Morphology-Based Identification of Surface Features to Support Landslide Hazard Detection Using Airborne LiDAR Data

DISSERTATION

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By

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Abstract

Landslides are natural disasters that cause environmental and infrastructure damage worldwide. In order to reduce future risk posed by them, effective detection and monitoring methods are needed. Landslide susceptibility and hazard mapping is a method for identifying areas suspect to landslide activity. This task is typically performed in a manual, semi-automatic or automatic form, or a combination of these, and can be accomplished using different sensors and techniques. As landslide hazards continue to impact our environment and impede the lives of many, it is imperative to improve the tools and methods of effective and reliable detecting of such events.

Recent developments in remote sensing have significantly improved topographic mapping capabilities, resulting in higher spatial resolution and more accurate surface representations. Dense 3D point clouds can be directly obtained by airborne Light Detection and Ranging (LiDAR) or created photogrammetrically, allowing for better exploitation of surface morphology. The potential of extracting spatial features typical to landslides, especially small scale failures, provides a unique opportunity to advance landslide detection, modeling, and prediction process.

This dissertation topic selection was motivated by three primary reasons. First, 3D data structures, including data representation, surface morphology, feature extraction, spatial indexing, and classification, in particular, shape-based grouping, based on LiDAR data
offer a unique opportunity for many 3D modeling applications. Second, massive 3D data, such as point clouds or surfaces obtained by the state-of-the-art remote sensing technologies, have not been fully exploited for landslide detection and monitoring. Third, unprecedented advances in LiDAR technology and availability to the broader mapping community should be explored at the appropriate level to assess the current and future advantages and limitations of LiDAR-based detection and modeling of landslide features. This dissertation is focused on developing robust landslide detection mapping techniques using precise and accurate surface models generated from airborne LiDAR data, as well as demonstrating potential capabilities of airborne LiDAR data for small landslide detection, monitoring, vulnerability and hazard mapping. Airborne data have been used for landslide detection, mostly for landslides with large spatial extents. With continuously improving hardware capability of airborne LiDAR systems, combined with the growing availability of low-altitude platforms, such as Unmanned Aerial Systems (UAS), the possibility of effective use of airborne LiDAR to detect and map small landslides is quickly becoming a reality.

Reviewing and testing commonly used surface feature extraction techniques, such as point-based, profile-based, shape-based, and change detection techniques, such as nearest neighbor and Digital Elevation Model (DEM) of Difference (DoD), led to a conclusion that no single technique could solve the landslide predisposition for all environments and circumstances. Alternatively, to develop a unified approach, two robust techniques for landslide detection are proposed that are based on a stepwise strategy that focuses on surface geometry. The first method is based on fusing a shape-based surface feature
extraction technique and change detection method using multi-temporal surface models, while the second method implements a technique to extract, identify, and map surface features found in landslide morphology using a single surface model. In addition, the impact of spatial resolution on small landslide mapping is demonstrated. Using experimental datasets available at the time of this research, the proposed methods showed that 66% and 84% of the landslides from the reference inventory could be detected by the first and the second method, respectively.
Dedication

Dedicated to my beloved wife, children, parents, brothers, family and friends.
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List of Acronyms

Bkf – Berks-Westmoreland complex
C2C – Clout-to-Cloud
CWT – Continuous Wavelet Transform
DEM – Digital Elevation Model
DFT – Discrete Fourier Transform
DGPS – differential Global Positioning System
DoD – DEM of Difference
FIR – Finite Impulse Response
GPS – Global Positioning System
GIS – Geographic Information System
GSD – Ground Sampling Distance
GT – Geotechnical Team
IMU – Inertial Measurement Unit
InSAR – Interferometric Synthetic Aperture Radar
IQR – Interquartile Range
LiDAR – Light Detection And Ranging
minLOD – minimum Level of Detection
MM – Mile Marker
ODNR – Ohio Department of Natural Resources
ODOT – Ohio Department of Transportation
OGE – Office of Geotechnical Engineering
PCA – Principal Component Analysis
RL – Resultant length of orientation vectors
RMSE – Root Mean Square Error
SR – State Route
SVM – Support Vector Machine
TLS – Terrestrial Laser Scanning
UAS – Unmanned Aerial Systems
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Chapter 1 Introduction

1.1 Motivation

Natural disasters due to geological processes cause property damage, loss of life and environmental change. One particular natural hazard known to cause economic, human and environmental damage worldwide is the landslide (Glenn et al., 2006). A “landslide” is defined by Cruden and Varnes (1996) as “the movement of a mass of rock, debris or earth down a slope.” It generally defines a variety of processes that occur over spatial and temporal scales in many mountainous landscapes (McKean & Roering, 2004), although several alternative terms are used. Since, the term landslide is well accepted in the research community, it will be used in this dissertation to describe all movement types and material properties; note that the term mass movement is often used interchangeably with landslide.

Hazard mapping for landslide susceptibility is a method for estimating areas suspect to mass movement. To prevent future risk posed by such events, effective methods to detect, map, monitor and remediate landslides are needed. This task is typically performed in a manual, semi-automatic or automatic form, or a combination of these, and can be accomplished using different sensors (Guzzetti et al., 2012; Jaboyedoff et al., 2012). Ideally, an automatic or semi-automatic landslide detection method should identify
early warning signs of potentially hazardous mass movement allowing for a better understanding of landslide behavior. This can help create better measures/designs for preventing future events and/or break the progress of ongoing occurrences.

The existing techniques, most of which require intensive manual effort, are typically based on field inspection, aerial photograph interpretation, and contour map analysis (Booth et al., 2009). However, these methods have limitations that may reduce the accuracy, completeness, and reliability, all of which are necessary to map small landslides with high confidence level (Booth et al., 2009; Galli et al., 2008). Additionally, many sites are not easily accessible for field inspections. Highly vegetated areas pose difficulties for both on-site inspections and aerial photographic interpretation. Historical contour maps do not have the spatial resolution necessary to map small failures in highly vegetated areas where conventional remote sensing methods cannot penetrate the vegetation (Booth et al., 2009; James et al., 2012; Van Den Eeckhaut et al., 2005). For these reasons, traditional methods are not sufficiently effective and new techniques for landslide detection, susceptibility and hazard mapping are needed.

In the past few years, much effort has been devoted to developing automatic and semi-automatic methods based on remote sensing technology to detect hazards posed by landslides (Ballabio & Sterlacchini, 2012; Booth et al., 2009; Glenn et al., 2006; McKean & Roering, 2004). However, current methods of identifying and assessing the conditions of small failures are inefficient, and their performance may be nonuniform and difficult to predict over large swaths of terrain under vegetation. One reason may be that the small failures require more precise and accurate surface models to increase the detectability of
landslide surface features. The spatial resolution of surface models needs to be relevant to the geomorphological features found in the landslides. Spatial resolution determines the smallest scale, to which surface features may be detected. Therefore, a technology capable of mapping small failures precisely and consistently over large swaths of terrain under vegetation is advantageous, in comparison to the existing methods.

In the past decade, the remote sensing technology has seen considerable advances in accuracy and accessibility and decreasing cost. One of the major improvements has been the spatial resolution of LiDAR technology. Until recently, only a coarse nominal point spacing (> 10 meters) was available, but the improvement of this technology has allowed for higher spatial resolutions (< 1 meter) (Shan & Toth, 2008). The increase made in the spatial resolution provides mapping opportunities at large scales, targeting mapping of the small spatial features. Modern LiDAR technology provides the means necessary to map surface models precisely and with high accuracy (Jaboyedoff et al., 2012; Shan & Toth, 2008). Furthermore, it has the potential to overcome many challenges faced in landslide detection, for example, the spatial resolution, broad terrain coverage, and vegetation penetration. A particular technology that is capable of overcoming these challenges is airborne LiDAR. This type of instrument is capable of penetrating vegetation, mapping areas up to thousands of square kilometers (Guzzetti et al., 2012; Shan & Toth, 2008) and providing sub-meter spatial resolutions. For these reasons, airborne LiDAR is considered in this dissertation as the primary method of landslide detection and mapping.
This dissertation topic selection was motivated by three primary reasons. First, 3D data structures, including data representation, surface morphology, feature extraction, spatial indexing, and classification, in particular, shape-based grouping, based on LiDAR data offer a unique opportunity for many 3D modelling applications. Second, massive 3D data, such as point clouds or surfaces obtained by the state-of-the-art remote sensing technologies, have not been fully exploited in landslide detection and monitoring. Third, unprecedented advances in LiDAR technology and availability to the broader mapping community has not been explored at the appropriate level to assess the current and future advantages and limitations of LiDAR-based detection and modelling of landslide features. Consequently, the potential of extracting spatial features typical to landslides, especially the small failures, provides a unique opportunity to advance landslide detection, modelling, and prediction process. For these reasons, the research focus of this dissertation is to provide reliable detection and monitoring of small landslides that are especially detrimental to roads and highways. In particular, the main objectives are: 1) developing a robust approach for landslide detection based on fusing a shape-based surface feature extraction technique and change detection method using multi-temporal surface models, 2) implementing a method to extract, identify and map surface features found in landslide morphology using a single surface model, 3) evaluating the success of landslide detection based on typical LiDAR data available commercially, and 4) assessing the required spatial resolution of the surface data needed to extract surface features indicative of small landslides, as well as demonstrating the potential of airborne LiDAR data to map surface models needed for small landslide detection. The focus is on
the small failures in low relief terrain, along the transportation networks and alongside rivers. As will be shown in the subsequent chapters, the proposed new approach offers a more comprehensive alternative, as compared to the prior studies. The performance of the developed approach is tested on particularly challenging landslide features of small spatial scope, located along transportation corridors.

1.2 Review of Landslide Processes and Mapping Methods

The following section will introduce the terminology used to characterize the landslide process, material type, nomenclature and velocity class. In addition we will provide a review of the state-of-the-art landslide vulnerability assessment and detection mapping techniques using single and multi-temporal datasets. Moreover, change detection methods and associated applications will be reviewed. Limitations to the current state-of-the-art methods will also be discussed.

1.2.1 Definitions, Classifications and Causes

Landslide classification is usually based on material and process types (Cruden & Varnes, 1996), as illustrated in Figure 1. The material types can be categorized as rock or soil. Rock is hard or firm mass intact before any movement. Soil is divided into two sub-categories, earth and debris, see Table 1. Earth describes material in which 80% or more of the particles are smaller than 2 mm, while debris describes material in which 20 - 80% of the particles are larger than 2 mm (Cruden & Varnes, 1996).
Figure 1. Types of movement (1) a fall; (2) a topple; (3) a slide; (4) a spread; (5) a flow. The extents of mass movement vary largely from a few meters to hundreds of meters (Cooper, 2007).

<table>
<thead>
<tr>
<th>Process type</th>
<th>Type of material</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fall</td>
<td>Rock fall</td>
</tr>
<tr>
<td>Topple</td>
<td>Rock topple</td>
</tr>
<tr>
<td>Slide</td>
<td>Rock slide</td>
</tr>
<tr>
<td></td>
<td>Translational</td>
</tr>
<tr>
<td></td>
<td>Rotational</td>
</tr>
<tr>
<td>Spread</td>
<td>Rock spread</td>
</tr>
<tr>
<td>Flow</td>
<td>Rock flow</td>
</tr>
<tr>
<td>Complex</td>
<td>Combination of two or more types of movement</td>
</tr>
<tr>
<td></td>
<td>Debris fall</td>
</tr>
<tr>
<td></td>
<td>Debris topple</td>
</tr>
<tr>
<td></td>
<td>Debris slide</td>
</tr>
<tr>
<td></td>
<td>Earth fall</td>
</tr>
<tr>
<td></td>
<td>Earth topple</td>
</tr>
<tr>
<td></td>
<td>Earth slide</td>
</tr>
<tr>
<td></td>
<td>Earth spread</td>
</tr>
<tr>
<td></td>
<td>Earth flow</td>
</tr>
</tbody>
</table>

Table 1. Landslide class based on material and process type (Cruden & Varnes, 1996).
Another landslide classification category is based on movement velocity, which ranges from extremely slow to extremely rapid, see Table 2. Landslides can also be distinguished by their state of activity, namely active, suspended, reactivated, inactive, dormant, abandoned, stabilized and relict mass movements (Cruden & Varnes, 1996). There are other methods to differentiate mass movement, for example, the water content of involved materials (Cruden & Varnes, 1996). The nomenclature for the observable landslide features is illustrated in Figure 2.

<table>
<thead>
<tr>
<th>Velocity class</th>
<th>Description</th>
<th>Velocity (mm/sec)</th>
<th>Typical velocity</th>
<th>Human response</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>Extremely Rapid</td>
<td>$5 \times 10^3$</td>
<td>5 m/sec</td>
<td>Nil</td>
</tr>
<tr>
<td>6</td>
<td>Very Rapid</td>
<td>$5 \times 10^1$</td>
<td>3 m/min</td>
<td>Nil</td>
</tr>
<tr>
<td>5</td>
<td>Rapid</td>
<td>$5 \times 10^{-1}$</td>
<td>1.8 m/hr</td>
<td>Evacuation</td>
</tr>
<tr>
<td>4</td>
<td>Moderate</td>
<td>$5 \times 10^{-3}$</td>
<td>13 m/month</td>
<td>Evacuation</td>
</tr>
<tr>
<td>3</td>
<td>Slow</td>
<td>$5 \times 10^{-5}$</td>
<td>1.6 m/year</td>
<td>Maintenance</td>
</tr>
<tr>
<td>2</td>
<td>Very Slow</td>
<td>$5 \times 10^{-7}$</td>
<td>16 mm/year</td>
<td>Maintenance</td>
</tr>
<tr>
<td>1</td>
<td>Extremely Slow</td>
<td>Nil</td>
<td></td>
<td>Nil</td>
</tr>
</tbody>
</table>

Table 2. Landslide class based on landslide velocity scale (Cruden & Varnes, 1996).

Figure 2. Block diagram providing the nomenclature of an idealized complex earth slide-earth flow (Cruden & Varnes, 1996).
Slope failures occur when the strength of the earth material is exceeded by gravity on a hill or mountain side. There are three main landslide causes: geological, morphological and human (Highland, 2004). Landslides are rarely caused by single event; they are usually a combination of factors such as: erosion, addition of moisture, shocks and vibrations, volcanic eruptions, over-development and deforestation (Highland, 2004). Furthermore, landslides occur in low relief areas due to cut-and-fill failures (e.g., roadway and building excavations), river bluff failures and lateral spreading landslides (Highland, 2004). All landslides have distinctive characteristics; however they tend to have similar geomorphologic features.

Detecting early warning signs of landslide hazards may help prevent future events by beginning remediation earlier. Landslide warning signs include, but are not limited to: saturated ground in areas typically not wet before, cracks or bulges in the ground, soil moving away from foundations, broken underground utilities, leaning poles, trees, walls or fences, and sunken road beds (Highland, 2004). Areas generally prone to landslide risk are areas where water drainage or soil hydrology is inefficient, areas with existing old landslides, areas on or at the base of slopes, areas in or at the base of minor drainage hollows, areas at the base or top of an old fill slope, areas at the base or top of a steep cut slope, and developed hillsides where leach field septic systems are used (Highland, 2004). Areas that are typically safe from landslide hazards are relatively flat areas away from abrupt changes in slope, and on hard bedrock that has not experienced movement in the past (Highland, 2004).
1.2.2 Surface Feature Extraction State-of-the-Art

Previous landslide detection techniques have revealed the potential that remote sensing technology has to offer in the identification and mapping of geomorphologic features related to landslide morphology (Booth et al., 2009; Glenn et al., 2006; McKean & Roering, 2004). However, their focus has been on mapping large landslides in hilly terrain and mountainous regions, along coastal bluffs and river basins (Ballabio & Sterlacchini, 2012; Booth et al., 2009; Tien Bui et al., 2012; Van Den Eeckhaut et al., 2005). Previous studies have paid less attention to mapping small landslides that impact our transportation networks. This is due to their impact being less severe, and due to the need for high spatial resolution to identify their relatively small geomorphological features. The spatial resolution needs to be relevant to the scale of the morphological features of the landslides in order to understand the spatial and temporal process evident in the landslide morphology (Glenn et al., 2006). To our best knowledge, detection and hazard mapping for small landslides has not been addressed in the literature, and an evaluation is necessary to understand and propose a means of landslide detection for the prevention of future events.

Rapid mapping is an emerging application that can support landslide detection, susceptibility and hazard mapping. To date, a few investigators have successfully attempted the use of LiDAR-derived DEMs to automatically or semi-automatically extract the surface features found in landslides. This task is challenging (Pike, 1988) and, if successful, it will ease the creation of landslide maps (Guzzetti et al., 2012).
McKean and Roering (2004) illustrated that the local surface roughness within an earthflow can be accurately measured from a high resolution DEM. In their attempt, they measured the surface roughness using different surface feature extractors (Pike, 1988; Turcotte, 1997), including direction cosine, eigenvalue ratios, local slope variability, circular statistics, two-dimensional spectral analysis and Laplacian operators (Zevenbergen & Thorne, 1987). In their evaluation, it was shown that the surface roughness of a landslide was generally higher than that of an undisturbed surface.

