMS layer and 8 April aerial photo
Source: DPCN

In lieu of a field visit to the study site, publicly available photographs were used to gain further knowledge of the scene (Figure 3-6 and Figure 3-7). Both tents and other objects can clearly be seen in these photos and corroborate visual interpretation of the EO imagery.

Figure 3-6: Oblique aerial view of part of the training area.
Photo: Peri Percossi/ EPA

Figure 3-7: Ground-based photograph of the training area.
Photo: Alessandro di Meo/EFE

3.3.2 Haiti

The primary study site in Haiti is defined by an aerial photograph obtained by the United States National Oceanic and Atmospheric Administration (NOAA) on 24 January 2010. The three-band visible image covers approximately four km^2 and centers on the city of Jacmel, 40 km southwest of Port-au-Prince. The approximate spatial resolution is 30 cm. An 18 January 2010 NOAA airphoto of a site within the city of Port-au-Prince containing different shelters was also used for comparison.

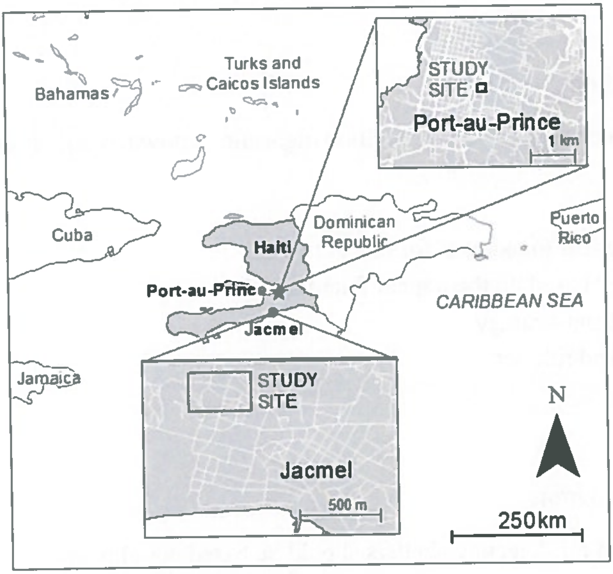

Figure 3-8: Haiti study sites
Sources: ESRI, OpenStreetMap

These particular aerial images were chosen because they contain several types of shelters. The primary Haiti site includes some tents that have similar blue hues to those in Italy. However, many of the temporary blue roofs appear to be made from blue tarpaulins rather than tents. Red tents are also visible, the presence of which can be verified by terrestrial photographs (Figure 3-9). Shelters comprised mainly of tarpaulins are visible on the Port-au-Prince image which makes it a good candidate to test robustness with regard to scene when the same sensor is used. Figure 3-10 shows a terrestrial photo of this second Haiti study site.

Figure 3-9: Group of temporary shelters in Jacmel, Haiti
Photo: Petra Canning

Figure 3-10: Improvised shelter camp in Port-au-Prince study area.
Photo: University of Buffalo

3.4 Algorithm Creation

The general method for constructing an eCognition algorithm, known as a rule set, is as follows:

(1) Establish theoretical foundation for rule set
(2) Develop strategy based on theoretical foundation
(3) Create rule set from strategy
(4) Refine and expand rule set
(5) Export Results

3.5 Theoretical Foundation

To be useful, an algorithm for detecting shelters should be based not only on relevant literature and theoretical ideals, but also on actual cases and the real needs of the disaster management community. With that in mind, it is important to carefully consider all parameters that go into the model. Though shelters and camps were discussed in section two, more precise technical descriptions are needed in the creation of the algorithm in eCognition.

3.5.1 Shelters

As described in section 2.2.3, shelters usually take the form of tents or tarpaulins, most often tents. Though some may be larger and some smaller, the algorithm will limit the areal extent for individual shelters to between 4-32 m^2. Shelters will also be assumed to be symmetrical in shape as seen from above.

3.5.2 Camps

Camps will be defined as areas having more than two recognized shelters within a 20 m radius. Both the number and distance measures may be rather arbitrary and situation-dependent. However, they were chosen based on manual interpretation of tent groupings on the validation data.

3.5.3 Transferability

The ability to transfer the algorithm to different scenes is a major research goal and as it will greatly increase its usefulness. With this in mind, any steps or procedures that are overly complicated or data-specific should be avoided. Fewer steps will also yield better transferability. These factors are important both in strategy conceptualization and rule set development. Also, ratios are preferred to fixed thresholds since they can be used independently of actual DN values (Lang et al., 2010).

3.6 Strategy

If the algorithm is to be used over large areas with fine resolution such as VHR satellite images, a logical first step is to exclude areas that obviously do not contain shelters. Therefore it is useful to exclude from analysis large homogenous areas such as empty fields and water bodies.

After excluding these large objects, a careful examination of the definitions set forth provides the framework for further scrutiny of tent candidates. Sticking to a strict definition for shelters in the initial analysis helps to avoid misclassifying objects having similar characteristics and introducing more error later in the analysis. When there is high confidence the objects identified are indeed tents, their spatial relation to each other can be used to determine if they are part of a camp.

This strategy can be systematized into a four-step process to aid in the creation of the eCognition rule set:

(1) Exclude from analysis areas unlikely to contain anthropogenic features
(2) Identify individual shelters
(3) Exclude shelters not in clusters
(4) Identify clusters of shelters as camps

3.7 Rule Set Development

Once the strategy is formulated into steps, it can be translated into CNL through the process of rule set development in eCognition. Rule sets are composed of individual steps called processes. Nearly limitless processes can be implemented. Many are built into the software. Others can be customized by the user. Processes can be combined into groups and subgroups and run together. In this study, the processes are grouped into three categories: initial segmentation, segmentation refinement, and classification.

3.8 Segmentation

The first step in OOA is usually segmentation, which cuts an image into component parts based on user-selected criteria (Definiens, 2009). Different segmentation methods can be used and combined to create meaningful output objects.

An ideally segmented image for shelter detection would differentiate each shelter into one segment. The actual area of each shelter would be delimited by one segment containing only pixels that are part of that shelter and no pixels that are not. Perfect segmentation would make it easy to classify shelter objects as shelters based on spectral and spatial parameters.

