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A Rapid Post-Hurricane Building Damage Assessment Methodology using Satellite Imagery

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Abstract: *In the immediate aftermath of a hurricane, rapid and reliable assessment of building damage is critical. The timely delivery of such information is essential for emergency responders to identify those areas that are severely impacted so that they can act accordingly. This step is crucial for saving lives and reducing economic losses. This paper demonstrates the potential of Remote Sensing for rapid building damage detection using an automated approach in small island states in the Caribbean. Object-Based and Pixel based methods were compared with visually identified reference information from high resolution imagery for the 2004 Hurricane Ivan impact on Grenada. The efficacy of the Object-Based approach is demonstrated using image segmentation and classification in eCognition Developer Software. This approach utilises not only the spectral content but also the context, morphological and textural properties of image objects. In relation to the reference data, the object-based method achieved over 85% classification accuracy among a three damages grade classification scheme in two separate scenarios with different study area extents.*

Keywords: *Hurricane Ivan, Rapid Assessment, Building Damage, Object-Based Classification*

1. Introduction

The Economic Commission for Latin America and the Caribbean (ECLAC) reports that the Caribbean has been impacted by more than 165 natural disasters since 1990, resulting in estimated losses of more than US$136 billion. With the likely increase in extreme natural disasters in years to come, especially in light of global climate change and sea level changes, Caribbean islands are increasingly challenged to give serious consideration to all matters relating to natural disasters (ECLAC, 2011). In the aftermath of natural disasters such as hurricanes or earthquakes, assessment is one of the first actions that usually take place. In this context, assessment refers to emergency response in which data is collected and analysed to get an impression of the extent and severity of damage and loss. These assessments must be done in a timely and accurate manner for effective response (Gusella, Adams and Bitelli, 2007).

Rapid detection and accurate assessment of damage and loss depend mainly on factors such as the quick identification of impacted areas, access to those impacted areas and efficient tools and techniques used to collect and analyse damage data. A higher priority is usually placed on assessing building damage, since these structures house the population and population represents lives that may be at risk (van Westen, 2013).

Traditionally, damage assessments have been conducted through ground-based field survey and aerial reconnaissance. These methods are not always safe, applicable, or cheap to execute (Kerle and Oppenheimer 2002). There is therefore a need for information, which does not depend on actual physical access to the disaster area. The objective of this paper is to develop a rapid post-hurricane building damage detection methodology to facilitate the timely acquisition of information to aid in post-disaster emergency response in Caribbean small island development states (SIDS).

2. Post Hurricane Damage Detection

Post-hurricane damage and loss assessments are conducted at various scales including: Global, Regional, National, City/Community and Building scale. There are several factors that influence what scale of assessment should be selected. van Westen (2013) suggests that these should be based on the objective of the assessment, the type of hazard and the operational scale whereby these hazard processes are set in motion and made manifest.

Building scale assessment provides the most amount of detail about damage and loss but is also the most time consuming. The assessment is carried out by local officials or certified engineers, and may require weeks to months to complete. The main outcomes are to determine an estimate of the recovery cost, structural integrity of buildings and approval for demolition, retrofitting or permission for continued use of buildings (CDC, 2010).

A summary of the Disaster Management Cycle is shown in Figure 1. The response, recovery, mitigation and preparedness stages are depicted in relation to an event. Rapid assessments seek to take place early in the response stage to assist in emergency activities while detailed assessments can potentially provide valuable information for restoration and activities. Collecting and storing detailed damage information is important (Friedland, 2009). However, rapid assessment should take priority during the emergency phase of disaster. A rapid damage assessment functions to estimate the magnitude and nature of damage, and to evaluate building conditions in a swift manner in damaged areas after the impact of a hurricane (Massarra, 2012). It may be noted that, while rapid assessments are less time consuming and generates significantly more building data than detailed assessments, the levels of detail and accuracy of the data collected are reduced. Figure 2 shows the relative difference between the results of rapid and detailed assessments for data collection based on the number of buildings, the time taken to collect information per building, the level of details collected and the assessment accuracy achieved.