Glenn et al. (2006) used geostatistics, specifically surface roughness, semi-variance, fractal dimension, and slope, to delineate surface roughness found in landslides from a LiDAR dataset acquired for two canyon-rim landslides in southern Idaho, USA. From this study it is noted that the lack of high-resolution data challenged the spatial and temporal mapping of landslides. In this study, they focused on the analysis of two large landslides with area size of 0.22 km$^2$ and 0.85 km$^2$. In addition, it is hypothesized that the active landslides have experienced higher degrees of surface deformation and topographic variability compared to older landslides.

Sato et al. (2007) obtained topographic information from an airborne LiDAR survey of the Tomari-no-tai area in Shirakami Mountains, Japan. The geomorphologic features extracted were slope, surface texture (feature frequency or spacing) and local convexity. The information extracted was used to perform an unsupervised classification of landform types. The results obtained identified 17 classes in the map that were subsequently compared to a map generated through visual interpretation of a 1:2500 scale contour map and 1:8000 scale aerial photographs. The automatic classification proved to
objectively describe the surface morphology but was not able to give information regarding the landform evolution. However, the results can help revise, update, and improve the maps generated by field-based manual mapping.

Booth et al. (2009) used two signal processing methods, specifically, the two-dimensional discrete Fourier transform (DFT) and continuous wavelet transform (CWT) to quantify and map more than 80% of the surface that had experienced landslide activity in the Puget Sound lowlands in the state of Washington and the Tualatin Mountains in the state of Oregon, USA. Two LiDAR-derived DEMs were used to characterize and delineate the spatial frequencies of morphological features typical to deep-seated landslides, including hummocky terrain, scarps and displaced blocks of material. However, most of the study site used for evaluation of the proposed algorithm consists of coastal bluffs; additionally, the study is focused on extracting the morphologic signatures of deep-seated landslides. One of the limitations of the proposed algorithm is that any abrupt change in elevation experiences high power spectrum, consequently classifying the local region as a landslide.

Kasai et al. (2009) used supervised classification to classify a LiDAR-derived DEM based on the extracted surface features of slope angle and eigenvalue ratios inside deep-seated landslides. The technique was trained using field investigations to extract, identify and map landslide surface features. The study area was in a mountainous terrain area along the Kii mountain range, Japan.

Passalacqua et al. (2010) and Tarolli et al. (2010) used a LiDAR DEM from the Rio Cordon basin in the Dolomites, Italy, for semi-automatic extraction of morphological
features, which includes forms related to shallow landslides and riverbank erosion. Local statistics of topographic curvature, standard deviation, interquartile range, median absolute deviation and quantile-quantile plots were computed where curvature data were plotted against the standard normal deviation of the exceedance probability. The variations in the surface were used to extract morphological features, which were subsequently filtered using a threshold derived from field observations. The method was rapid; however, it was imprecise for areas of complex morphology. Even so, Tarolli et al. (2010) considered the method useful for assisting geomorphologists in the visual detection of landslide features.

A problem in existing attempts of automatic or semi-automatic landslide surface feature extraction and related morphological features from LiDAR-derived DEMs is associated with the pixel-based approach. These attempts hardly consider the local geomorphological setting and “context” (e.g., size, shape and position) in the extracted topographic features (Guzzetti et al., 2012). For this reason, it is difficult to understand how a single feature or feature type may be indicative of different forms and processes of landslide activity, especially over large swaths of terrain (Guzzetti et al., 2012). However, attempts have displayed relationships between the topographic features and landslides. Applying any of these methods is not easy since expert criteria are necessary to interpret the results (Jaboyedoff et al., 2012).

1.2.3 Surface Change Detection State-of-the-Art

Topographic data acquired from airborne LiDAR can provide important post-event topographic change detection over broad swaths of terrain, only if pre-event data are
accessible. In addition, it can also measure rates of continuous and irregular landscape change not related to particular events (DeLong et al., 2012). Multi-temporal airborne LiDAR can be used to detect changes that may be too difficult using other means or detecting changes in areas that would otherwise go undetected (DeLong et al., 2012).

In the early 1990s, Lane et al. (1994) introduced repeat topographic surveys to produce DoD maps (Difference of DEMs or vertical difference maps) by utilizing rigorous analytical photogrammetry with ground survey. DoD is a common method of comparison in earth sciences and provides a general form to measure surface changes. This method is fast and includes explicit calculation of uncertainties related to data registration, data quality, surface roughness and interpolation uncertainty, especially in areas of missing data due to occlusion (Brasington et al., 2003; Wheaton et al., 2010b).

The ability to observe surface deformation from change detection on DEMs presented a new opportunity to identify, predict and quantify mass movement (James et al., 2012). Assuming that real surface deformations can be distinguished from measurement uncertainties, DoD maps are highly effective means to monitor temporal changes (DeLong et al., 2012; Wheaton et al., 2010a; Wheaton et al., 2010b). However, to monitor temporal changes properly, it is essential that DEM generation and multi-temporal registration be performed appropriately (DeLong et al., 2012).

Multi-temporal remote sensing techniques have been used to measure surface processes by performing change detection to map erosion, deposition and volumetric changes (DeLong et al., 2012; Lane et al., 1994; Wheaton et al., 2010a; Wheaton et al., 2010b). Topographic change detection over large areas in landslide terrains have consisted of
methods such as field observation, traditional surveying, aerial photograph interpretation, Global Positioning System (GPS), Interferometric synthetic aperture radar (InSAR) and airborne LiDAR (Baum et al., 1998; Coe et al., 2009; Glenn et al., 2006; Kelsey, 1978; Mackey & Roering, 2011; Mackey et al., 2009; Malet et al., 2002), or a combination thereof. While these methods provide landslide kinematics and mechanics (DeLong et al., 2012), none of them has provided efficient and reliable sub-meter horizontal and vertical maps of topographic changes that are necessary to monitor temporal changes of small slides over terrain under canopy or vegetation.

Corsini et al. (2007) and Corsini et al. (2009), analyzed large scale post-failure and active earth slides using multi-temporal LiDAR data acquired from helicopter platforms. The maps provided meter-scale vertical changes of landslide terrains in Italy, in addition to volumetric change. Bull et al. (2009) used multi-temporal airborne LiDAR data for detailed mapping of debris flow deposits and volumetric computation. The study used a 4 m spatial resolution DEM and provided confidence in elevation comparisons at the 0.40 m level.

Burns et al. (2010) used multi-temporal airborne LiDAR data acquired in landslide terrain to compare data acquired by the same technology during different seasons in heavily forested terrain. Their evaluation addressed the challenges of airborne LiDAR acquisition during ‘leaf on’ conditions. In their study it was concluded that in the given environmental setting, subtle landslide changes were not easy to identify; however, multi-temporal airborne LiDAR collection in ‘leaf off’ conditions for heavily forested terrain may hold more promise. Based on volumetric estimates made between the datasets,
however, they suggest that they are unable to delineate errors in the data from actual landscape changes with great confidence. DeLong et al. (2012) quantified the landscape change after aligning the datasets by performing a cell-by-cell subtraction, thus creating elevation difference maps. However, the quantification of landscape change was only up to meter-scale.

Guido et al. (2011) used surface roughness, residual topographic surface, and the statistical analysis of the temporal variations of these parameters to reconstruct and track an active landslide at Montaguto (Southern Italy). Four airborne LiDAR datasets were acquired between May 2006 and June 2010 to perform the landslide monitoring, where a 1 by 1 m grid DEM was generated from irregularly spaced bare-earth points. Since, the study solely focuses on the analysis of one of the largest and most complex landslides in Europe having a length of about 3 km, ranging in width between 45 m and 420 m, and covering an area of about 0.5 km², it can’t be applied to evaluating smaller and less active slides.

Terrestrial laser scanning (TLS) has been used in Baldo et al. (2009) and Olsen et al. (2012) for landslide monitoring. Olsen et al. (2012) used TLS to map and assess landslides along transportation networks. Their approach provides a rapid mapping technique capable of identifying changes in the field. Baldo et al. (2009) used TLS for three-dimensional change detection, which provided a detailed approach to landslide monitoring. However, both approaches are labor intensive, cover small areas per occupation, and require substantial effort to compile complete landslide maps.
The aforementioned studies and improvement in spatial resolution of airborne LiDAR data motivate future research to cover larger spatial extents and provide higher spatial resolution and accuracy for analyzing landscape changes (DeLong et al., 2012). Although DEMs generated from remote sensing data can be differenced to produce DoD maps, further analysis is necessary to quantify elevation differences at sub-meter scale for small failures. In doing so, research may provide a new form to evaluate surface deformation and potentially provide a means to better monitor the spatial and temporal processes of small landslides.

1.2.4 Effects of Spatial Resolution

The impact of spatial resolution of surface data required to extract surface features indicative of landslides is vital and has not been properly addressed in previous studies to the best of our knowledge. Razak et al. (2011) evaluated the minimal point density necessary to analyze scarps, cracks, and displacement structures in a DEM. The data for this study was acquired using a helicopter at a flying height of 300 meters and an airborne hand-held laser scanning system. It was observed that a point density of more than 6 pts/m² was appropriate for a thorough examination in their study area. Due to the climatic and geomorphic components in the study area, rotational and translational shallow landslides usually affect the uppermost 2 to 6 m of the surface. A limitation of the study is that the study area is highly susceptible to landslides and the proposed results are focused on a very active slope segment. In addition, the only morphological features analyzed are those that can be characterized by displacement.
Recent developments in LiDAR technology in both spatial resolution and accuracy now provide an opportunity to map landslide morphological surface features of small spatial extents. This is because small spatial extents require higher spatial resolution and accuracy compared to landslides of larger spatial extents, and the proposed point density in existing literature may not be adequate for small failures experiencing very slow mass movement.

Studies to date have not focused on assessing the impact of spatial resolution for landslide mapping because the resolutions acquired were adequate for their assessment and provided promising results in their respective studies. In addition, the need for high-resolution LiDAR with a spatial resolution pertinent to the scale of the morphological features of the landslides is crucial to understand the spatial and temporal processes apparent in the landslide morphology (Glenn et al., 2006). The optimum density and distribution are connected to the traits of the terrain surface (Li et al., 2005). Moreover, from the fundamental sampling theorem, it can be concluded that variations having twice the sampling interval or more can be represented from the sampled data (Li et al., 2005). Therefore, an assessment is crucial to evaluate the impact of spatial resolution on small landslide detection and mapping.

Guzzetti et al. (2012) concludes in their evaluation of future landslide hazard assessments that prospective advancements made in remote sensing technologies (e.g., spatial resolution, accuracy) will improve the quality of landslide detection and mapping, additionally facilitating the production of landslide maps.
1.3 Significance and Organization of the Dissertation

This dissertation is focused on how to extract surface features and identify surface deformations susceptible to landslides from airborne LiDAR data. In particular, we focus on small failures that impact transportation infrastructure, which often go undetected, and thus unremediated. In the early stages of this research, a comprehensive literature review on landslide mapping and monitoring yielded a number of possible solutions to the general problem of landslide detection; note almost all of these aimed at detecting larger landslides. These solutions included performance evaluation of surface feature extraction using a LiDAR-derived DEM, and change detection using a time-series of LiDAR-derived DEMs; all methods were hence investigated and tested with respect to our specific objectives. Our experimental results revealed that airborne state-of-the-art LiDAR data has the potential to create detailed and accurate surface models for landslide detection and monitoring. In addition, the experiments and analysis performed helped us understand the complexity and challenges of this research topic, and inspired us to derive and propose alternative solutions for landslide detection and mapping.

In Chapter 2, the core components of surface feature characterization are introduced. The characteristics of point-based, profile-based and shape-based surface extraction methods are described and discussed. Subsequently, these surface extraction methods are introduced in detail, followed by the analysis of those methods tested in an experimental setting. Finally, a conclusion describing the limitations and benefits of each is described.

In Chapter 3, the main elements of change detection are introduced. The characteristics of Cloud-to-Cloud (C2C) and DoD change detection methods, and the uncertainty in data
for each of these methods are described and discussed. Next, a probabilistic approach to characterize real surface change is discussed, followed by the analysis of those methods tested in an experimental setting. Finally, a conclusion discussing the advantages and disadvantages of each is provided.

In Chapter 4, a robust approach for landslide detection based on surface feature extraction is proposed, which is one of the main contributions of the dissertation. This method consists of several successive steps. First, major geomorphologic features are extracted from the surface model to analyze the local topography, including, the direction cosine eigenvalue ratios (\(\lambda_1/\lambda_2\) and \(\lambda_1/\lambda_3\)), resultant length of orientation vectors, aspect, roughness, hillshade, slope, a customized Sobel operator (Gonzalez & Woods, 2002) and soil type. Next, a sample set extracted from the data is used as observations of landslides and stable terrain to train the supervised classification algorithm of Support Vector Machine (SVM). The trained SVM model is subsequently used to classify the LiDAR-derived DEM based on the extracted surface features. Then, as a post-classification step, flat terrain is filtered and classified as stable terrain; a conditional dilation/erosion filter is applied to minimize misclassified locations by the SVM algorithm, and additionally to suppress noise and generate landslide susceptible regions (clusters). Landslide susceptible regions are then analyzed to map areas of potential landslide activity. Finally, in order to evaluate the performance of our proposed approach, we assess how well the algorithms mapped landslides match the reference inventory mapped landslides. In addition, a probabilistic approach for landslide detection utilizing multi-temporal airborne LiDAR-derived DEMs is proposed, which is also one of the main contributions of the
dissertation. The approach analyzes cell-by-cell vertical differences between two surfaces. Next, the vertical changes observed are evaluated probabilistically by employing the non-parametric signed rank test to evaluate if the median of the observed vertical differences within a local neighborhood is greater than the propagated uncertainties. Then, high-probability neighborhoods (clusters) consisting of landslide features and desired probabilities are mapped. Finally, a minimum area threshold is set to help suppress noise of the generated clusters. To assess the performance of the proposed landslide detection technique, a comparison is performed to quantify the surface deformation of new and existing landslides with respect to the provided landslide inventory map.

In Chapter 5, we demonstrate the impact of spatial resolution on landslide mapping at varying spatial resolutions. A base DEM is used to generate a series of coarser spatial resolutions. Each DEM is classified using the proposed approach to landslide surface feature extraction of single surface models. The classification at each spatial resolution is examined to determine the effects of spatial resolution on both landslide classification and surface feature extraction. Obviously, the loss of detail in the geomorphological features, driven by the lack of spatial resolution, is not new topic, yet the issue of spatial resolution needs to be addressed and analyzed in order to thoroughly understand how spatial resolution can potentially impact the performance of landslide detection.

Chapter 6 concludes with observations related to the research process of the landslide detection method, surface deformation method and spatial resolution assessment to map small failures. Future recommendations are also discussed.
1.4 Data

The following section will introduce the data used to test and validate the proposed solutions. The details described will provide a review of the environmental setting of the study area, LiDAR data used to generate the DEMs, and the compilation of the landslide inventory map used as a reference of mapped landslides to help verify our algorithm’s performance.

1.4.1 Study Area

The study area available for this research was along the transportation corridor of state route (SR) 666 in Zanesville, Ohio, located in north-central Muskingum County (Approx. Latitude: N39° 58’ 00”, Longitude: W81° 59’ 00”) along the east side of the Muskingum River. The study area begins at the intersection of SR 60 within the City of Zanesville just north of Interstate 70 (I-70) and south of the Muskingum River at mile marker (MM) 0.00 and ends at the intersection with SR 208 east of the Village of Dresden at MM 14.34. The extent of the study area is 23 kilometers in length along SR 666 with a varying swath width of 75-180 meters. The area is characterized by high vegetation densities, stream and river channeling, some residential development and post mining activity in sloped terrain. The study area was chosen due to the availability of multi-temporal airborne LiDAR-derived DEMs, a detailed landslide inventory map and its prolonged history of slope instabilities, especially, in areas where the river is close to the roadway. In 2004 and 2005, Muskingum County was declared a National Disaster Area due to extensive flooding in both tributaries and the main river channel of the Muskingum River. Along the road seven separate sections damaged by landslides were
corrected as a result of these storm events. Figure 3 presents an overview map of the study area.

![Figure 3](image)

Figure 3. SRTM (Shuttle Radar Topography Mission) hillshade map (left), and environmental setting (right) of the study area along the transportation corridor SR-666, north of Zanesville, OH. The white squares indicate the location of the six independent segments along the study area that were used for the LiDAR interpolation accuracy assessment.

