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Automatic Detection of Building Damages Following the Beirut Port Explosion Using Satellite Data

Analysis and Recommendations

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Abstract

Across global and local applications, the integration of earth observations throughout different stages of disaster management is promoted due to its main advantage of increasing the effectiveness of cities' prevention, preparedness, and response towards hazards. Concurrently, automatic information extraction methodologies are being increasingly employed in various spatial analysis contexts, revealing invaluable knowledge to better inform data-driven decision making. This study follows Dell'Acqua et al.'s methodology (2011) to perform a damage assessment using satellite data following the Beirut Explosion, Lebanon. The Random Forest classifier was used to perform a pixel-based supervised classification on the affected area to extract severe infrastructure damages. The classification results were validated using statistical indicators and crowdsourced data, and compared to the traditional surveying methods that were used on the grounds following the event. The analysis proved that employing such methodology reveals invaluable insights with shorter processing times and fewer manpower, especially when operating in limited resources settings. Further, the research advocates for the formation of a disaster management unit in Lebanon that profits from the integration of Earth Observation in the response. Using the Beirut Port explosion as a case study, the paper reflects on the local and international disaster management policies to demonstrate that incorporating remote sensing and machine learning methods could be applied to a range of cities and events.

Declaration Of Authorship

I hereby declare that this dissertation is all my own original work and that all sources have been acknowledged. It is 11,754 words in length.

Sara Moatti

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List of acronyms and abbreviations

HFA	Hyogo Framework for Action
3RF	Lebanon Reform, Recovery and Reconstruction Framework
DPER	Disaster Preparedness for Effective Response
GIS	Geographic Information System
GPS	Global Positioning System
EO	Earth Observation
VHR	Very High-Resolution
ESA	European Space Agency
UNDRO	Office of the United Nations Disaster Relief Co-Ordinator
UNOSAT	United Nations Satellite Centre
OBIA	Object-Based Image Analysis
RGB	Red Green Blue
VGI	Volunteered Geographic Information

Chapter 1

Introduction

Following natural and man-made catastrophes, the delivery of the vital emergency response faces challenges related to swiftly identifying damages, accurately quantifying losses and risk factors, and effectively organising relief (Ortiz, 2020). Traditionally, damage detection has been assessed using direct surveys that require on-ground volunteering and takes long period to collect, process and analyse. This type of assessment is deemed difficult in certain disasters where accessibility is severely impacted, e.g. flooding, fire, war, etc. Recently, the issue was highlighted in the Hyogo Framework for Action (HFA) 2005-2015 (UN, 2005) aiming to build the resilience of nations and communities to disasters. Currently, this remains an international challenge as declared by the Sendai Framework for Disaster Risk Reduction 2015-2030 (UN, 2015) that aims to provide key stakeholders with concrete actions to protect development gains from the risk of disaster. This is aligned with Goal 11 of the Sustainable Development Goals that aspire to make cities safe and resilient (see Section. 5.3).

Over the last few years, the progressive advancements of the earth observations sensors, processors and methods, and improved accessibility of geo-information due to launching more satellites, facilitated capturing these events and delivering information in near-real-time, to support the stakeholders and organisations in such critical situations (Agapiou, 2020). Moreover, the growing adoption of an open-access and collaborative approach was critical for the delivery of a swift response and accelerated the integration of the remote sensing field in the disasters management and humanitarian assistance (Akbari, V. et al., 2016; Ortiz, 2020). The latter is extremely relevant in less developed countries, as Van Westen highlighted the inverse relationship between the casualties and the development level in the context of a disaster, where 95% of total casualties occurred in developing countries (Van Westen, 2000).

Projecting on the case of the Beirut Port Explosion, where this study is focused, the lack of an organised disaster management strategy due to the complicated political reality the country is facing, emphasised the importance of the international support of the humanitarian rescue efforts (see section 3.2). Consequently, the Lebanon Reform, Recovery and Reconstruction Framework (3RF) was developed by the World Bank in 2020 as part of a comprehensive response towards a medium-term recovery (see Section 5.3).

Further, the use of earth observations in the post-disaster phase was formerly explored in several contexts using different satellite data, radar and optical, employing a wide range of techniques and algorithms, both automated and manual. However, Pham et al. argued when assessing the emergency response years after the Haiti earthquake that 'although semi- or fully automatic techniques to detect and estimate damage have been increasingly proposed, they have not been used during emergency situations' (Pham et al, 2014, p.54). Moreover, the spatial resolution of satellite sensors reached less than 1m in recent years, which facilitated the detection of damage (Stramondo et al, 2016). In the case of Beirut Explosion, investigations following the blast worked widely with relatively low resolutions -in comparison to the resolutions available at the time of the study-. This research will benefit from the high-resolution data available in order to assess the post-disaster damage in a rapid manner and will present a practical model of an automatic information extraction, that can be applied on different sectors, aspects and events.

1.1 Research Question

The main aim of this research is to explore how to optimise the emergency response through the integration of the earth observation data in the post-disaster assessment of damages. It is recognised that adopting an optimal approach is affected by time consumption, accuracy, data availability and expertise, therefore, a holistic investigation is performed benefiting from the limited resources and accessible data due to the high sensitivity of such event. Thus, the research question can be formed as *determining the effectiveness of post-disaster damage identification using satellite* *earth observation data to accelerate the humanitarian response and help identify the Beirut explosion affected areas.*

The study will look at different satellite data acquired before and after the explosion by different official and commercial agencies. The research will explore automatic information extraction techniques to help identify damaged areas and employ a machine learning algorithm classification methodology in a spatial analysis context, to address the research question. Concurrently, this research also seeks to tackle the following objectives:

- How to overcome the limited resources and restricted data accessibility constraints, and benefit from the publicly available data and algorithms to guide the response and prioritise the relief?
- How to validate the results' accuracy through a practical framework, especially when operating in less advantaged countries?
- Substantially, how to use the research as an example case for introducing a local disaster management policy and organise data-driven response efforts efficiently?

In recent years, the coordination challenge, where several local and international organisations have to operate side to side, was highlighted by Ozdamar and Ertem (2015) that promoted the use of geo-collaborative web platforms and open-source tools to build an interconnected response. In Beirut, "Open Map Lebanon" web platform[1] was established after the explosion. The initiative played a crucial role in facilitating the data collection, organising data sharing, and connecting different stakeholders and expertise. Inspired by the latter, the study contributes to the disaster management efforts by exploring an automatic detection technique applied on earth observation using accessible low budget crowdsourced tools. It is worth noting that the study area and event, the Beirut port explosion, is used only as a case study to developing a practical methodology that can be applied, ultimately, on different contexts and occurrences.

[1] https://openmaplebanon.org/

Chapter 2

Literature Review

Resilience, in Holling's words is "..the ability of ecological systems to absorb changes of state variables, driving variables, and parameters, and still persist.." (Holling 1973, p. 18), has been always the main accelerator to achieving aspiring social and economic targets to improve human life in various contexts. Recently, there have been great recognition in regard to enabling communities and governments to overcome obstacles and challenges in various sectors. Following the 90s' UN declaration of the International Decade for Natural Disaster Reduction, prevention and mitigation of disaster impacts were more recognised, and several global plans and strategies were set to reduce human, economic and infrastructure losses. More recently, and despite Disaster Preparedness for Effective Response (DPER) -detailed in the Hyogo Framework of Action discussed earlier- being integral to a sustainable economic and social development, disaster management that constitutes one if its essential aspects, is still often conceived as an event 'aftermath', especially when disasters hit the most vulnerable nations (Tozier de la Poterie and Baudoin, 2015).

On the other hand, the DPER incorporates a spatial element in almost all its stages, from spotting the event, to the distribution of the relief, till the final recovery stage (Van Westen, 2000). This chapter expands on the integration of technology and Geographic Information System (GIS) in the humanitarian context that has proven to be revolutionary in various events (Ortiz, 2020). First, the evolution of the GIS field is visited through key issues highly affecting its adoption in the disaster management, which reflects on the Beirut explosion's case. Then, wider applications are discussed to draw a robust structure on substantial response strategy stages. Afterwards, different techniques and methodologies for post-disasters analysis are pointed out. It concludes by situating this research on the Beirut explosion as a case study of working with high resolution data, using feasible computation and comprehensible algorithms, and producing effective humanitarian mapping to ultimately inform future response strategies.

2.1 Geomatics[2] Evolution

Geomatics relate to the acquisition, manipulation, interpretation and management of earth observation and spatial data (RICS, 2018). Since the Cold War, US & Soviet military agencies invested in this field to guide their plans and improve their targeting skills. Since then, several factors contributed to its integration in governmental and non-governmental intelligence supporting tool and finally, as a civilian user-based tool that informs decision making (Vergee, 2005). It started by employing the Global Positioning System (GPS), that is a network of radio-navigation satellites conceived in the 1970's in the space to get precise positioning of any point on the surface of Earth. Another factor was the declassification of Satellite Data that moved from a governmental military commodity to a public decision-making collaborative tool. In 1991, several countries ended the American and Russian dominance and launched Satellites with High-Resolution Sensors, capable of capturing imagery with 10 m initially. This has increased since and reached less than 0.5 m nowadays.

Further, it is undoubtedly recognised that digital innovations contributed immensely to the advancement of this discipline and facilitated the accessibility to geospatial technologies through benefitting from a relatively low-cost microprocessors, user-friendly software, and high-speed network. This highly benefited this research as the working methodologies developed where downloading satellite data to an inexpensive or free processing software allowed the extraction of invaluable intelligence and information in a timely manner.

[2] Commonly defined to include the tools & techniques used in land surveying, remote sensing, Geographic Information Systems (GIS), Global Positioning System (GPS), and related forms of earth mapping. Originally used in Canada, the term "geomatics" has been adopted by the International Standards Organization, the Royal Institution of Chartered Surveyors, and many other international authorities (Vergee, 2005).

2.1.1 Earth Observation[3] Data Quality

It is difficult to precisely define Earth Observation (EO) quality as it is highly relative to the end user and the context where it is being investigated. Main considerations discussed in the literature were best summarised by Yang et al.'s (2013) review on the data quality of the EO, however, the paper considered that is 'generally impossible' to characterise all the requirements needed for the data to be deemed as 'good' quality (Yang et al., 2013, p. 3). A recent technical definition of data quality highlighted quantifiable indicators that highly reflect, not only on the data itself, but on the processing quality (Sudmanns et al., 2020). To name a few, resolution, mapping accuracy, computation complexity, time consumption and memory occupation, automation vs. user interaction ratio, timeliness[4], robustness to parameters and data changes, and finally, scalability to different sensors and product specifications (Sudmanns et al., 2020; Yang et al., 2013). Consequently, the aim of this research is not assessing how 'good' the datasets or the methods employed are, however, how to optimise employing an automatic information extraction approach from EO based on the aforementioned data characteristics.