3.8.1 Initial segmentation

The first part of implementing the strategy is to limit processing to areas likely to contain anthropogenic features. A successful method used by Niemeyer and

Nussbaum (2006) to accomplish the same goal was applied here. First, a chessboard segmentation was performed to divide the image into 50 × 50 m tiles. The average visible-band standard deviations for each tile were then computed. Tiles having standard deviation values less than 10% of the value for the tile with the highest standard deviation were excluded as they are unlikely to contain groups of man-made structures. Further analysis was only performed on the remaining tiles.

This first step not only helps to narrow down the search for shelters, but also significantly reduces processing time through the rest of the analysis since further execution is only conducted on the chosen tiles.

3.8.2 Segmentation Refinement

To segment the tiles of interest further into shelter-sized objects, multiresolution segmentation was performed. For this type of segmentation, the software begins by analyzing single pixel values and mergers them together in a repeating sequence until individual objects contain a specific level of homogeneity of spectral reflectance and shape. These levels are determined based on user-defined input parameters including scale, color, shape, smoothness, and compactness. Resulting objects are heavily influenced by these inputs. (Definiens, 2009).

Segmentation parameters are often determined using trial and error. However, several methods to more objectively determine appropriate parameters have been proposed. The Estimation of Scale Parameter method described in Drăguţ et al. (2010) was initially performed to obtain approximate parameters. The tool suggested a scale parameter below 10 would be optimal based on local variance and its rate of change (Figure 3-11). This estimate was tested against larger values using trial and error. While a scale parameter of 40 yielded good segmentation for some tents set up on gravel, many tents on the grass were undersegmented at this level (Figure 3-12). Indeed, values under 10 yielded the best results and a scale parameter of 8 found to be the highest value that avoids any undersegmentation (Figure 3-13). Levels of 0.3 for shape and 0.8 for compactness were found to be optimal using trial and error, though these values had less influence on segmentation than the scale parameter.

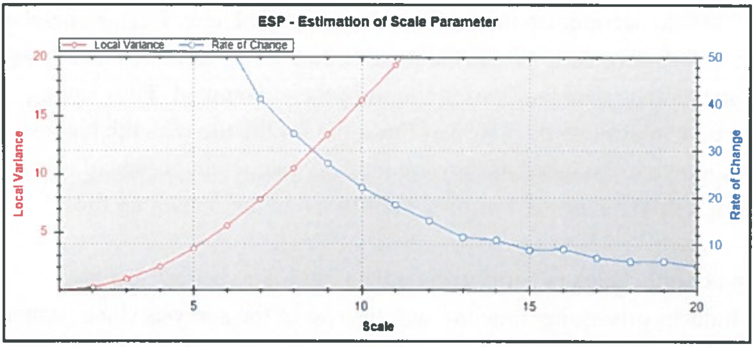

Figure 3-101: ESP tool results

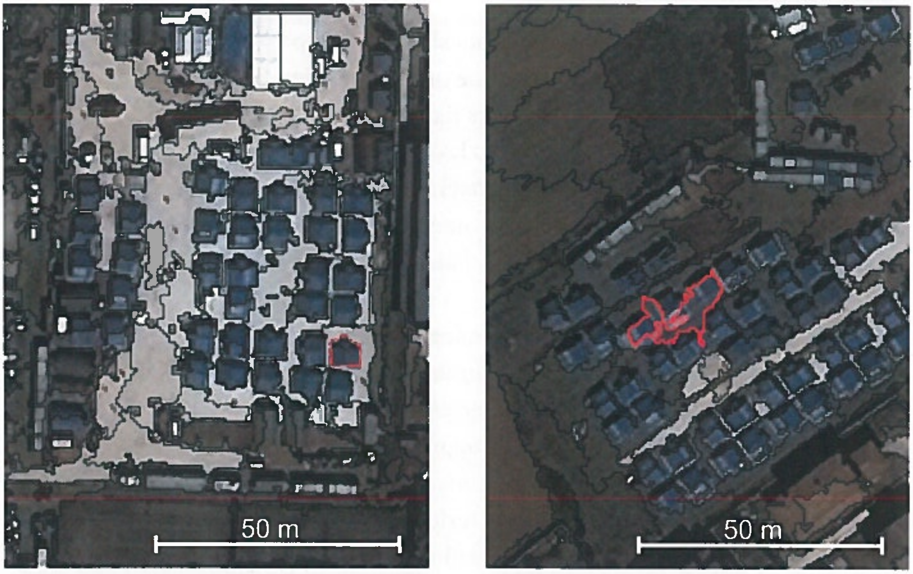

Figure 3-12: Multiresolution segmentation result with a scale parameter of 40

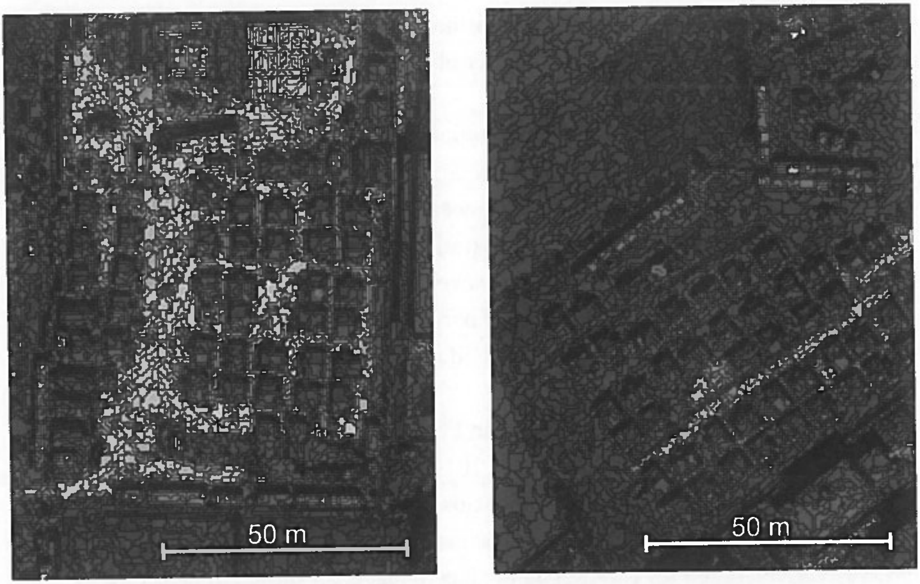

Figure 3-13: Multiresolution segmentation result with a scale parameter of 8

3.9 Classification

Once best possible objects were segmented they were classified. The classification paradigm in this context separates each image object into two parts or "classes": shelters and non-shelters. Other features such as buildings and grass were classified as an interim step to better understand potential misclassification. However, these other classes were not part of the output product for this research and can thus all eventually be considered unclassified.