1.4.2 LiDAR Data

LiDAR data were acquired in the winter of 2008 and spring of 2012 by ODOT using an Optech’s ALTM 2050 onboard an aircraft. The laser rangefinder data were computed in
conjunction with measurements from the onboard differential GPS (DGPS) and inertial measurement unit (IMU), producing x, y, z coordinates of all LiDAR points. The irregular point cloud datasets, bare-earth filtered by the TerraScan post-processing software to point densities of 3 and 5 pts/m², were used in this research. Normally, a thin and smooth filtering on the hard points and a smooth and model key point filtering on the soft points are performed in TerraScan. However, in an effort to keep the LiDAR data as dense as possible, the ground points were neither thinned nor smoothed. The error budget of the LiDAR data was evaluated by field surveying of ground objects that are clearly visible in the point cloud. The vertical accuracy of the points was assessed after the LiDAR survey was adjusted to the hard-surface control, which is a standard practice to remove systematic errors due to sensor bias, and to biases in GPS, aircraft attitude, scanning angle, and time measurements. Then, the vertical accuracies for both hard- and soft-surface controls were compared to the adjusted LiDAR. In the accuracy evaluation, there were a total of 249 hard- and 88 soft-control points, surveyed by the ODOT virtual reference station network, with accuracies within 9-15 mm horizontally and 15-25 mm vertically. Hard surface control points are located on paved surfaces, such as asphalt and concrete, while soft-surface control points are located on vegetated surfaces, thus are more ambiguous. The vertical accuracy of the LiDAR points was assessed by the root mean square error (RMSE), which was 9 cm and 5 cm for soft and hard surfaces, respectively. Additionally, the vertical standard deviation was 6 cm and 5 cm for soft and hard surfaces, respectively. The vertical standard deviations indicate that there is a bias in the vegetated areas along the soft surfaces. The LiDAR characteristics are shown in Table
3. The irregular bare-earth point cloud was interpolated to a regularly gridded spatial resolution of 50 cm using kriging after evaluating the average point spacing to be 47 and 56 cm for the 2012 and 2008 LiDAR datasets, respectively. The statistical results based on test data demonstrated that among several interpolation methods, kriging provided the minimum error between the interpolated surface (DEM) and the bare-earth filtered LiDAR point cloud. This test was performed on flat and sloped terrain consisting of varying surface complexities (high and low surface roughness). For this reason, kriging was selected as the prime interpolation method in this study. Subsequently, the interpolation accuracy was assessed by examining six independent soft/complex surface segments along the study area (the segments are shown by white squares in Figure 3), and then comparing the interpolated elevations to the LiDAR point cloud elevations, resulting in standard deviation of 11 cm and 10 cm, for the 2008 and 2012 DEMs, respectively. The preprocessing of the bare-earth LiDAR data, including conversion to a regular grid, was done via LAStools (Isenburg, 2012) and ArcGIS software. All sequential processing was performed in MATLAB. The results of all processing steps were integrated into the study Geographical Information System (GIS) database.
### LiDAR Characteristics of the System

<table>
<thead>
<tr>
<th></th>
<th>2008</th>
<th>2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. Survey Points</td>
<td>9,458,131</td>
<td>13,873,656</td>
</tr>
<tr>
<td>Ground Sampling Distance (GSD)</td>
<td>1.84 (0.56 m)</td>
<td>1.54 (0.47 m)</td>
</tr>
<tr>
<td>Density</td>
<td>0.29 (3.12 m)</td>
<td>0.43 (4.63 m)</td>
</tr>
<tr>
<td>Date of Survey</td>
<td>12/ 30/2008</td>
<td>4/5/2012</td>
</tr>
<tr>
<td>Accuracy of Ground to Hard Surfaces</td>
<td>US Survey Feet</td>
<td>US Survey Feet</td>
</tr>
<tr>
<td>Average Difference in Height</td>
<td>0.00 (0.00 m)</td>
<td>N/A</td>
</tr>
<tr>
<td>Root Mean Square</td>
<td>0.15 (0.05 m)</td>
<td>N/A</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.15 (0.05 m)</td>
<td>N/A</td>
</tr>
<tr>
<td>Accuracy of Ground to Soft Surfaces</td>
<td>US Survey Feet</td>
<td>US Survey Feet</td>
</tr>
<tr>
<td>Average Difference in Height</td>
<td>0.19 (0.06 m)</td>
<td>N/A</td>
</tr>
<tr>
<td>Root Mean Square</td>
<td>0.28 (0.09 m)</td>
<td>N/A</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.21 (0.06 m)</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 3. LiDAR characteristics of the system used for 2008 and 2012 data acquisition of SR 666.

The spatial resolution of the airborne LiDAR data acquired at approximately 50 cm is clearly not the spacing needed to map the relevant surface features found in small landslides. Therefore, the airborne LiDAR data is limited for extracting small features and this resolution will impact the performance of the proposed landslide hazard detection methods.

#### 1.4.3 Landslide Geohazard Inventory

For the study area, a geohazard inventory and evaluation of mass movement affecting the transportation network was completed in 2006 by the ODOT Office of Geotechnical Engineering. This provided important information about the general location of landslides affecting the road prism. An updated landslide inventory map was compiled by a team of experts from Kent State University and The Ohio State University through contour map analysis, landslide inventory evaluation and on-site validation in the summer of 2012. The updated landslide inventory was used as a reference for the investigation.
Typical landslides affecting the road prism are: rotational, translational, complex, rockfall debris and mudslides. The slopes for areas of instability range from 18° - 80°, in which the most frequently observed slope was 45°; additionally, the landslides described have a range of ages per the historical documents. The inventory map is important because it provides a reference against which the performance of our proposed approach can be evaluated. A limitation found in the reference map is that it only provides the coarse extent of the mapped landslides but offers no information about the rate of change experienced. The mapped landslides provided in the inventory range from 200 m² to 27,000 m² in area. The soil map used for this study was available online from the Ohio Department of Natural Resources (ODNR) website (http://www.dnr.state.oh.us/tabid/9051/Default.aspx). Examples of slides affecting the embankment are shown in Figure 4 and Figure 5.

Figure 4. Example of a rotational slide, affecting the embankment, near MM 7.3 that has since been stabilized. The extents affected by landslide movement are outlined in red.
This inventory map, consisting of 34 sections, is provided in Appendix A. This inventory map includes the following features:

1. Location of SR 666.
2. Location of mile markers.
3. Polygons indicating the boundaries of potential landslides affecting both the embankment and the natural hill-slope.
4. 5 foot contours underlying the rasterized hillshade DEM.

The inventory maps in Appendix A indicate 80 potential landslide locations that could be considered for development of the computer model as well as for the verification of the model. As for the extent of landslide activity, the inventory map reveals three categories of landslides: (i) those affecting the embankment, (ii) those affecting the natural hill-slope, and (iii) those affecting both embankment and natural slopes.
1.4.3.1 Field Surveys

To support the investigation required by the project, several field surveys have been carried out with the objective of collecting ground reference data and hypothesis validation, including:

- Checking the currency of the former OGE and Consultant reports that is the base reference for the SR 666 road. This work is focused on selected areas, and therefore, only part of the road section is surveyed.
- Precise boundary surveying of the selected areas based on highly accurate GPS and total station measurements. The fieldwork was done by identifying landslide boundaries to be surveyed.
- Performance validation of the landslide prediction method, including surveying and geotechnical assessment of areas identified as potential landslide by the developed method, but not listed in the inventory database.
- Updating the existing inventory data of SR 666 to the extent it is feasible based on the fieldwork.

1.4.3.2 GPS Surveying of Selected Landslides

To support the study, accurate GPS data were acquired for a selected number of landslides; a team of geotechnical experts identified nine landslides, shown in Appendix B. The landslides were selected to convey most types of landslides, including size, shape and general location along the transportation network. These sites included four landslides affecting the natural slope, three affecting the embankment, and two affecting both the natural slope and the embankment. Appendix B shows that four of these
Landslides are rotational in nature, two are translational slides, and three are complex slides involving both rotational and translational elements. To facilitate surveying, a team of experts consisting of geologists and geotechnical engineers identified points along the landslide boundaries in the field, which were then used to collect GPS data used for testing and developing the model. The exact boundaries of the selected sites are shown in Figure 6, including the environment of the surveyed landslide areas.

Figure 6. GPS surveyed landslide locations along SR 666.
Shown in Figure 7 is the surface morphology of landslide 7. The surface features shown illustrate the challenge involved in detecting and modeling landslide areas that are not easily delineated from stable terrain. Ideally, it is desired to observe some discrepancies between the mapped landslide and the stable terrain, which is not the case shown here. Therefore, to characterize the landslide morphology is not easy and requires an in-depth evaluation.

Figure 7. Surface morphology of landslide 7 shown in detail.

1.4.3.3 Observed Landslide Activity

Field observations revealed that many of the remediated landslide sites show evidence of new movement. Also, slope movement is a continual activity along SR 666. The landslide boundaries shown in the inventory maps in Appendix A are likely to change with time, and additional landslides may develop. Considering this, it is imperative to
compare the latest LiDAR imagery (2012) with the one used in the study to this point (2008).

1.4.3.4 GIS Data Compilation

The field survey information provides the geometrical and location information for the selected landslides areas and is part of the GIS inventory system. The team of experts collected and analyzed data regarding bedrock geology, soil type and hydrogeology (if available). These data form the basic GIS map layers developed by the experts; this information is provided in standard shapefile format and may be subsequently used in the classification process if desired.

1.4.3.5 Comparison of Geotechnical Experts’ Evaluations

A comparison was performed to evaluate the consistency between three independent geotechnical teams (GT) that compiled reference landslides throughout the study area, where Team 1 is the University of Cincinnati, Team 2 is Kent State University and Team 3 is The Ohio State University. Shown in Figure 8 is a diagram that compares the evaluation performed by each and the consistency amongst each other. In the diagram it is shown that the correspondences are relatively low. In addition, of the nine areas surveyed, shown in Figure 6, only 3 were in agreement for all teams. There are often times where opinion differs among landslide experts in defining the spatial extent of specific slides, particularly small ones, where features are not easily discerned from the surrounding environment. For this reason without a consistent reference, the development
of landslide hazard detection and classification techniques based solely on morphology becomes more complicated.

Figure 8. Comparison of Geotechnical Experts’ Evaluations

1.4.4 Independent Test Data

Two independent datasets were used in the course of this research with the objective of testing the proposed landslide surface feature extraction algorithm. The 70 cm spatial resolution DEM from HAM-75-5.58 (approx. Latitude: 39° 09’ 38”, Longitude: W84° 30’ 43”), acquired in February 2014 covering part of Interstate 75 in Cincinnati, OH, USA, and 70 cm spatial resolution DEM from TUS-77-1.12 (approx. Latitude: 38° 34’ 05”, Longitude: W81° 34’ 39”) acquired in February 2014 covering part of Charleston, West Virginia, USA area, represent a typical mix of terrain topography and landscape, including residential areas, roads, and vegetated areas. Both airborne LiDAR datasets acquired by ODOT as irregular point clouds were used after Kriging interpolation was
performed to rasterize the irregular point cloud to a regularly gridded DEM. Unfortunately, there is no detailed landslide inventory map (reference) available that would accurately display the landslides extents to rigorously evaluate the algorithms performance on both dataset. Personal communication with ODOT experts, however, confirmed that for both test areas there is a good match between the detected landslides and available information over those areas. In one a slide had occurred and was consequently repaired in the area, while in another one a landslide started to develop.
Chapter 2 Surface Feature Extraction Techniques

In this chapter we present and analyze the performance of surface feature extraction for characterizing and delineating landslide activity. In particular, we focus on the surface shape, surface features and surface geometry found in landslide morphology. First, the general problem is described. Then, various methods are introduced in detail considering their basic components and characteristics. Understanding the problem will help us decide how surface feature extraction may be useful for identifying, mapping and detecting landslide morphology. Subsequently, the surface features are tested and evaluated on our data. From these tests, we observe that landslide surface feature extraction is feasible from airborne LiDAR data with good vertical accuracy and modest spacing. Lastly, we discuss the limitations and potential problems found.

2.1 Overview

Landslide hypothesis can be obtained from the terrain surface. Surface features and properties are analyzed to identify parameter values typical for landslides. This procedure may be performed in three different forms by characterizing local surface points, surface profiles, and surface shapes. The performance of landslide prediction depends on spatial sampling and accuracy of the surface representation. The more detailed and accurate the surface model, the higher the chance to detect landslide suspect areas. Shown in Figure 9 is the conceptual workflow of the surface geometry characterization of landslides.
Identifying surface features based on irregular point data is a difficult task, and therefore only rasterized data are considered.

2.2 Surface Characterization Methods

The morphology of landslides and, in general, land formations can be parameterized by various surface features derived from surface models. The parameters discussed below and subsequently used in this study, have been proven in the literature to characterize and
delineate landslide morphology from stable surfaces (Glenn et al., 2006; Kasai et al., 2009; McKean & Roering, 2004).

2.2.1 Point-Based Surface Characterization

To characterize landslide morphology, the surface feature parameters are computed for every surface point, which is an element of the DEM and may be referred interchangeably with the terms of grid cell and pixel. Subsequently, statistical analysis and classification based on surface features are used to develop landslide hypothesis. Depending on landslide types and shapes, the distribution of these parameters may show correlation with the landslide areas. The definition of the selected six parameters is discussed in the following subsections. The computation of the parameters is rather straightforward, and so is the derivation of the usual statistical parameters, such as mean, median, STD, min, max, etc. Note that while the definition of the parameters is simple, the implementation is not because of the finite spatial resolution of the surface model (gridded/raster representation), and consequently, the error introduced in the computation is not always negligible.

2.2.1.1 Aspect

Slope orientation is the compass direction that a land surface faces. To evaluate the slope orientation, also known as aspect, for a DEM grid point $Z_{11}$ (see Eq. (1)) of a $(3 \times 3)$ local neighborhood, the surface normals need to be computed. Subsequently, the mapping system is converted from a two-dimensional Cartesian coordinate system to a polar coordinate system: $\theta = arctan \left( \frac{N_x}{N_y} \right)$, where $\theta$ is the angle in the polar coordinate system.
and \( N_x \) and \( N_y \) are the surface normals in the east-west and north-south direction, respectively. Finally, the slope orientation of a cell can be computed: \( aspect = \frac{\theta}{\pi} \times 180^\circ + 180^\circ \).

\[
\begin{bmatrix}
Z_{02} & Z_{12} & Z_{22} \\
Z_{01} & Z_{11} & Z_{21} \\
Z_{00} & Z_{10} & Z_{20}
\end{bmatrix}
\]

Eq. (1)

Where, \( Z_i \) refers to the elevation of a DEM grid point.

2.2.1.2 Curvature

Curvature, in general, is the second derivative of the surface. Profile curvature is defined as the curvature computation along the steepest downward gradient, and plan curvature is the curvature perpendicular to the downward gradient. The simplest implementation of curvature for rasterized surface, DEM, is described below. The indexing of an 8-connected neighborhood for a point in a grid follows Eq. (1). The first-order derivatives along the X and Y axes, \( \hat{Z}_x \) and \( \hat{Z}_y \) describe the rate of change of elevation and can be estimated as:

\[
\hat{Z}_x = \frac{\Delta z}{\Delta x} = \frac{z_{21} - z_{01}}{2h}
\]

Eq. (2)

\[
\hat{Z}_y = \frac{\Delta z}{\Delta y} = \frac{z_{12} - z_{10}}{2h}
\]
where, \( h \) is the grid spacing of the DEM. Then the second-order derivatives describing the rate of change of the first derivative in the X and Y axes, or the curvature in those directions, can be derived as:

\[
\hat{z}_{xx} = \frac{\Delta^2 z}{\Delta x^2} = \frac{z_{21} - 2z_{11} + z_{01}}{h^2} \quad \text{Eq. (3)}
\]

\[
\hat{z}_{yy} = \frac{\Delta^2 z}{\Delta y^2} = \frac{z_{12} - 2z_{11} + z_{10}}{h^2}
\]

Next, the mixed second-order derivative that describes the rate of change of the X derivative in the Y direction, called the twisting of the surface can be derived as:

\[
\hat{z}_{xy} = \frac{\Delta^2 z}{\Delta x \Delta y} = \frac{-z_{02} + z_{22} + z_{00} - z_{20}}{4h^2} \quad \text{Eq. (4)}
\]

And introducing two terms as:

\[
p = \hat{z}_x^2 + \hat{z}_y^2 \quad \text{Eq. (5)}
\]

\[
q = p + 1
\]

The plan curvature is defined as:

\[
K_p = \frac{\hat{z}_{xx} \hat{z}_x^2 + 2\hat{z}_{xy} \hat{z}_x \hat{z}_y + \hat{z}_{yy} \hat{z}_y^2}{pq^{3/2}} \quad \text{Eq. (6)}
\]
The profile curvature is defined as:

\[ K_c = \frac{2_{xx}Z_y^2 - 22_{xy}Z_xZ_y + 2_{yy}Z_x^2}{q^{3/2}} \]  

Eq. (7)

2.2.1.3 Hillshade

The relief depiction of a grid point in a DEM is described by the lighting effect of the angle between the surface and the incoming light beam. The approach uses illumination from a single direction for the shading of the terrain relief. Hillshading is typically used to display shaded relief images. The shaded relief images used throughout this dissertation and surface feature extractor follow the approach described in Katzil and Doytsher (2003).