From a practical perspective, especially in humanitarian contexts where this research is focused on, data quality cannot be clearly categorised as valuable insights can still be extracted even when certain aspects of data quality are compromised. For example, Very High-Resolution (VHR) images that emerged as a result of the digital revolution in sensors and satellites, enabled the detection of change in a highly dense urban area (Pham et al, 2014). However, these novel technologies introduce novel problems that were not encountered. The large amount of information comprised in the VHR image increases the complexity of its processing and handling. Accounting for frequently changing objects (e.g. cars), shadows and vegetation were less apparent in medium to low resolution imagery. In this research, morphological approaches of the pre- and post-event images were adopted in the computation to address this issue following the thoroughly discussed methodology in Dell'Acqua et al.'s paper on the earthquake damages rapid mapping on L'Aquila, Italy event in 2009 (Dell'Acqua et al., 2011).

[3] Earth Observation in this research follows the historical definition as Satellite-Based remote sensing Data (Yang et al., 2013)
[4] defined as the time interval between data acquisition and product generation (Sudmanns et al., 2020)

2.1.2 Data Accessibility

Traditional workflows in the analysis of geographic information often requires high levels of human input and skilled expertise (Sudmanns et al., 2020). In addition, a download-driven approach is often adopted where the data is processed locally on the user's machine. This implicates large data volumes stored on personal machines which complicates the analysis process. In parallel, data availability is highly influenced by political, governmental, and commercial decisions that can control the distribution of the data. Moreover, the increased demand from the user side on geolocated data due to the integration of the field in different disciplines was pointed by Baumann (2018) in the notion of executing 'any query, anytime, on any size', simultaneously, duplicating the pressure on the data provider 'to bring the user to the data, not the data to the user' (Baumann, 2018, p. 20151). For example, it was reported that data acquired by the NASA Shuttle Radar Topography Mission was accessed by more than 750,000 users from 221 countries and cited in various studies (Farr et al., 2007). Data accessibility have always been an issue when operating in disasters management contexts, the following sub-sections will highlight few of the main issues discussed din literature and that relates to the Beirut Explosion event.

2.1.2.1 Open Access Data

Open data refer to the availability and distribution of acquired Satellite data in a free or low-cost manner, especially when used for scientific, educational, and humanitarian purposes. This allows the analysis of data collaboratively at a global scale, regardless of localities. Although the term 'open data' was firstly adopted to describe early satellite programmes data policies, only up until 2016, data from less than half of the 458 satellites launched between 1957 and the beginning of the 2016, was made freely available (Borowitz, 2017).

In the case of Beirut Explosion, the event was captured by several agencies but not all data was made fully publicly available, therefore, studies and analysis or low-resolution data were published. Where the benefit of doing so is undoubtedly invaluable, it added availability limitations, which highly affected the on-ground operating team that is usually more aware of certain characteristics and localities specific to the area. Immediate post-event actions would have included getting the extent of the explosion, conducting a risk assessment of the structure of damaged buildings imagery to warn against unstable structures or identifying the explosion affected areas characterised by a highly urban density with the existence numerous listed buildings.

2.1.2.2 Technical Challenges

Data 'accessibility' does not entail 'availability' solely. In this section, accessibility refers to the technically simplified processed data that do not restrict the user level to the highly skilled expert, especially when data is being employed in critical situation such as disasters management and emergency response contexts. Recently, pre-processed satellite imagery are still rare to find and are usually restricted by the huge amount of data generated, for example, the optical Sentinel-2 A and B satellites generate an average of ~3.4 TB of data per day (Sudmanns et al., 2020). In 2020, Sudmanns et al. envisioned a workflow -that was partly implemented at that time- that differs from the traditional approach where datasets are downloaded locally and analysed using the size and performance constrained tools to deliver for the end user. The new process consists of generating analysis-ready datasets that are accessible to analysts in a cloud environment. Google Earth Engine[5] is a good example on the latter, and is deemed useful despite some exclusivity, accessibility, and computation limitations (Gomes et al., 2020).

In the case of Beirut, different datasets were used by private agencies with various quality, especially in the first fortnight after the blast to produce maps. One of the prominent ones is the NASA's ARIA team that worked with Copernicus Sentinel data processed by European Space Agency (ESA) to map the extent of the damage as shown in Figure 2.1. Arguably, the resolution is deemed relatively low (30m) -compared to the data available at the time of the study- however, different insights were extracted that helped with the allocation of damages and gave better understanding on the event.

[5] a platform launched in 2010 by Google that allows the storage, analysis, and visualisations of geospatial datasets on the cloud (Gomes et al., 2020).

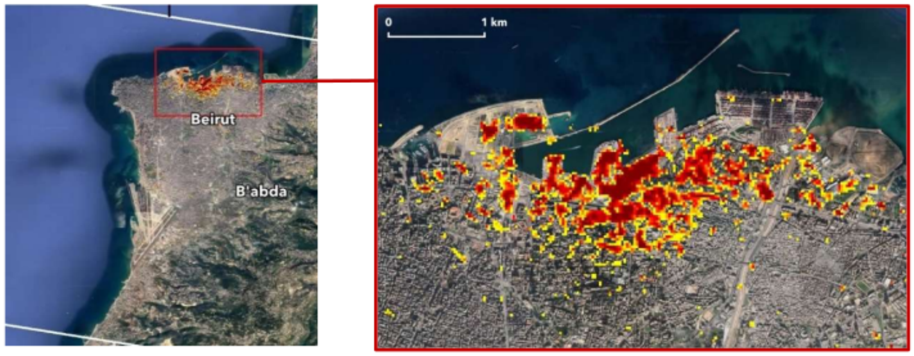

Figure 2.1: The NASA'S ARIA Damage Map developed to map the extent of the damage. The map was made public on August 7, 2020, three days only after the blast. The NASA team worked with 30m resolution Copernicus Sentinel data in collaboration with ESA.

2.1.2.3 Political Challenges

It is worth stating that political strategies were the main motives that allowed the distribution of Satellite data and in 1961, US officials recognised it as peaceful 'weapons' against others (Borowitz, 2017). However, due to the increasing security concerns, data storage and protection are still affected by political decisions, especially in relation to governmental agencies whether data should be stored centrally or replicated at different locations. For example, decisions on whether high resolution imagery should be released covering a sensitive area or event are highly biased by specific political agendas. In the case of Beirut explosion event, the government is still demanding the US governmental agencies to release high resolution imagery pre- and post- the blast. The data was censored due to the sensitivity of the event and the unstable geo-political reality of the country.

2.2 Geomatics in Humanitarian Contexts

In the first instance, satellites enabled the capturing of the event on a near-real-time basis, which allocated the needs and exposed the aftermath of disasters. The chaotic and extreme conditions that supersede the disaster, require strong response strategies that are often insufficient, especially when operating in populated settings. The process starts by monitoring the event, identifying the disaster and quantifying the effect in numerous contexts, e.g. flooding, earthquakes, fires, hurricanes and civil wars (Morelli and Cunha, 2019; Li et al., 2019; Trianni & Gamba, 2008) and even predict some of them, e.g. tsunamis (Romer et al., 2012).

In addition, following a catastrophic event, international and non-profit organisations commonly support in addressing the emergent needs of the region (Olsen et al., 2003). Therefore, it is crucial to adopt response methodologies that overcome the geographical challenges, ensure continuous cooperation and coordination, address the uncertainties in demand and supply, and most importantly, accelerate the response and increase the relief impact (Ortiz, 2020).

Subsequently, post-disaster management is relying less and less on huge on-ground efforts and surveys solely, owing to the rapid development of the remote sensing discipline. It allowed the allocation of the spatial extent of the disaster, which concentrates the relief efforts and increases the effectiveness of the logistics deployment, that are deemed in certain circumstances, lifesaving (Pham et al., 2014).

It is worth stating that integrating remote sensing in disaster management is not novel. The concept was pointed by David Alexander in 1991, where it had made humble starts at that time, when he argued that satellite and microprocessors revolutionised the monitoring and managing of the disasters (Alexander, 1991).

In 2012, Kunz and Reiner attempted to quantify the importance of Geographic Information in humanitarian contexts by identifying 'situational factors'[6] that dominated the humanitarian logistics research through developing a new framework using word count to perform a content analysis on a wide range of academic papers (Kunz & Reiner, 2012, p. 119). They concluded that governmental at 23%, Socio-Economic at 19%, Infrastructural -roads, railways, ports and electricity- at 32%, and environmental -geography and topography- at 26% are the main factors affecting the humanitarian performance after disasters. Having the spatial component characterising the latter two factors which, combined, accounted for 58%, justifies what Saito and Spence (2004) considered as 'one of the most important aspects of disaster assessment and management', referring to the Geographic Information (Saito and Spence, 2004, p.2272).

[6] as defined by the authors, "exogenous contextual variables which are present in the disaster affected area and impact the performance of humanitarian logistics." (Kunz & Reiner, 2012, p. 119).

The following paragraphs illustrate how analysing spatial information provided through remote sensing and GIS technologies can affect the humanitarian response before, during and after the event, using specific case studies and following the UNDRO (Office of the United Nations Disaster Relief Co-Ordinator) classification of disaster management stages into disaster prevention, disaster preparedness, and disaster relief, rehabilitation, and reconstruction (1991).

Pre-disaster at t_{-1}, disaster prevention: Indian Ocean Tsunami Simulation on Banda Aceh, Indonesia area

Wang & Li proposed an optimisation of tsunami warning systems by taking full advantages offered by the remote sensing and GIS on forecasting tsunamis (2008). They simulated three scenarios for the December 26, 2004 Indian Ocean tsunami disaster on a different pilot area where each scenario lacked (scenario 1), had the existing Pacific Ocean system (scenario 2) and would have the optimised warning system fully using remote sensing and GIS (scenario 3). They measured the daily deaths in each scenario and defined the efficient time interval[7] indicator δ, that represents the efficiency of the system. In their research, they proved that employing an optimised warning system fully integrated with remote sensing and GIS technologies, could shorten the delay of warning and risk assessment while lengthening evacuation, thus, saving lives. Their simulation showed that live loss could have been dramatically decreased from 300,000 (the actual loss figure) to 3000 deaths. Where a disaster prevention in the case of Beirut Explosion is not directly applicable in the same sense due to the sudden nature of the event, the advantage of continuously monitoring changes using earth observation in Lebanon is significant e.g. identifying deforestation, fire alerts, tree cover changes, land uses, carbon & biodiversity changes.

Disaster and post-disaster at t_0 and t_{0+1}, disaster preparedness*: Haiti Earthquake*

Boccardo and Tonolo (2012) performed an analysis on the remote sensing role in the damage assessment following the Haiti Earthquake that hit on 12 January 2010. Immediately after the earthquake, damage maps were developed by different international organisations and relied on manual and visual mapping. In a matter of four

[7] the larger δ values are, the less the losses.

days only, United Nations Satellite Centre (UNOSAT)[8] published the "Damage Assessment for Major Buildings/Infrastructure in Port-au-Prince, Haiti" based on VHR GeoEye images (0.5 m), which allowed an effective allocation of temporary shelter and spontaneous camp and the identification of road damages that were crucial for the relief (Pham et al, 2014). A more complete building damage classification was developed by published one month later. The authors highlighted how benefiting from remote sensing related capabilities such as acquiring earth observations, processing using cloud-based and GIS software, and adopting a collaborative approach through volunteer mapping, was able to deliver, in few days, several maps to the rescue teams. To prove the latter, they reviewed the accuracy maps that what was produced using in-situ data validation captured throughout times, and concluded that the maps reached 70% of overall accuracy value, which despite of the figure, is considered remarkably informative for guiding the disaster management efforts. In the case of Beirut, high resolution images were not published immediately after the explosion which made the NASA's ARIA map, mentioned in section 2.1.2.2, one of the first damage maps produced following the explosion where it worked with low resolution images (30m), however, helped in identifying the extent of the explosion. This underlines the need of a local disaster management strategy that can deliver similar results in short times and increase the country's preparedness towards disasters.