Figure 1. Disaster Management Cycle
Source: Abstracted from Quora (2018)

Data required in post-hurricane disaster management has an important spatial as well as a temporal element. Remote sensing combined with Geographic Information Systems (GIS) has proven to be of significant importance for the different phases of disaster management (Barrington et al., 2011; Vatsavai, 2011; van Westen and Hofstee, 2000; World Bank, 2010; CHARIM, 2016; Tu et al., 2016). Remotely sensed data may provide the most rapid post-disaster data. These data are particularly useful in disaster response, especially for severely impacted and inaccessible areas (Yamazaki, Vu, and Matsuoka, 2007).

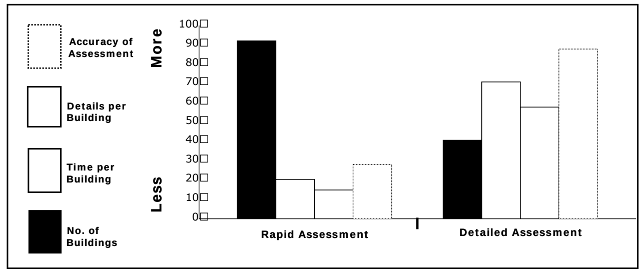


Figure 2. Comparison between rapid and detailed assessments using four measures
Source: Massarra (2012)

Additionally, comprehensive multi-temporal coverage of large areas in real time and at frequent intervals is the main advantage of using remotely sensed data in post-disaster management (Ozisik, 2004). Various qualitative and quantitative methods can be applied to remotely sensed data to assess the damage near real-time and after impact of the hurricane (Vatsavai, 2011). However, remote sensing methods also present several challenges when compared to traditional methods. Key challenges include spatial, temporal and spectral resolution of the data available. Friedland (2009) adds, a remotely sensed damage method must also be verified against ground-based data in order to provide meaningful results.

During the emergency response phase of disaster, emergency managers need to make crucial decisions that would affect the lives of the impacted population. They need to know the geographical extent of the disaster, the damage distribution, and information about the status of infrastructure and critical facilities (Lindell et al., 2006). Table 1 identifies the critical geospatial and non-geospatial baseline data required for rapid damage and preliminary loss assessment.

After hurricane impact, rapid information concerning damage to infrastructure and affected regions is crucial for immediate response in terms of relief efforts and situation reporting. Whatever the method of assessment selected, certain key information products must be generated: (i) general building damage maps; (ii) damage to critical facilities including hospitals, shelters, fire services, police, utilities, and prisons and government offices; and (iii) damage to transportation facilities such as roads, bridges, hubs, airports, and ports are critical

3. Damage Detection Approaches

Building and other infrastructural damage usually manifest themselves as disturbed spatial or spectral patterns, detectable using optical remote sensing methods.

Table 1. Baseline Data for Post-Hurricane Damage and Loss Assessment

Data type	Description
RS Data	May include variety of pre and post aerial and satellite imagery options but not limited to, HR optical images and multiband optical sensors such as IKONOS (1m), QuickBird (0.6m), Worldview1 (0.5m), SPOT 6&7 (1.5m), Landsat 7&8. Active sensor data options such as Radarast-2 (1-3m), LiDAR (0.25-2m), TerraSar-X (0.25-3m)
Buildings	Predominant type (e.g. residential, commercial, industrial) construction material, type of roof, building height, building age, total floor space, replacement costs, age of building or structure, photo.
Critical Facilities	General location and number of facilities, including but not limited to, Emergency Shelters, Schools, Hospitals, Fire Brigade Stations, Police Stations etc.
Population	Density, distribution in space (parish, community, enumeration district), age distribution, gender distribution, disabled, daytime population, nighttime population, people per building, single parent households, low income groups.
Transportation Facilities	General location of transportation facilities including, Roads, Railways Public Transportation Routes, Harbor Facilities, Airport Facilities. General traffic density information, classification (main road, minor road etc).
Life Lines	Location of detailed network of life lines facilities such as Water Supply, Waste Water, Electricity Supply and Communication.
Environmental Data	Location and status of environmental assets including Ecosystems, Protected areas, Natural Parks, Forests, Marine environment.
Economic Data	Spatial distribution of economic activities, type of economic activities.
Agricultural Data	By parish or community - Crop variety, crop yield, crop cycle, agricultural buildings, fiscal activities, rate of employment
Administrative Boundaries	Location, names, of Parish, Community, Districts.