3.9.1 Classification Parameters

In eCognition, the assignment of objects to a class is based on parameter thresholds. A limitless number of parameters may be used for classification including those based on spectral values, geometry, texture, and position.

3.9.2 Shelter Classification

The classification of objects at the shelter level is obviously one of the most significant parts of the algorithm. There are several ways to choose which parameters and thresholds should be used to distinguish individual shelters. Since a foundation of OOA is the aim to replicate how the human eye distinguishes meaningful objects (Blaschke, 2010), it is helpful as a first step to try to understand how one differentiates shelters from other objects by visual interpretation.

However, eCognition also allows for a more objective determination of suitable parameters using a process called Feature Space Optimization (FSO). This built-in tool calculates minimum separation distances between classes for a given threshold condition. It was used to analyze the separation of threshold values for shelters and the rest of the image as well as between several user-created classes. Though they do not always yield the best combination of parameters to use, the results give a mathematical foundation for choosing good parameters.

Many of the built-in features were used in FSO. In addition, since ratios are preferred for transferability (Lang et al., 2010) and also may yield better results, several were manually calculated. The ratios of object mean DN values were computed for each visible band. Also, the normalized difference vegetation index (NDVI) was averaged for each segment since it has been shown to be useful in differentiating vegetation (Carlson and Ripley, 1997).

Classification can be enhanced by refining the processes and thresholds contained within the eCognition rule set using trial and error.

3.9.3 Classification Refinement

Non-shelter objects having similar spectral properties were then eliminated from the tent class based on shape and area criteria. Finally, tents existing in isolation were excluded by setting the requirement that each tent be within 20 m of another to be classified.

The resultant classification contained polygons representing tents detected by the rule set. These were then output as point vector files for further analysis in a GIS.

3.9.4 Camp Classification

Camp classification is quite different than shelter classification because camps are determined on the basis of tents that have already been classified. To establish camp boundaries from shelter points, two steps were used in ArcGIS. First, the points were assigned to a camp based on distance to one another using a 20 m point buffer. The polygonal extent of the camps was determined by creating a convex hull of each point group (Figure 3-14).

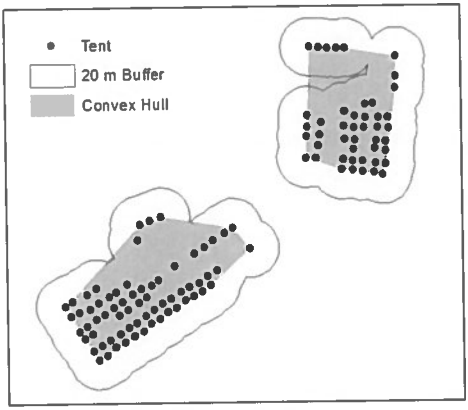

Figure 3-14: Camp delineation procedure

4 Results and Analysis

Suitable features selected using FSO are presented as results along with a description and analysis of the final classification output and rule set.

4.1 Feature Space Optimization

Candidate features for tent classification were based on manually selected samples of six visually identifiable classes within the training site (Figure 4-1). Tents were considered positive samples. All others were considered negative.

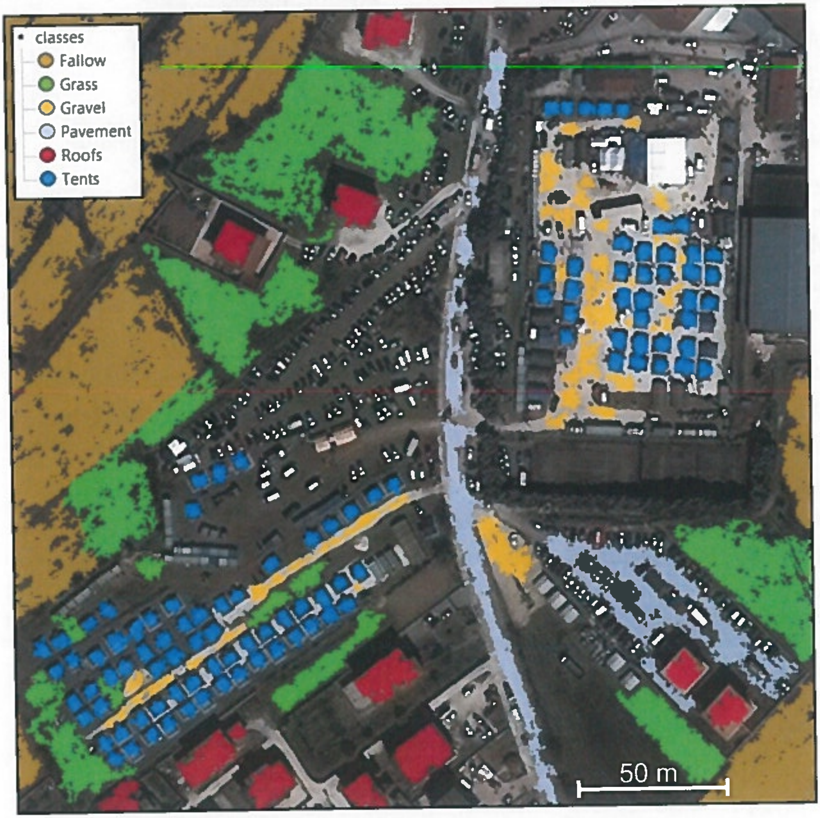

Figure 4-1: Class samples

FSO was implemented in eCognition first for spectral properties. These included object mean digital number (DN) values from each band of the QuickBird image as well as brightness and the eCognition-calculated value maximum difference (Table 4-1).