Post-disaster at $t_{0+\infty}$: disaster relief, rehabilitation, and reconstruction, L'Aquila Earthquake

Dell'Acqua et al. performed an in-depth damage assessment using available Satellite data following the earthquake that hit L'Aquila on April 6th, 2009. They conducted analysis on pixel level using VHR optical data and on a block scale using SAR data (2011). Both methods were effective in detecting damages, pixel-based classifications on optical images were able to identify damage and non-damage areas, where SAR data provided information on the level of damage (low or high) by extracting co-occurrence texture parameters and setting thresholds and comparing between the pre- and post-images. A complimentary approach was recommended to inform future reconstruction plans in a systematic manner. Similarly, in the case of the Beirut explosion, this research

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[8] United Nations Satellite Centre, hosted at the United Nations Institute for Training and Research UNITAR. The centre employs geospatial information technologies to promote evidence-based decision making for peace, security and resilience.

will focus on the post-disaster due to several factors. First, the nature of the event, being a very sudden occurrence, eliminate the need of monitoring the disaster as the time is relatively seconds. Second, the type of the disaster as being an explosion, was not anticipated or predicted, as it was caused by a chemical substance stored poorly in the port, which made a pre-disaster analysis unviable. Lastly, initiating from a post-disaster analysis is regarded as a trigger for developing other stages of the disaster management where same approaches can be employed in the future in various contexts.

In conclusion, Geomatics is deemed indispensable throughout different stages of disasters (Pham et al, 2014); from the event acquisition and distribution, post-event assessment and relief planning, and ultimately, infrastructure mapping and reconstructions (Kerle, 2010; Voigt et al., 2007,2011). The next sub-section will expand on the different methods and approaches discussed in the literature to conduct a post-disaster analysis where this study is focused.

2.3 Post-Disaster Analysis

This section will outline fundamental analysis techniques that were adopted in different contexts to analyse earth observations, particularly in the context of damage assessment and humanitarian contexts. As discussed above, the first line of response starts with information extraction. Priorities are usually for the human fatalities, injuries and displaced population, especially in urban dense areas. In numerous disasters locations, reliable information is not available at hand, especially in less developed countries where they lack an official disaster management unit and statistics are not regularly updated, which impose a critical challenge that would prevent relief from reaching to the most affected. In the first instance, allocating infrastructure damages, especially roads, are essential for the relief operations, e.g. making sure that roads are accessible for the shelter, food and medical needs distribution. This is followed by population rescue and evacuation, e.g. in case of flooding, earthquakes and fires. Afterwards, a detailed damage assessment is carried out to guide future reconstruction and recovery. Throughout the process, remote sensing is deemed a powerful tool in providing real-time information on the situation through acquired satellite images.

2.3.1 Manual Information Extraction

Visual interpretations are still a popular approach that is adopted by humanitarian agencies due to several factors, especially in the very first days following the disaster. This might be due to the high level of cloudiness covering the area at the time of the disaster, low resolution captured for an urban dense area or due to high cost of imagery especially when captured by commercial agencies (Trekin et al., 2018). Simultaneously, despite volunteering efforts and international agencies assistance, manual and visual information extraction is still time-consuming (Lang et al., 2020). Also, these inspections are prone to human-made errors like generalisations or under-estimation (Lang et al., 2020). For example, Albuquerque et al. (2016) analysed Missing Maps[9] data and identified that in urban areas, small buildings footprints with low contrast to surroundings were overlooked. Similarly, Elia et al, (2018) evaluated OpenStreetMap[10] data through comparison with other professional resources and concluded that, even though the same method of collecting data is employed, which is crowdsourcing, the quality of the post-event data was less accurate than the pre-event, as mappers tended to over-estimate the damages. Therefore, new approaches are being explored that benefit from the available more than ever satellite data.

2.3.2 Automated Extraction Approaches & Methods

Due to the aforementioned limitations, new methods were developed to achieve reliable, yet quick results. Mainly, two approaches were identified in the literature and were used to classify satellite data.

2.3.2.1 Pixel-Based Analysis

Classification attempts adopted this approach from the early beginnings as the pixels have been considered the fundamental spatial component of a satellite imagery. Per-pixel approaches consider the image's individual pixels as the main analysis unit. This method uses the spectral information of pixels to assign them into different classes based on certain similarities between the classes (Richards, 1993, Zerrouki &

[9] a project that maps parts of vulnerable areas prone to natural disasters, conflicts, and disease epidemics.
[10] a project to create a free editable map of the world through collaboration and crowdsourcing.

Bouchaffra, 2014). Moreover, the feature data vector of each pixel is compared to the prototype vector of the class where the feature vector consists of the pixels grey level values from multispectral bands (Shackelford and Davis, 2003). Among the most used classical schemes that were developed are Maximum-likelihood (Jensen, 1996; Lillesand and Kiefer, 2000), minimum distance to the mean and Minimum-Mahalanobis-distance, that all use the same measure, distance to the mean, to decide pixels in each class.

2.3.2.2 Object-Based Image Analysis (OBIA)

OBIA is a semi-automated analysis that uses spatial concepts to identify classes where objects, so-called segments -not single pixels-, are identified following a segmentation process that highlights geometric and topological features & attributes (Benz et al., 2004). A hierarchical approach is adopted for the multi-scale analysis, e.g. working with different resolutions. The method is used widely in several damage assessment contexts; however, it is highly effective when applied in urban areas as geometrical objects are well defined (roads, buildings, etc.) (Benz et al., 2004). Hussain et al., 2011 performed a building extraction and rubble mapping following the Haiti Earthquake and achieved high levels of overall accuracy (87%) that was enabled using a combination of optical high-resolution images and lidar based elevation information.

2.3.3 Recent Classification & Machine Learning Methods

In order to achieve a reliable, yet quick results that is deemed critical especially in humanitarian contexts, new methods of automated information extraction were explored with the assistance of the developing machine learning algorithms (Lang et al., 2020). An overview on the algorithms is presented with a focus on the Random Forest classifier that is being used in the research.

2.3.3.1 Recent Algorithms Overview

Numerous machine learning algorithms were developed and used in the remote sensing context. One of the earlier statistical models is the Support Vector Machines (SVM), a supervised non-parametric algorithm that separates a dataset following a non-linear infinite number of hyperplanes and assign points to classes (Vapnik, 1978). The algorithm is known to balance between accuracy and generalisation to unseen data, which reduces overfitting (Mountrakis et al., 2011). In recent years, SVM have been increasingly adopted in remote sensing applications, e.g. land cover types (Pal and Mather, 2005), monitoring biophysical types such as chlorophyl concentration (Kwiatkowska and Fargion, 2002) and soil erosion (Andermann and Gloaguen, 2009).

A more complex multivariate statistical model is the Artificial Neural Network (ANN) that has been developed based on the human brain. It consists of a knowledge-based artificial intelligence technology that adopts an interconnected approach to associate elements in a dataset or multiple datasets (Pao, 1989). Higher accuracy and rapid processing compared with other statistical classifiers, and the ability to incorporate different types of data taking into consideration its non-linear distribution, were among the main advantages reported in the analysis of satellite data (Atkinson and Tatnall, 1997; Cooner et al, 2016).

On the other hand, and unlike other classification algorithms, the Decision Tree is based on a hierarchical process that split a complex decision into several simpler ones which facilitate the interpretation of the results and control the outcome. Decision Tree algorithms are top-down algorithms that starts with one node and branch to group all observations to a class. It has been widely used in the classification of remote sensing data such as vegetation cover, forest mapping and urban landscape dynamics (Simard et al., 2000; Huang et al., 2001). Moreover, Kohara and Sugiyama (2013) combined Decision Tree with multiple regression analysis in a new approach of disaster modelling for the typhoon damage forecasting in Japan.

2.3.3.2 Random Forest Classification

Based on Decision Tree algorithms discussed in the previous section, Leo Breiman (2001) introduced the Random Forests algorithm that is a non-parametric ensemble of decision trees instead of one tree model, in other words, it uses a single base algorithm or a combination of different based classifiers on the same data or subsets of the data (Breiman, 2001; Friedl et al., 1999; Mountrakis et al., 2009). The algorithm classifies data based on the maximum voting rule base for each decision tree that is randomly subdivided following predefined variables and bagging procedure (Cracknell and Reading, 2014). The user can determine the number of trees and features at each node, while bagging generates the training data by selecting a random sample for each tree.

The algorithm determines the split using the Gini Index that reflects the heterogeneity between the initial produced nodes. The method is being increasingly used in the remote sensing field to classify satellite imagery due to its 'non-parametric nature, high accuracy, and capability to determine variable importance'- in this case, bands or imagery- especially when limited data are available as Rodriguez-Galiano et al. concluded following an assessment of the effectiveness of the classifier (Rodriguez-Galiano et al., 2011, p. 93). Therefore, for this research, an automated information extraction using Random Forest algorithm is chosen for the classification due to its rapid processing, workable complexity, less computational requirement and its ability to achieve high accuracy and to handle large datasets (Breiman, 2001; Pal, 2005; Rodriguez-Galiano et al., 2011).

Finally, the study aims to benefit from the available earth observations and machine learning algorithms methodologies mentioned above to create an action plan that can be implemented following emergency situations to support the response following the Beirut Port explosion. To do so, a damage assessment on the port area is performed to extract damaged infrastructure and buildings from available Satellite Imagery. Optical & Radar Satellite Data captured the area before and after the blast, reported damages observation data and the adopted methodologies are discussed in the following section. The results are followed by a discussion of how efficient is adopting such methodologies to guide the response and prioritise the relief through validating the results accuracy.

Chapter 3

Methodology

For this study, High Resolution Optical Satellite data from the commercial agency, MAXAR Technologies[11], were made available online and publicly accessible as an exception, as part of the company's Open Data Program to help assist the relief efforts during disasters. Medium to low resolution Sentinel-2 Radar Data were explored as well. For the Random Forest classification, several approaches were investigated. Multi-temporal change classification and post-classification change detection on the images acquired before and after the blast are discussed in this section. In addition, reported damages observation data collected by NGOs are analysed and are available on the Open Map Lebanon website.

