Remote Sensing for Geotechnical Earthquake Reconnaissance

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Abstract: This paper describes recent efforts that incorporate remote sensing techniques and platforms into geotechnical earthquake reconnaissance to document damage patterns, collect three-dimensional geometries of failures, and measure ground movements. The most-commonly used remote sensing techniques in geotechnical engineering (satellite imagery and LIDAR), as well as unmanned aerial vehicles (UAV), are introduced and recent case histories of the use of these techniques in reconnaissance efforts are provided. These examples demonstrate the potential for remote sensing to improve our understanding of geotechnical effects both at a regional scale and at a local level. The use of remote sensing to measure ground movements is particularly noteworthy and has the potential to provide data sets that will improve our ability to quantitatively predict the consequences of liquefaction and landslides. However, to realize this potential, investments must be made in collecting appropriate pre-earthquake data.

Keywords: remote sensing, satellite imagery, LIDAR, unmanned aerial vehicles.

1. Introduction

Advances in geotechnical earthquake engineering have been initiated in large part by observations documented during previous earthquakes. Thus, reconnaissance efforts are critical for evolving our field, and organizations such as the Geotechnical Extreme Events Reconnaissance (GEER) Association have placed significant emphasis on collecting perishable data after earthquakes. Over the last ten years remote sensing has increasingly played a role in geotechnical earthquake reconnaissance through the use of satellite imagery and LIDAR, and more recently the use of unmanned aerial vehicles (UAV). Remote sensing can provide a more holistic view of the geotechnical effects of an earthquake and this view can be integrated with other data within a geospatial framework, allowing for the identification of relationships that could not be recognized otherwise (e.g., Rathje et al. 2006a, Rathje and Adams 2008, Frost and Turel 2011).

There are three general application areas in which remote sensing has been used to document the geotechnical effects of earthquakes: (1) documenting the locations of earthquake damage and damage patterns, (2) developing three-dimensional digital elevation models of failure geometries, and (3) measuring ground movements. When identifying the relevant remote sensing techniques for any of these applications there are always tradeoffs in terms of the spatial resolution/accuracy of the data relative to the aerial coverage (Rathje and Adams 2008). Higher resolution data with higher accuracy typically only cover relatively small areas, such as a single failure site. To capture a larger area, such as an entire city, one must often sacrifice spatial resolution and accuracy. However, depending on the eventual use of the data, the larger aerial context may be more important than the spatial resolution and higher accuracy. Another consideration is the availability of pre-earthquake data that can be used with post-earthquake data to evaluate changes and movements due to the earthquake. The availability of pre-earthquake data, and the cost required to obtain it, influences the types of remote sensing data analysis that can be performed and the information that can be produced.

This paper describes recent and on-going research in which remote sensing has been

integrated into the reconnaissance of earthquakes, and other natural hazards, to better understand the geotechnical effects of these events. In particular, the use of satellite imagery, LIDAR, and unmanned aerial vehicles is highlighted within the context of documenting damage patterns, developing digital elevation models, and measuring ground movements. After a synthesis review of activities in these areas, three detailed case histories are presented regarding landslide identification, measurement of liquefaction movements, and measurement of ground movement.

2. Remote Sensing Techniques and Platforms

2.1 Satellite and Aerial Imagery

Satellite and aerial imagery can provide important information about the geotechnical effects of earthquakes at a regional scale, and in some instances at the scale of a single site. A multitude of satellite sensors currently are imaging the earth at different pixel resolutions, at different repeat cycles between acquisitions, and within different spectral bands of the electromagnetic spectrum. The available sensors are continuously changing as new sensors are launched and others are retired. Today, the highest resolution commercial sensor is WorldView-3, launched in August 2014, which provides panchromatic data (450-800 nm wavelengths, typically viewed in grayscale) at 0.30 m resolution. Multispectral data (finer spectral bands about 50-60 nm wide within the visible and near-infrared wavelengths of the electromagnetic spectrum, between 400 and 1000 nm) are available at ~1.25 m resolution and shortwave infrared data (SWIR, 1000-2500 nm wavelengths) at ~4 m resolution (<http://www.satimagingcorp.com/satellite-sensors/worldview-3/>). The highest spatial resolution is available only for panchromatic data because the wider spectral range is required to collect enough solar radiation for small pixel sizes. For the same reason, the narrower multispectral bands are available at larger pixel sizes, and the SWIR bands are available at even larger pixel sizes because of the reduced solar radiation at these wavelengths. The data within the finer multispectral and SWIR bands provide important information about the different types of

landcover (e.g., vegetation, soil, moisture, etc.), which can be important for some applications such as identifying liquefaction ejecta.

Satellite sensors that collect reflected solar radiation from the earth surface are considered passive sensors because they passively collect the availability solar radiation. These passive sensors are negatively impacted by clouds because clouds impede the travel of the solar radiation towards the sensor. An alternative to a passive sensor is an active sensor, such as synthetic aperture radar (SAR), which generates its own energy and operates at longer wavelengths (anywhere from 2 cm to 30 cm depending on the sensor) such that clouds do not significantly influence the travel of the waves. In addition to recording the amplitude of the backscattered radar waves, SAR also records the phase of the waves, which allows SAR image pairs to be processed to measure precise ground movements within the line of sight of the radar. Although sensors like SAR can image at night and through clouds, they often have lower spatial resolution (10 to 30 m) and require significant data manipulation and processing to provide useful information. Nonetheless, it has become almost commonplace to use SAR to image surface fault rupture movements (e.g., Wang and Fialko 2015), and others have used the loss of SAR phase coherence as an indicator of liquefaction (e.g., Atzori et al. 2012).

In some ways, satellite imagery is a variant of aerial photography, which has been used for decades to document earthquake effects. Aerial photographs commonly are acquired from an aircraft and, similar to satellite imagery, can collect data within different parts of the electromagnetic spectrum. Both aerial photographs and satellite imagery can be taken in stereo such that three-dimensional models can be made of the ground surface. Aerial photographs are typically of higher spatial resolution than satellite imagery due to the closer proximity to the ground surface.