Manually calculated ratios yielded better separation, though average NDVI was less effective as a separation feature (Table 4-2). In addition to spectral parameters, textural features were also explored and had separation values below 0.01. A full list of all features used in FSO appears in Appendix B.

Feature	Value
Mean Red	0.152
Mean Green	0.139
Brightness	0.116
Mean Blue	0.083
Mean IR	0.078
Max Diff	0.013

Table 4-1: Original feature separation values

Feature	Value
Mean Blue/Mean Green	0.194
Mean Blue/Mean Red	0.175
Mean Green/Mean Red	0.054
NDVI	0.067

Table 4-2: Calculated feature separation values

The results of FSO suggest ratios of visible bands are a better way to separate the tents from other objects than DNs alone. The Mean Blue to Mean Green ratio (MBGR) was found to be especially useful. The MBGR was explored further by implementing FSO for it on samples of six classes that were manually classified (Figure 4-1). These relationships can also be expressed and understood slightly differently by graphing Mean Green values as a function of Mean Blue values (Figure 4-2).

	Pavement	Grass	Roofs	Fallow	Gravel
Tents	0.381	0.322	0.400	0.373	2.638
Gravel	0.047	0.091	0.024	0.133	
Fallow	0.001	0.001	0.028		
Roofs	0.003	0.006			
Grass	0.001				

Table 4-3: Class separation distance matrix for MBGR

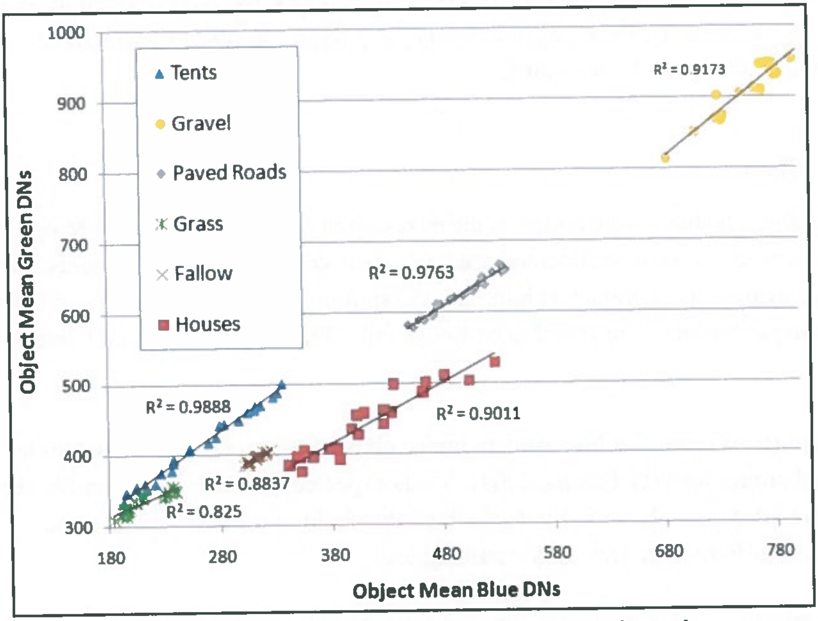

Figure 4-2: Mean Green values as a function of Mean Blue values

Figure 4-2 shows the strength of using the blue and green bands to separate tents from other objects. The least separation occurs where both tents and grass have low reflectance in the green and blue bands. This analysis helps to explain the difficulty in segmenting grass and tents in parts of the image (Figure 3-12 andFigure 3-13).

A regression analysis of the Mean Blue/Mean Green relationship shows it to remain strong with varying brightness. The R^2 value of 0.9888 for tents is higher than that of the other classes. Regressions of the tent object values for other band ratios were also analyzed for comparison. The R^2 value for Mean Blue and Mean Red was 0.9569 while that of Mean Blue and Mean Green was 0.8507.

Based on the simplicity and effectiveness of MBGR for separating tents from other objects, it was used in the first classification step. Several threshold values were tested using trial and error, with the optimal value found to be 0.75.

When all objects classified as tents with these features were merged, many tents become one object but some were still connected to others with tiny "bridges" of classified pixels between the tents. A watershed transformation was used to split these bridges. Based on hydrological principals, this built-in eCognition algorithm is often used to split objects (Definiens, 2009). It worked effectively to separate tents since they are seen by the algorithm as relatively large "basins" into which the extraneous pixels can be separated.

4.2 Shape

Object shape features were added as the next step in image classification. Many shape parameters were considered based on expert knowledge regarding tents and trials of many of the parameters built into eCognition. The three simplest and most effective parameters were found to be Rectangular Fit, Length\Width, and Size in m^2.

Rectangular fit quantifies how well an image object fits into a rectangle of similar size and proportions (Definiens, 2009). It was expected that tents are generally seen as rectangular from above and indeed a high threshold of 0.85 was found to be suitable to differentiate tents in the training area.

Length\Width quantifies the ratio of an object's length to its width. Setting a value of 1.5 ensure that objects whose length is more than 50% greater than its width will not be classified as a tent.

Size is one of the most important parameters to distinguish tents. It can be expressed in pixels or actual size in eCognition. The threshold value range of 4-32 m^2 was taken directly from the theoretical foundation of the algorithm.

4.3 Results for Italy

After the rule set was created and refined using the Italy training area, it was run for the entire QuickBird image. Though many individual tents on the image were missed, all camps on the image were classified in the general vicinity of actual camps. Figure 4-3 shows one of the camps that was outlined quite well by the algorithm.