Source: Adapted from Planning Institute of Jamaica (2012)

There are several different methods that involve manual and automatic building damage detection using high-resolution satellite images. However, selection of a particular method requires an understanding of the damage characteristics displayed, which depends on the damage mechanism. In some cases, detection methods may be similar despite the damage mechanism (wind, flood, and quakes). Damage from hurricane events is mainly direct wind damage, which results in significant roof and structural impact and may also be subject to significant water damage due to flooding.

3.1 Visual Analysis

Visual analysis of an image is a traditional method that uses visual interpretation to identify features and damage characteristics through vision and perception. This form of analysis is costly since it is labour intensive, tedious, time consuming and always subject to error; especially if low-resolution images are used. However, when applied to high spatial resolution imagery it yields the most accurate and detailed assessments (Olwig et al., 2007).

3.2 Pixel-Based Image Analysis

Pixel-based image classification uses spectral data to classify the image by considering the spectral correspondence in distinct classes (Gao and Mas, 2008; Kim and Shan, 2007). Pixel based supervised classification can easily discern distinct spectral classes including water, buildings, trees, and bare land. However, high spectral variation within the same land cover class and the low spectral variation between different land cover types, make the classification difficult. Hay and Castilla (2006) argue that “traditional pixel-based image analysis is limited because image pixels are not true geographical objects and the pixel topology is limited, and pixel based image analysis largely neglects the spatial photo-interpretive elements such as texture, context, and shape.”

3.3 Object-Based Image Analysis

Object-based techniques have been developed as an alternative to manual digitisation through visual assessment and pixel-based methods (Laliberte, Rango, and Fredrickson, 2005). Land cover types including buildings, roads and parking lots have very similar spectral signatures and thus it is difficult to separate buildings through spectral analysis of high resolution images (Salehi et al., 2012).

Object-based image analysis (OBIA) allows the analyst to decompose the scene into many relatively homogenous, continuous, and contiguous image objects or segmentation. Three (3) main approaches to segmentation include thresholding, edge-based methods and region-based methods. Research has focused on multi-source classification which incorporates ancillary data including LiDAR, DEMs and vector data (Watanachaturaporn, Arora, and Varshney, 2008; Zhang, 2010; Tuia et al., 2010). As a result, there is reduced mis-registration between different objects/layers in the scene. Multi-source classification however, may be problematic due to the lack of co-registration of layers.

OBIA was used to classify building damage from post-hurricane image by developing rule sets to detect damaged building feature values and thresholds that indicate their various levels of damage. The first step is a multi-resolution segmentation, which groups areas of similar pixel values into objects. Subsequent refinements exploit the content (scale), context (shadow and contrast) and morphological (shape) image object information. To do this, a hierarchical rule-set framework was executed in eCognition® Developer software using Cognition Network Language (CNL) (Definiens, 2009). Rule-sets for automated damage indication and change detection are coded in CNL, which presents a modular programming background for image-object management. Rule-sets were developed using a subset of QuickBird imagery as input. Then, algorithms to be executed on an image object domain (buildings) were defined and combined with different rule-set development parameters in an iterative manner until a satisfactory result was achieved (see Figure 3).

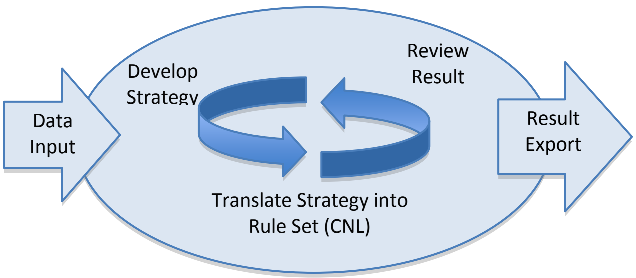
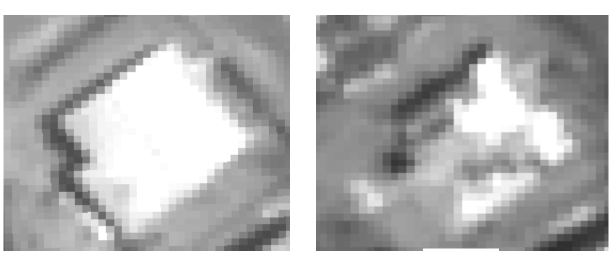