Various techniques are available to document the effects of earthquakes using satellite and aerial imagery. These techniques range from simple visual/manual classification methods to semi-automated thematic classification and change detection techniques. Important issues to consider when selecting the appropriate analysis technique are the availability of pre-event

imagery, the size of the area of interest, and the time required for analysis. Generally, visual/manual classification and thematic classification can be applied successfully using post-event imagery alone, while change detection requires pre- and post-event imagery. Nonetheless, visual/manual classification still can benefit from the availability of pre-event imagery.

2.2 LIDAR

LIDAR is an active remote sensing technique that involves the collection of reflected and backscattered light from the active illumination of the ground using a laser source. A laser beam scans across an area, repeatedly shooting out a pulse of light that hits the surface and scatters a portion of the light back to the sensor. By timing the round trip of each laser pulse, the distance is determined for each scan position. Knowing the position and orientation of the laser, a group of (x, y, z) coordinates, referred to as a point cloud, is acquired and the point cloud can be processed to develop a digital elevation model (DEM). The small size and modularity of LIDAR instruments allow these systems to be mounted in small aircraft to collect data over large areas, or on a tripod to collect more detailed data for smaller areas (Figure 1).

For airborne LIDAR, the location and orientation of the sensor is provided by differential GPS and an inertial measuring unit (IMU). Synchronization of the independent times between the sensor, GPS, and IMU is one of the most challenging aspects of system design. The primary sources of error in airborne LIDAR data result from timing errors with the laser, GPS related errors, misalignment of the IMU, and integration of the data streams (Rathje et al. 2006b). Ground-based terrestrial LIDAR does not suffer from the same issues because often the sensor is located in a single, fixed location during data collection. However, the location of the LIDAR must be tracked when the terrestrial LIDAR system is mounted on a moving vehicle. Ground-based LIDAR cannot see behind objects and thus the first surface encountered casts a shadow over objects behind it, as shown in Figure 1b. To obtain full coverage, the LIDAR scanner must be moved to other locations surrounding the target area and the multiple scans

georeferenced to one another. Through data processing techniques, a digital surface model of the feature can be developed (Figure 1c) that can be used for analysis (Figure 1d).

2.3 Unmanned aerial vehicles

Unmanned aerial vehicles (UAVs, also commonly referred to as “drones”) are aerial robots that can be remotely controlled by one or more operators (though some can operate with various levels of autonomy) and can carry a wide variety of sensors. While strictly not a remote sensing technique, this technology is becoming more common as a platform for remote sensing. The size and number of sensors that can be carried on a UAV depends upon the size, flight endurance, and payload capacity of the UAV. In particular, exploding interest in the use of small UAVs (i.e., sUAVs), which are often defined as having a combined total platform plus sensor weight of less than 23 kg (~50 lb), is leading many scientists and engineers to explore new UAV applications in their respective fields of study. sUAVs offer the advantage of obtaining data from a low-altitude aerial vantage point at a relatively low cost, thus allowing the scientist and engineer to economically and repetitively obtain a birds-eye view of their site of interest while avoiding many of the obstacles and occlusions that are often encountered with terrestrial remote sensing techniques. Today, the most common sensor deployed on a UAV is a digital camera. Although LIDAR systems can be deployed, they are currently very expensive and are used far less often.

A wide range of sUAV platform types are currently available, and many more are being developed and evaluated as interest in sUAVs continues to grow. One can currently classify most sUAV platforms into three general types: (1) single-rotor platforms, (2) multi-rotor platforms, and (3) fixed-wing platforms. Figure 2 shows examples of each of these types of sUAV platforms. The collection of data using sUAVs is potentially much cheaper and quicker than collecting similar data using a traditional aircraft. A few researchers have recently documented the use of UAVs for performing post-earthquake reconnaissance and damage assessment. For example, Gong et al. (2010) and Hu et al. (2012) experimented with UAVs to

evaluate their potential to detect earthquake-induced landslides.

3. Geotechnical Application Areas for Remote Sensing

The three most common application areas in which remote sensing has been used to document the geotechnical effects of earthquakes are assessing damage patterns, developing digital elevation models of failure geometries, and measuring ground movements. A summary of research activities in these areas is provided below.

3.1 Assessment of Post-Earthquake Damage Patterns

Geotechnical conditions often play an important role in the spatial distribution of damage from an earthquake. The pattern of collapsed/damaged structures may indicate amplification of ground shaking due to soil conditions, and the occurrence of liquefaction and landslides is clearly related to the subsurface soil and geology. The use of remote sensing to document these effects across a larger region of interest often provides a broader view of the damage than is possible through ground-based reconnaissance alone. Examples in which remote sensing has been used to identify earthquake-induced landslides and liquefaction are discussed below.

3.1.1 Identification of Earthquake-Induced Landslides

Earthquake-induced landslides often are shallow soil slips in which the surface vegetation is stripped as the soil/rock translates downslope. These characteristics are readily visible in satellite imagery and air photos, which allows landslides to be identified through thematic classification of post-earthquake imagery or through change detection of pre- and post-earthquake imagery (e.g., Moine et al. 2009, Xu 2015). Additionally, because earthquake-induced landslides can occur over very large areas (e.g., more than 10,000 km² for the 2008 Wenchuan, China earthquake, Rathje and Carr 2010), analysis of remote sensing data can provide an assessment of the landslide distribution more quickly than traditional techniques that use visual interpretation of air photos.