2.2.1.4 Roughness

The metric used to quantify deviations of a surface is called roughness. If the deviations are small, the surface is considered to be smooth, and if the deviations are high, it is considered to be rough. Roughness can be evaluated by computing the largest inter-cell difference of a central pixel and its surrounding cells using Eq. (1), \( R = \text{Max}(Z_{ij} - Z_{i1}) \), where \( i = 0-2, \ j = 0-2 \) denote the DEM grid points in a (3 x 3) local neighborhood (see Eq. (1)).

2.2.1.5 Slope

The maximum rate of change between a cell and its neighbors is known as slope. It is evaluated by computing the steepest descent of a DEM using Eq. (1), \( S_{DB} = \)
\[ \max \left[ \frac{Z_{ij} - Z_{ii}}{\phi(i,j)} \right], \] where, \( i = 0-2, j = 0-2 \) denote the DEM grid points in a (3 x 3) local neighborhood (see Eq. (1)). Where \( \phi(ij) = 1 \) for the cardinal (north, south, east and west) and \( \phi(ij) = \sqrt{2} \) for the diagonal neighbors.

2.2.1.6 Performance Evaluation

This investigation is aimed at assessing the feasibility of using local surface point characterization to identify landslide areas. First, the overall LiDAR data characteristics were computed for the nine surveyed areas (see Figure 6), which are shown in Table 4. Note that surrounding areas, marked by T around the respective sites, are used for control purpose as non-landslide regions. The surrounding areas are described as the total area, excluding the surveyed area of landslide boundaries. T1234 is the area surrounding landslides 1-4 (see Figure 6 detail A), T56 is the area surrounding landslides 5 and 6 (see Figure 6 detail B), T7 is the area surrounding landslide 7 (see Figure 6 detail C) and T89 is the surrounding area of landslides 8 and 9 (see Figure 6 detail D). The grand total is the surrounding areas combined, T1234, T56, T7 and T89. The surface features were subsequently analyzed statistically to characterize the surfaces.
Table 4. LiDAR data characteristic of the ground truth landslides surveyed by GPS method combined with a total station (see Figure 6) used to test the point-based surface characterization methods.

Table 6 - Table 11 illustrate the parameter statistics for the LiDAR dataset collected in 2012. Although, the 2008 LiDAR survey was available, only the 2012 LiDAR dataset was tested and evaluated since the inventory map was compiled after the 2012 LiDAR survey was acquired. From parameter evaluation, it is revealed that the landslide and stable morphology cannot be delineated from the single point surface features, since the comparisons illustrate that the surface features have a large overlap in parameter values. For example, the statistics for the hillshade surface feature shown in Table 6, demonstrate that the landslide and stable surface features are similar, where the range for the mean is between 0.71 – 0.88 for the landslide terrain and 0.69 – 0.80 for the stable terrain. In addition, the standard deviations range from 0.14 – 0.19 for landslide terrain and 0.15 –
0.19 for stable terrain. Similarly shown in Table 9 are the statistics for the roughness surface feature, where the range of the mean is between 0.5 – 1.1 ft for landslide terrain and 0.6 – 0.9 ft for stable terrain. Furthermore, the standard deviations range from 2.4 – 14.9 ft for landslide terrain, and 7.6 – 19.3 ft for stable terrain. Similarly, this pattern is observed for the surface features of aspect, slope, plan curvature, and profile curvature, where the statistics of surface features of landslide and stable terrain are quite comparable.

Since the simple statistical evaluation between stable and landslide terrain, using only the surface feature was unsuccessful, a threshold-based classification was proposed to classify each area based on all the surface features extracted. The thresholds, listed in Table 5, for the threshold-based classification were determined after careful evaluation of the mean, median and standard deviation. Ideally, a high percentage of the landslide surface features should meet each threshold and exclude those of stable morphology.

<table>
<thead>
<tr>
<th>Topographic Feature</th>
<th>Thresholds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hillshade</td>
<td>Data &gt; 0.78</td>
</tr>
<tr>
<td>Slope</td>
<td>Data &gt; 0.50</td>
</tr>
<tr>
<td>Profile Curvature</td>
<td>Data &lt; -0.22</td>
</tr>
<tr>
<td>Plan Curvature</td>
<td>Data &gt; 0.09</td>
</tr>
<tr>
<td>Aspect</td>
<td>Data &gt; 260</td>
</tr>
<tr>
<td>Roughness</td>
<td>0.50 &gt; Data &gt; 0.70</td>
</tr>
</tbody>
</table>

Table 5. Thresholds used to test and evaluate the threshold-based classification, based on the point-based surface characterization of topographic features. The thresholds are based on the mean.
After evaluating the performance of the threshold-based classification, it was determined that the performance was still low since the landslide and stable surface features could not be reliably delineated. The percentage of surface points meeting the criteria vary between 22.4 – 90.5 percent for the mapped landslide surface features and 30.2 – 87.1 percent for the stable surface features, consequently illustrating that the performance is similar for both types of terrain. In particular, the roughness surface feature (see Table 9) illustrates that a high percentage of the landslide surface points meet the criterion (0.50 > Surface point value > 0.70), which vary between 73.3 – 89.5 percent for the mapped landsides surface features. However, the stable surface features also have a high percentage of surface points meeting the criterion, which vary between 81.0 – 87.1 percent. In addition, a comparable performance as the one described is observed for the profile curvature surface feature, where the surface points meeting the criterion is between 25.5 – 46.0 percent for the mapped landslide surface features and 30.2 – 34.6 percent for the stable surface features. Similarly the hillshade, slope, aspect, and plan curvature surface features tested (see Table 6 - Table 11) demonstrate that the performance of the threshold-based classification is comparable between the two types of terrain. For this reason, it can be said that through the analysis of a threshold-based classification, an apparent differentiation was unsuccessful.
### Statistics of Hillshade

<table>
<thead>
<tr>
<th>Units: None</th>
<th>Mean</th>
<th>Median</th>
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<th>Max</th>
<th>STD</th>
<th>Data &gt; 0.78</th>
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<tbody>
<tr>
<td>Landslide 1</td>
<td>0.78</td>
<td>0.83</td>
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<td>60.46</td>
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<td>Landslide 2</td>
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<td>0.82</td>
<td>0.03</td>
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<td>0.17</td>
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<td>Landslide 3</td>
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<td>0.17</td>
<td>58.15</td>
</tr>
<tr>
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<td>0.00</td>
<td>1.00</td>
<td>0.14</td>
<td>66.51</td>
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<tr>
<td>Landslide 5</td>
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<td>1.00</td>
<td>0.17</td>
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<td>Landslide 6</td>
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<td>1.00</td>
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<td>Landslide 9</td>
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<td>1.00</td>
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<td>1.00</td>
<td>0.17</td>
<td>43.00</td>
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<td>1.00</td>
<td>0.19</td>
<td>63.99</td>
</tr>
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<td>T89</td>
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<td>0.00</td>
<td>1.00</td>
<td>0.18</td>
<td>34.52</td>
</tr>
<tr>
<td>Grand Total</td>
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<td>0.77</td>
<td>0.00</td>
<td>1.00</td>
<td>0.17</td>
<td>48.01</td>
</tr>
</tbody>
</table>

Table 6. Statistics of Hillshade surface characterization parameter for GPS surveyed areas, including results of threshold-based classification. Data that meets the threshold are considered as landslide susceptible (Pass), and those that do not, are stable (Fail) surface features.

### Statistics of Slope

<table>
<thead>
<tr>
<th>Units: Radians</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>STD</th>
<th>Data &gt; 0.50</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landslide 1</td>
<td>0.68</td>
<td>0.52</td>
<td>0.00</td>
<td>14.20</td>
<td>0.71</td>
<td>51.96</td>
</tr>
<tr>
<td>Landslide 2</td>
<td>0.61</td>
<td>0.49</td>
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<td>4.62</td>
<td>0.53</td>
<td>49.32</td>
</tr>
<tr>
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<td>0.75</td>
<td>0.67</td>
<td>0.00</td>
<td>4.72</td>
<td>0.61</td>
<td>60.57</td>
</tr>
<tr>
<td>Landslide 4</td>
<td>0.53</td>
<td>0.43</td>
<td>0.00</td>
<td>3.66</td>
<td>0.46</td>
<td>42.83</td>
</tr>
<tr>
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<td>0.70</td>
<td>0.59</td>
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<td>3.70</td>
<td>0.57</td>
<td>56.62</td>
</tr>
<tr>
<td>Landslide 6</td>
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<td>3.65</td>
<td>0.46</td>
<td>52.58</td>
</tr>
<tr>
<td>Landslide 7</td>
<td>0.37</td>
<td>0.33</td>
<td>0.00</td>
<td>2.72</td>
<td>0.22</td>
<td>22.98</td>
</tr>
<tr>
<td>Landslide 8</td>
<td>0.36</td>
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<td>4.60</td>
<td>0.35</td>
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</tr>
<tr>
<td>Landslide 9</td>
<td>0.34</td>
<td>0.27</td>
<td>0.00</td>
<td>4.16</td>
<td>0.30</td>
<td>22.37</td>
</tr>
<tr>
<td>T1234</td>
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<td>0.29</td>
<td>0.00</td>
<td>23.48</td>
<td>0.45</td>
<td>33.74</td>
</tr>
<tr>
<td>T56</td>
<td>0.46</td>
<td>0.28</td>
<td>0.00</td>
<td>14.37</td>
<td>0.51</td>
<td>32.79</td>
</tr>
<tr>
<td>T7</td>
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<td>0.00</td>
<td>22.52</td>
<td>0.71</td>
<td>46.69</td>
</tr>
<tr>
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<td>0.00</td>
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</tr>
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<td>Grand Total</td>
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<td>0.00</td>
<td>23.48</td>
<td>0.52</td>
<td>36.62</td>
</tr>
</tbody>
</table>

Table 7. Statistics of Slope surface characterization parameter for GPS surveyed areas, including results of threshold-based classification. Data that meets the threshold are considered as landslide susceptible (Pass), and those that do not, are stable (Fail) surface features.
### Statistics of Aspect

<table>
<thead>
<tr>
<th>Units: °</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>STD</th>
<th>Pass (%)</th>
<th>Fail (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landslide 1</td>
<td>268.22</td>
<td>290.67</td>
<td>0.00</td>
<td>360.00</td>
<td>79.06</td>
<td>77.62</td>
<td>22.38</td>
</tr>
<tr>
<td>Landslide 2</td>
<td>269.70</td>
<td>291.07</td>
<td>0.00</td>
<td>360.00</td>
<td>81.50</td>
<td>78.78</td>
<td>21.22</td>
</tr>
<tr>
<td>Landslide 3</td>
<td>273.10</td>
<td>288.49</td>
<td>0.00</td>
<td>360.00</td>
<td>71.77</td>
<td>81.96</td>
<td>18.04</td>
</tr>
<tr>
<td>Landslide 4</td>
<td>275.13</td>
<td>291.64</td>
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<td>360.00</td>
<td>71.09</td>
<td>81.61</td>
<td>18.39</td>
</tr>
<tr>
<td>Landslide 5</td>
<td>271.51</td>
<td>287.59</td>
<td>0.00</td>
<td>360.00</td>
<td>68.46</td>
<td>79.44</td>
<td>20.56</td>
</tr>
<tr>
<td>Landslide 6</td>
<td>259.65</td>
<td>270.00</td>
<td>0.00</td>
<td>360.00</td>
<td>66.48</td>
<td>63.51</td>
<td>36.49</td>
</tr>
<tr>
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<td>360.00</td>
<td>80.78</td>
<td>90.51</td>
<td>9.49</td>
</tr>
<tr>
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<td>360.00</td>
<td>79.28</td>
<td>55.22</td>
<td>44.78</td>
</tr>
<tr>
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<td>250.95</td>
<td>268.87</td>
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<td>360.00</td>
<td>70.37</td>
<td>58.08</td>
<td>41.92</td>
</tr>
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<td>284.77</td>
<td>0.00</td>
<td>360.00</td>
<td>86.39</td>
<td>70.73</td>
<td>29.27</td>
</tr>
<tr>
<td>T56</td>
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<td>277.34</td>
<td>0.00</td>
<td>360.00</td>
<td>91.37</td>
<td>64.90</td>
<td>35.10</td>
</tr>
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<td>360.00</td>
<td>101.94</td>
<td>78.98</td>
<td>21.02</td>
</tr>
<tr>
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<td>265.96</td>
<td>0.00</td>
<td>360.00</td>
<td>70.10</td>
<td>55.42</td>
<td>44.58</td>
</tr>
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<td>Grand Total</td>
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<td>281.56</td>
<td>0.00</td>
<td>360.00</td>
<td>86.84</td>
<td>67.51</td>
<td>32.49</td>
</tr>
</tbody>
</table>

Table 8. Statistics of Aspect surface characterization parameter for GPS surveyed areas, including results of threshold-based classification. Data that meets the threshold are considered as landslide susceptible (Pass), and those that do not, are stable (Fail) surface features.

### Statistics of Roughness

<table>
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<tr>
<th>Units: ft</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>STD</th>
<th>Pass (%)</th>
<th>Fail (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landslide 1</td>
<td>1.0</td>
<td>0.8</td>
<td>0.0</td>
<td>14.9</td>
<td>0.8</td>
<td>83.56</td>
<td>16.44</td>
</tr>
<tr>
<td>Landslide 2</td>
<td>0.9</td>
<td>0.7</td>
<td>0.0</td>
<td>3.8</td>
<td>0.5</td>
<td>80.94</td>
<td>19.06</td>
</tr>
<tr>
<td>Landslide 3</td>
<td>1.1</td>
<td>1.0</td>
<td>0.0</td>
<td>4.3</td>
<td>0.6</td>
<td>89.53</td>
<td>10.47</td>
</tr>
<tr>
<td>Landslide 4</td>
<td>0.8</td>
<td>0.7</td>
<td>0.0</td>
<td>3.0</td>
<td>0.5</td>
<td>81.17</td>
<td>18.83</td>
</tr>
<tr>
<td>Landslide 5</td>
<td>1.0</td>
<td>0.9</td>
<td>0.0</td>
<td>3.0</td>
<td>0.5</td>
<td>87.80</td>
<td>12.20</td>
</tr>
<tr>
<td>Landslide 6</td>
<td>0.8</td>
<td>0.7</td>
<td>0.0</td>
<td>3.0</td>
<td>0.4</td>
<td>80.11</td>
<td>19.89</td>
</tr>
<tr>
<td>Landslide 7</td>
<td>0.5</td>
<td>0.5</td>
<td>0.0</td>
<td>2.4</td>
<td>0.2</td>
<td>73.26</td>
<td>26.74</td>
</tr>
<tr>
<td>Landslide 8</td>
<td>0.5</td>
<td>0.4</td>
<td>0.0</td>
<td>3.8</td>
<td>0.4</td>
<td>82.85</td>
<td>17.15</td>
</tr>
<tr>
<td>Landslide 9</td>
<td>0.5</td>
<td>0.4</td>
<td>0.0</td>
<td>3.4</td>
<td>0.3</td>
<td>80.85</td>
<td>19.15</td>
</tr>
<tr>
<td>T1234</td>
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<td>0.5</td>
<td>0.0</td>
<td>19.3</td>
<td>0.5</td>
<td>86.52</td>
<td>13.44</td>
</tr>
<tr>
<td>T56</td>
<td>0.6</td>
<td>0.5</td>
<td>0.0</td>
<td>11.8</td>
<td>0.6</td>
<td>87.03</td>
<td>12.97</td>
</tr>
<tr>
<td>T7</td>
<td>0.9</td>
<td>0.7</td>
<td>0.0</td>
<td>18.6</td>
<td>0.8</td>
<td>81.01</td>
<td>18.99</td>
</tr>
<tr>
<td>T89</td>
<td>0.6</td>
<td>0.5</td>
<td>0.0</td>
<td>7.6</td>
<td>0.5</td>
<td>85.01</td>
<td>14.99</td>
</tr>
<tr>
<td>Grand Total</td>
<td>0.7</td>
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<td>0.0</td>
<td>19.3</td>
<td>0.5</td>
<td>84.91</td>
<td>15.09</td>
</tr>
</tbody>
</table>

Table 9. Statistics of Roughness surface characterization parameter for GPS surveyed areas, including results of threshold-based classification. Data that meets the threshold are considered as landslide susceptible (Pass), and those that do not, are stable (Fail) surface features.
### Statistics of Plan Curvature