Figure 3. Rule-set Development Process
Source: Adapted from Definiens (2009)

Damage assessments may include both exterior and in-house components. However, the main focus is the assessment of the building's roof to classify damage. Unlike earthquakes and other phenomena, hurricane damage is unique. The damage characteristics are mainly roof and structural wind force damage and sometimes coupled with flood damages as well. In this context, damage classes therefore depend heavily on the textural and spectral distinction in the post-event image. Damage grade was therefore selected based on key damage cues detected in the post-hurricane image (Brunner, Lemoine, and Bruzzone, 2010). Figure 4 shows the textural, spectral and morphological properties of damage.

The output of the remote sensing image analysis is the detection of damage in the form of a damage classification map.



(a) (b)

Figure 4. Textural, Spectral and Morphological Properties of Damage (a) Intact roof characteristics, (b) damaged roof characteristics

4. Methods and Procedures

4.1 Study Area

The State of Grenada is located between latitudes 11°59´ and 12°20´ North and longitudes 61°36´ and 61°48´ West (see Figure 5). The main island, Grenada, is 18 km (11 miles) wide, 34 km (21 miles) long with an area of 312 square km (121 sq. miles) (OECS 2004). Grenada is located on the southern end of the hurricane belt. Over the past century, three devastating hurricanes had hit the island, in addition to numerous tropical storms and hurricanes that passed north of the island (World Bank 2005). The study area is located in the parish of St. George, situated on the southwestern portion of the main island. St. George parish is approximately 65 km2 with a population of 36,823; which accounts for about 36 % of the total population of the country.

Hurricane Ivan struck Grenada on the 7th of September 2004. The hurricane was classified as a Category 3 hurricane on the Saffir-Simpson scale with sustained winds of 193 Km/h (120 mph) and gusts of up to 233 Km/h (145 mph) as it passed over the island, lasting for about six hours (OECS 2004). Thirty-nine people died and most of the population of Grenada was affected. Damage from flooding and mudslides was not extensive since the hurricane did not produce heavy rainfall (World Bank, 2005). Approximately 90% of the houses were damaged or destroyed amounting to economic losses of approximately EC $1,381M. Total direct and indirect losses from all sectors of the economy amounted to EC $2,389.6M (CDERA, 2005). The other hurricanes of this magnitude to impact Grenada were Hurricanes Janet in 1955 and Flora in 1963.

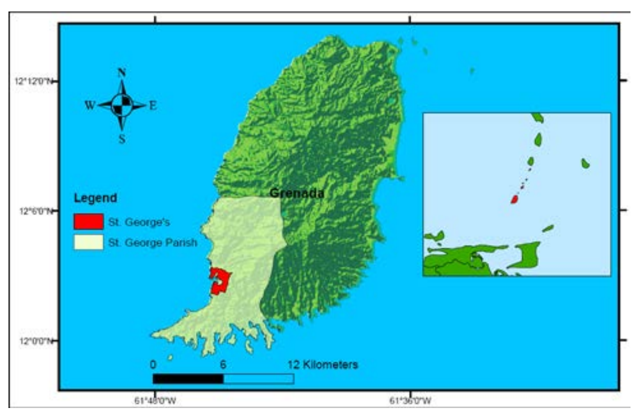


Figure 5. Map of Study Area

4.2 Data Used

Data used in this research is divided into three (3) main types: remotely sensed imagery, GIS data and ancillary data. Two archived QuickBird satellite scenes captured on April 26th 2003 and September 19th 2004 (pre and post hurricane Ivan) were acquired. Each epoch had both multispectral (MS) and panchromatic (PAN) scenes of the study area. The pre-event scene was captured fifteen months before hurricane Ivan and the only available post-event scene, 11 days after impact. In order to exploit the high spatial resolution of the PAN image (0.6m), the MS image was pan-sharpened to the resolution of the PAN (see Figure 6).