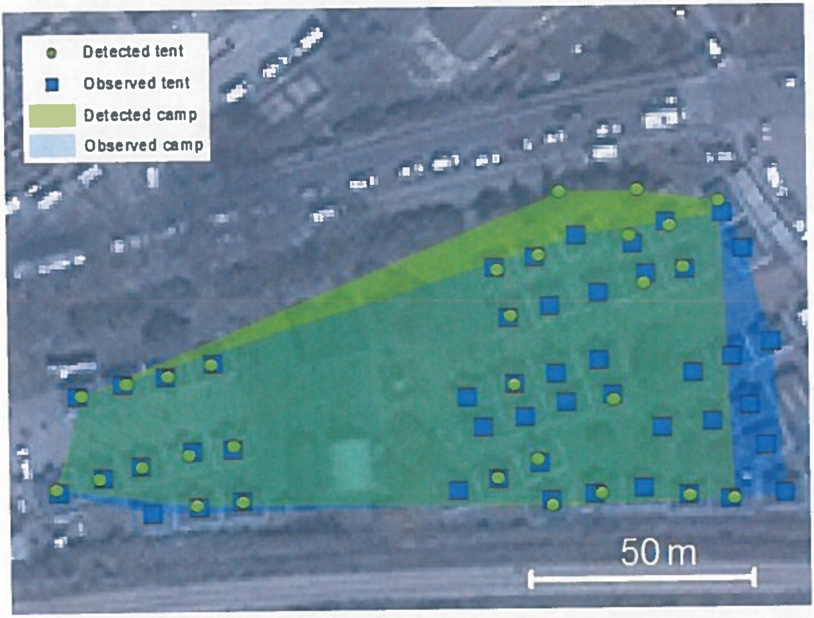

Figure 4-3: Classification for camp in Italy

4.4 Implementation in Haiti

Without making any adjustments to the rule set, it correctly identified several blue tents in the Jacmel, Haiti aerial photograph. However, this image contains many more red tents than blue tents. Therefore after identifying blue tents, the process was re-run using the Mean Red to Mean Green Ratio, which correctly identified many of the red tents (Figure 4-5).

Figure 4-4: Unclassified Haiti study site

Figure 4-5: Haiti study site with tent and camp classes

When run on the image of the Port-au-Prince study site only one shelter was identified. However, if only the MBGR and MRBR were used without shape and size considerations, more shelters could be classified.

Figure 4-6: Port-au-Prince study site shelter detection

Figure 4-7: Port-au-Prince study site shelter detection using only spectral ratios

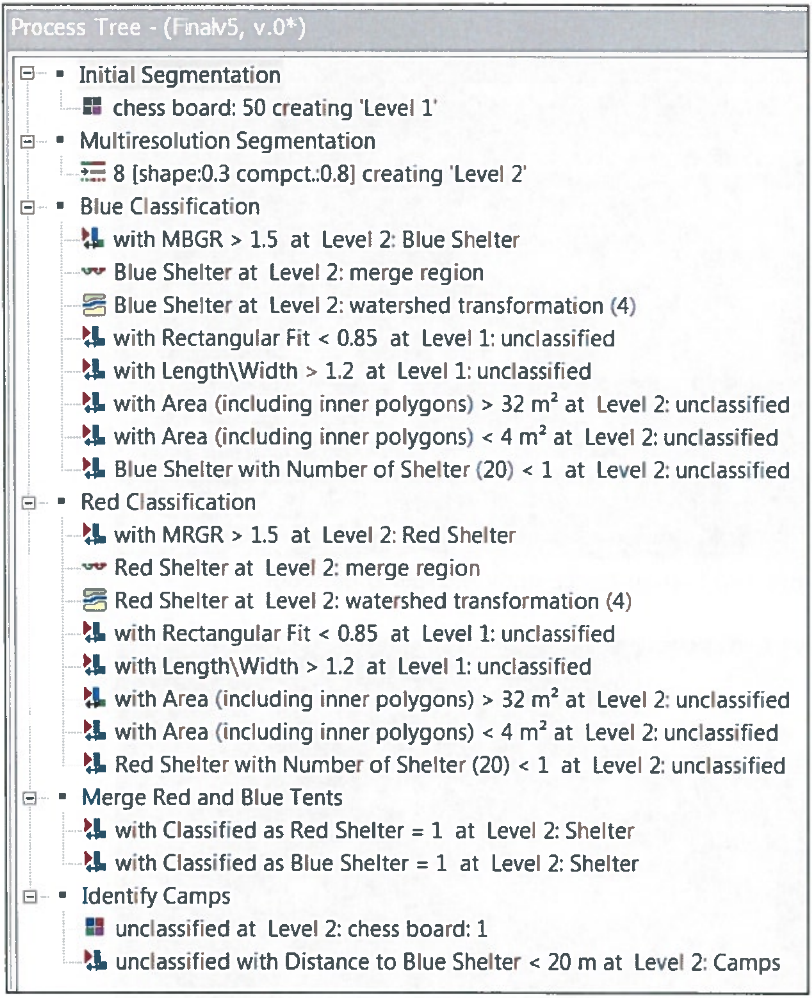

Figure 4-8: eCognition tent and camp detection rule set

The final rule set (Figure 4-8) includes the entire procedure of segmentation and classification of both tents and camps. The procedure for the classification of red tents was added after the initial rule set was created using the Haiti training site.

5 Accuracy assessment

For a useful accuracy assessment, classified data should be compared with a second source that can provide a greater degree of confidence as to what is actually on the ground (Congalton, 2007). For the Italy study site, such ground truth data were created by visually inspecting the QuickBird image and manually plotting tent locations using ArcGIS. DPCN's WMS tent layer (Figure 3-5) was consulted during the process. However it was not suitable as a source itself because WMS layers cannot be analyzed as GIS vectors. Also, the layer appeared to have been digitized from other data sources, not the QiockBird image being analyzed, leading to temporal inconsistency as tents were being set up. Camp polygons were generated from the ground truth points the same way they were for the OOA-generated points. An error matrix was then constructed to compare the OOA results with the ground truth map.

5.1 Error Matrices

The construction and analysis of error matrices is a standard way to determine the accuracy of classified maps (Jensen, 2005). Oftentimes a sampling of points on the ground that fall within different classifications is used. However, this exact methodology is impractical for an evaluation of shelter detection since the process seeks to merely detect presence and not precise extent. Moreover, the relatively small amount of shelters and camps in this case allows for manual enumeration, eliminating the need for random sampling. Therefore a variation of the standard error matrix method was used for assessment of both shelters and camps.