Remote sensing certainly has a role to play in documenting the locations of earthquake-induced landslides at a regional scale after an earthquake, although it cannot provide information regarding landslide depth or volume. Both thematic classification and change detection can provide rapidly a broad picture of the density of landslides across an affected area, and the results can be easily integrated with other geospatial data (e.g., geology, topography) to investigate relationships between the landslides and these parameters (e.g., Rathje and Carr 2010). However, the completeness of a landslide inventory (Harp et al. 2011) developed directly from remote sensing data analysis, in terms of issues such as the smallest identifiable landslides and the detection of the full area of each landslide, must be considered. Although the most complete landslide inventories are obtained by careful visual inspection of imagery, this process can take months to years to develop when a large area is affected.

3.1.2 Identification of Liquefaction

Liquefaction can be identified at a regional scale through satellite imagery or documented more thoroughly using aerial images from UAVs. The simplest approach to identifying liquefaction from satellite imagery is through visual interpretation of high-resolution images to identify ejecta, cracking, etc. This approach was used for the 2010 Haiti earthquake (Ghosh et al. 2011) and the 2010-2011 Canterbury earthquake sequence (Canterbury Geotechnical Database 2013). Alternatively, pre- and post-earthquake satellite images can be used to identify liquefaction in an automated manner, typically through the identification of changes in soil moisture as an indicator of the occurrence of liquefaction. The success of this approach requires that the post-earthquake imagery be acquired quickly before the surface dries and that other sources of surface moisture (e.g., water main breaks) are not present. Ramakrishnan et al. (2006) defined a Liquefaction Sensitivity Index based on combinations of bands from the SWIR and near infrared (NIR) wavelengths from the Indian Remote Sensing Satellite (IRS-1C) and used this index to identify liquefaction from the 2001 Bhuj earthquake in Gujarat, India. Oommen et al. (2013) investigated the use of LANDSAT 7 ETM+ data to quantify changes in

soil moisture. These analyses used a wetness index and the land surface temperature derived from the thermal band as proxies for soil moisture. The changes in these indices were computed for the 2001 Bhuj earthquake to identify liquefaction. They found that changes in the wetness index better distinguished areas of liquefaction than temperature. Others have investigated the use of thematic classification of post-earthquake imagery to identify liquefaction (Broszeit and Ashraf 2013), but with limited success. SAR has also been used to identify zones of liquefaction via a reduction in phase coherence between pre- and post-earthquakes images due to the change in the surface characteristics. This technique has been used to identify liquefaction from the 2010-2011 Canterbury earthquake sequence (e.g., Atzori et al. 2012) and the 2011 Tohoku, Japan earthquake (e.g., Ishitsuka et al. 2012), with the results showing qualitatively good comparisons with the regional distribution of observed liquefaction. However, loss of coherence can also be caused by other types of damage and thus these maps cannot be considered to represent predominantly liquefaction without field verification.

Aerial images from UAVs can provide a broader view of liquefaction effects at a site-specific level, as opposed to the regional level provided by satellite imagery. Rollins et al. (2014) used two sUAV platforms as part of the GEER geotechnical reconnaissance to Iquique, Chile following the 2014 M8.2 earthquake. In this example, the sUAV platforms were flown at two large liquefaction sites: the Port of Iquique and the Tana Bridge along Interstate-5 between Iquique and Arica. Observable evidence of liquefaction and corresponding damage at both sites was extensive, and it often became difficult from a terrestrial standpoint to see the significance of many of the crack patterns in the ground (Figure 3a). However, the crack patterns became much clearer and understandable from the aerial viewpoint of the sUAV (Figure 3b), thus helping the reconnaissance team to better interpret and explain the observed damage at the pier. This experience shows that the use of sUAVs in geotechnical reconnaissance allows engineers to see the site from above, thus helping them to document and see the “bigger picture” from which it is often easier to detect the important damage patterns of interest.

3.2 Digital Elevation Models of Geotechnical Failures

Characterizing the detailed 3D geometry of geotechnical failures can provide important insights into failure mechanisms. However, collection of the data required to generate a 3D model can be time consuming using traditional techniques, such as a topographic survey using a total station. New techniques, such as LIDAR and digital photogrammetry, can be used to develop 3D geometries in much less time and, potentially, at less cost.

3.2.1 Using LIDAR to Develop DEMs

The size of most geotechnical failures during earthquakes is relatively small such that terrestrial LIDAR may be more appropriate than airborne LIDAR to capture the geometry. Terrestrial LIDAR has been used consistently during GEER-sponsored earthquake reconnaissance efforts over the last decade to develop geometries of important failures (e.g., Kayen et al. 2006, 2011, Bray and Frost 2011). For example, Figure 4 shows an approach embankment that failed during the 2010 Maule, Chile earthquake. The photograph of the failure does not provide the full context of the failure, as compared with the 3D geometry provided by the terrestrial LIDAR. The 3D LIDAR data, derived from two scans taken from the crest of the non-failed slope for this site, show the full extent of the failure and allow for direct measurement of key site parameters, such as height, slope angle, etc. These 3D models are particularly useful for any subsequent numerical modelling of the failure and are paramount for understanding 3D effects.

3.2.2 Using Digital Photogrammetry to Develop DEMs

Another form of remote sensing that can be used to develop 3D failure geometries is the integration of digital photographs with stereo photogrammetry/computer vision techniques, such as Structure from Motion (SfM; Marr and Nishihara 1978; Snavely et al. 2008). SfM identifies distinguishing features (e.g., corners, edges, and/or boundaries between high-contrast objects) from a collection of digital photographs and back-calculates the location (in three dimensions) of

those features relative to one another. Typically, SfM results in a 3D point cloud similar to that produced by LIDAR, but generally with lower resolution and accuracy. Geo-referencing of the point cloud usually is performed by either including surveyed ground control points (GCPs) in the SfM processing, or by using a GPS device and/or IMU with the optical sensor to tag each photograph with GPS coordinates and/or information regarding the relative movement of the sensor. Sub-centimeter point cloud resolutions and median 3D point accuracies as high as 3-4 cm using SfM from sUAV-based images have recently been reported in the literature (e.g., Turner et al. 2015).