Developing a pre-event inventory for assessing building loss involves obtaining geospatial and attribute information on building stock within the study area. Once building footprints were acquired, other pertinent attribute information were collected and added to the attribute database on a per-building basis. Information fields stored in the building attribute database were determined by reviewing literature (van Westen and Hofstee, 2000; Eguchi et al., 2008; Friedland, 2009; PIOJ, 2012).

Figure 6. Pan-sharpened QuickBird MS image in false color

4.3 Methods

A rapid post-hurricane damage detection and preliminary loss assessment methodology was developed to increase the delivery and efficiency of these assessments in disaster response for Caribbean countries. Three different damage detection methods are applied to multi-temporal images of St. Georges, Grenada, taken before and after Hurricane Ivan. They include Visual Interpretation/Analysis, Pixel-Based Image Analysis and Object-Based Image Analysis.

4.3.1 Visual Interpretation

Figure 7 shows the damage map overlaid on building footprints in the study area as a result of visual damage classification.

4.3.2 Pixel-Based Image Differencing

Figure 8 shows the image differencing result, processed using a change detection algorithm. Areas in red represent ‘change pixels’ above a determined threshold. The pixel-based analysis provides a quick, simple and relatively cheap method for damage detection. However, the main disadvantage of this technique is that it does not account for radiometric differences between images, such as atmospheric noise or haze. The image differencing result is binary (change/no change) and does not give an indication to the degree of change and therefore cannot be graded using visual and object based methods.

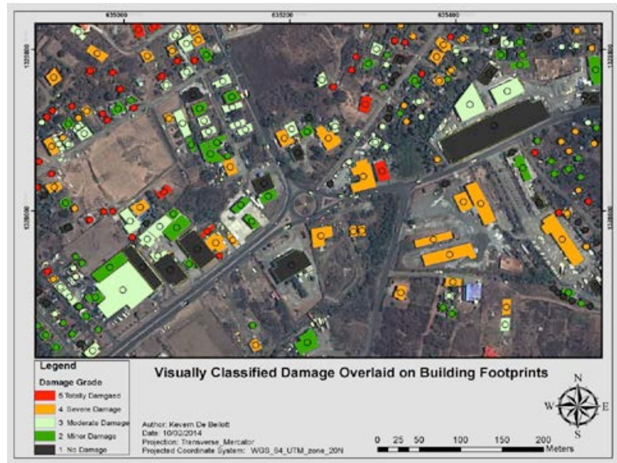


Figure 7. Visually interpreted Map Overlaid on Building Footprints

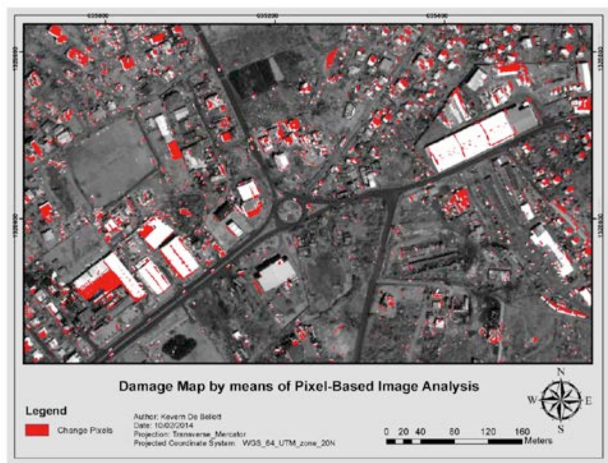


Figure 8. Image Difference Results

4.3.3 Object-Based Image Analysis

The OBIA procedure used is summarised in Figure 9. First, a multi-resolution segmentation of the ‘Post Image,’ is completed. This divides the image into a number of image objects or ‘image object primitives’ using spectral and shape criterion, thus minimising the average heterogeneity and maximising its homogeneity. Homogenous areas result in larger objects. Subsequent steps involve the identification of the appropriate feature values and thresholds then translating these into rule-sets in the eCognition image analysis software.