First, the image was divided into gridded tiles. The size of the tile was determined by doubling the size of the minimum length of the feature. For instance, since camps have a minimum width of 40 m, the squares were 80 m × 80 m. Grids for tent validation were 20 m × 20 m.

Next, an evaluation for each tile was made as to whether it contained an observed feature as determined by the ground truth map and a detected feature as determined by the output OOA file (Figure 5-1).

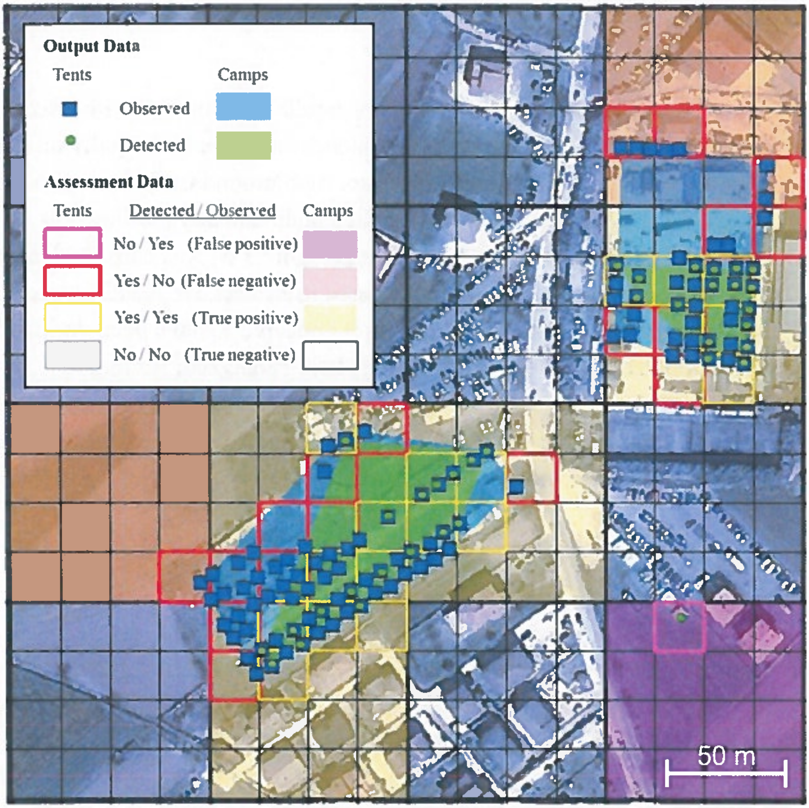

Figure 5-1: Example of accuracy assessment parameters for Italy study site

The data from the evaluation were next put into simple error matrices so a quantitative analysis could be carried out for both tents (Table 5-1: **Error matrix for tents for entire Italy study site**Table 5-1 and 3) and camps (Table 5-2 and 5-4).

5.2 Italy Error Matrices

		Tents Observed in Tile			User's Accuracy	
		Yes	No	Total		
Tents Detected in Tile	Yes	30	7	37	30 / 37	81.08%
	No	45	47 246	47 291	45 /47 291	99.90%
	Total	75	47 253	47 328		
Producer's Accuracy		30 / 75	47 246 / 47 253			
		40.00%	99.99%			

Table 5-1: Error matrix for tents for entire Italy study site

		Camps Observed in Tile			User's Accuracy	
		Yes	No	Total		
Camps Detected in Tile	Yes	10	2	12	10 / 12	83.33%
	No	2	2 828	2 830	2 / 2 830	99.93%
	Total	12	2 830	2 842		
Producer's Accuracy		10 / 12	2 828 / 2 830			
		83.33%	99.93%			

Table 5-2: Error matrix for camps for entire Italy study site

5.3 Haiti Error Matrices

		Tents Observed in Tile			User's Accuracy	
		Yes	No	Total		
Tents Detected in Tile	Yes	42	2	44	42 / 44	95.45%
	No	106	217	323	106/ 323	67.18%
	Total	148	219	367		
Producer's Accuracy		42 / 148	217 / 219			
		23.38%	99.09%			

Table 5-3: Error matrix for tents for first Haiti study site

		Camps Observed in Tile			User's Accuracy	
		Yes	No	Total		
Camps Detected in Tile	Yes	10	0	10	10 / 10	100.0%
	No	2	2	4	2 / 4	50.00%
	Total	12	2	14		
Producer's Accuracy		10 / 12	2/ 2			
		83.33%	100.0%			

Table 5-4: Error matrix for camps for first Haiti study site

6 Discussion

Though the accuracy assessment seems to show good results, a further analysis is warranted. Factors such as data, transferability, and usefulness must be considered.

6.1 Accuracy

The quantitative analysis of the method used shows the shelter detection algorithm to consistently have an overall accuracy over 99%. However, this statistic is problematic and may be misleading. The assessment is overwhelmingly affected by the method's accuracy in correctly determining the absence of shelters within the image (i.e. true negatives). For example, over 47 000 cells were analyzed within the Italy study site. However, only 82 cells contained either observed or detected tents. The rest had none of either, leading to a very high percentage of true negatives that dominated the overall accuracy. Therefore, the most important metrics to be considered are user's accuracy and producer's accuracy for cells where tents were either observed or detected. These metrics ignore instances of feature absence, and only analyze how well the process detects the presence of shelters and camps.

Producer's accuracy for positive results ranged from 40% to 83% with camp detection having better results than tent detection in each case. Many tents were likely missed because of the strict criteria used to detect them in order to avoid false positives. However, the accuracy was increased when camp polygons were created since undetected tents fell within these. It is clear the accurate detection of tents on the edge of camps strongly influences the accuracy of camp polygons.

6.2 Data

Due to the wide variety and availability of data for analysis and validation, many factors must be considered with regard to its use in shelter detecting activities.