The code used for the analysis along with the QGIS steps are available here: https://github.com/SaraMoatti/Automatic-Detection-of-Building-Damages-following-the-Beirut-Port-Explosion-using-Satellite-Data

3.1 Case Study: the Beirut Port Explosion

On the 4th of August 2020, a massive explosion at the Beirut port was triggered by improperly storing highly explosive chemical substances, Ammonium Nitrate, see Figure 3.1 (Agapiou, 2020). According to the United States Geological Survey (USGS) Earthquake Hazard Program (2020)[12], the blast generated seismic waves of 3.3 magnitude earthquake and destroyed large part of the capital. The shockwave impacted the industrial waterfront and penetrated the densely populated residential neighbourhoods that dwelt more than 750,000 inhabitants. Within two miles radius

[11] data available at: https://www.maxar.com/open-data/beirut-explosion
[12] see https://earthquake.usgs.gov/earthquakes/eventpage/us6000b9bx/executive

from the epicentre of the explosion, buildings were severely damaged and debris such as broken glass, concrete, bricks, etc. were dispersed (ACTED, 2020[13]).

Figure 3.1: WorldView-2 high-resolution images. Captured over the Beirut harbour area on the July 31 and August 5 2020, before and after the blast. The zoomed shots show the explosion ground zero container, where the explosive Ammonium Nitrate were poorly stored.

3.2 Building Damage Typology

The explosion ignited in the Port area that is located in the heart of the capital Beirut. The blast struck a highly dense urban area that enclosed several building typologies, where residential buildings were a majority (Mady et al., 2020). Following observations from the High-Resolution Optical imagery, damages mainly affected buildings and the port area with damage debris laying on few streets, mainly on the highway in front of the port. Buildings were built using mainly concrete and masonry structures, where a substantial amount is deemed of a significant heritage character (Naccache, 1998).

[13] see https://www.acted.org/en/acted-lebanon-response-to-the-beirut-explosion/

Building damage extraction is a specific type of change detection and different methods were developed to produce a damage assessment following natural and man-made disasters (Al-Khudhairy et al., 2005; Li et al., 2010; Pagot and Pesaresi, 2008). The classification of the damage grades was defined by different regulating bodies, and the European Microseismical Scale 1998 (EMS-98) is one of the most used in remote sensing studies (Pham et al., 2014). The EMS consists of 5 grades (I to V), that classifies the damage according to its severity (see Figure 3.2). Where different types of damages can be identified using visual interpretations, especially when dealing with very high-resolution images, numerous studies that used automatic change detection were able to reliably detect building collapse and severe damages (Yamazaki et al., 2005). Moreover, it is acknowledged that Grades I and II are not identifiable from satellite images and are usually combined to one class, where grade III is confused with IV and V. Therefore, the target class in this study is set to Grade IV and V under a severe damaged buildings class (Pagot and Pesaresi, 2008).

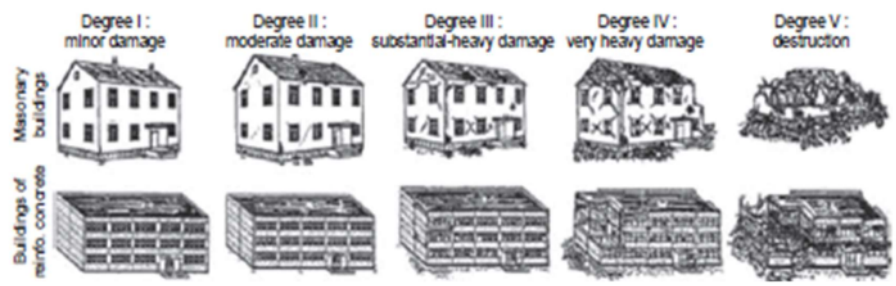

Figure 3.2: Illustrations of five grades of building damages according to the EMS-1998, obtained from Pham et al. (2014, p. 55). Two building materials are selected, for masonry and reinforced concrete buildings as they represent the majority of building materials in the Beirut study case.

3.3 Data

The study area boundaries were set following the newly developed Beirut Operational Zones that included the Beirut Port and the surrounding damaged zones. It was created by the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA) after the explosion as the Level 3 Administrative boundaries in Lebanon (Cadastres) are too large for humanitarian operational purposes, therefore, they were divided into zones where relief can be better organised (OCHA, 2020)[14].

[14] see https://data.humdata.org/dataset/beirut-port-explosion-operational-zones.

The VHR optical satellite images (1m resolution) are sourced from MAXAR Technologies and were processed by the Humanitarian OpenStreetMap Team (HOT) and UN Spider. Images are accessible via cloud-optimised GeoTIFFs (COG) and covered periods before and after the blast. The images are pre-processed where orthorectification, atmospheric compensation, dynamic range adjustment and pan-sharpening is applied. Medium to low resolution (60m, 20m, 10m) Sentinel-2 imagery were explored from the Copernicus Open Access Hub as well.

Satellite images are cropped and masked to the Beirut Operational Zones extent to facilitate the computation and focus on the damaged zones. MAXAR data analysis was advanced in favour of Sentinel-2 raw data due several factors:

- Very high resolution, in comparison with the sentinel data (10m resolution) that were not publicly shared due to political constraints and the high sensitivity of the event.
- Better coverage and views on the area before and after the explosion.
- Less clouds and better visibility.
- The pre-processing characteristic yielded better results with less computation.

For cross validation, reported damages observation were analysed and will be discussed in section 3.4.3 in an attempt to evaluate the classification performance.

3.4 Identifying the damage

A pixel-based supervised classification is performed on the satellite imagery following Dell'Acqua et al.'s methodology on the damage assessment after the earthquake in L'Aquila (2011). Random Forest classifier is used for the classification relying on a training data that is created to automatically classify each image pixel according to a single class label. Two approaches were examined on both datasets, the optical Maxar data and the Sentinel-2, to identify which dataset reveal better information and is deemed more useful in identifying the damages: a multi-temporal change classification and a post-classification change detection.

A workflow chart is added to summarise the methodology steps and a detailed overview of the methods used to automatically extract the damages using Satellite data is expanded in the next sections.

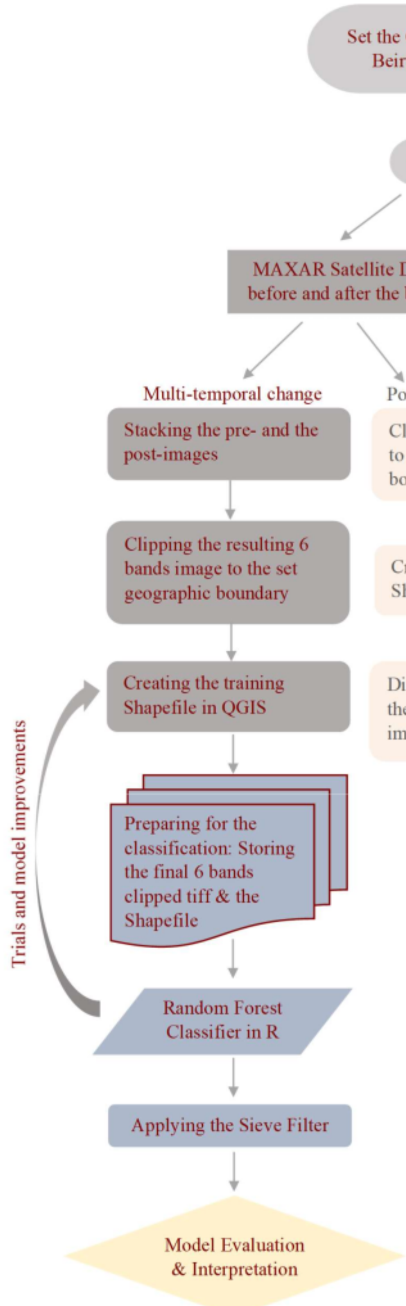

Figure 3.3: Methodology Flowchart showing the progress of datasets and methods evaluation and trials. The Random Forest classification performed on the MAXAR High Resolution Optical images showing the model building, evaluation, and improvement.

3.4.1 Multi-temporal Change Classification

In order to perform the classification, Random Forest algorithm was used to classify the severe damaged buildings where a training data is identified as predictors in order to automatically extract the damages in a speedier manner. For the analysis, High Resolution Optical Satellite Images were used as they were considered to generate better information due to the small footprint of buildings that limited the information extraction using lower resolution datasets e.g. Sentinel-2 with 20m resolution.

The used images were captured before and after the explosion, on the 31st of July and 5th of August respectively. In order to perform the multi-temporal change classification, the post image was appended to the pre disaster image, forming a six bands imagery (three for pre disaster and three from post), clipped to the UN Beirut Operational Zone extent, and stacked to produce the base image. Afterwards, a shapefile was created as the training data, by selecting different attributes from the resulting image. Polygons are randomly selected for each attribute forming the base samples in order to identify classes and train the model on recognising each class and ultimately, distinguish the severely damaged buildings from all other classes as a target class. Final classes were defined and are listed in Table 3.1.

Table 3.1: Classification classes created as part of the training Shapefile.

ID	Class	Description
0	Water	Class distinguishes water as the explosion is at the port
11	Severe Damage	From no damage in pre-image to severe damage in post-image
12	No Damage	No damage in pre- and post-image; buildings not damaged
13	Greenery	Class created to identify trees and bushes
14	Heights & Shadows	Class created to improve the classifier performance

The classifier generates an internal unbiased estimation of generalisation error known as OOB error. As discussed by Rodriguez-Galiano et al., the Random Forest classifier is characterised by avoiding overfitting as the Law of Large Numbers[15] does apply to

[15] as the number of identically distributed, randomly generated variables increases, their sample mean (average) approaches their theoretical mean (Routledge, 2016).

it, and it requires minimal user input, the number of trees and the number of random split variables. Both parameters are proportional to the accuracy where the parameters can be calibrated in a way that the generalisation error converges to an approximately stable result (Rodriguez-Galiano et al., 2011). In other words, the user increases the tree numbers and the splits and monitors the OOB, to reach a point where the error converges and the difference between the values is less than 10% (Rodriguez-Galiano et al., 2011). Multiple attempts were required to improve the model performance and accuracy and will be discussed in section 4.1.

It is worth mentioning that the algorithm creates number of trees to bootstrap samples from original dataset. The out-of-bad data that consists of having about one third of the data being left out and not used in the construction of the next tree. This sampling method is considered a built-in validation tool for the results where the sample data is considered as a reference data that is used to generate several validation figures e.g. the OOB error estimate mentioned earlier, and the accuracy matrix (Cracknell and Reading, 2014).

Finally, the model is fit to the Random Forest classifier and a classification image is produced. It is acknowledged that with pixel based classification, the 'Salt and Pepper' effect is commonly visible when working with Random Forest classifier, therefore, a filter was applied. A pixel threshold is set as the filter works by removing polygons comprising pixels smaller than the threshold and replaces them with the class of the largest neighbour polygon (QGIS documentation). Threshold was assigned by choosing random samples of the classification image, and visually verify the resulting classified classes with the high-resolution image.
The analysis is conducted using QGIS and R using the RandomForest package.