5. Strategy and Rule-set Development

5.1 For Grade 1 Damage

The strategy for classifying undamaged buildings (Grade 1) was based on the fact that spectral values for an undamaged building would be higher than a damaged one; an undamaged building will remain elevated; undamaged buildings cast a distinct shadow; and undamaged buildings maintain shape and smooth texture. This first round of classification also includes some moderately damaged buildings, since not all damaged buildings will collapse. However, it was a starting point prior to further refinement. Next, 'Class Related' context information (neighbor objects) was used to refine the undamaged building class. In this case, the rule-set must represent the situation where a 'building class' that has a low common border to a neighborhood object (shadow); that building should be classified as undamaged.

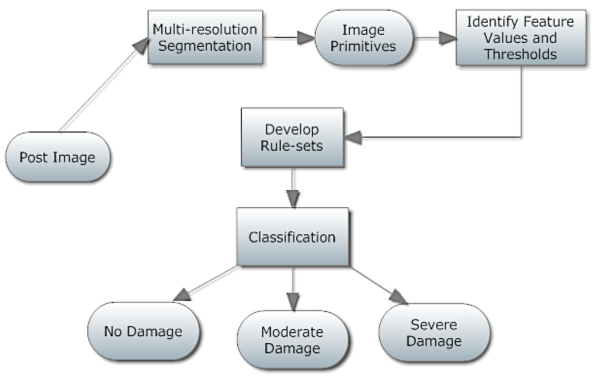


Figure 9. Summary of OBIA Approach

5.2 For Grade 2 Damage

The strategy for classifying moderately damaged buildings (Grade 2) was based on the following characteristics: spectral values for a moderately damaged building would be lower than an undamaged one; partially damaged buildings would have moderately contrasting neighbor objects; and partially damaged buildings' texture is moderately altered.

To translate these characteristics into rule-sets, threshold values were determined by visualising the range of spectral values for all building class objects, classified in the segmentation step. These threshold values were then used to assign a damage 'grade 2' to all buildings that satisfy these values. Initially, this step included buildings that belonged to 'damage grade 3' so the result needed to be refined to remove these from this class. To do this, a threshold for the standard deviation of sub-objects was determined (see Figure 10).

In this context, damage is detected by how different pixels are to one another within the extent of a classified building object. Severely damaged buildings exhibit a high standard deviation while moderately damaged buildings would have a lower value. Finally, objects were then refined using geometry/area criteria.

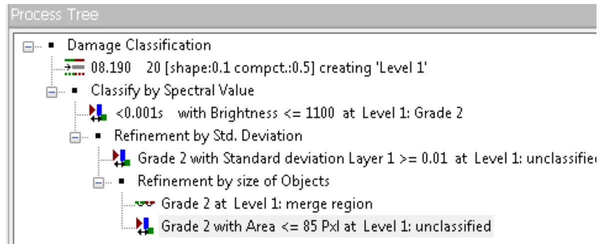


Figure 10. Process Tree with Rulesets for Damage Grade 2

5.3 For Grade 3 Damage

The strategy for classifying severely damaged buildings (Grade 3) was based on the following characteristics: spectral values for a severely damaged building would be very low compared to an undamaged or moderately damaged one; these buildings would have highly contrasting neighbor objects; severely damaged buildings' texture and geometry is heavily degraded; these buildings may also collapse and thus lack neighboring shadows; and additionally, some sampling was carried out to use as 'training sites' to help the classifier. Figure 11 presents the final damage classification map using the OBIA approach in eCognition Developer Software.