<table>
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<tr>
<th>Units: None</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>STD</th>
<th>Data &gt; 0.09</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landslide 1</td>
<td>0.13</td>
<td>0.04</td>
<td>-11.89</td>
<td>17.31</td>
<td>0.74</td>
<td>Pass (%) : 45.12, Fail (%) : 54.88</td>
</tr>
<tr>
<td>Landslide 2</td>
<td>0.12</td>
<td>0.02</td>
<td>-3.88</td>
<td>3.66</td>
<td>0.59</td>
<td>Pass (%) : 42.30, Fail (%) : 57.70</td>
</tr>
<tr>
<td>Landslide 3</td>
<td>0.12</td>
<td>0.01</td>
<td>-3.87</td>
<td>5.69</td>
<td>0.72</td>
<td>Pass (%) : 44.36, Fail (%) : 55.64</td>
</tr>
<tr>
<td>Landslide 4</td>
<td>0.08</td>
<td>0.03</td>
<td>-3.83</td>
<td>3.04</td>
<td>0.53</td>
<td>Pass (%) : 43.20, Fail (%) : 56.80</td>
</tr>
<tr>
<td>Landslide 5</td>
<td>0.11</td>
<td>0.02</td>
<td>-4.23</td>
<td>4.23</td>
<td>0.54</td>
<td>Pass (%) : 44.05, Fail (%) : 55.95</td>
</tr>
<tr>
<td>Landslide 6</td>
<td>0.09</td>
<td>0.00</td>
<td>-2.29</td>
<td>3.49</td>
<td>0.49</td>
<td>Pass (%) : 35.93, Fail (%) : 64.07</td>
</tr>
<tr>
<td>Landslide 7</td>
<td>0.04</td>
<td>0.02</td>
<td>-2.29</td>
<td>2.46</td>
<td>0.27</td>
<td>Pass (%) : 36.00, Fail (%) : 64.00</td>
</tr>
<tr>
<td>Landslide 8</td>
<td>0.06</td>
<td>0.01</td>
<td>-5.15</td>
<td>5.10</td>
<td>0.37</td>
<td>Pass (%) : 35.78, Fail (%) : 64.22</td>
</tr>
<tr>
<td>Landslide 9</td>
<td>0.05</td>
<td>0.02</td>
<td>-5.26</td>
<td>3.48</td>
<td>0.32</td>
<td>Pass (%) : 37.02, Fail (%) : 62.98</td>
</tr>
<tr>
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<td>0.00</td>
<td>-23.95</td>
<td>14.95</td>
<td>0.43</td>
<td>Pass (%) : 33.90, Fail (%) : 66.10</td>
</tr>
<tr>
<td>T56</td>
<td>0.08</td>
<td>0.00</td>
<td>-9.50</td>
<td>15.94</td>
<td>0.49</td>
<td>Pass (%) : 35.13, Fail (%) : 64.87</td>
</tr>
<tr>
<td>T7</td>
<td>0.10</td>
<td>0.00</td>
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<td>26.00</td>
<td>0.68</td>
<td>Pass (%) : 38.33, Fail (%) : 61.67</td>
</tr>
<tr>
<td>T89</td>
<td>0.08</td>
<td>0.01</td>
<td>-8.67</td>
<td>7.53</td>
<td>0.47</td>
<td>Pass (%) : 36.90, Fail (%) : 63.10</td>
</tr>
<tr>
<td>Grand Total</td>
<td>0.07</td>
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<td>-23.95</td>
<td>26.00</td>
<td>0.50</td>
<td>Pass (%) : 36.57, Fail (%) : 63.43</td>
</tr>
</tbody>
</table>

Table 10. Statistics of Plan Curvature surface characterization parameter for GPS surveyed areas, including results of threshold-based classification. Data that meets the threshold are considered as landslide susceptible (Pass), and those that do not, are stable (Fail) surface features.

### Statistics of Profile Curvature

<table>
<thead>
<tr>
<th>Units: None</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>STD</th>
<th>Data &lt; -0.22</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landslide 1</td>
<td>-0.28</td>
<td>-0.14</td>
<td>-17.31</td>
<td>16.89</td>
<td>0.93</td>
<td>Pass (%) : 43.69, Fail (%) : 56.31</td>
</tr>
<tr>
<td>Landslide 2</td>
<td>-0.23</td>
<td>-0.08</td>
<td>-5.64</td>
<td>5.04</td>
<td>0.72</td>
<td>Pass (%) : 39.73, Fail (%) : 60.27</td>
</tr>
<tr>
<td>Landslide 3</td>
<td>-0.33</td>
<td>-0.13</td>
<td>-5.76</td>
<td>4.54</td>
<td>0.88</td>
<td>Pass (%) : 44.98, Fail (%) : 55.02</td>
</tr>
<tr>
<td>Landslide 4</td>
<td>-0.21</td>
<td>-0.10</td>
<td>-4.47</td>
<td>3.21</td>
<td>0.66</td>
<td>Pass (%) : 39.66, Fail (%) : 60.34</td>
</tr>
<tr>
<td>Landslide 5</td>
<td>-0.30</td>
<td>-0.15</td>
<td>-4.51</td>
<td>3.58</td>
<td>0.85</td>
<td>Pass (%) : 46.01, Fail (%) : 53.99</td>
</tr>
<tr>
<td>Landslide 6</td>
<td>-0.23</td>
<td>-0.03</td>
<td>-4.45</td>
<td>4.45</td>
<td>0.62</td>
<td>Pass (%) : 35.84, Fail (%) : 64.16</td>
</tr>
<tr>
<td>Landslide 7</td>
<td>-0.09</td>
<td>-0.05</td>
<td>-3.19</td>
<td>2.14</td>
<td>0.32</td>
<td>Pass (%) : 25.51, Fail (%) : 74.49</td>
</tr>
<tr>
<td>Landslide 8</td>
<td>-0.14</td>
<td>-0.06</td>
<td>-5.61</td>
<td>4.77</td>
<td>0.46</td>
<td>Pass (%) : 29.74, Fail (%) : 70.26</td>
</tr>
<tr>
<td>Landslide 9</td>
<td>-0.12</td>
<td>-0.07</td>
<td>-5.73</td>
<td>3.88</td>
<td>0.39</td>
<td>Pass (%) : 29.18, Fail (%) : 70.82</td>
</tr>
<tr>
<td>T1234</td>
<td>-0.18</td>
<td>-0.05</td>
<td>-54.23</td>
<td>18.74</td>
<td>0.55</td>
<td>Pass (%) : 30.22, Fail (%) : 69.78</td>
</tr>
<tr>
<td>T56</td>
<td>-0.19</td>
<td>-0.05</td>
<td>-17.52</td>
<td>10.30</td>
<td>0.62</td>
<td>Pass (%) : 30.88, Fail (%) : 69.12</td>
</tr>
<tr>
<td>T7</td>
<td>-0.21</td>
<td>-0.06</td>
<td>-27.47</td>
<td>27.47</td>
<td>0.84</td>
<td>Pass (%) : 34.61, Fail (%) : 65.39</td>
</tr>
<tr>
<td>T89</td>
<td>-0.19</td>
<td>-0.06</td>
<td>-11.29</td>
<td>8.87</td>
<td>0.60</td>
<td>Pass (%) : 32.77, Fail (%) : 67.23</td>
</tr>
<tr>
<td>Grand Total</td>
<td>-0.19</td>
<td>-0.05</td>
<td>-54.23</td>
<td>27.47</td>
<td>0.63</td>
<td>Pass (%) : 32.12, Fail (%) : 67.88</td>
</tr>
</tbody>
</table>

Table 11. Statistics of Profile Curvature surface characterization parameter for GPS surveyed areas, including results of threshold-based classification. Data that meets the threshold are considered as landslide susceptible (Pass), and those that do not, are stable (Fail) surface features.
The methods tested to evaluate the point-based surface characterization approach illustrate that if all surface features within a mapped landslide are assumed to enclose landslide characteristics, the differentiation between landslide and stable surface features becomes unreliable and ineffective. However, the approach may have some success if uniquely defined surface features are used exclusively, as opposed to our approach where all surface features were considered. In addition, a more sophisticated rule-based classification may be used.

2.2.1.6.1 Principal Component Analysis

Parameters derived from the same observation domain are frequently correlated. To remove this functional correlation, it is important to reduce the parameter space to potentially better support classification. Principal Component Analysis (PCA) is a rigorous method for parameter decorrelation, which generates a new set of variables called principal components. Each principal component is a linear combination of the original variables. All of the principal components are orthogonal to each other, so there is no redundant information. The principal components as a whole form an orthogonal basis for the space of the data.

To test and evaluate PCA thirteen datasets were compiled, the ones described earlier and shown in Figure 6: landslides 1-9, T1234, T56, T7 and T89 (see previous section for description of ground truth area). Also, there are three main types of data used to compute the principal component coefficients, also known as loadings: joint (consisting of both landslide and stable features, being case 1), landslide features only (case 2) and
stable features only (case 3). The principal components were computed using the three data types and thirteen datasets mentioned.

Shown in Figure 10 - Figure 13, it is revealed that PCA analysis for the LiDAR dataset from 2012 has shown little or no correlation with most of the test sites. As mentioned earlier, although the 2008 LiDAR survey was available only the 2012 LiDAR dataset was tested and evaluated. The decorrelation, see principal component plots in Figure 10 - Figure 13, was unsuccessful due to the similarities between the surface features of both terrain types. The principal components in all figures are clustered together, which is not desired. Similar to the statistical analysis and threshold-based classification evaluated in the previous section, the delineation by means of PCA is also ineffective.

Figure 10. Principal components are illustrated for all 3 cases for the area shown in Figure 6A, where landslides 1, 2, 3, and 4 are located.
Figure 11. Principal components are illustrated for all 3 cases for the area shown in Figure 6B, where landslides 5 and 6 are located.

Figure 12. Principal components are illustrated for all 3 cases for the area shown in Figure 6C, where landslide 7 is located.
2.2.2 Profile-Based Surface Characterization

Geomorphologic shape features have been used to describe landslide and stable areas. In particular, surface profiles are analyzed, including 1\textsuperscript{st} and 2\textsuperscript{nd} derivatives and geomorphological openness, which is defined broader than a profile. The surface profiles, similarly to point based methods, are computed in the areas investigated to detect and analyze the shapes of landslides. Depending on landslide types and shapes, the profiles evaluated may show correlation within the landslide areas.

2.2.2.1 Surface Filtering

The unfiltered DEM was processed through a smoothing filter in order to remove noise and anomalies in the data to perform the profile-based analysis. By processing the DEM
through a filter, the DEM will be smoother as the variability in the terrain will diminish. The classical method of windowed linear-phase Finite Impulse Response (FIR) digital filter design was applied (Acoustics et al., 1979). The filter was designed as a standard low-pass filter. The Hamming filter (Oppenheim et al., 1999) was chosen due to its simple implementation when applying to a gridded dataset; note other filter types are also applicable, such as Gaussian low-pass filter.

As usual, the filter is normalized so that the magnitude response of the filter at the center frequency of the passband is 0 dB. The filter is defined by a vector, $u$, containing $n + 1$ coefficients for a low-pass FIR filter of order $n$. The 2D version of the Hamming window-based FIR is formed from the two vectors. In general, the vectors, $u$ and $v$, could be different in the two dimensions, but in our case they were identical $u = v$. For a 16 x 16 filter window, the parameter formation is shown below:

$$u \otimes v = uv^T = \begin{bmatrix} u_1 \\ \vdots \\ u_{16} \end{bmatrix} [v_1 \ldots v_{16}] =$$

$$\begin{bmatrix} u_1v_1 & \ldots & u_1v_{16} \\ \vdots & \ddots & \vdots \\ u_{16}v_1 & \ldots & u_{16}v_{16} \end{bmatrix}, \text{where } u = v$$

Where, $\otimes$ is the kronecker product (operation) of two matrices of arbitrary size resulting in a block matrix. If the window size is not too large, then convolution is used to compute the filtered DEM; Figure 14 shows the parameter values of the 16 x 16 Hamming window. High-frequency terms in the DEM are nearly reduced to zero as the Hamming filter moves away from the center of the filter. For larger windows, Fast Fourier
transform can be used for fast implementation. If the smoothing is amplified, the reduction will occur more rapidly, as gradually more of the higher frequencies are filtered out of the DEM.

Figure 14. Shape of the 2D Hamming low-pass filter. The Hamming filter is considered a smoothing filter and a low-pass filter, since it only allows low-frequency terms to pass through.

In our investigation, a convolution based implementation of a FIR was used to filter the data to smooth out high-frequency fluctuations in the DEM. The filter uses a 16 x 16 2-D convolution to implement the filtering operation. The 2-D convolution applies a straightforward formal implementation of the two-dimensional convolution equation in spatial form. If \( a \) and \( b \) are functions of two discrete variables, \( n_1 \) and \( n_2 \), then the formula for the two-dimensional convolution of \( a \) (DEM) and \( b \) (Hamming filter) is:

\[
c(n_1, n_2) = \sum_{k_1 = -\infty}^{\infty} \sum_{k_2 = -\infty}^{\infty} a(k_1, k_2) b(n_1 - k_1, n_2 - k_2)
\]

Eq. (9)
2.2.2.2 Detrending surfaces/profiles

The dominant surface trend, practically average slope, can be easily removed and, therefore, making surface profile comparisons easier, as only the relevant changes are preserved in the profiles. Since most of the surface parameters are computed for smaller areas/profiles, this surface patch can be easily modeled by a plane/line. The trend from the profile is eliminated by removing the best straight-line fit (in a least-squares sense) from the equation of a straight line \( y = mx + b \).

2.2.2.3 1st and 2nd Derivatives

The derivatives described here differ from those evaluated using the parameter curvature in the surface point-based section, as we evaluate the derivatives along profiles. Therefore, the methods are similar but applied to different data types. The first-order derivative along the profile, \( \hat{Z}_x \), describes the rate of change of elevation and is computed from a total of \( n \) elements, where \( Z_i \) are the elevation of DEM points along the profile, \( X_i \) are the horizontal locations, \( \Delta z \) is the elevation difference along the profile between neighboring points, \( \Delta x \) is the horizontal distance between them, and \( \hat{Z}_x \) is the resulting first derivative, which can be estimated as:

\[
\hat{Z}_x = \frac{\Delta z}{\Delta x} = \frac{Z_i - Z_{i-1}}{X_i - X_{i-1}}
\]

Eq.(10)

Then the second derivative is computed using the results of the first derivative, describing the rate of change of the first derivative along the profile, or the curvature, where \( \Delta^2 z \) is the elevation difference along the profile between neighboring points, \( \Delta x^2 \) is the
horizontal distance between them, and \( \hat{Z}_{xx} \) is the resulting second derivative, can be derived as:

\[
\hat{Z}_{xx} = \frac{\Delta^2 z}{\Delta x^2} = \frac{Z_i - Z_{i-1}}{X_i - X_{i-1}} \quad \text{Eq. (11)}
\]

Since irregularities can be related to surface trends, the profiles can be computed from a filtered normalized surface, which means that the surface is smoothed and subsequently detrended before processing. By removing the trend in the profiles, the focus of the profile analysis is on the fluctuations in the profiles.

2.2.2.4 Geomorphologic Openness

The openness expresses the degree of dominant surface irregularities, typically considered as cone type of deviations. Openness incorporates the terrain line-of-sight, or viewshed, concept and is calculated from multiple zenith or nadir angles. The emphasis of terrain convexity and concavity in openness maps facilitates the interpretation of landforms on the Earth’s surface (Yokoyama et al., 2002). The two cases, positive and negative openness, are shown in Figure 15.
Figure 15. Positive (A) and negative (B) openness (Yokoyama et al., 2002). Where L is the length scale along the profile to be analyzed.

The algorithm to determine the geomorphologic feature of openness, described in Yokoyama et al., (2002) was implemented as follows:

1. for each azimuth direction D (D = 0°, 45°, 90°, 135°, 180°, 225°, 270° and 315°), calculate the elevation angles along the profile from point A (center circle in Figure 16A and big black dot in Figure 16B) out to length scale L. In Figure 16B, there is an elevation angle for each grid point along the profile represented by the small black dots. The elevation angle is positive if the distant point is higher than A and negative if distant point is lower than A. These angles form a set $D\beta_L$ for each azimuth direction D.

2. calculate maximum elevation angle; $D\beta_L = \text{max}(D\beta_L)$;

3. calculate minimum elevation angle; $D\delta_L = \text{min}(D\delta_L)$;

4. calculate zenith angle: $D\phi_L = 90^\circ - D\beta_L$;

5. calculate nadir angle: $D\psi_L = 90^\circ - D\delta_L$;

6. obtain positive openness: $\phi_L = (0\phi_L + 45\phi_L + ... + 315\phi_L)/8$

7. obtain negative openness: $\psi_L = (0\psi_L + 45\psi_L + ... + 315\psi_L)/8$
During these processing steps, profiles are computed in eight directions as shown in Figure 16A. A profile view along an azimuth is given in Figure 16B. Here, the surface is smoothed but not detrended before processing as the trend is an important component needed to evaluate the viewshed/line-of-sight of a DEM.