3.4.2 Post-classification change detection

This approach differs from the latter in the image processing step only. Pre- and post-images are classified separately, and two separate training shapefiles are created with the damage class included only in the post-event image. Two models are fit, and two classification images are produced and compared by producing a change image and extracting the difference. The approach was visited as an attempt to check if the analysis will yield better results, however, it was dropped and the multi-temporal change classification was finally adopted for further analysis. This was mainly due to the nature of the event, in the case of the Beirut explosion, where the damage layer did not exist in the before images, which differs from other phenomena where adopting the approach might have yielded better results e.g. area of deforestation, water flooding, etc.

3.4.3 Manual Detection of Damage in the Case of Beirut

Reported observations datasets from different NGOs were published on 'Open Map Lebanon' as an attempt to facilitate data collection, data sharing and deliver a better response. Since datasets were prepared by different bodies, the lack of a unified assessment criteria generated different metadata, therefore, few datasets were dropped due to irrelevant information e.g. observations did not reflect on building damages - relevant to the study- but on injuries (Lebanese Red Cross), non-geolocated observations ('Nusanad' and 'Rebuild Beirut' datasets). The datasets are visualised in Figure 3.5 and a Flowchart summarising the methodology steps is shown in Figure 3.4.

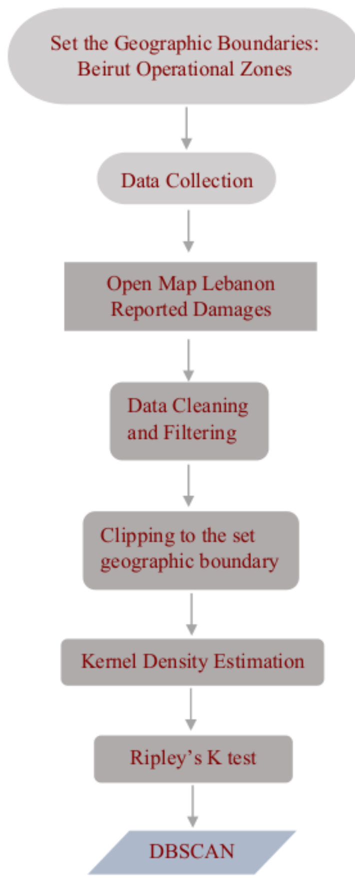

Figure 3.4: Methodology Flowchart showing the progress of detecting a pattern from the reported damages observations data and performing the DBSCAN.

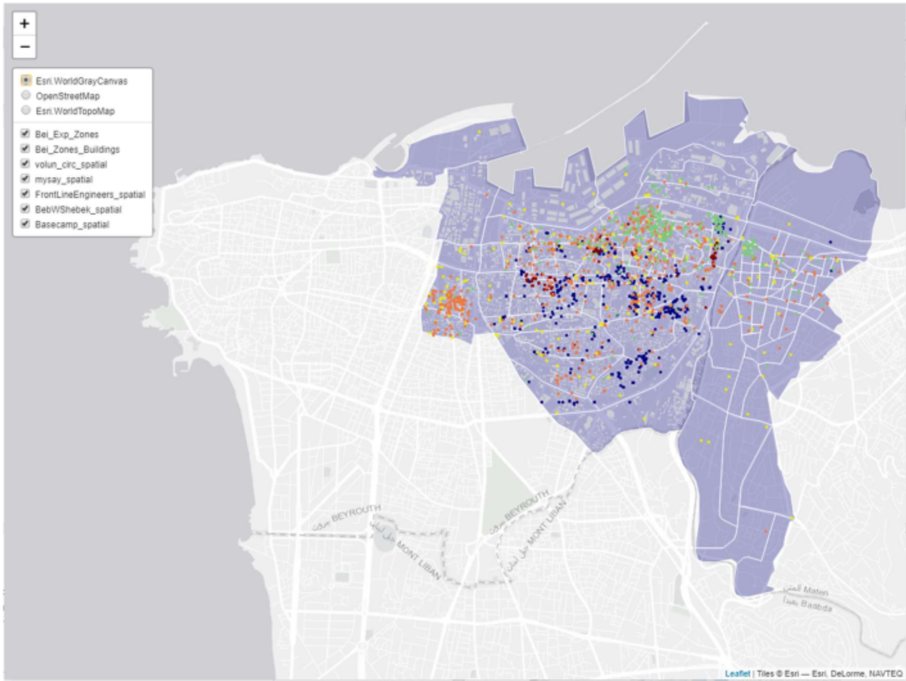

Figure 3.5: Interactive map showing the NGOs reported damage observations. Due to the difference in reporting, few datasets were dropped. The datasets are cleaned to display only damages and grouped by NGO. Map can be accessed on: https://rpubs.com/SaraMoatti/810671

A Kernel Density Estimation to look for any possible spatial patterns is plotted (see Appendix B). A reported damages pattern is observed with a dominant large cluster comprising several groups of observations. To verify that the clustering of observations is not random, datasets are fit in a Ripley's K test (see Appendix C). The test shows that all data was above the Poisson assumption of Complete Spatial Randomness, therefore, damages are not randomly distributed (Boots & Getis, 1988).

Finally, a Density-Based Spatial Clustering of Applications with Noise DBSCAN is performed to locate the clustering of observations. Based on the results of the Ripley's K test, the epsilon was then specified to 100m being the highest distance value with minimum cluster points selected to 30 reported damages.

3.5 Ethical Considerations

For this study, open-sourced data is used to assess the effect of having Satellite Data freely available in the public domain, especially when operating in a critical humanitarian context and limited resources conditions. The optical Satellite data from the commercial agency, MAXAR Technologies, were made available online and were made publicly accessible as an exception, as part of their Open Data Program to help assist the relief efforts in specific disastrous events. As the damage can be detected on residential blocks, the crowdsourced data will not allow the identification of any specific individual. Moreover, the crowd-sourced photos from Mapillary mentioned in the discussion to further validate the result, see section 5.2, recorded only damaged infrastructure and did not capture residents and human casualties. This is granted as the application blurs the faces of individuals and vehicle license plates and other information that contain personal information.

This research was conducted taking into consideration the aforementioned considerations and was not subject to UCL ethical approval.

Chapter 4

Results

The multi-temporal change classification is performed on the high-resolution imagery in order to extract the damages. The random forest algorithm produced 500 trees using the training data which is the polygons Shapefile that was created to help classify the pixels. Different classes were identified in the imagery to help detect the damage caused by the explosion. The classification performance was improved by increasing the training dataset size so the algorithm has enough data to identify different classes, and increasing the number of pixels gradually that were used in the training data, as all pixels couldn't be used due to the computation challenge. One of the Satellite data challenges is the size, which can limit the processing, especially when using local machines. Results' accuracy is assessed following multiple tests and will be discussed in section 4.1.

Following several attempts of altering the training data size and pixels, the final model's performance is discussed in the following section, using different statistical indicators and accuracy index. Moreover, the reported observation analysis results are presented in this section as well.

4.1 Accuracy Assessment

In land classification studies, the most reported accuracy measure is obtained in the form of an error matrix, known as well in the literature as confusion matrix, as it is deemed to provide a standardised foundation for the accuracy assessment (Campbell, 1996). It is used to calculate several descriptive and analytical statistics (Foody, 2001; Manandhar, 2009). Where numerous methods were developed to interpret and assess the classification results and with the absence of a standardised methodology, the model results were assessed and improved following Giles Foody's paper on the assessment of land cover accuracy methods (2001) where the following figures were reported the most used in the literature to assess the classification accuracy. The percentage of pixels allocated to the correct class, defined as accuracy, is calculated for the whole classification and reported as overall accuracy. In addition, it is assigned for each class, and divided into user and producer accuracies (Campbell, 1996; Janssen & Van Der Wel, 1994). Moreover, it is found that the percentage of correctness of classes, whether overall accuracy, user accuracy or producer accuracy, have been criticised when reported on their own, as it is argued that the randomness nature of the samples' selection might lead to allocating classes correctly by chance (Pontius, 2000). Therefore, Cohen's kappa coefficient was also calculated to compensate for the change agreement that was recommended by Smits et al. (1999) to be adopted as a standard assessment measure (Foody, 2001). These figures provide a practical allocation of the errors which helped improve the performance of the classification and generate better estimates and results.

In the first trial, a training shapefile was generated to be used as a reference class and guide the classification. Afterwards, the model was improved by assessing the results accuracy using the figures discussed earlier that allowed the identification of several elements that increased the errors in allocating the pixels to correct classes. For example, the class error rate highlighted which classes needed more samples to be added in the training shapefile. On the other hand, the overall accuracy and Cohen's kappa coefficient provided a holistic review of the classification and increasing the samples pixels used from the training data yielded better results. Moreover, the algorithm performed poorly with building heights and shadows as the acquisition angles differed between the before and after images. In order to overcome this issue, a "height and shadow" class was added to reduce the confusion which improved the overall performance. Table 4.1 shows the improvements following four trials.

Table 4.1: Model Performance Improvements following four trials

Trials	Overall Accuracy	Kappa Coefficient	Pixels Nb. selected in Training Samples	Description
Trial 1	60%	0.50	200	Classes were created except the 'Height & Shadows'

Trial 2	65%	0.56	200	Height & Shadows' class is added
Trial 3	66%	0.57	300	More sample polygons for each class are identified
Final Model	72%	0.65	800	Nb of Pixels set to maximum, higher number could not be set due to computation challenges

In the final model, an overall accuracy of 72% is achieved. In other words, the algorithm was successful in assigning 72 in 100 pixels accurately in the correct classes. This result combined with a 0.65 kappa measuring the agreement between classification and truth results, is deemed acceptable (Pham et al., 2014; Foody, 2001). Noting that the overall accuracy is an average and does not reveal if the error was evenly distributed between classes, a deeper verification was needed. Congalton simplified the notion of accuracy in his review of classifications accuracy of remote sensed data (1991) where the error of commissions and omissions were calculated. Afterwards, the producer's and user's accuracy are extracted (see Table 4.2).

Table 4.2: Final Model Classes Accuracy Figures

Class	**Error of Omission**	**Error of Commission**	**Producer's Accuracy**	**User's Accuracy**
Water	20%	1%	80%	99%
Severe Damage	35%	33%	65%	67%
No Damage	39%	48%	61%	52%
Greenery	18%	17%	82%	83%
Heights & Shadows	30%	38%	70%	62%

Following Congalton's interpretations, water and greenery had higher accuracy producer and user accuracies. Initiating from the classification's main objective of identifying damages, the target class is the 'severe damages', therefore, the accuracy of this specific class is deemed an indicator in assessing the classifier's performance, not the overall accuracy solely, as the latter can be skewed by the high figures achieved by the greenery and water as mentioned earlier.

From the perspective of the user of the classified map, the user's accuracy of severe damages is 67%. In other words, although 65% were correctly identified as severe damage by the algorithm (producer's accuracy), 67% of the areas are severe damage. The difference between the two figures is deemed low, therefore, there is no significant confusion in discriminating the damages between the classifier and the actual damages. Therefore, the classifier is considered helpful in identifying the severe damages, as the classified pixels were close to the existing conditions (Congalton, 1991).