Three-dimensional surficial failure geometries of geotechnical phenomena can be evaluated using various types of models and/or representations of surficial geometry produced from the SfM processing. For example, many of the popular SfM modelling software today use geo-referenced 3D point clouds (based on surveyed ground control points) to develop orthorectified images and/or DEM images of the site. These images are typically produced at a superior resolution than what can be obtained from satellite or high-altitude aerial imagery, and are compatible with most traditional GIS analysis functions.

An example of a 3D surficial geometry that was developed from SfM is shown in Figure 5 for a 370-m long landslide that occurred in February 2013 along U.S. Highway 89 (i.e., US-89) approximately 32 km south of Page, Arizona. A subsequent geotechnical investigation (McCormick and Richmond 2013) determined that the landslide failure surface extended approximately 41 m below the ground surface. Prior to stabilization of the landslide, a hexacopter UAV carrying a Nikon® D7100 digital SLR camera was used to image the landslide at elevations of 10, 30, 60, and 120 m above the roadway surface. The ground sample distance (GSD) of the UAV-collected digital images ranged in from 0.07 cm/pixel to 0.90 cm/pixel. The images were processed using the SfM software *PhotoScan v1.1.6*, and a variety of model representations were subsequently developed including a 3D point cloud (Figure 5a), an orthorectified image (Figure 5b), and a DEM (Figure 5c). The accuracy of these models is generally limited to the accuracy of the SfM 3D point cloud (~4 cm), but is adequate for most geotechnical

analyses and interpretations.

3.3 Measurement of Ground Movements

A significant amount of earthquake damage caused by geotechnical phenomena is due to permanent ground movements. These movements may be generated by liquefaction or slope failures, and they damage lifelines, bridges, buildings, and other infrastructure. It is very difficult to measure earthquake-induced ground movements directly because of a lack of appropriate instrumentation installed before an earthquake. Traditionally, researchers have inferred ground movements through the measurement of horizontal and vertical crack offsets along a horizontal transect; however, field crack measurements assume that all displacement is manifested in cracks (i.e., no ductile movement of the ground) and that the crack widths can be measured accurately after an earthquake. Differencing of pre- and post-earthquake remote sensing data provides an alternative method to measure permanent ground movements. Differencing can be performed on images to measure two-dimensional movements in the horizontal direction or it can be performed on point clouds to measure vertical movement or the full three-dimensional displacement field.

3.3.1 Two-Dimensional Horizontal Differencing

Hamada et al. (1987) pioneered the use of pre- and post-earthquake aerial photographs to measure horizontal displacements due to liquefaction and lateral spreading. Using photographs taken under identical conditions, the movement of visually identifiable features was measured manually for two earthquakes in Japan. These measurements represent the first quantitative estimates of liquefaction displacement from imagery. This type of approach more recently has been applied to measuring displacements of landslides using images obtained from a UAV (e.g., Niethammer et al. 2012). However, manually identifying features can take significant time and effort.

Computer analysis can accelerate the time and reduce the effort required to measure

displacements from imagery, and potentially can also increase the accuracy. Crippen (1992) proposed an optical image correlation technique that correlates segments (i.e., square chip windows of pixels) of optical satellite images collected at different times to derive two-dimensional movements of an area. Given the lower resolution of available imagery at that time (15-30 m), the technique was applied to large scale phenomena such as sand dune migration (e.g., Crippen 1992) and earthquake fault rupture (e.g., Van Puymbroeck et al. 2000). With the launch in 2008-2009 of optical sensors that collect panchromatic imagery at approximately 0.5 m resolution it became possible to measure sub-meter displacements at high spatial resolution, making the approach appropriate for investigating geotechnical phenomena. Additionally, improvements by Leprince et al. (2007) to the various processing steps have addressed some of the observed limitations in the method and improved the lower bound of achievable displacements. The algorithms developed by Leprince et al. (2007) are available in the publically available software COSI-Corr (http://www.tectonics.caltech.edu/slip_history/spot_coseis). COSI-Corr has been used by geotechnical engineers to measure liquefaction-induced horizontal displacements (Martin 2014, Martin and Rathje 2014) and landslide displacements (e.g., Suncar et al. 2013).

Even in the absence of a baseline model, 3D point cloud models can be used to manually detect and measure/sum crack widths along a transect, similar to the traditional techniques used in field reconnaissance. This approach was applied to data from the Molo Pier in Iquique, Chile that was significantly damaged by liquefaction during the 2014 earthquake (Figure 3). The 3D point cloud model developed from UAV-based images using SfM computer vision was augmented with a mesh and texture to provide a scaled virtual model of the damaged pier on the day of the UAV flight. On the same day of the UAV flight, GEER team members manually surveyed and recorded the horizontal crack widths along three separate transects at the pier (Rollins et al. 2014). An undergraduate student researcher, unfamiliar with the efforts of the GEER team, measured and recorded crack widths from the scaled virtual model along approximately the same transects as the GEER team. The sum of the recorded crack widths from

the virtual model are compared with those from the field in Figure 6. Despite challenges in some areas due to insufficient imaging, the final cumulative crack widths from the virtual model are within less than 5% of the final cumulative crack widths as reported by the GEER field team (Rollins et al. 2014). While these results are considered preliminary and are still being evaluated, they demonstrate the potential for high resolution 3D virtual models to provide valuable information regarding ground movements.