6.2.1 Availability of Data

A stark contrast between the Haiti and Italy earthquake situations is easily seen in the availability of data to the public. Several factors may help explain this disparity including the magnitude of the disasters and diverging abilities of the respective communities to cope with them. Strikingly, the ICSMD was not invoked for the Italy quake. However, Google set up web sites devoted to both events that offer geospatial data for each. The L'Aquila web site (Google Italy, 2009) includes only a KML file linking to an unspecified high resolution image which cannot be downloaded for manipulation. On the other hand, the Google site for Haiti (Google Crisis Response, 2010) consists of several pages solely devoted to downloading high-resolution satellite and aerial imagery.

6.2.2 Spectral Bands

Since there is scant research devoted to detecting tents using EO data, the choice of useful spectral bands is not obvious. In extracting refugee tents, Giada et al. (2003) used four band imagery but set a lower weight for the near infrared band due to its lower spatial resolution. No mention was given as to how useful the IR band actually was in that study. However, the present research found the use of the IR band for segmentation and classification to have little influence. Based on its success in distinguishing vegetation, it was thought that incorporating the IR band into the standard NDVI equation might be useful in distinguishing tents from grass. Analysis showed this not to be the case. Indeed, some tents objects had the same NDVI values as those of grassy areas.

Despite its ineffectiveness in this particular study, the usefulness of IR bands cannot be fully established for all cases since the IR band used here in an attempt to distinguish a particular kind of tent in a small area on a QuickBird image. Seasonal and climatic differences were not considered. Moreover, other EO sensors have different specifications for IR band acquisition.

Even so, the fact that decent results were obtained only using visible bands could enhance the usefulness of the algorithm. To wit, EO data acquired from NOAA did not contain IR spectra. Though a thorough analysis of post-disaster data availability was not part of this thesis, many of the data for Haiti consisted only visible bands. Even if bands beyond the visible are acquired, they may not be made available for analysis. Or as is the case with most VHR satellites, are available but only at courser resolutions.

6.2.3 Shared Data

As more and more organizations share EO data acquired after disasters, the imagery available does not always meet the needs of users, and its usefulness for image processing may be diminishing as data availability increases. For both Italy and Haiti, much data were supplied as Google Earth layers or WMS services. Though possibly suitable for visual interpretation, these generally do not allow for automatic or even manual processing of data in a GIS. Moreover, when data are available either as services or raw files, metadata is often not immediately available or never created or shared.

6.3 Transferability

Transferability of the algorithm is influenced by several factors including simplicity and robustness. A simple and understandable rule set can be transferred from one situation to another and modifications can be made if needed by a user who was not involved in the origination of the procedure. The overall process is fairly simple and relies heavily on expert knowledge about shelter shape and spectral characteristics. These factors may not be universal to post-disaster shelters, but showed considerable utility for the study sites ued.

If a process is robust, it will work in a wide range of environments without adjustments. It is difficult to establish how globally robust the algorithm is from the analysis undertaken since only two types of data were used. However, the results in running a rule set created in Italy on different situations in Haiti without modification suggest it may be useful over a range of conditions. The ability to count tents in Jacmel while maintaining limited false positives make a strong case that shelter detection can work in urban environments and when tents are in rows and not just clusters. The results of the Port-au-Prince data imply limits to transferability when more ad-hoc shelters are the target.

6.4 Usefulness

Usefulness lacks a clear scientific definition when it comes to post-disaster mapping products. However, it is obviously an objective demanded by map users. Some measures of usefulness can be determined by assessing the accuracy and transferability of the algorithm, more importantly, the process and resulting products should fit within and enhance the current disaster management process chain.

6.4.1 Comparison with Existing Products

Scrutiny of the DPCN WMS service showing tent locations in Italy (Figure 3-5) is a helpful way to look at the classification results. Obviously the OOA-generated results missed many of the tent locations found on the WMS layer. However, the automated process did identify tents comprising a camp that did not appear on the layer. Also missing from the layer were several tents clearly visible within a camp that appear to have been missed during the tedious process of hand digitizing.

It may seem the algorithm would be more useful and applicable to post-disaster situations in a developing country like Haiti than wealthier regions such as Europe. However, no place on the globe is immune to crippling crises that could render governments useless (Lang et al., 2010). Therefore, a method that could successfully map temporary settlements comprised of commonly used shelters could be beneficial worldwide. What's more, an automated procedure could be employed over very large areas for use in commensurate crises.

6.4.2 Meeting Aims and Needs

The main question this research aims to a help answer is one likely asked by a variety of disasters managers in the days and months following a disaster: "Where are the people?" To this end, the algorithm and product will likely be useful to some of them. The product emulates current products currently being created that do not provide specific tent counts and accurate polygons but simply show the approximate locations of places people are gathering and setting up camps after a disaster (see Appendix A). Also, the OOA method may be more useful in explaining the situation in that it includes polygons where tents exist but were not digitized on the SERTIT map of Jacmel.

Perhaps a better way to evaluate how well needs are met is to review the organizations need to know what illustrated in Table 2-1. As discussed, the basic and most important question of a general knowledge of where people are is likely to be answered for some organizations by the algorithm and resulting maps. It might even detect camp boundaries well depending on conditions. However, as needs grow more specific, the algorithm becomes less useful. It does not detect all shelters and cannot be relied upon to count them. The even more detailed information of shelter characteristics is very much beyond the abilities of the algorithm and scope of this research but can help put into context what it can answer.

6.4.3 Meeting Aims

The algorithm was developed with the aim of keeping false positives to a minimum. The accuracy assessment shows that false positives are few for individual shelters and even fewer for camps. This is important because it limits the possibility that areas not containing people are identified as camps and sent resources that are desperately needed elsewhere.

7 Conclusion and Recommendations

As post-disaster EO data gathering and dissemination have increased, there is clearly a trend toward creating automated methods to create useful products this imagery. This research has shown that these aims of automated product creation can be furthered by employing OOA in the task of shelter and camp detection. There remains some difficulty in distinguishing individual tents while keeping false positives low. However, the method works well for a quick determination of large congregations of tents.