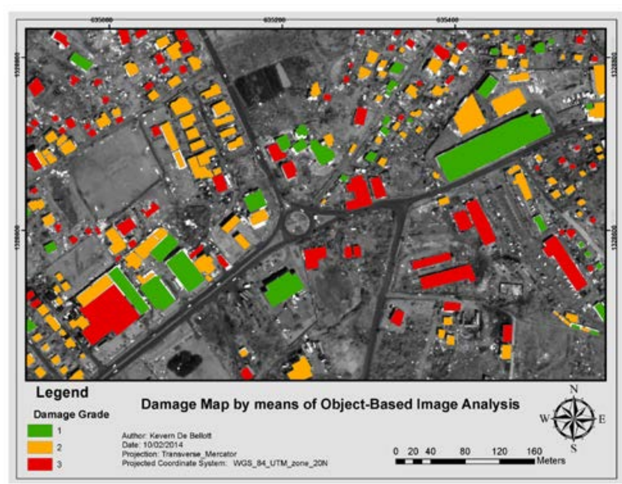


Figure 11. Damage Map by means of Object-Based Analysis

6. Accuracy Assessment of Methods

By using the information obtained through Visual Interpretation (VI) as reference data, relative accuracy percentages were calculated. Pixel-Based damage detection method had a relative accuracy of 98.5%

Table 2. Confusion Matrix of Object-Based Damage Classification

OBIA Classification Results	Damage Grade	Reference Data (Visual Interpretation) No. of Buildings				
		No Damage	Moderate Damage	Severe Damage	User's Acc. (%)	Comm. Error (%)
	No Damage	32	5	0	86.5 %	13.5%
	Moderate	9	101	11	83.5%	16.5%
	Severe	0	3	81	96.4%	3.6%
	Producer's Acc (%)	78.1%	92.7%	88.0%	----	----
	Omission Error (%)	21.9%	7.3%	12.0%	----	----
Overall Accuracy: 88.4%						

Table 3. Classification Error Matrix for Validation of Object-Based Method

OBIA Classification Results	Damage Grade	Reference Data (Word Bank Assessment) No. of Buildings				
		Grade 1	Grade 2	Grade 3	User's Acc. (%)	Comm. Error (%)
	Grade 1	483	67	4	87.2	12.8%
	Grade 2	86	2644	457	82.9	11.1
	Grade 3	7	344	6659	95	5
	Producer's Acc. (%)	83.85	86.5	93.5	----	----
	Omission Error (%)	16.15	13.5	6.5	----	----
Overall Accuracy: 86.1%						

(Number of Pixel-Based 'Damage' buildings/ VI 'Damage' buildings*100) and an over-classification of 3 buildings in the 'No Damage' class. Object-Based detection method produced an over-classification of 4 'Damage' buildings and 90.2% accuracy in the 'No Damage' class. Although these accuracy estimates are high, these may not be reflected on a building-to-building correlation. Table 2 presents the confusion matrix used to assess the accuracy of the Object-Based approach against the reference data provided by means of visual identification.

To validate the performance of the object-based classification result, the method was put under further scrutiny by expanding the study area. The expanded study area includes terrain that significantly varies in elevation, slope, vegetation cover and building density and is therefore more reflective of landscapes found on many other Caribbean islands. The reference data classification scheme (World Bank, 2004, 2005) was condensed from 6 to 3 classes (Grade 1 – Grade 3). This process is summarised as follows: 'Grade 1' consists of buildings categorised as 'No Damages' and 'Level 1'. 'Grade 2' consists of both 'Level 2' and 'Level 3' and 'Grade 3' comprise both 'Level 4' and 'Level 5' categories. Table 3 provides the Classification Error Matrix generated from expanding the analysis to the St. George's Parish level.

A total of 11,367 buildings were classified in the reference data. A total of 9,786 were correctly classified at the parish level, giving an overall accuracy of 86.1%. A minimum and maximum class accuracy of 82.9% and 95% respectively was achieved.

The classification result of the OBIA at the parish level was used to prepare a damage intensity map shown in Figure 12. A damage intensity map is a typical geospatial information product used to show the locations and intensity of damage across a large study area.