The variables used to predict the classes are the Red Green Blue (RGB) stacked bands extracted from the before and after the explosion optical satellite images. The mean decrease Gini and the Mean Decrease Accuracy reflects the variable importance. The mean decrease Gini positive range of all bands is deemed low (around 200), with bands 1 and 2 (from the before image) and 6 (from the after image) having the higher value. Same applies for the Mean Decrease Accuracy with a positive range of 50 with bands 1 and 3 (pre-) and 6 (post-) having the higher values (see Appendix A). Therefore, all bands were included in the classification and deemed useful in classifying the pixels and no band was omitted. Finally, Figure 4.1 shows the final model's 'severe damage' class projected on the MAXAR optical image.

Figure 4.1: "Severe Damages" Class extracted following the Random Forest classification with the Sieve filter applied, and projected on the Optical Satellite image downloaded from Maxar dated 31st July.

4.2 Observations DBSCAN Clusters

DBSCAN results are shown in Figure 4.2, and ten clusters were identified. The four largest clusters are located in proximity to ground zero. Following Diaz Alonso's interpretations of shockwave damages due to the nature of disaster, an explosion, the damage is negatively correlated with proximity, where distance is an essential parameter (Diaz Alonso, 2006). Moreover, the four largest reported observations clusters were concentrated in highly dense residential area. This might be due to lower urban densities on the coast, where less damages occurred or were reported. In addition, damages are less likely to be reported to NGOs due the typology of buildings in the coastal area, being the port, public buildings, and related services.

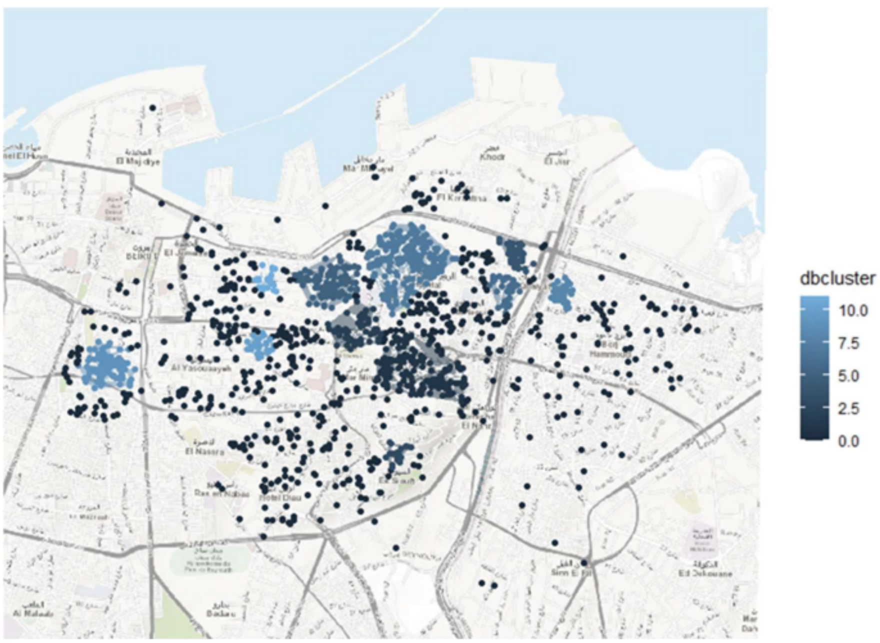

Figure 4.2: Reported Damage Observations clusters following the DBSCAN. Ten clusters are identified with the four largest clusters located in front of the port.

It is worth noting that due to the difference in the reporting process and within the absence of a unified assessment criteria between the NGOs that were operating on the ground in the case of the explosion, reporting and operations aiming to survey and report damages are not systematic which affected the dataset building.

In summary, the Random Forest classification yielded acceptable results when assessing the model from the perspective of statistical indicators and accuracies. In the next section, the automated information extraction method is compared with the manual methods (the reported damage observations results) and the discussion is further extended to assess the results from an efficiency perspective, especially when operating in disaster management contexts where time is crucial. Moreover, the results are further evaluated by proposing a practical validation framework. Furthermore, the research conclude by highlights several local and international policies to underline the need of adopting an efficient data-driven response.

Chapter 5

Discussion

In this chapter, the results presented earlier are discussed in line with the main study aim of how to benefit from available satellite imagery in accelerating the immediate post-disaster response, allocating the severely impacted areas and guiding the relief. Moreover, on-ground results validation is addressed from a practicality and efficiency perspectives in a country that is facing one of the most severe economic crises in the 21^{st} century. Finally, the research is positioned in the wider context of local and international policies highlighting the need of a data-driven response through the creation of a local disaster management plan.

5.1 Interpretation of Classification

The results presented in the previous section demonstrate that the Random Forest classifier was able to capture building damages in a comparable accuracy range achieved by numerous studies conducted on automatic detection of building damages (Pham et al, 2014). As argued by Foody (2001), the classification will certainly not achieve 100% accuracy and emphasised the importance of contextualising the results, as some classifiers can yield different results when used with different datasets or assigned different classes. Moreover, within the absence of a standardised reporting of the accuracy assessment, Smits et al. argued that the outcome of the classification is highly influenced by 'the subjectivity inevitably induced by the choice of the classification scheme (labels), the training samples (in the case of supervised classification), and the reference data sampling size and strategy' following a quality assessment of image classification algorithms (1991, p. 1463). Consequently, as long as the classification process is clearly reported and the results are well interpreted and transmitted to the user, especially when operating in a humanitarian disaster management, the classification results are deemed valuable within the context (Foody, 2001). In the following subsections, results are discussed according to the latter.

5.1.1 Automatic Detection vs. Observations

This section expands on the results of the classification and investigates beyond the technical accuracy and outcome presented earlier in section 4.1, to reflect on the main objective of the study of assessing the effectiveness of integrating satellite data in damage detection and guiding the relief. Previous work developed by Hölbling et al. (2017) performed a detailed evaluation of manual and semi-automated mapping methodologies using Optical Satellite Images of landslide prone areas mapping in the Alps. The paper concluded that both methods have similar accuracies that varied between study areas, as five different regions were selected. However, subjectivity and time consuming were among the main characteristics of manual information extraction discussed whereas 'the use of replicable classification rules' -referring to the semi-automated method- delivered a more transparent approach (Hölbling et al., 2017, p.17). Initiating from a similar approach -where the manual and the automatic methods in this research represent the reported observations gathered by the NGOs and the classification results respectively-, the 'severe damage' class is extracted from the classification results, and a density analysis in operational zones is performed as shown in Figure 5.1. Simultaneously, reported damages density is calculated as well and shown in Figure 5.2.

In comparing Figures 5.1 and 5.2, almost all the damage observation clusters overlapped with the highly damaged zones extracted from the classification analysis. However, in line with D. Hölbling et al.'s findings on limitations related to long processing times (2017), it is worth mentioning that when discussing the effectiveness of a method in comparison to another, time is crucial, particularly in the disaster management field, where a delayed identification of a risk can have enormous impact on the affected population. Therefore, the aim of the research is not limited to detecting the damaged buildings solely, but doing so in a timely manner, without overlooking certain areas. The model was successfully able to do the latter as demonstrated.

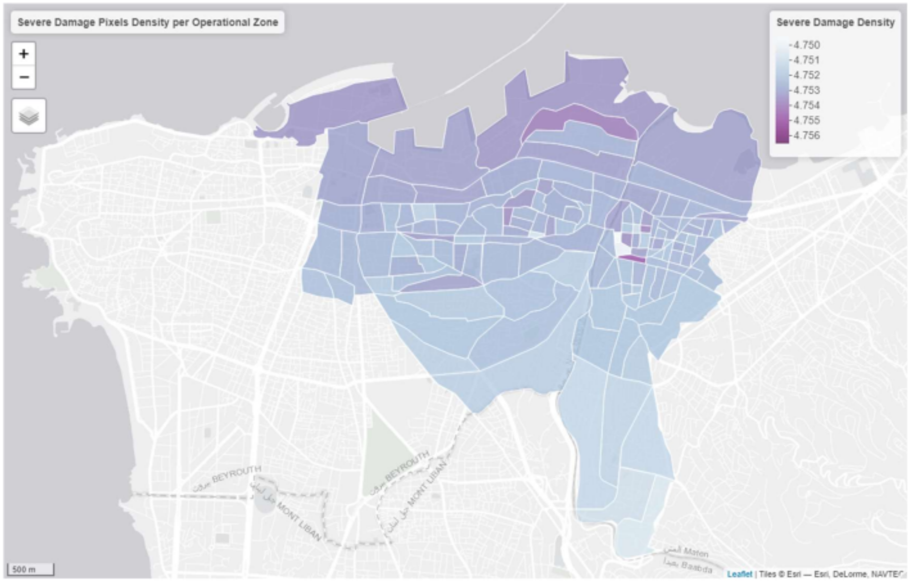

Figure 5.1: Severe Damages Pixels Density per Operational Zone. Density is calculated using the 'Severe Damage' class pixels count obtained from QGIS using the zonal statistics plugin. Map can be accessed on: https://rpubs.com/SaraMoatti/810736

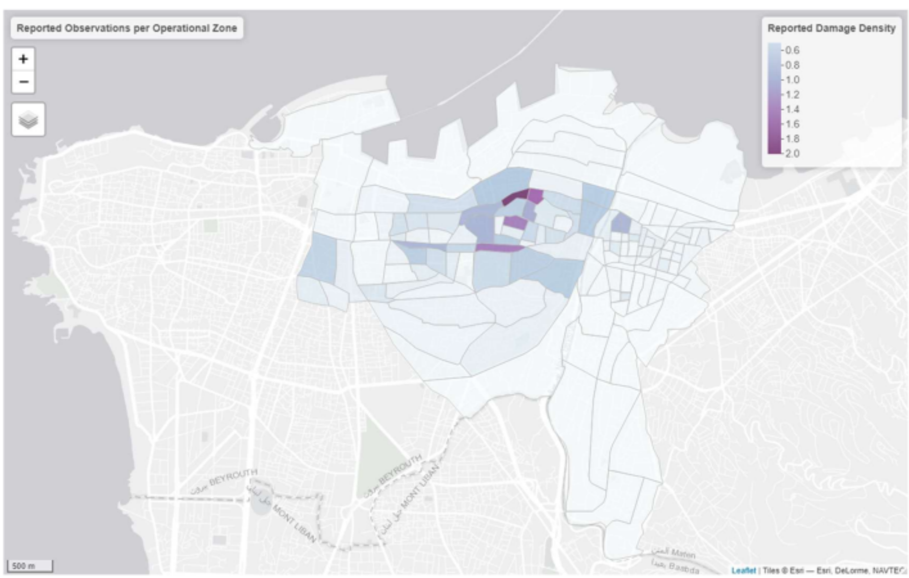

Figure 5.2: Reported Damages Observations Densities per Operational Zone. Reported damages observations densities were calculated using the Open Map Lebanon datasets. The data was mainly collected by volunteers and surveyors and organised by different NGOs. The process lacked a unified reporting criteria which made few datasets to being disregarded (see section 4.2. Map can be accessed on: https://rpubs.com/SaraMoatti/810671

On the other hand, it is observed that the detected damages by the Random Forest classifier were validated by the surveys data, however, the opposite is not entirely accurate. In the case of Beirut, where severe damages were captured by the algorithm in the port and the north-eastern areas. However, the DBSCAN results (see Figure 4.2) indicates that reported observations clusters were located in front of the port area, with little to no reported damages in the port and the north-eastern areas. First, this is partially due to some non-residential areas like the port, therefore, no reporting was done as discussed in section 4.2. However, another reason is related to the sensitivity of some of the locations. Following a deeper analysis on the localities of the area, in the first fortnight of the explosion, areas like “Karm el Zaytoun” and “Karantina” -located in the northeast of Beirut- were declared as crime scenes as they were in proximity to military points, therefore, access was restricted which prevented the surveyors from entering the areas, which led to fewer observations reported. Therefore, the research extends on Hölbling et al.’s findings and demonstrates that accessibility can be a limiting factor when adopting traditional surveying methods of the damages as they failed to allocate great areas of severely affected zones that were successfully identified by the algorithm.