Figure 16. (A) Top view of selected cells in a DEM grid illustrating openness calculation along azimuth D. (B) Profile view along azimuth D out to length scale L to evaluate the positive \((D\phi_L)\) and negative \((D\psi_L)\) openness (Yokoyama et al., 2002).

2.2.2.5 Performance Evaluation

Profiles are frequently used for surface analysis and visualization, as they represent an easily imaged one-dimensional data domain. In particular, they seem to be adequate to distinguish rotational landslides from their surroundings. Note that rotational landslides usually have a nice “S” shape profile after detrending. Figure 17 shows the surveyed area of landslide 1 (see Figure 6) with five profiles; note the DEM is filtered. All of the...
profiles were analyzed, four of them in the four cardinal directions and one along the steepest slope direction. The reason for electing the profile along the major slide direction was to compare it with the others and, thus, to assess whether using only the cardinal directions is sufficient for rotational landslide detection.

Figure 17 shows both the filtered profiles and profiles before the DEM was filtered, so the impact of smoothing is also demonstrated. The statistics of the vertical differences between the filtered and unfiltered profiles are shown in Table 12. The NW/SE profile has the highest variation between the filtered and unfiltered profile and may be due to the profile being along the main landslide detection. In general, the mean and median profile differences are similar for all profile directions. The profiles along the steepest slope and also the NW/SE directions reveal the typical “S” shape of rotational landslides.

The landslides 2 - 9 (see Figure 6) were also tested and evaluated; however, none of them display the “S” profile shape.

<table>
<thead>
<tr>
<th>Profile</th>
<th>Mean (m)</th>
<th>Median (m)</th>
<th>STD (m)</th>
<th>Min (m)</th>
<th>Max (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max</td>
<td>0.00</td>
<td>-0.01</td>
<td>0.11</td>
<td>0.00</td>
<td>0.61</td>
</tr>
<tr>
<td>North-South</td>
<td>-0.01</td>
<td>-0.01</td>
<td>0.11</td>
<td>0.00</td>
<td>0.31</td>
</tr>
<tr>
<td>West-East</td>
<td>0.01</td>
<td>-0.02</td>
<td>0.10</td>
<td>0.00</td>
<td>0.40</td>
</tr>
<tr>
<td>NorthWest-SouthEast</td>
<td>0.00</td>
<td>-0.01</td>
<td>0.19</td>
<td>0.00</td>
<td>0.92</td>
</tr>
<tr>
<td>NorthEast-SouthWest</td>
<td>0.02</td>
<td>0.03</td>
<td>0.11</td>
<td>0.00</td>
<td>0.38</td>
</tr>
</tbody>
</table>

Table 12. Vertical difference statistics between the filtered and unfiltered profiles in Figure 17.
Figure 17. (A) Landslide 1 (see Figure 6A) with respective profiles in all directions and (B – F) display the profiles derived from the filtered and unfiltered DEM.

2.2.2.5.1 1st and 2nd Derivatives

The initial derivative evaluation was performed along the 4 cardinal directions of landslide 1. Since the NW/SE direction reveals the typical “S” profile shape of the rotational landslide, the steepest slope direction was not included in this test. The derivatives along the profiles are evaluated in two steps: first, the profile is extracted, and
second, at a desired horizontal spacing along the profile, the derivatives are computed. The profiles are extracted and evaluated at a horizontal spacing of 25 cm, which is half of the spatial resolution of the DEM. The center or mid-point of the profiles is the common intersection point for all 4 cardinal directions (see Figure 17).

The investigation of the derivatives reveals that abrupt changes in elevation (e.g. scarps) along the DEM can be identified by analyzing the profile shapes and are represented as spikes in Figure 18. The profile (NW-SE) of the typical “S” shaped rotational slide shown in Figure 18 exhibits higher first and second order derivatives than all other profiles. These spikes occur at the location of the scarp. Between the two tests, a stronger representation is shown by the second derivative. The W-E, SW-NE, and N-S profiles tested do not exhibit a particular trend or pattern that uniquely identifies a landslide surface feature.

![Figure 18. Profile derivatives for landslide 1 along W-E, SW-NE, N-S, and NW-SE directions.](image)

Since initial tests were promising, profiles were evaluated for two different cases (see Table 13) using the areas of the nine landslides surveyed. The main difference between the two cases is in the angular and spatial resolution: case 2 requires more evaluations
compared to case 1, thus making it more computationally costly. The parameters for both cases are shown in Table 13. For a DEM grid cell, profiles of 123 ft in length are extracted, where the DEM grid cell is the center of the profile. The selection of the profile length was to have sufficient coverage along the scarp of landslide 1. Next, along the profile at a spacing of 0.82 ft, the derivatives are evaluated. This evaluation is repeated for all profiles extracted at angle intervals along the horizontal plane of 15 and 5 degrees for case 1 and 2, respectively. The Easting and Northing spacing are the spacing locations between test points along the DEM and were chosen to reduce the computational cost of the proposed approach, similarly so were the angle intervals.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Case1/Case2</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Angle Interval (°)</td>
<td>15.00 /5.00</td>
<td>Angle between profiles from E to W</td>
</tr>
<tr>
<td>Profile Length (ft)</td>
<td>123.00(37.49 m)/123.00(37.49 m)</td>
<td>The total length of the profile</td>
</tr>
<tr>
<td>Spacing Easting (ft)</td>
<td>20.50(6.25 m)/16.40(5.00 m)</td>
<td>Spacing between locations tested</td>
</tr>
<tr>
<td>Spacing Northing (ft)</td>
<td>61.50(18.75 m)/16.40(5.00 m)</td>
<td>Spacing between locations tested</td>
</tr>
<tr>
<td>Profile Spacing (ft)</td>
<td>0.82(0.25 m)/0.82(0.25 m)</td>
<td>Spacing between points on profile</td>
</tr>
</tbody>
</table>

Table 13. Parameters used to evaluate the surface topography of case 1 and 2. Units: feet (meters)

After testing and evaluating various thresholds to identify the scarp surface feature from the typical “S” shaped rotational slide, a criterion was determined. The threshold values were selected after careful evaluation of the spikes or peaks and are shown in Table 14. Note the thresholds were determined based on only one landslide, and thus they may be biased that can affect the size of the scarp that can be detected.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Thresholds</th>
</tr>
</thead>
<tbody>
<tr>
<td>1&lt;sup&gt;st&lt;/sup&gt; Derivative</td>
<td>$\geq 1.00$ ft/ft (0.30 m/m) or $\leq -1.00$ ft/ft (-0.30 m/m)</td>
</tr>
<tr>
<td>2&lt;sup&gt;nd&lt;/sup&gt; Derivative</td>
<td>$\geq 0.10$ ft/ft$^2$ (0.03 m/m$^2$) or $\leq -0.10$ ft/ft$^2$ (-0.03 m/m$^2$)</td>
</tr>
</tbody>
</table>

Table 14. 1<sup>st</sup> and 2<sup>nd</sup> derivative thresholds used to classify the extracted profiles. Units: ft (m).

The profile shape analysis was designed to investigate all surface points within a DEM and along profiles in all directions. If any criteria shown in Table 14 is met, then it marks the profile as having landslide characteristics. While the derivatives are capable of identifying abrupt changes in the surface, the performance for landslide classification is still low, as this classifier is restricted to identifying one type of surface features and then all other surface features, representative of landslide activity, go undetected (e.g., hummocky terrain). The reason case 2 has more identified landslide locations than case 1 is because it performs more evaluations than case 1 and smaller features are better detected as previously mentioned (see Figure 19 and Figure 20).
Figure 19. Classified landslide map for area 1 with landslides 1 - 4 (see Figure 6A). Shown are case 1 (A) and case 2 (B) as described in Table 13.
2.2.2.5.2 Geomorphological Openness

The geomorphological openness computation is performed on a profile basis, similar to the first and second derivatives described in the previous section. This investigation revealed similar findings to those observed from the derivative approach, where abrupt changes in elevation (e.g. scarps) along the DEM could be identified along the profiles and are illustrated as spikes or peaks in Figure 21. The profile in Figure 21 along the typical “S” shaped rotational slide has a sharp change in positive openness. The negative
openness also has a sharp change; though, it is not as uniquely defined as the positive openness. Despite that it still has the ability to identify the scarp surface feature.

This investigation reveals similar findings to those of the first and second derivatives, and subsequently was not developed further.

2.2.3 Shape-Based Surface Characterization

This method can be considered a “mini” surface patch approach, where surface neighborhoods are analyzed. The surface feature parameters of the shape-based approach are computed similarly to those of single points described earlier. Here, however, we are interested in assessing the variability of a local neighborhood which can be done by computing, for example, the standard deviation. The variability for every surface point in the areas examined is computed and the associated distributions are used to develop landslide hypotheses. The distribution of these parameters may show patterns and trends, correlated to the landslide areas. The definition of the selected parameters is discussed in the following subsections; note some were already discussed in the single point section.
2.2.3.1 Direction Cosine Eigenvalue Ratios

The eigenvalue ratios express the amount of surface roughness in three-dimensional surfaces (Kasai et al., 2009). The vectors are defined by their direction cosines: 

\[
x_i = \sin\theta_i \cos\phi_i, \quad y_i = \sin\theta_i \sin\phi_i, \quad z_i = \cos\theta_i,
\]

where \( \theta_i \) is the colatitude and \( \phi_i \) is the longitude. The direction cosines are the angles between the vector and the three coordinate axes, equivalently they are the element contributions of a unit orientation vector as described in McKean and Roering (2004). When considering \((x_1, y_1, z_1), \ldots, (x_n, y_n, z_n)\) as a set of \( n \) unit vectors perpendicular to each cell in the DEM, the orientation matrix, \( T \), may be constructed, see Eq. (12). Next, the eigenvalues are computed for \( T \), and subsequently, \( \ln(\lambda_1/\lambda_2) \) and \( \ln(\lambda_1/\lambda_3) \) are evaluated, where, \( \lambda_k \) is the eigenvalue for \( k = 1,2,3 \). The ratios of normalized eigenvalues are often not normally distributed; for this reason, the logarithms of the ratios are evaluated (McKean & Roering, 2004). Lower eigenvalue ratios indicate that the unit orientation vector of the cells will have higher degrees of surface roughness (McKean & Roering, 2004; Woodcock, 1977).

\[
T = \begin{bmatrix}
\sum x_i^2 & \sum x_i y_i & \sum x_i z_i \\
\sum y_i x_i & \sum y_i^2 & \sum y_i z_i \\
\sum z_i x_i & \sum z_i y_i & \sum z_i^2
\end{bmatrix}
\]  

Eq. (12)

2.2.3.2 Resultant Length of Orientation Vectors

Another way to evaluate topographic variability is by computing the resultant length of orientation vectors in three dimensions in a sampling window from the direction cosines
used to compute the eigenvalue ratios as illustrated in McKean and Roering (2004),

\[ RL = (\sum x_i)^2 + (\sum y_i)^2 + (\sum z_i)^2)^{1/2}, \]

where \( RL \) is the resultant length of orientation vectors and \( x_i, y_i \) and \( z_i \) are described in section 2.2.3.1. This measure can be used to define surface roughness, as small variations within local neighborhoods will be coincident for smooth topography and greater variations will be displayed for rough topography (McKean & Roering, 2004).

2.2.3.3 Customized Sobel Operator

The Sobel operator computes an approximation of the gradient of the image intensity function; the height value in our case. At each point in the image, the result of the Sobel operator is defined as either the corresponding gradient vector or the norm of this vector. The Sobel operator is based on convolving the image with a small and separable filter usually, in a horizontal and vertical direction (Gonzalez & Woods, 2002).

Various kernels were evaluated, but none provided unique characteristics which would robustly detect landslide morphology. However, the kernels selected did extract distinctive features, and the chosen kernels are as follows:
The kernels used to compute the gradients in horizontal ($\hat{G}_x$), vertical ($\hat{G}_y$), diagonal left ($\hat{G}_{dl}$) and diagonal right ($\hat{G}_{dr}$) directions are illustrated in Eq. (13A, B, C, and D), respectively. The magnitude of the gradient was computed by modifying the typically used form illustrated in Gonzalez and Woods (2002) to include all directions:

$$
\hat{G} = \sqrt{\hat{G}_x^2 + \hat{G}_y^2 + \hat{G}_{dl}^2 + \hat{G}_{dr}^2}
$$

2.2.3.4 Soil Types

Soils have been widely considered in landslide susceptibility mapping studies (Wieczorek, 1996; Gomez & Kavzoglu, 2005). The six primary soil types found in the study area consists of alluvium, glacial outwash, lacustrine soils, colluvium, residual soils, and manmade fill. Berks-Westmoreland complex (Bkf) soil found in 40 to 70
percent slopes was the soil type for approximately 92 percent of the mapped landslides in our study area, and was considered highly susceptible to landslides compared to all other soil types. Bkf has the most rugged terrain in the county, where permeability is moderate or moderately rapid in the Berks soil and moderate in the Westmoreland soil and runoff is very rapid on both soils. The available water capacity is very low in the Berks soil and moderate in the Westmoreland soil. It is common to see unstable slopes in this soil type, and, in addition, the soil has a severe hazard of erosion. Moreover, cuts made along these slopes are unstable for building sites (Steiger, 1996). For these reasons, the underlying soil was considered an important additional parameter to surface features to detect and map landslides.

2.2.3.5 Performance Evaluation

Fixed sampling windows of size (9 x 9) were used to evaluate the direction cosine eigenvalue ratios and the length of orientation vectors. Similarly, a statistic measure of the standard deviation is evaluated from the same sampling windows to define the local topographic variability of aspect, hillshade, roughness, slope, resultant length of orientation vectors, and customized Sobel operator. Areas experiencing higher degrees of surface deformation should exhibit higher topographic variability, thus help delineate rough and smooth terrain. As described in section 2.2.3.4, 92% of the inventory mapped landslides are of Bkf soil type, and therefore, the soils were categorized into two categories: Bkf and all other soil types. The soils were labeled numerically by 1 if they were Bkf and -1 if they were not.
To determine characteristics of landslide surface features in the study area, we first need to select a representative patch of a mapped landslide and stable terrain. We decided to use a section 450 m north of mile marker 9 as representative patches, see Figure 22. The size of the training sample patch was 30 x 40 m (1,200 observations) for stable and 60 x 25 m (1,500 observations) for landslide terrain; a section of the surveyed landslide 8. Next, we compute the surface features for both patches. Figure 23 shows the distribution of the samples selected for each surface feature. The topographic variability is higher for landslide than for stable terrain, clearly indicating that the landslide surface in our study area tends to experience higher amounts of surface deformation, meaning it is rougher in texture.
Figure 22. LiDAR-derived hillshade map of SR 666, Zanesville, Ohio study area with the entire sample evaluated outlined on top (in blue) and bottom (in red), for stable and landslide terrain, respectively. The map is displayed in U.S survey feet for the state plane coordinate system, Ohio South Zone.

The distributions of the box plots of the data shown in Figure 23 can be described as follows: the central mark in each box is the median ($Q_2$), the limits of the box are the 25$^{th}$ ($Q_1$) and 75$^{th}$ ($Q_3$) percentiles of the samples, the interquartile range (IQR) is equal to $Q_3 - Q_1$, the dashed line (whiskers) extend to the typically used $Q_1 - 1.5(IQR)$ and $Q_3 + 1.5(IQR)$ range which is about $\pm 2.7\sigma$ and 99.3 percent of the data for normally distributed samples. The remaining samples not lying within these limits are considered outliers (not plotted). It is expected to observe outliers as not all landslide and stable
terrain will have complete coverage of surface features representative of each. Therefore, it is possible to observe a few instances of landslide surface features in stable terrain and vice versa. These instances can be caused by noise in the data or irregularities observed within the terrain.

The representative patches demonstrate that 75% or more of the samples are linearly separable for all surface features as shown in Figure 23 and tabulated in Table 15, where the 75th (Q₃) percentiles of the samples do not overlap. It was found that the direction cosine eigenvalue ratios express the behavior described in McKean and Roering (2004), where the ratios are lower for landslide than stable terrain. Additionally, roughness, customized Sobel operator, aspect, hillshade, slope and resultant length of orientation vectors, all experienced higher topographic variability for landslide terrain as described in McKean and Roering (2004) and Glenn et al. (2006). The variation of the surface features extracted is less for stable terrain for all surface features (Figure 23). This behavior is expected as stable terrain will experience lower rates of mass movement, and, therefore, most stable surface features are expected to express the same behavior. For the soil type characterization, the landslide terrain was in Bkf soil, while the stable terrain was not.
Figure 23. Distribution of geomorphological features extracted before being normalized between \([-1, 1]\), where, stable and landslide terrain are represented on the left and right, respectively. The surface features were extracted from the surface patches shown in Figure 22.
The delineation of landslide and stable surface features was accomplished by comparing local surface neighborhoods. The approach’s success was due to the evaluation of representative surface patches that uniquely define landslide and stable terrain in the study area. It is important to only consider those surface features that are uniquely defined; otherwise, the test sample results may be polluted.