3.3.2 Vertical and Three-Dimensional Differencing

Vertical differencing measures ground settlement, while three-dimensional differencing provides the X, Y, and Z displacement field across a study area. Both of these techniques require pre- and post-event point clouds. These point clouds can be obtained directly from LIDAR (e.g., Figure 4) or derived from photogrammetric/computer vision techniques such as SfM (e.g., Figure 5). When using LIDAR data (particularly for three-dimensional differencing), there are important issues to consider regarding the point density and the altitude of acquisition. Point densities greater than 10 pts/m² and lower acquisition altitudes (Craig Glennie, personal communication) will produce point clouds that allow for more accurate measurements of displacement. When using photogrammetric techniques, terrestrial digital photographs typically offer the best image resolution in terms of image area per pixel, but are often limited in their usefulness due to the relatively small area imaged in each photograph and the many occlusions that are typically encountered on the ground. Aerial photographs offer lower image resolutions, particularly when taken from higher elevations, but cover much larger areas per image and are usually not impacted by occlusions except significant vegetation. Digital photographs taken from low elevations such as those captured from a sUAV can offer a good balance between image coverage and resolution, while avoiding many of the occlusions that can hamper terrestrial photography efforts.

Vertical differencing of LIDAR DEMs has been used for many years to effectively measure vertical displacements associated with earthquakes, in particular the vertical movement along a

fault rupture (e.g., Oskin et al. 2012). Three-dimensional differencing requires more significant computation and typically uses the iterative closest point (ICP) technique (Besl and McKay 1992) or its variants (e.g., Zhang et al. 2015). ICP computes the 3D rigid body translation and rotation required to minimize the sum of the squared error between the two point clouds. As noted earlier, 3D features or texture must be present in the point clouds to accurately measure horizontal displacement from point clouds or DEM.

To develop a displacement field across a study area using ICP, the point clouds are split into smaller spatial cells (e.g., 100 m by 100 m) and the translation and rotation are computed for each cell. This approach was used to measure fault displacements from the 2010 El Mayor–Cucapah earthquake (Glennie et al. 2014). The vertical and EW displacements clearly identified the fault rupture, but the NS displacements showed features associated with the flight lines from the pre-earthquake LIDAR acquisition due to the lower quality of the pre-event LIDAR survey. These results show the need for high-quality pre-event data when computing horizontal displacements using 3D differencing and ICP. To date this technique has not been used to measure displacements due to liquefaction or lateral spreading.

Another example of using ICP to develop 3D displacement estimates is shown in Figure 7. In this example, digital photographs were used to measure ground movements after a significant landslide in a residential suburb in the City of North Salt Lake, Utah in August 2014. Numerous surveyed ground control points on and around the landslide were established immediately following the initial movement, and a sUAV was used to capture approximately 700 photographs of the landslide from the air using a Nikon[®] D7100 DSLR camera with a 35mm prime lens. Approximately eight months later (May 2015), additional images using the sUAV were collected. SfM processing was performed using *PhotoScan v1.1.6* to develop 3D point cloud models of the landslide from the two image sets, and the absolute differences between the two clouds were evaluated using the ICP technique. Figure 7 presents the results of this analysis, with Figures 7a and 7b representing the resulting 3D point cloud models, and Figure 7c showing the displacement vector amplitudes. The largest computed displacements (~ 2-3 m) occurred at the

edges of the main scarp, and these areas represent zones of sloughing that occurred between acquisition of the two sets of images.

4. Case Studies of Remote Sensing in Geotechnical Reconnaissance

To provide more detailed information about the use of remote sensing in geotechnical reconnaissance, three case histories are selected for detailed discussion. These case histories are landslide identification from the 2004 Niigata-ken Chuetsu earthquake in Japan, measurement of lateral spread movements from the 2010-2011 Canterbury Earthquake Sequence in New Zealand, and measurement of ground movement due to liquefaction remediation near Lake Havasu in the United States.

4.1 Landslide Identification from the 2004 Niigata-ken Chuetsu Earthquake in Japan

The 2004 Niigata-ken Chuetsu (M_w 6.6) earthquake in Japan generated a significant number of landslides and represents one of the first earthquakes where satellite imagery was used to investigate the landslide distribution. Both moderate resolution (30 m) and high resolution (4 m) multispectral data were available for this event, as well as a traditional landslide inventory map, which allowed for the evaluation of different semi-automated techniques that can be used to identify landslides (Carr 2009). For this event, landslides occurred across an area of approximately 250 km², with the largest density of landslides occurring in an area of roughly 100 km² around the fault rupture (Figure 8). Data collected from the LANDSAT 7 ETM+ sensor (30 m resolution) was used to perform a change detection analysis over the affected area using pre- and post-event data. The raw digital numbers were converted to reflectance for both the pre- and post-event imagery, and the histograms of the reflectance values across the two images were matched so that the images would exhibit similar brightness distributions, causing landslides to exhibit the largest possible changes in reflectance relative to other land covers.

Selection of the appropriate spectral band for change detection analysis focused on determining which spectral band best identified changes in reflectance caused by the removal of

vegetation and the exposure of bare soil and rock. For this event the Red band (630-690 nm wavelengths) provided the best results, although in other cases longer wavelength bands have been used in an effort to minimize cloud issues (Rathje and Carr 2010). Change detection was based on the difference in Red reflectance values between the pre-earthquake and post-earthquake data for each individual pixel. A change detection threshold of $>+0.14$ change in reflectance was selected to identify landslides. The results were evaluated quantitatively through comparison of the total landslide area identified relative to the landslide area identified by traditional mapping techniques by the Geographical Survey Institute of Japan (2004). The change detection analysis identified 2.66 km² of landslide area, compared to 6.30 km² identified by the traditional landslide map. The identified landslides from these two datasets are shown in Figure 8. Overall, the change detection analysis produces an overall spatial distribution of landslides similar to that shown in the landslide map, although the landslide map identifies more than twice the landslide area as the change detection analysis. The differences are primarily due to (1) missing smaller landslides in the change detection analysis due to the 30 m resolution of the data and (2) underestimating the size of landslides because large portions of the mapped landslides are covered with displaced vegetation, which leads to minimal change in reflectance relative to the landcover before the earthquake occurred. A similar level of underestimation was reported for the same type of LANDSAT change detection analysis for the 2008 Wenchuan, China earthquake (Rathje and Carr 2010).