Further, Pham et al. highlighted the issue of identifying damages in building structures in their paper following the 2010 Haiti earthquake as the automatic detection of building damage yielded less accurate results than manual mapping (2014). On the contrary, in the case of Beirut, with the absence of a unified damage reporting criteria, little metadata was extracted from the traditional surveying methods therefore, the automatic detection was able to detect the overlooked areas. However, in an ideal situation, manual detection of damages can provide valuable insights and metadata and provide a complimentary approach to machine learning classifications. The following section expands on the latter and propose a holistic methodology that is deemed effective for the response.

5.2 Model Validation through a Practical Framework

Where visual validation is widely used to verify the classification results, especially when using the high-resolution optical images, a robust validation of the classifier performance was needed. Van Western accentuated the latter stating that ‘Remote sensing data should generally be linked or calibrated with other types of data, derived from mapping, measurement networks or sampling points, to derive at parameters, which are useful in the study of disasters.' (Van Westen, 2000, p. 1613). Where reported observations clustering is deemed useful for validation, traditional inquiry methods and conducting surveys require an extended timeframe in situations where emergency resources are often insufficient (Yuan and Lui, 2018). Therefore, a versatile tool is proposed to help in achieving the holistic objective of effectively integrating remote sensing in assisting the relief. Volunteered Geographic Information (VGI) term was first introduced by Goodchild, 2007 and defined the notion of having the 'Citizens as sensors' (Goodchild, 2007, p.211).

Although crowdsourcing has emerged in recent years (Besaleva & Weaver, 2013), the available tools are mostly used in the context of coordinating the emergency response and not often extended to the post-response. Schnebele & Cervone proposed to improve the remote sensing analysis by integrating crowdsourced data as a validation tool and produce a more accurate and comprehensive flood assessment (2012), however, this approach was applied exclusively in flooding management and monitoring. This research proposes the integration of VGI in the remote sensing enabled disaster management as a practical validation tool to calibrate the classification's result.

In that sense, Mapillary was used after the blast by ground volunteers[16] that took photos on a street-level in the affected areas as part of an initiative organised by volunteers to create an archive for the damaged areas after the blast. The photos are georeferenced and publicly available. It is worth acknowledging that faces of individuals and vehicle license plates or any personal information visible in the captured images are automatically blurred by the developers.

Figure 5.3: Screenshot taken from Mapillary's website accessed on September 1st 2021 for the upper 'Route Gouraud' and lower 'Route Pasteur'. The crowdsourced data is freely available on the website.

[16] in the case of Beirut, mobiles were used. Ultimately, drones can be flown on low height and connected to the Mapillary app.

Projecting on this research, the effect of integrating the crowdsourced open data to validate the model is assessed and a novel way of incorporating the tool in the disaster management is proposed. Two case study streets, 'Route Gouraud' and 'Route Pasteur', are selected to allow the comparison of the on-ground damages with the classified ones. First, Figure 5.3 shows a screenshot of Mapillary website. The dots represent photos captured along with the direction of the shot. In addition to the photos being geolocated, images are dated, which helps in not only capturing the damage after an event, but to monitor the reconstruction on the medium to long term.

On the other hand, there is very limited research and applications on the integration of VGI in damage assessment analysis. Yuan et Lui highlighted the latter in 2018 when assessing the geolocated social media data and damage data at the county level in Florida following the Hurricane Matthew, and identified critical affected areas. Similarly, the proposed tool does not only verify the classification results, but helps in highlighting the geographic distribution of damages which can help the authorities in the response prioritisation.

In general, the tool was successful in validating the existence or absence of damages, thus, validating the result and the performance of the classifier in a systematic way that can be easily adopted during disaster management. However, for the specific incident of the Beirut explosion, a further holistic investigation might have been essential due the following factors. The algorithm was set to only classify severe damages, as minor to moderate façade damages like shattered glass, wood and door breakage, vertical facades damages like masonry and concrete breaks (see Figure 5.4) are difficult to capture. This is caused by the vertical view angle of satellite images that captures the horizontal planes well and performs poorly in capturing details on the vertical elements. Moreover, where the resolution of images is considered high (1 m), it did not make building debris like glass, door frames and windows visible on a single building scale, as large debris where only captured around the port and the adjacent highway. Consequently, where the crowdsourcing integration helped in identifying the damage extent in line with Tyan et Lui's paper and validating the classification results following Schnebele & Cervone's recommendations, the research expands on the latter by highlighting the tool's ability to uncover missing data and providing a detailed level of metadata. For example, Shot C represents a severely damaged building that was not captured by the classifier. Therefore, the overlooked damages can be used to improve the classifier performance and in the relief distribution. An improved framework would have been similar to the one proposed by Pham et al., where manual (Reported Observations) and automatic detection methods (Random Forest Classification) were conjointly used, with an addition of the volunteered geographic information (Mapillary), ultimately, yielding better metadata (Pham et al., 2014).

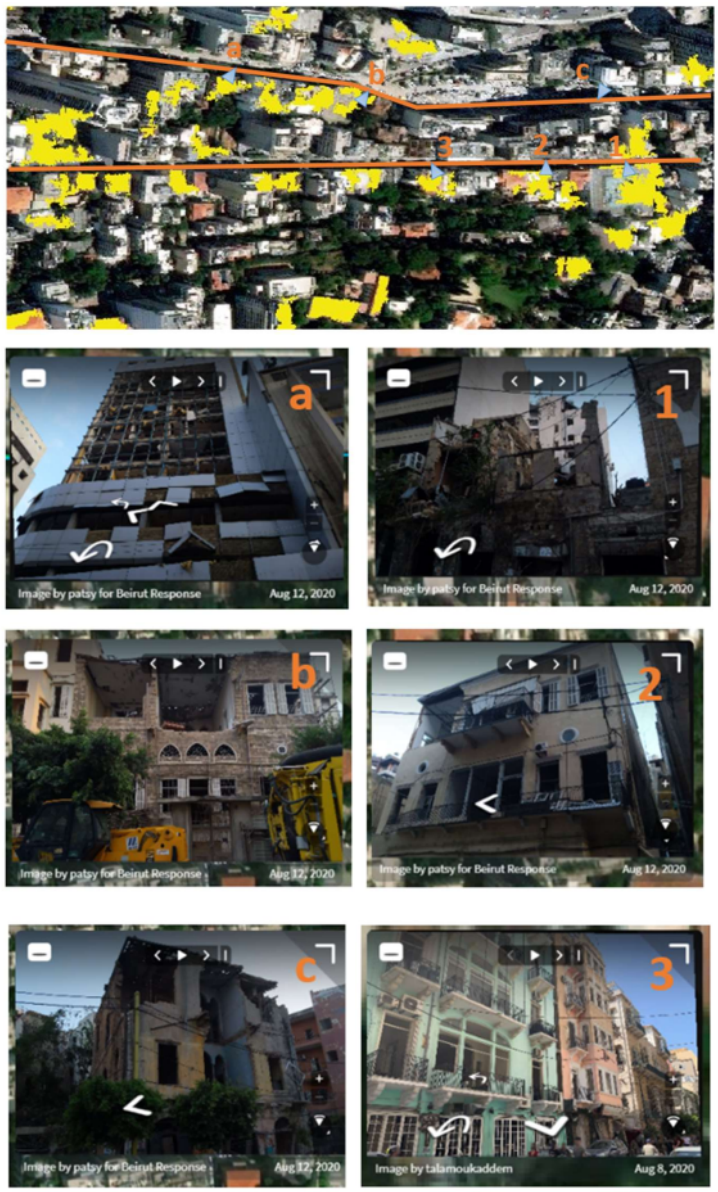

Figure 5.4: Classification results validated by Mapillary photos. The 'Severe Damage' class is shown in yellow. Random samples were chosen and were validated by the Mapillary photos captured after the explosion.

5.3 Towards a Rapid Automatic Detection of Building Damages using Remote Sensing for Disaster Management

Initiating from the local context of the event, as part of the World Bank efforts to bridge the humanitarian response and reconstruction efforts, The Lebanon Reform, Recovery and Reconstruction Framework (3RF) was developed following the explosion in 2020 (World Bank, 2020). Based on the results of the classification, the analysis conducted in the research directly helps inform on one of the main pillars of the framework, infrastructure reconstruction. As the automatic detection methodology was successfully able to identify damaged buildings, the research provides a quantitative base for the relief operations on a micro level, especially when the event is impacting high density urban areas where buildings are the main infrastructure element.

Expanding to a macro level, Van Westen acknowledged the importance of allocating the affected areas known as hazard zonation mapping stating that it 'must be the basis for any disaster management project and should supply planners and decision-makers with adequate and understandable information.' (Van Westen, 2000, p.1612). The paper extends and argues that the process typically implicates large volumes of data that are deemed 'clearly too much to be handled by manual methods in a timely and effective way.' (Van Westen, 2000, p.1612). Indeed, the methodology discussed in the research benefits from the relatively short processing period required to conduct such analysis -in comparison to traditional surveying methods- which can potentially accelerate the response in periods where time is crucial.

Expanding to a complimentary approach, incorporating remote sensing and machine learning methods in assessing the progress of the Sustainable Development Goals (SDG) have been recently discussed (Holloway et al., 2018). In 2017, the United Nations Task Team on Satellite Imagery and Geospatial Data discussed the viability of producing official statistics, including statistics related to SDGs using Satellite data (United Nations, 2017). Likewise, the Group on Earth Observation (GEO) in their report 'Earth Observation in support of the 2030 Agenda for Sustainable Development' identified that earth observation can be used to measure and monitor the Sustainable Development Goals (GEO, 2017). According to the report, one of the measurable criteria that benefit from integrating the earth observation in the management process is related to ‘Hazards, disaster and environmental impact monitoring’ where this study is focused. In the case of Beirut, in addition to the occurring physical damage, the explosion exposed the country’s vulnerable position within the absence of an organised response which underline the need of an organised response.