### 2.3 Summary

There were various findings learnt from the surface characterization. The single point-based analysis revealed that the surface parameters were similar for both landslide and stable surfaces. The statistical and classification tests performed were incapable of successfully delineating the surface types. The attempt to decorrelate the data using PCA was unsuccessful. This single point-based method showed little promise for robustly characterizing landslide surfaces and was subsequently abandoned from further studies.
The profile-based approach clearly showed more potential than the single point-based approach. In this attempt, the derivatives and openness were capable of identifying scarp surface features, frequently found in landslides. However, the approach is computationally inefficient and is limited to identifying one type of surface feature along a profile. Since landslides may consist of many surface features, this approach would limit itself to detecting a single landslide surface feature, and, consequently causing others to go undetected. For these reasons the profile-based approach was also not further developed.

The shape-based approach revealed the most promise of all attempts. In this approach, we analyzed surface patches representative of landslide and stable surfaces. By analyzing training patches of terrain, features representative of each are evaluated. This method was capable of delineating stable and landslide terrain, and consequently was further developed in this study.
Chapter 3  Surface Change Detection

This chapter evaluates surface change detection techniques for characterizing temporal changes susceptible to landslide activity. In order to achieve the potential of surface change detection, it is necessary to review the general problem, including mechanisms and attributes. Comprehending the difficulties will assist us in the decision-making of how temporal changes may be helpful for detecting and mapping landslide suspect areas. The selected techniques are tested and evaluated on our data. Although limitations and potential problems are found, the tests performed demonstrate that change detection is feasible based on airborne LiDAR data.

3.1 Overview

Temporal changes can be determined from comparing terrain surface models acquired at different times. Major change detection techniques and properties are analyzed to identify proper methods to detect surface changes. With respect to landslide detection the general procedure may be performed in two different forms by characterizing temporal changes from the C2C and DoD approaches. The performance of the change detection depends on the surface representation in terms of spatial sampling and accuracy. The more detailed and accurate the surface model, the higher the chance to detect temporal changes. Figure 24 shows the conceptual workflow of the change detection-based identification of landslides.
Detecting changes between two surface datasets, acquired at two reasonably different times, gives the best potential to identify changes in surfaces, including motion and deformation. This investigation is aimed at assessing the feasibility of using change detection to identify possible landslide areas.

3.2 Evaluating Uncertainty

Characterizing uncertainty found in the data is an important factor that helps determine the real surface deformation from changes that may occur due to other factors (e.g., noise,
In order to perform change detection with high confidence, it is necessary to evaluate the uncertainties found in the data sources and introduced in the data preparation steps (e.g., interpolation, LiDAR acquisition). This section is intended to review the steps and procedures necessary to evaluate the uncertainties in the data before change detection is performed.

3.2.1 LiDAR measurement uncertainty

The uncertainty found in LiDAR measurements can be separated into horizontal and vertical components. The positional error in the horizontal component, is generally larger in magnitude than the vertical component for airborne LiDAR. Furthermore, it has an effect on the observed vertical differences, especially in sloped areas. Unfortunately, LiDAR is rarely characterized by horizontal errors, only the vertical component is analyzed. Consequently, our interest is limited to analyzing the vertical changes. The vertical positional error ($\delta z$) can be associated with the true vertical component ($Z_{Actual}$) as follows:

$$Z_{Actual} = Z_{DEM} + \delta z$$  \hspace{1cm} \text{Eq. (15)}$$

where $Z_{DEM}$ is the observed vertical component. Many approximations, ranging from manufacturer instrument precision to error budget analysis, have been proposed to evaluate $\delta z$ (Lichti et al., 2005). In addition, there are many factors that affect $\delta z$ other than manufacturer instrument precision, including measurement errors, spatial sampling and interpolation methods (Wheaton et al., 2010a). Furthermore, experimental error
budget analysis requires data collection and testing techniques that go beyond conventional surveying methods, and are dominated by the collection of ground control, utilizing GPS, to evaluate the data quality in order to estimate $\delta z$. Statistically characterizing the precise magnitude of $\delta z$ including distribution type, RMSE, and standard deviation requires more information than what is normally compiled during data acquisition (Wheaton et al., 2010a).

3.2.2 Interpolation uncertainty

Once the DEMs are generated, soft surface sloped segments distributed along the study area are evaluated to compare the uncertainties between the adjusted LiDAR point cloud and the rasterized DEM. Landslides are known to occur along sloped areas where the spatial resolution and point distribution of LiDAR may be lower or higher with respect to the average point density. For these reasons, it is important to evaluate the uncertainties in complex terrain (sloped terrain with high surface roughness). For each DEM segment, the vertical differences were computed for every point in the validation data by following the equation used in Bater and Coops (2009):

$$\delta E_i = S_i - I_i$$

Eq. (16)

where $\delta E_i$ is the vertical difference at location $i$, $S_i$ is the LiDAR measured value from the validation data at location $i$, and $I_i$ is the interpolated value of the DEM at location $i$. It is noted that the LiDAR validation points are unlikely to occur at the same location of the cell center, where the interpolated elevation value was estimated in the DEM. As a result,
there may be some additional errors introduced when comparing the interpolated and LiDAR measured elevation values, as the surface of each cell in the DEM is assumed to be constant (Bater & Coops, 2009). Note that there are bilinear, spline, etc. interpolation methods to help minimize this error. To assess the performance of the interpolation method, mean error, RMSE and standard deviation of the errors were calculated to measure the accuracies of the interpolated surface compared with the bare-earth filtered LiDAR data. The estimated accuracy will determine the uncertainty introduced by the interpolation method.

3.2.3 Propagation of uncertainty

Assuming that the uncertainties in the DEMs are normally distributed and uncorrelated, individual errors in the DEMs can be propagated by modifying the equation used in Brasington et al. (2003) to include the uncertainty between the LiDAR and ground control, and the LiDAR and the DEMs as follows:

\[
\delta u_{C2C} = \sqrt{(\delta z_1)^2 + (\delta z_2)^2}
\]

\[
\delta u_{DoD} = \sqrt{(\delta z_1)^2 + (\delta E_1)^2 + (\delta z_2)^2 + (\delta E_2)^2}
\]

where \( \delta u_{C2C} \) is the propagated error in the C2C change detection, \( \delta u_{DoD} \) is the propagated error in the DoD, \( \delta z_2 \) and \( \delta z_1 \) are the errors between the LiDAR data and the ground control, for example, in the 2012 and 2008 datasets, respectively, and \( \delta E_2 \) and \( \delta E_1 \) are the errors between the LiDAR data and DEM\(_2\) and DEM\(_1\), respectively. It should be noted that for the C2C approach that the measured points are not necessarily at the same
horizontal locations (see Figure 25). Note that a limiting factor not considered on the data quality is the spatial resolution (Wang et al., 2013), which is an important factor that needs to be addressed to model surfaces precisely. The assumption made here is that the errors are independent and random. Moreover, the error can be computed to be consistent throughout the change map if $\delta z_2, \delta z_1, \delta E_2$ and $\delta E_1$ do not exhibit patterns, and they are coherent and predictable in spatial variability (Wheaton et al., 2010a). In our approach, we have accounted for complex terrain which is along sloped topography with high surface roughness, representing a conservative assessment of the propagated uncertainties. This conservative approach is not ideal for terrains that are less complex (e.g., flat terrain), but, our interest is in identifying topographic changes susceptible to landslide activity which is known to occur in complex terrain.

Figure 25. Change detection techniques. (A) DoD where horizontal locations are aligned (regularly distributed). (B) C2C where horizontal locations are not aligned (irregularly distributed).
3.2.3.1 Evaluating propagated uncertainty

The propagated uncertainties in the surface models were evaluated in two steps: 1) the adjusted LiDAR point cloud was compared to hard surface ground control, and 2) the interpolated DEM was compared to the adjusted LiDAR point cloud. This procedure can be performed in one step by comparing the ground control to the interpolated surface; however, the two-step approach was used here. In the C2C approach only the uncertainties in Step 1 are considered, while in the DoD approach both error sources are considered, see Eq. (17).

The uncertainties found in each step were subsequently propagated into the DEMs (2008 and 2012), showing approximately a normal distribution for the error sources of each case. The error sources in the first step were presented in the LiDAR data section as part of the data acquisition quality assessment. The error sources for the second step were evaluated based on 6 segments distributed along the study area, distributions and statistics are shown in Figure 26 and Table 16, respectively. The RMSE and standard deviation are 0.11/0.12 m and 0.10/0.10 for the 2008 and 2012 DEMs, respectively. Using Eq. (17), the uncertainties of the DoD were propagated to 0.17 m, based on the uncertainties: $\delta z_1 = 0.06$ m, $\delta z_2 = 0.06$ m, $\delta E_1 = 0.11$ m and $\delta E_2 = 0.10$ m, while the uncertainties of the C2C approach were propagated to 0.08 m. The propagated uncertainties were subsequently used to evaluate probabilistically whether or not the surface changes detected were real.
The segments mean differences between the interpolated DEM and LiDAR point cloud range from -0.03 to 0.06 m and 0.01 to 0.02 m for the 2008 and 2012 surveys, showing that the 2012 survey has more consistency between all segments, as the mean differences are similar. The overall/total mean differences were similar between the two surveys and were computed to be 0.02 m and 0.01 m for the 2008 and 2012 surveys, respectively. Segment 2 has the highest difference in STD and RMSE between the two surveys, while the remaining segments are quite comparable. The maximum vertical differences are mainly caused by occlusions during data acquisition, and therefore, this is where most of the error is introduced when interpolating. However, they do not impact the overall statistical evaluation as the total number of outliers (maximum vertical differences) is low compared to the total number of points used in the evaluation. Overall, the statistics between the two LiDAR surveys are alike, which is desired, and, thus, both surveys can be applied to our study with similar level of confidence.
Table 16. Accuracy assessment (in meters) of the differences between the interpolated DEM and LiDAR point cloud of the six segments shown in Figure 26 for the 2008 and 2012 DEMs.

<table>
<thead>
<tr>
<th>Segment</th>
<th>No. Pts</th>
<th>STD</th>
<th>Min</th>
<th>Max</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4,241</td>
<td>5,448</td>
<td>0.12</td>
<td>0.12</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>3,181</td>
<td>3,710</td>
<td>0.14</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>7,589</td>
<td>10,057</td>
<td>0.09</td>
<td>0.09</td>
<td>0.00</td>
</tr>
<tr>
<td>4</td>
<td>4,610</td>
<td>6,597</td>
<td>0.08</td>
<td>0.08</td>
<td>0.00</td>
</tr>
<tr>
<td>5</td>
<td>4,564</td>
<td>5,460</td>
<td>0.13</td>
<td>0.13</td>
<td>0.00</td>
</tr>
<tr>
<td>6</td>
<td>4,866</td>
<td>7,125</td>
<td>0.08</td>
<td>0.09</td>
<td>0.00</td>
</tr>
<tr>
<td>Total</td>
<td>29,051</td>
<td>38,397</td>
<td>0.11</td>
<td>0.10</td>
<td>0.00</td>
</tr>
</tbody>
</table>

3.2.4 Assessing the uncertainty

A common approach to the evaluation of DEM uncertainties incorporates a minimum level of detection (minLoD) threshold to distinguish real surface deformation from noise (Fuller et al., 2003), which is typically measured by the propagated uncertainties. Observed elevation changes below this threshold are typically ignored and those above are treated as real. However, an argument can be made as to whether the propagated error used to estimate the minLoD also should be used to evaluate changes over a threshold. For example, if the minLoD is 15 cm and the observed change was 50 cm, should the change be 50 cm or 50 cm ± 15 cm? In our approach, we consider the observed change to be 50 cm (no threshold-corrected data) and the propagated uncertainties (δ_uC2C , δ_uDoD) will be used to characterize the change map. The importance of the propagated uncertainty (δ_uC2C , δ_uDoD) is that it helps define the probability that the observed changes in the change map are real.
3.3 Change Detection Methodology

3.3.1 C2C

Assuming that point clouds have been aligned properly, C2C change detection can be performed. The approach uses the open source software CloudCompare developed by D. Girardeau-Montaut et al. (2005). The method detects changes of point clouds in 3D by comparing distances that can be defined several ways. The nearest neighbor approach was selected after comparing the C2C distance calculation models available in the software, which are:

- nearest neighbor (calculates distance from point to nearest point)
- least square plane (calculates the distance using the local approximation of the cloud by a plane)
- 2.5D triangulation (calculates the distance using the local approximation of the cloud by a 2.5D Delaunay triangulation)
- height function (calculates the distance using the local approximation of the cloud by a height function of the type \( z = ax + by + cx^2 + dy^2 + exy \), where \( x, y \) and \( z \) are the surface points, and \( a, b, c, d \) and \( e \) are the estimated coefficients to define the plane)

Although all models were tested, they produced nearly identical results, which may be due to the modest spacing of the LiDAR data.
3.3.2 DoD

In order to perform DoD accurately, it is important to have an accurate registration of the data between dates (as in the C2C approach) to avoid discrepancies and improve the data quality. Then, the DEMs can be subtracted by using a cell-by-cell approach, resulting in detecting 1D elevation changes.

3.3.3 Probabilistic Change Detection

For any surface changes to be detected, it is important to know the probability of the change detected is real or not. The higher the probability, the higher the chance of the change detected being a real surface deformation detected. Subsequently, the lower probability changes can be filtered.

3.3.3.1 Non-Parametric signed rank test (Wilcoxon)

A probabilistic signed rank test is proposed to evaluate if local neighborhoods exhibit highly probable vertical changes. Mass movement occurs along surface patches and not individual DEM grid points, and, therefore, evaluating local neighborhoods is preferred. The non-parametric signed rank test, developed by Wilcoxon (1945), makes no assumption about the underlying distribution, thus making our predictions more robust in the sense that the distribution is not dependent of any parent distribution or of its parameters. The signed rank test evaluates the null hypothesis \( H_0: \Delta \geq M \) that the observations in the local neighborhood (window size of \( w \times w \) cells for the DoD approach and nearest neighbors for the C2C approach) come from a continuous distribution with a median greater than \( M \) (Hollander & Wolfe, 1999), where \( \Delta \) is the
treatment effect (in our case vertical changes). For this assessment, we compute $P$, the probability that the null hypothesis is true. The left-tail test is performed at a given ($\alpha$) level of significance to test the following:

$$H_0: \Delta \geq M \text{ vs. } H_1: \Delta < M$$  \hspace{1cm} \text{Eq. (18)}$$

Throughout this dissertation, the 95% level of significance ($\alpha$) is used as a threshold for this technique.

### 3.4 Performance Evaluation

Both DoD and C2C techniques were compared to evaluate which approach is most suitable for identifying and mapping temporal changes. Both methods follow the procedure described in earlier sections; the main difference between them is one approach works with Rasterized data (DoD) and the other with irregular LiDAR point clouds (C2C). In the C2C technique, there are two different steps taken compared to the DoD approach to compute the vertical differences and the probability map; all criteria are the same for both techniques. The different steps taken are as follows: First, the C2C approach determines the vertical differences using the nearest neighbor method instead of using the cell-by-cell approach. Second, the non-parametric signed rank test finds a certain number of nearest neighbors to each grid cell in the DEM (same as is done in the DoD method) to use as samples to generate the probability map instead of using a sliding window approach as the DoD does. The subsequent steps and criteria used for both approaches are the same to detect and map high probability temporal changes.
Here we compare and analyze the difference between the DoD and C2C approach for mapping temporal changes for an area shown in Figure 27. The two methods display similarities where the highest topographic change occurs in complex (rougher) terrain and the difference is the lowest in smoother surfaces. The C2C approach displays higher density along the smoother topography, while along the complex terrain the density is much lower, as expected. Rougher surfaces are difficult to model due to the effect of occlusions generated during data acquisition. In addition, in complex surfaces, DoD maps may produce the highest uncertainty due to the data interpolation in sparse areas. The C2C approach produces larger vertical differences, which may be caused by the greater spatial extents between the data points along sloped surfaces.
Figure 27. (A) DoD map, (B) C2C vertical changes. Both maps display the vertical changes detected between the 2008 and 2012 surveys. The changes are displayed as absolute values, thus not differentiating between subsidence and uplift.
The statistics for the segment studied were computed and evaluated to compare the two methods described, see Table 17. The average change observed was 0.09 m and 0.06 m for the DoD and C2C approach, respectively. Therefore, the mean change was below the propagated uncertainty level, hence changes were insignificant. Note that the median for both approaches was the same (0.04 m). The standard deviation, RMSE and maximum change were all larger for the DoD approach. Higher vertical differences may be produced by the DoD approach due to the uncertainty introduced by the interpolation method, especially in complex terrain. The C2C approach computes its vertical differences using the nearest neighbor approach; for this reason, complex terrain having low density usually generates higher vertical changes due to the distribution of the points and surface roughness in the topography.