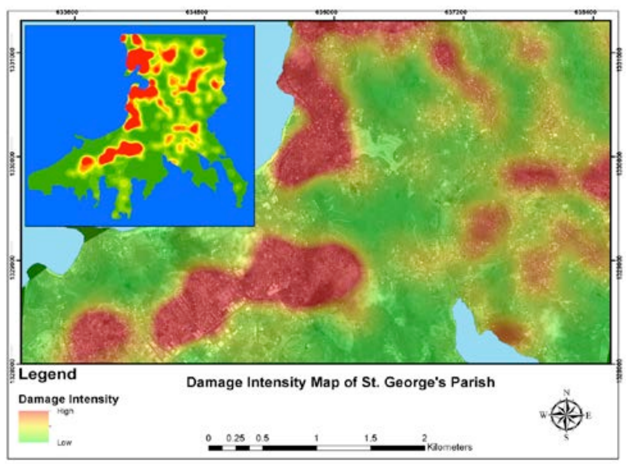


Figure 12. Map showing Damage Intensity across St. George's Parish

7. Discussion

In order to verify the reliability and accuracy of the processing outputs it was necessary to have a normalised format to evaluate on equal terms, hence the condensation of VI and Object-based classification into 'Damage/No Damage' for comparison with pixel-based image differencing. This binary scale classification revealed a high level of relative accuracy between the various methods to detect damage.

Compared to the reference data, which identified 201 buildings as damaged, Pixel-Based Image Differencing reproduced 98.51% (198 buildings) as damaged.

Although a high accuracy was achieved this may be misleading to some extent. This was also evident in object-based result which was compressed into a binary classification, indicating that all the buildings classified as damaged in the visual truth data were also classified as damaged in the object-based output with an excess of four buildings totaling to 205. This information was put in a more accurate context by generating the confusion matrix to verify the accuracy of the Object-Based classification scheme. Overall accuracy of the object-based classification was 88.4% with a minimum and maximum class performance of 83.5% and 96.4% respectively.

Many of the damaged buildings (Grades 2 and 3) were correctly identified but 'Undamaged' class had a high error of omission, which was not anticipated since that particular class seemingly had the strongest rule-set strategy in theory. However, the results were still within an acceptable error margin. The individual class accuracies establish the robustness of the object-based analysis method for damage detection. Reviewing the user's accuracy indicates the capacity to accurately detect undamaged and severely damaged (Grade 1 and Grade 3) buildings using the object-based method. This may be attributed to the fact that a robust rule-set strategy was achieved based on image object values and thresholds that were consistent with those particular damage grades. On the other hand, detection of moderately damaged buildings (Grade 2) was less accurate. Out of 121 buildings, 20 (16.5%) were classed incorrectly. Strengthening of the rule-set development strategy may help in reducing this margin of error.

One of the main difficulties with the object-based detection is the presence of false positives caused by the presence of debris in the immediate surroundings of buildings. In review of the rule-set development result for each individual damage grade, one can notice the difference in the segmentation of objects that comprise the class. Damage grade 1 has very compact outlines that fall mostly within the extent of the building footprint. However, for grade 2 and 3 the objects classified as damage extends beyond the extent of the building boundaries. These classified areas outside the bounds of the actual building are referred to as false positives. Clusters of debris can actually be mistaken for entire buildings. This effect however, did not affect the overall accuracy of the classification since the error matrix produced deals with buildings as objects and not pixels.

8. Conclusions

The overall aim was to develop a rapid post-hurricane building damage detection methodology in order to facilitate the timely dissemination of these information products to aid in post-disaster emergency response in small island states in the Caribbean. Several shortcomings still limit the application of remote sensing for rapid damage detection in the Caribbean. These are associated with the image acquisition time span, availability of cloud free images immediately after the event, and access to computer systems and software resources. Additionally, OBIA techniques require skilled and experienced personnel to develop and execute segmentation and classification rule-sets. Nonetheless, this methodology can be used to aid post-hurricane emergency responders and decision makers by providing quick and reliable information about the extent, location and intensity of building damage.

It was noted before that many Caribbean countries have mountainous terrains with steep slopes and dense vegetation that may limit the value of image analysis in rural areas. However, the focus here is on developed areas. It may also be observed that no single data acquisition technique is likely to address all the pre or post disaster data needs of a country. The strategy is to be able to draw one or more relevant methodologies from a suite of available options.

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