In addition to the change detection analysis, landslide identification was performed using pixel-based and object-oriented thematic classification of the high-resolution (4 m), post-earthquake multispectral imagery. Image classification involves assignment of a land cover classes to an image. Classification can either be pixel-based, meaning each individual pixel in an image is assigned a class, or object-oriented, meaning groups of similar pixels (known as objects) are assigned classes (Campbell 2007). In either case, the analyst must define a set of land cover classes that embody all of the major types of land cover in the imagery (e.g., landslides, landslide debris, agricultural, vegetation, water, shadows for landslide identification)

such that the class of interest, landslides in this case, can be distinguished from the others (Carr 2009). Training data were identified in the imagery (~ 1000 pixels/class) to train the pixel-based classifier and each of the remaining pixels was assigned to the class to which it had the highest probability of being a part (Campbell 2007). Object-oriented classification methods classify image objects rather than individual pixels, and can be performed on objects of varying size and shape. Object-oriented classifications can also utilize GIS-like post-classification procedures and rules, which can result in a final classified product optimized for the highest overall accuracy. The accuracy of the results was assessed by comparing the results from the remote sensing analyses with visually identified ground truth data at the pixel level (~ 2000 pixels/class) and by comparing the identified landslide densities within 1-km² blocks with those from the mapped landslides from the Geographical Survey Institute (GSI) of Japan (i.e., Figure 8b).

The pixel-based classification using the Maximum Likelihood Classification (MLC) technique accurately identified 78% of the landslide pixels, but also had 15% false positives for the landslide class (Carr 2009). The object-oriented classification accurately identified more of the landslide pixels (94%) but at the expense of more false positives (39%). Computing landslide densities within 1-km² blocks provides a broader assessment of the accuracy of the landslide classification results across an area of interest, although the assessment does not evaluate whether the landslide pixels are precisely located in space. The mapped landslide density for each of 85 map blocks was computed by taking the total area of landslides within the block, defined by all the mapped landslides and head scarps from the GSI map, and dividing by the total area of the block (Carr 2009). Landslide density for each block in the classification results was computed using the total area of both the landside and landslide debris classes. The remote sensing landslide densities are plotted against the mapped landslide densities in Figure 9. For both classification methods (MLC and object oriented), about 74% of the blocks exhibit classified landslide densities within +/- 5 percentage points of the mapped values. The MLC results show more overestimation in landslide density at small densities, and both the MLC and

object-oriented results show underestimation at large landslide densities (although the underestimation is larger for the object-oriented results). The overestimation of landslide density at very small mapped landslide densities (e.g., Block #77) is caused by overestimation of the landslides debris class, mainly due to false positives associated with the agricultural and muddy water classes (Carr 2009). The underestimation of landslide density at larger mapped landslide densities appears to be caused by many landslides being covered with intact vegetation and thus not identified by the classification algorithm.

4.2 Liquefaction Movements from the 2010-2011 Canterbury Earthquake Sequence in New Zealand

The optical image correlation technique was used to measure liquefaction-induced displacements from the 2010-2011 Canterbury earthquake sequence (Martin 2014, Martin and Rathje 2014, Secara 2016, Rathje et al. 2017) Christchurch earthquake. Analyses were performed for the 2011 Christchurch earthquake and the full 2010-2011 Canterbury earthquake sequence. An important consideration when applying this technique to satellite images is that the images must be acquired from a similar orientation. This criterion can be difficult to achieve when using archived imagery from commercial satellites because the desire for commercial satellite sensors to be agile enough to capture events soon after they occur means their acquisition orientation is highly variable. For the analysis of the Christchurch earthquake, the pre- and post-earthquake panchromatic (i.e., gray-scale) images were acquired on September 21, 2010 and February 26, 2011, respectively, with off-nadir angles of 19.8° and 18.2° and target azimuths of 55.1° and 51.1° , respectively. Importantly, the pre-event image was acquired after the September 3, 2010 Darfield earthquake such that the measured displacements represent those only from the Christchurch earthquake. The analyses were performed using a correlation chip window of 128 by 128 pixels (64 m) and a step size of 32 pixels, which produced a displacement estimate every 16 m. Horizontal displacements as small as 0.2 to 0.3 m were measured with an accuracy of less than 0.1 m (Rathje et al. 2017). Further details regarding the optical image

correlation analysis of the images, including the processing steps associated with orthorectification (i.e., correction for terrain and parallax) and co-registration (i.e., warping one image to match the coordinate system of another image), can be found in Martin (2014) and Secara (2016).

The correlation analysis for the Christchurch earthquake was performed along the Avon River east of the Christchurch Central Business District, and the results within the Avonside and Dallington neighborhoods of Christchurch are shown in Figure 10. The analysis provides displacement measurements in the North/South (NS) and East/West (EW) directions. Displacements in the EW direction are shown in Figure 10b with red/yellow used for the east displacements and blue/purple for the west displacements. Areas to the west of the river displaced eastward and areas to the east of the river moved westward, which indicates lateral spreading towards the river. The largest displacements occur immediately adjacent to the river. There are significant lengths of the river that experienced 2 m or more of displacement (red and purple areas). These large EW displacements are focused predominantly along the Avon River in the eastern parts of Dallington where the river runs north-south. The total displacement amplitude at each location can be computed from the vector sum of the NS and EW displacements. Figure 10c shows the displacement amplitudes across the study area. Most amplitudes are 1.5 m or less with localized zones of 2.5 m of displacement, and displacements extend 100 to 200 m from the river. Also shown in Figure 10c is a map of field-identified crack locations (larger than 50 mm wide) from the Christchurch earthquake as presented in the Canterbury Geotechnical Database (2012). The observed cracks run parallel to the waterways indicating displacement towards the river. The concentration of cracking is consistent with areas of displacement from the optical image correlation analysis. Figure 10d shows quantitative comparisons between the displacements from optical imagery correlation and those measured from crack widths by Misko Cubrinovski and Kelly Robinson (personal communication) along two transects within the Avonside area. The transect locations are indicated in Figure 10b. The imagery displacements were computed by rotating the EW and NS displacements to an

orientation consistent with the orientation of each transect. The displacements from the imagery analysis and ground surveys agree remarkably well at the river bank (0.6 m for transect AS-1 and 1.5 m for transect AS-3) and both show the displacements extending a similar distance from the river. The detailed patterns of displacement are somewhat different, but this is not unexpected considering the very different techniques and assumptions employed in the two approaches. These results indicate that optical image correlation of satellite imagery can provide important measurements of lateral spread displacements that can be used to better understand lateral spreading.