In summary, benefitting from the publicly available data and algorithms to guide the response and prioritise the relief through employing an automatic information extraction on the case of Beirut explosion to identify the severe damages was deemed effective, especially when operating in limited resources and restricted accessibility events. In addition, the research integrated crowdsourced volunteered geographic information to validate the classification accuracy as part of a practical framework to be adopted during disasters. Ultimately, the study is intended to be used as an example case for introducing a local disaster management policy in Lebanon. This was supported by underlining local and international policies to demonstrate the urgency of adopting data-driven approaches and integrating remote sensing methodologies in the response.

5.4 Limitations

While the research offers valuable insights on the benefit of the automatic detection of damages in the Beirut Port explosion case, several limitations are observed. First, the Random Forest algorithm results are often affected by the user’s input, especially when designating classes to the training Shapefile. Moreover, the research did not distinguish between different degrees of damages as the Random Forest classifier was successful at detecting only severe damages. Where the automatic information extraction from satellite data methodology is promoted, other datasets such as high-resolution Radar data, if available, and different classification algorithms might have yielded different results. Therefore, a generalisation of the algorithm outcome on all datasets and events must be avoided. Finally, the validation tool discussed in section 5.2 relies heavily on the availability of photos captured ideally by drones, or using smart phones, which can be deemed challenging especially in less advantaged countries where these tools are not accessible. Moreover, future improvements can include automating the Mapillary validation photos through the integration of an image recognition technology that helps in detecting the damages such as glass breakage automatically.

Chapter 6

Conclusion

While automatic information extraction from satellite data has been widely developed and applied in different disciplines, the integration of the methodology in the disaster management is still relatively novel (Holloway et al., 2018). Through this work, a methodological framework is proposed, that can be adopted as part of an organised disaster management strategy, where limited resources countries, like Lebanon, can benefit from the freely available open-access spatial analysis methods and resources to increase its preparedness towards hazards, and ultimately the city's resilience. This work explored the accuracy and practicability of employing such methodology using the Beirut Port Explosion as a case study.

The research implemented a pixel-based damage assessment imagery following Dell'Acqua et al. (2011). It adopted an automatic detection of building damages following the Beirut Port Explosion to explore its feasibility in optimising the emergency response. Random Forest algorithm was used for the pixel-based classification of the high-resolution optical satellite data. The methodology outcome is compared to the developed methods following the blast and damages identified from traditional surveys and reported observations. The study proved that incorporating an automatic damage extraction translated the reality of the post-disaster where the classifier results overlapped with the reported damages simultaneously, several limitations and improvements were recommended. Achieving the latter in relatively shorter periods, using open data and methods, increased the efficiency of adopting such approach in the disaster management process.

Further, where results accuracy assessments remain controversial and widely debatable in the absence of a standardised framework used for validation, the research proposed a practical tool that would help in not only the validation of results, but in monitoring of the response in the medium to long term. The crowdsourced tools are proved beneficial responding to the absence of an organised response strategy in the case Lebanon. The analysis conducted here shows that the same process can be adopted in other limited resources contexts, particularly in humanitarian mapping contexts to increase the existing operations efficiency through reducing processing periods, lowering operations cost and manpower.

Furthermore, the research is positioned within the local and international disaster management policies where main recommendations are projected on the specific event of the Beirut explosion. Therefore, the contextualisation of the research findings further helps in extending the urgency of integrating rapid and efficient spatial analysis tools in the country's strategies and improving future operations through remote-sensed enabled development planning and methodologies. Initiating from the latter, the research aspires to use the applied approaches as an exemplar to demonstrate the need of a new model, in this case, an organised disaster management unit that benefits from the integration of remote sensing data in the different phases of response, as underlined in the 3RF report 'Lebanon must develop a new governance model, turning the crisis into an opportunity to restore confidence in state institutions and build back better. This will require that the government takes responsibility for delivering on the recovery and reconstruction, while adopting a different approach by working collaboratively with civil society and the international community' (2020).

It is hoped that the research will be regarded as a foundation for data-driven disaster management applications profiting from the statistical and technological advancement of machine learning algorithms. Future work would employ the proposed methods in different contexts related humanitarian mapping, e.g. from mapping refugees camps, to assessing vulnerabilities through economic activities captured by night satellite data, expanding to land use and vegetation monitoring. On the other hand, this study does not intend to limit the application to the classifier used -RandomForest- however, it promotes the automatic information extraction as a whole, where exploring different classification algorithms and methods is recommended. In Lebanon, informing decision making through data-driven approaches is at the heart of the reform that is endorsed and is one of the 3RF pillars. Adopting such approaches is aspired to be the drive towards promoting structural changes, controlling the collapse that the country is facing, and ultimately, elevating Lebanon on the path of sustainable development.

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Appendix A

Random Forest Variable Importance

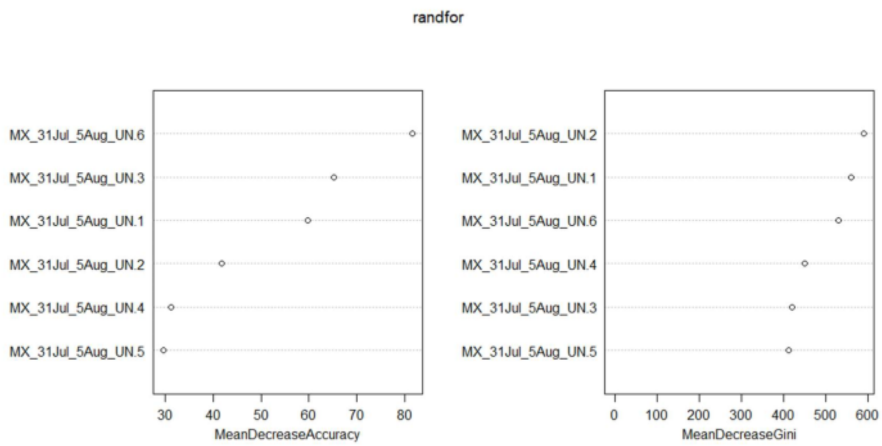

Figure A.1: Mean Decrease Accuracy & Mean Decrease Gini generated by the RandomForest package in R. The plots show that the accuracies are positive and the range of both indicators is relatively low, therefore, all bands were deemed useful for the classification and were kept in the different trials and improvements attempted.

Appendix B

Kernel Density Estimation

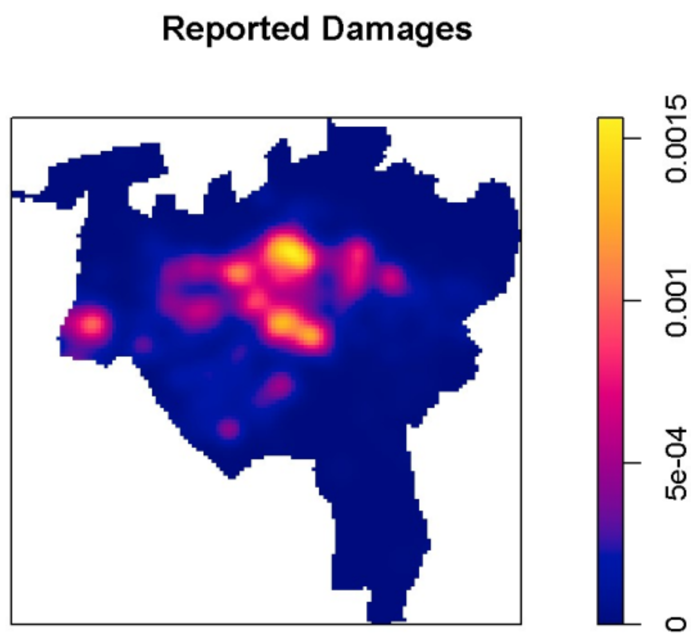

Figure B.1: Reported Damages Observations Kernel Density Estimation Plot. A concentration of high density damages is observed in the centre of the operational zones boundaries, mainly in the areas directly facing the port where the explosion ignited.

Appendix C

Ripley's K test

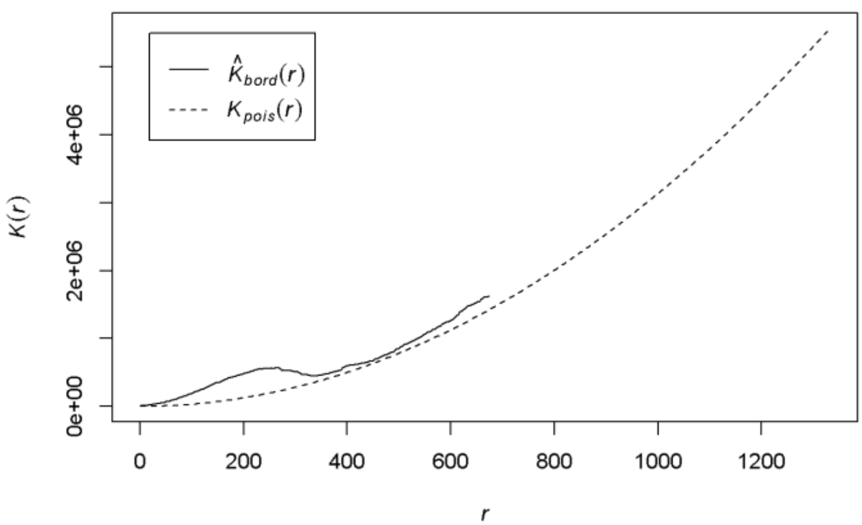

Figure C.1: Ripley's K test is performed on the Observations dataset to compare the observed distribution of reported damages with the Poisson random model for a whole range of different distance radius. The plot helps in setting the epsilon value to be used for the DBSCAN, and it is set at 100, where a sharp increase in the radius is observed.

Appendix D

Research Log

Date	Tasks
April	Setting the context of the research
April 22nd	Checking with Andy and pitching the idea. Formulating potential research questions, objectives and aims
May	Elaborating on the proposal and exploring methodologies that could be used for the research as new techniques were explored
May 20th	Reviewing the conceptual framework of the research with Andy
May 26th	Working on machine learning classification tutorials to improve the technical side of the research
June	Working on literature review and research methodology
June 7th	Extensive research on previous work and methods applied to similar contexts
June 14th	Deciding on the final algorithm to be used for the classification
June 21st	Drafting the literature review
July	Methodology progress summary
July 5th	Meeting with Andy on the methodology progress and sharing the classifications results
July 12th	Trying with different datasets
July 21st	Meeting with Andy and sharing the Literature review and introduction sections. Discussing the comments and possible improvements and additions

August	Developing the Methodology and Results sections and reviewing the previously submitted ones in parallel
August 9th	Improving the classification model through research and trials
August 16th	Developing Results sections and including the reported damages observations DBSCAN analysis
August 27th	Meeting with Andy to discuss the reviewed sections including results and discussion sections. Receiving recommendations and improvements.
September	Wrapping up and improvement on the discussion and conclusion sections
September 9th	Final draft sent to Andy and received final comments
September 13th	Wrapping up and amending the final comments received on the discussion section