The spectral proprieties of tents proved to be an important factor in classification. This limited the detectable shelters to those having a blue hue. However, a very slight change in the algorithm yielded good results for detecting red shelters. Modifications could potentially be easily integrated into the algorithm to improve its ability to find other shelter colors. Though spectral properties were found to be significant, the study shows visible bands to be sufficient in carrying out this process. Furthermore, both VHR satellite imagery and fine scale aerial photographs had adequate spatial resolution to detect shelter clusters.

Other advances in data acquisition, image processing, and OOA in particular could help to improve this algorithm. For example, Tiede et al. (2008) used LIDAR to separate individual tree crowns based on local maximum heights. A similar approach might be useful in shelter detection as well if high-resolution LIDAR data were integrated into the rule set. Other research has used shadow characteristics to aid in identifying objects which could add another parameter to increase the number of individual shelters detected.

Problems encountered during the research highlight issues regarding data that makes effective advancement of automated procedures difficult. Many of the dataset made available to the public lacked any sort of metadata. Though it is understandable effort is focused on dissemination and not exhaustive documentation, a little more effort to help users determine data sources and collection information is warranted. Moreover, data must be downloadable to be manipulated in current image processing software.

Future research could build on the approach presented in this paper to expand both the colors and type of shelters. A strong foundation for detecting the predominant colors of blue and red has been made and shape characteristics seem to be sufficient but could be refined. However, the biggest hurdle remains the unplanned, uncoordinated unmatching shelters that were seen in much of Haiti and may resemble similar camps that could spring up in other parts of the world after major disasters. Other approaches could be used that rely more on texture or multi-level analysis that were not explored here.

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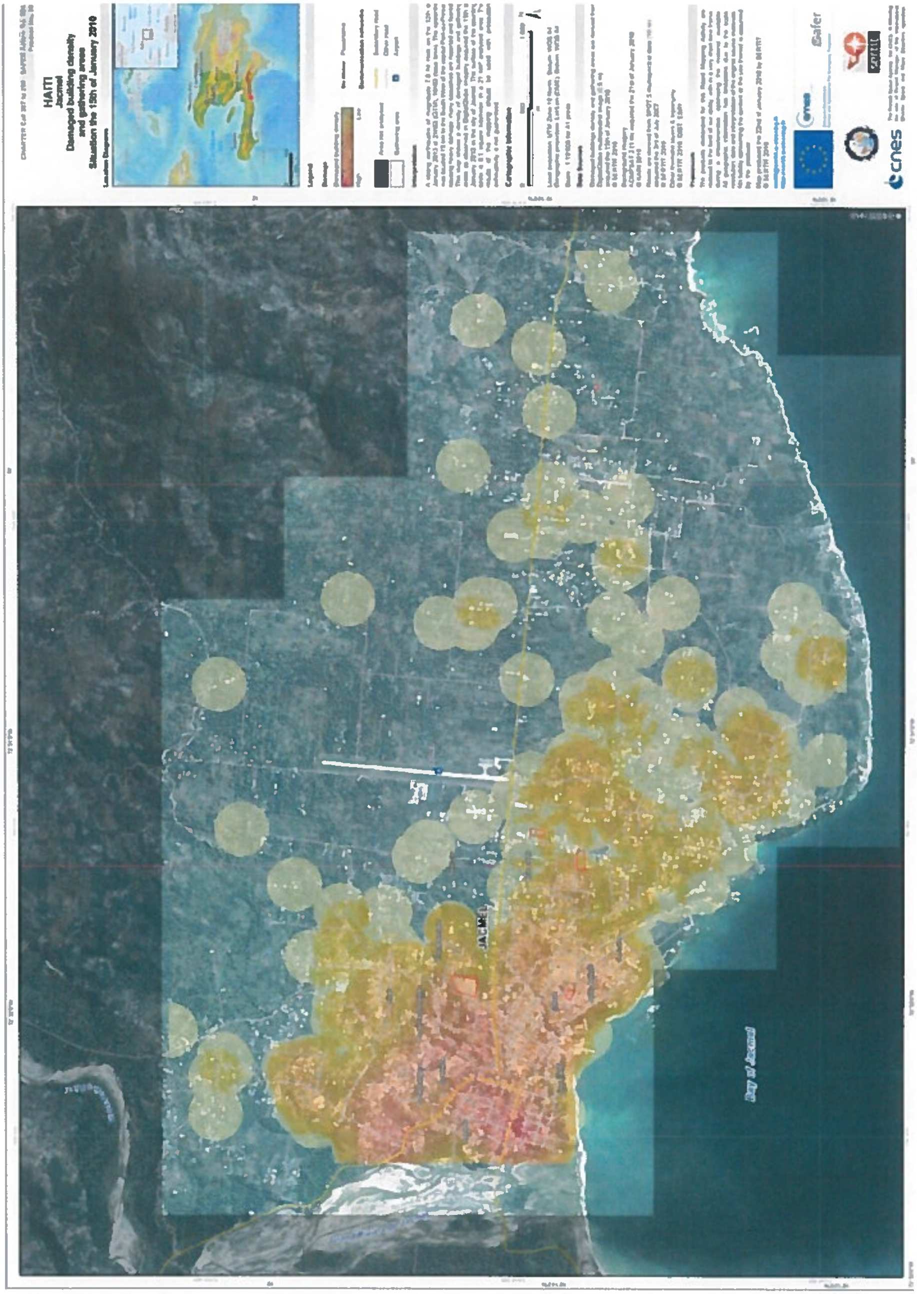
Appendix A: SERTIT Map



Appendix B: Feature Space Optimization Parameters Used

Mean Blue / Mean Green
Mean Blue / Mean Red
Mean Green / Mean Red
Mean NDVI
Mean Blue
Mean Green
Mean Red
Mean IR
Brightness
Stdev Blue
Stdev Green
Stdev Red
Stdev IR
Blue Ratio
Green Ratio
Red Ratio
Mean diff. to neighbors
Mean diff. to darker neighbors
Mean diff. to brighter neighbors
GLCM Homogeneity dir.
GLCM Contrast all dir.
GLCM Dissimilarity dir.
CLCM StdDev all dir.
GLCM Correlation all dir.