The correlation approach can be applied to any single band data set (i.e., geospatial data in which a single value is associated with each pixel), such as satellite images, aerial photographs, or even the elevations within a DEM. It is more difficult to apply the technique to aerial photographs because one must correct for many variables, including the internal orientation of the camera, the external orientation of the aircraft, and the camera model (Leprince, personal communication). When applying the correlation technique to elevations, the DEM may be derived from LIDAR (e.g. Beavan et al. 2012) or from SfM applied to sUAV images (e.g., Lucieer et al. 2014, Turner et al. 2015). The displacement accuracy and precision derived from correlation of elevations is similar to those derived from satellite imagery; however, features must be contained in the elevation data such that patterns are available upon which the correlation analysis can focus.

Figure 11 presents North/South (NS) lateral displacements along the Avon River, east of the Central Business District in Christchurch, New Zealand, for the full Canterbury earthquake sequence measured using two separate techniques: horizontal optical image correlation of satellite imagery (Secara 2016) and horizontal correlation of LIDAR DEMs (Beavan et al. 2012). These displacements represent displacements over the entire Canterbury earthquake sequence because each pre-event data set was acquired before the M_w 7.1 Darfield earthquake in September 2010 and each post-event data set was acquired after the M_w 5.9 earthquake in December 2011. The results from the two sets of analyses are similar across much of the study

area, such as the large areas of displacement along the two meander sections of the river in the southwest part of the image. However, the results from the LIDAR analysis (Figure 11b) show systematic, diagonal displacement patterns across the study area that are associated with the LIDAR flight lines. The results from the satellite imagery also show displacements away from the river, but these displacements are randomly distributed across the study area and generally are less than 0.3 m. The results in Figure 11 demonstrate that the quality of regional horizontal displacements derived from satellite imagery is as good as, and likely even better than, the horizontal displacements derived from LIDAR. The value of using satellite imagery is increased further when one considers the difference in costs for obtaining the two datasets (i.e., hundreds of dollars for the satellite imagery vs. hundreds of thousands of dollars for the LIDAR) and the availability of archived satellite imagery for pre-event data.

4.3 Ground Movements due to Liquefaction Remediation near Lake Havasu City, US

In 2015, UAV-based remote sensing with SfM 3D modeling and displacement detection was used to validate ground improvement at a site for liquefaction remediation at Lake Havasu, which is located directly on the border between the states of Arizona and California. The site is located on the west shore of Lake Havasu, and therefore is on the California side of the lake.

The geotechnical investigation performed at the 90 m by 70 m site indicated that the soils consisted primarily of loose to medium-dense poorly-graded sands, well-graded sands, and silty sands to depths ranging from depths of 7 m to 14 m below the ground surface. Groundwater was encountered at depths ranging from 2 to 5 m below the native ground surface. A liquefaction hazard analysis performed by the geotechnical engineer for the site indicated that liquefaction triggering was a significant hazard at the site under the design ground motion. Predicted free-field post-liquefaction settlements at the site ranged from 0.6 cm to 8.9 cm across the site, and predicted lateral spread displacements at the site exceeded 0.2 m. The engineer and the owner therefore chose to implement deep dynamic compaction (DDC) to increase the density of the soils at the site and to remediate liquefaction.

The DDC improvement plan consisted of dropping a 26,300 kg weight from a height of 26 m across a triangular grid spacing of 3 m. In total, over 1200 craters were formed at the site as part of the ground improvement, with the energy of the DDC predicted to densify soils to a depth of 7.6 m below the ground surface. Accurate depth measurements of the crater depths by the contractor indicated that the average induced subsidence across the site from the DDC was equal to 37 cm.

An octa-rotor UAV with a mounted Nikon D7100 DSLR camera a 35mm prime lens was used to collect low-altitude aerial imagery over the ground improvement site both before the DDC and after the DDC and site smoothing/grading. Each aerial reconnaissance mission consisted of four separate UAV flights over the site, each one lasting approximately 10 to 12 minutes in duration. A total of 800 digital images were collected from each set of flights, but this number of images was reduced to approximately 460 images per image dataset as blurry images were removed during image pre-processing and masking. Twelve ground control points were laid out across the site and were surveyed at sub-cm accuracy using GPS equipment. Additionally, a 30 m measuring tape was laid across the site as an additional scaling resource to assess the horizontal accuracy of each 3D model. The two image datasets were subsequently processed at half image resolution with *PhotoScan v.1.1.6*, and absolute differences between the two generated 3D point cloud models were calculated using the ICP algorithm. Figure 12 presents both the pre-DDC and post-DDC point cloud models. Each of these point clouds contains approximately 235 million points spaced at an average horizontal distance of less than 1 cm.

Because the only induced change in the soil due to the DDC was vertical (i.e., elevation), all measured absolute differences between the two point clouds was interpreted as induced subsidence of the ground surface from the DDC. Using an ICP algorithm, subsidence across the site was computed and is presented in Figure 13. From this analysis, the average induced subsidence across the entire liquefaction remediation site was approximately 38 cm, which was within about 1 cm of the estimated average subsidence based on measured crater depths.

Additionally, the volumetric change across the improvement zone was calculated as approximately 2,395 m³. These results demonstrate that UAV-based remote sensing using SfM can be effective tool for measuring the surficial volumetric changes at a particular site due to compaction-based liquefaction remediation.

5. Discussion and Conclusions

The use of remote sensing in geotechnical reconnaissance is becoming more common and the techniques to analyze these data are maturing such that important quantitative information is being derived from remote sensing data. As a result, there is significant potential for these techniques to be used on a more routine basis for reconnaissance after earthquakes and other natural hazards (e.g., landslides, coastal storm surge), and some techniques may even become a part of typical geotechnical field monitoring efforts.

Perhaps the most exciting advancements are related to measuring ground movements using remote sensing. The computational techniques that derive movements from remote sensing data are being improved and are providing more precise and accurate displacements. One of the most significant challenges associated with the measurement of ground movement is the collection of “baseline” or “initial” data from which ground movements can be measured through comparisons with the post-event data. For most forms of remote sensing, including satellite imagery and LIDAR, this means the active collection of data at potential sites of interest *prior* to the occurrence of ground movement. For satellite imagery, this is not a significant concern because the cost of image acquisition from the commercial satellite companies is relatively small and the companies are continuously collecting archive imagery of areas of interest. For LIDAR, however, collecting pre-event data can be a difficult and costly task, which may inhibit its collection. Even if pre-event LIDAR is collected at the highest quality available at the time of acquisition, it is likely that the technology will advance significantly over time before the event occurs. Therefore, it is important to continue to collect baseline data every 3 to 5 years such that the pre-event data can take advantage of these advancements. An

important alternative to LIDAR for measuring detailed ground movements is photogrammetry/computer vision techniques, such as SfM. These techniques offer a significant advantage in that they can develop pre-event 3D models from pre-event digital photographs taken from different cameras and at different times. Photographs can even be harvested from the internet and social networking media to develop the image sets needed for the development of the pre-event model (Snavely et al. 2008).

In terms of technologies, UAVs represent an area of potential dramatic and rapid growth. The explosive popularity of UAVs is currently driving both academia and industry to develop better UAV platforms with more sophisticated automated capabilities and improved multi-platform coordination. Current techniques that use a single UAV platform to image an area in 1-2 hrs will evolve into techniques that use a swarm of very small UAVs to image the same area in only minutes but with superior resolution and coverage. UAV portability and endurance will also improve with advances in battery technology and as various sensors become smaller lighter, and more energy efficient. Ongoing advances in computer processing, data storage, and hardware are now making many onboard processing capabilities possible. Intelligent UAVs will soon be able to navigate and image objects that they have never before seen, continually optimizing their flight plan to capture the most useful information from the most critical locations – all with minimal human interaction.

Finally, to fully exploit remote sensing for geotechnical applications, significant cross-disciplinary research is required in which geotechnical engineers collaborate closely with remote sensing specialists. This collaboration can be difficult due to differences in language, skills, culture, etc., and it requires that geotechnical engineers be willing to step out of their comfort zone and acquire new skills from different fields. However, the potential payoff is significant and the results will certainly transform our understanding of geotechnical effects.

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Figure 1. Example of terrestrial LIDAR collection and processing (Rathje et al. 2006a)

Figure 2. Various general sUAV platform types including (a) single-rotor platform, (b) and (c) multi-rotor platforms, and (d) fixed wing platform

Figure 3. Liquefaction damage at the Port of Iquique, Chile following the 2014 M 8.2 earthquake. Photographs were taken from (a) the ground (Rollins et al. 2014) and (b) sUAV.

Figure 4. Photograph and LIDAR point cloud of failed approach embankment from the 2010 Maule, Chile earthquake (Frost and Turel 2011)

Figure 5. SfM results showing: (a) a point cloud model, (b) an orthoprojection, and (c) a DEM of a landslide on US-89 near Page, Arizona in the U.S. These models were developed from UAV-collected digital photographs processed with the software *PhotoScan v.1.1.6*.

Figure 6. Crack widths from the Molo Pier in Iquique, Chile measured in the field by the GEER team (Rollins et al. 2014) and from preliminary analysis of the UAV-based 3D model.

Figure 7. SfM 3D point clouds of a landslide in the City of North Salt Lake in Utah, US. 3D model from: (a) images captured on August 28, 2014 (soon after the slide); (b) images captured on May 20, 2015; and (c) amplitudes of 3D displacement vectors (in meters) derived from the two models.

Area circled in red is an area of sloughing that occurred between the acquisition of the two datasets.

Figure 8. Landslide distribution from the 2004 Niigata-ken Chuetsu earthquake in Japan. (a) Landslides identified from pixel-based LANDSAT change detection, (b) Landslides identified using traditional mapping (Geographical Survey Institute of Japan 2004).

Figure 9. Remote sensing (RS) landslide density for 1-km² blocks from (a) pixel-based maximum likelihood classification (MLC) and (b) object-oriented classification

(a)

(b)

(c)

(d)

Figure 10. Horizontal displacements measured by optical image correlation for the 2011 Christchurch earthquake (a) Liquefaction study area in Christchurch, New Zealand, (b) East-West displacements from optical image correlation, (c) total displacement amplitudes from optical image correlation, (d) comparisons of displacements from optical imagery and ground surveys. Ground survey displacements from Cubrinovski and Robinson (personal communication)

Figure 11. North/South lateral spread displacements from the Canterbury earthquake sequence measured from (a) horizontal optical image correlation using satellite imagery and (b) horizontal correlation of LIDAR DEMs (data from Beaven et al. 2012). The LIDAR displacement have had the tectonic component removed.

Figure 12. SfM 3D point clouds of the liquefaction remediation site using Deep Dynamic Compaction (DDC). 3D models from: (a) images captured before DDC was performed, and (b) images captured after DDC was performed and the site was smoothed/graded

Figure 13. Computed subsidence (in cm) at the Lake Havasu liquefaction remediation site from the pre- and post-DDC 3D point cloud models. Average computed subsidence across the entire site was 38 cm.