<table>
<thead>
<tr>
<th>Method</th>
<th>Mean (m)</th>
<th>Med (m)</th>
<th>Min (m)</th>
<th>Max (m)</th>
<th>STD (m)</th>
<th>RMSE (m)</th>
<th>No. Pts</th>
</tr>
</thead>
<tbody>
<tr>
<td>DoD</td>
<td>0.09</td>
<td>0.04</td>
<td>0.00</td>
<td>2.47</td>
<td>0.16</td>
<td>0.18</td>
<td>151,601</td>
</tr>
<tr>
<td>C2C</td>
<td>0.06</td>
<td>0.04</td>
<td>0.00</td>
<td>2.02</td>
<td>0.11</td>
<td>0.12</td>
<td>155,173</td>
</tr>
</tbody>
</table>

Table 17. Statistics of the vertical differences detected between the DoD and C2C approach. The statistics were determined by using the absolute values of the changes observed.

Before computing the probability map, the effect of the sample size was tested and evaluated by having varying window widths between 3 and 11 cells for the DoD approach and 5 – 40 samples for the C2C approach. After assessing a potential window size, it was found that the window size of $7 \times 7$ cells ($3m \times 3m$) already provided enough samples to determine if the local neighborhood exhibited high probability surface change for the DoD approach. Similarly, for the C2C approach it was observed that 15 nearest
samples were enough to estimate the probability. It was also observed that the sample size affected the size of the high-probability clusters but did not change their location. Therefore, as the sample size increased, the cluster size decreased, as expected. For the DoD and C2C approach, the signed rank test evaluates the probability that the medians of the samples in the neighborhood are greater than 0.17 m and 0.08 m, respectively (computed using Eq. (17)); being above the uncertainty level corresponds to the fact that the local neighborhood does indeed experience surface changes with high-probability.

The probability map generated using the signed rank test displays various magnitudes and locations of probable topographic change, as shown in Figure 28. The map exhibits similarities between the vertical changes observed in Figure 27, as expected. The higher the vertical change within the local neighborhoods and the propagated uncertainties, the higher the probability that the change is real. The C2C approach clearly demonstrates neighborhoods experiencing high probability changes, especially in areas of complex surfaces. Although the same is observed for the DoD approach, the size of the areas are smaller compared to the C2C approach. Nonetheless, both approaches are capable of identifying highly probable changes in the area.

The surface along the riverbank for both approaches (West end of DEM shown in Figure 28) experiences similar high probability changes. This behavior is clearly visible along the western extent of the DEMs. The C2C seems to classify most complex surfaces as highly probable change compared to the DoD approach, which seems to be more conservative. However, this is not critical as the general locations between the two
approaches are the same and the different spatial extents may be caused by the different uncertainty levels used to characterize the probability map for each approach.

Figure 28. Probabilistic maps computed from (A) DoD and (B) C2C vertical changes. The probabilistic maps display the probability of areas susceptible to real vertical changes.
3.5 Summary and Discussion

The change detection techniques revealed findings that were promising for detecting real surface deformations with high probability. Both approaches follow the same methodology and use the same parameter criterion with slight modifications, as the data type is different for each method. Nonetheless, strong similarities were found between the two methods. The most problematic component was the low spatial resolution, which did not allow the methods to be tested to their full potential. The LiDAR data spatial resolution of 0.56 m for the 2008 and 0.47 m for the 2012 datasets is clearly not ideal in our test data, as there are many occlusions in complex areas, causing large gaps in the LiDAR data. For this reason, a higher spatial resolution is needed to evaluate and compare the techniques with higher confidence.

Both methods were able to identify high probability surface changes, such as motion and deformation, at the same general locations; note each approach had a different point distribution along identical surface complexities. The C2C approach detected larger probabilities of vertical change compared to the DoD approach. This may be due to the uncertainties being lower for the C2C method, as the uncertainty due to interpolation is not introduced, which is a clear advantage of the C2C approach. On the contrary, in complex surfaces the spatial resolution is lower due to occlusions and the variations in the surface topography, which causes the C2C approach to detect highly probable change in most complex surfaces, which is a clear disadvantage. Therefore, the lower the spatial resolution, the farther in horizontal distance the C2C approach must travel to find the
nearest neighbor LiDAR point to compute the elevation change. For these reasons, the terrain changes are expected to be higher. Although the DoD approach introduces higher uncertainty levels that make it conservative at the given spatial resolution, but the changes detected are more realistic compared to the C2C approach as not all complex surfaces are detected as high probability change. This may be due to the interpolations’ estimation of a surface point in areas where occlusions exist, therefore minimizing the amount of change detected. For the above mentioned reasons, the DoD approach seems like the better suited approach and will be studied further in the following sections.
Chapter 4 Proposed Techniques to Landslide Detection

Recently, LiDAR data have become a promising tool for creating accurate DEMs for rapid and emergency mapping, including landslide detection. In this chapter, we propose two distinct techniques for detecting landslides. The first method is based on single and the second on multi-temporal surface models. These methods are based on a stepwise strategy approach and use a combination of the methods that are focused on the surface geometry, which is fundamental in the development of the proposed techniques to provide solutions to landslide mapping and reduce current limitations.

4.1 Landslide Detection Based on Surface Feature Extraction

So far, we have tested point-based, profile-based and shape-based surface point characterization on our data and learned lessons from those techniques. The point-based fails in part because it cannot delineate landslide and stable features due to the substantial similarities in characteristics. Since the point-based surface features are difficult to directly delineate in the DEM, surface profiles were extracted as the next best approach. This means reference landslides would be used to establish surface profiles found in landslide surfaces. Subsequently, the profiles are matched throughout the DEM. However, the profile-based approach is not robust and can mainly identify slides that have evident scarps, thus limiting this approach to one surface feature, which is not evident in all landslides. In contrast, the shape-based approach was capable of delineating landslide
and stable surface features as shown in section 2.2.3. In our method, the shape-based surface feature extraction is further modified to resolve the problems mentioned in previous sections and to provide robust detection of landslide surface features.

The objective of this approach is to identify surface features indicative of landslide activity and map their locations in the study area. The entire workflow is based on a stepwise strategy inspired by the new composition of the tasks composed of state-of-the-art techniques. The process to detect landslide surface features, in summary, is as follows:

1) Filter the airborne LiDAR point cloud to contain bare-earth points only.
2) Rasterize the bare-earth point cloud using kriging interpolation method.
3) Perform surface feature extraction using the shape-based approach.
4) Classify the LiDAR-derived DEM.
5) Perform post-classification filtering.
6) Map areas experiencing landslide activity.

The feature extraction algorithms used are those described and tested in the shape-based approach in section 2.2.3. In this section, the developed method for landslide surface feature extraction is introduced in greater detail.

4.1.1 Introduction

The effects of mass movement are important and greatly dependent on their spatial pattern of occurrence, frequency and amount of activity (McKean & Roering, 2004). The temporal processes of landslides can reveal a wealth of information regarding the magnitude of surface deformation experienced and the expected change over time. While temporal changes cannot be revealed from individual surface models, identifying
landslide-specific spatial features from single surface models is important, as not all the changes detected by temporal analysis represent mass movement due to a landslide. The technique discussed here is focused on examining and evaluating single surface models and the developed method can serve as a tool to detect landslide activity.

Landslides are known to have rougher surfaces than neighboring stable terrain. This is due to the mechanics, subsidence, lift and surface deformation experienced. The surface roughness of landslide terrain (bottom in Figure 29) experiences higher topographic variability than stable terrain (top in Figure 29). McKean and Roering (2004) and Glenn et al. (2006) exploited the surface roughness to detect and map landslides and confirmed that the surfaces of landslides are rougher than neighboring stable terrain. For these reasons, the surface roughness morphology will be the foundation of the proposed algorithm.

Figure 29. The figure illustrates surface normal’s representing topographic variability (surface roughness) in a DEM. Smooth terrain (top), illustrates less variation. Rough terrain (bottom), illustrates higher variability (McKean & Roering, 2004).
4.1.2 Components of Classification Methodology

Extracting landslide surface features is the core step in landslide detection. To quantify topographic surface roughness, it is necessary to understand and delineate the characteristics found in landslide morphology. Therefore, a sample set representing these distinct features is necessary (see Figure 22). In addition, a classification algorithm capable of distinguishing the landslide morphology is needed. Support Vector Machine (SVM) is a supervised classification method that is well established and known to produce acceptable results in landslide detection (Ballabio & Sterlacchini, 2012; Marjanović et al., 2011; Micheletti, 2011; Samui, 2008; Tien Bui et al., 2012; Yao et al., 2008). The objective is to classify the LiDAR-derived DEM based on the extracted surface features. In order to automatically map terrain with surface features indicative of landslide activity, we analyze the surface features extracted as a single observation for each DEM grid cell with a vector of nine dimensions (surface features described earlier in section 2.2.3, see Figure 23, plus soil type) to determine if the observation is representative of a landslide surface feature for each cell in the DEM. If it is, then it is mapped as a landslide surface feature, otherwise, it is mapped as a stable surface feature.

4.1.2.1 Support Vector Machine

SVM was developed by Vapnik (2000). The idea of SVM is to determine the optimal hyperplane for linearly separable patterns (Figure 30). If the patterns are not linear then, the data are projected into a higher dimensional space using a kernel. Support vectors are selected to delineate the two classes and maximize the margin between them. Support
vectors in general are the most difficult data points to classify, as they are lying closest to the decision surface (Tien Bui et al., 2012).

In machine learning, SVM is a supervised learning model connected by learning techniques to evaluate data and determine patterns, used for classification. Given a sample set, in which each observation is grouped into one of two categories, SVM training may be performed to develop a model that can classify new observations into one of the two categories, assuming the classification is linear. If the model is non-linear a kernel may be used to map the input features into high-dimensional feature spaces.

SVM was chosen for its advantages which are: its effectiveness in high dimensional spaces, it utilizes a subset of the training sample in the decision function (support vectors), various kernel functions may be applied for the decision function, and it works well when there is only a small sample available for training.
The representative terrain selected for training the SVM model was less than 1% of the entire study area (see Figure 22). The kernel function used to map the data into the kernel space was Multilayer Perceptron where the kernel function \( K = \tanh(P_1 U V' + P_2) \), and the scale \( P_1 = 1 \) and \( P_2 = -1 \), and \( U \) and \( V \) are the kernel arguments. The scales were determined after testing and evaluating the performance of the classifier on a sample dataset of the OH SR 666 2012 dataset. In general, the SVM algorithm is trained through a sample set of two classes enclosing all features (dimensions) desired to be evaluated (see Figure 23, plus soil type). The two classes are landslide and stable terrain and the extracted surface features are: the direction cosine eigenvalue ratios \( \lambda_1 / \lambda_2 \) and \( \lambda_1 / \lambda_3 \), resultant length of orientation vectors, aspect, roughness, hillshade, slope, a customized Sobel operator and soil type. This results in a nine dimensional space for each observation or DEM grid cell. After training is complete, the algorithm is tested on an independent dataset to evaluate its performance.

4.1.2.2 Flat Terrain Filtering

Landslides occur more often on steeper slopes (Gomez & Kavzoglu, 2005), which have a direct relationship to the weight of material type, the driving force and the resisting force. Locations are safer in terms of potential failures where the slope is near flat. Therefore, as the slope increases so does the probability of failure. Table 18 illustrates unstable slopes for various types of mass movement taken from Soeters and van Westen (1996).
<table>
<thead>
<tr>
<th>Mass Movement Type</th>
<th>Slope Instability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fall and Topple</td>
<td>20° - 30°</td>
</tr>
<tr>
<td>Rotational Slide</td>
<td>20° - 40°</td>
</tr>
<tr>
<td>Lateral Spread</td>
<td>&lt; 10°</td>
</tr>
<tr>
<td>Mudslide</td>
<td>15° - 25°</td>
</tr>
<tr>
<td>Earth flow</td>
<td>&gt; 25°</td>
</tr>
<tr>
<td>Debris avalanche</td>
<td>&gt; 35°</td>
</tr>
</tbody>
</table>

Table 18. Slope instability for mass movement type.

Given the ranges of slope instabilities in Table 18 and those found in our study area, it was determined that DEM grid cells having slopes less than fifteen degrees would be considered stable. Consequently, the filter was applied to ensure that flat stable surfaces were correctly classified.

4.1.2.3 Conditional Dilation/Erosion Filter

Mathematical morphology is a method used to extract useful features found within an image that characterize shapes of objects (Gonzalez & Woods, 2002). In addition, it is helpful in spatial filtering. Two common morphological operations are dilation and erosion. Dilation expands the shapes found within an image, while erosion reduces them; both draw conclusions from a given structuring element (e.g., kernel). In our algorithm, we used a conditional dilation/erosion filter as we wanted the components to satisfy a surface area threshold (Shapiro & Stockman, 2001). The filter was designed as a sliding window of size $n \times n$ ($n$ must be an odd integer), with a given threshold, to determine if the center cell should be dilated or eroded, with respect to the local neighborhood Eq. (19).
The effect of the window size and threshold was tested and evaluated by having varying window widths between 3 and 21 cells and varying thresholds between 50% and 100%. After assessing various combinations, the most suitable window size and threshold found based on our data was 11×11 (5m x 5m) and 60%, respectively. If 60% or more of the cells within the sliding window of 11×11 are mapped as landslide cells, then the center cell will be mapped as a landslide cell, otherwise if the criterion is not met it will be mapped as stable. Note this particular window size and threshold did not distort the information produced from the classification algorithm, it only dilated and eroded the classification results as intended. For these reasons, the threshold and window size selected were subsequently used. The dilation/erosion filtering process was executed after the flat terrain filtering step was performed.

4.1.2.4 Noise Suppression

The clusters are generated by grouping adjoining classified landslide cells. The analysis of point clusters is a vital component of feature extraction. The importance of this step is to analyze clusters and suppress noise. Small regions that are smaller than a desired threshold do not provide useful information, and, therefore, they are not of interest and are ignored. The importance of determining a good threshold is so that the noise level (misclassified cells) is minimized and useful information is not lost. In our approach
clusters of cells classified as landslide terrain are analyzed and evaluated to determine if the cluster will be classified as a landslide or stable area given by the following criterion:

\[
\text{Cluster Area} \geq \text{Minimum Area Threshold} \quad \text{Eq. (20)}
\]

The minimum area to be considered as a detected landslide was tested and evaluated by having varying areas of 50 – 250 m\(^2\). This range was selected after evaluating the minimum size of the mapped landslides provided by the reference inventory map, which was 200 m\(^2\). After evaluating potential thresholds, it was determined that 150 m\(^2\), was the most appropriate threshold, and for this reason, all clusters smaller than 150 m\(^2\) were ignored and not considered. The criterion selected will allow for clusters of said size to be mapped as a detected landslide, thus minimizing the probability of small landslides being overlooked. This is the final step of the proposed technique to detect and map landslide surface features.

4.1.2.5 Algorithm

An approach for small landslide detection utilizing an airborne LiDAR-derived DEM is presented. The approach employs several geomorphologic features to analyze the local shape of the topography forming a 9-dimensional feature vector. The trained SVM model is used to classify the LiDAR-derived DEM based on the feature vectors. Then, as a post-classification step, flat terrain is filtered and classified as stable terrain. Consequently, a conditional dilation/erosion filter is applied to minimize misclassified locations by the SVM algorithm, in addition to suppressing noise and generating landslide susceptible
regions (clusters). Landslide regions are then analyzed to map areas of potential landslide activity. Finally, in order to evaluate the performance of our proposed approach, we assess how well the algorithms mapped landslides match the reference inventory mapped landslides. More details are provided in Table 19.
Algorithm 1: Landslide detection based on surface feature extraction

Inputs: DEM, SoilMap, SVMclassifier

Geomorphological surface feature extraction:

// Extract the following surface features for each DEM grid point Z_{ij}
1. $\frac{\lambda_2}{\lambda_1}$ eigenvalue ratio = ER_{1_{ij}}
2. $\frac{\lambda_3}{\lambda_1}$ eigenvalue ratio = ER_{2_{ij}}
3. Strength of mean vector $R = SMV_{ij}$
4. Aspect = A_{ij}
5. Roughness = R_{ij}
6. Hillshade = H_{ij}
7. Slope = SP_{ij}
8. Sobel operation = SO_{ij}
9. Soil Type = ST_{ij}

// Each DEM grid point is now nine dimensional, ten if DEM elevation is included
$SR_{ij} = [ER_1(i,j)A(i,j)R(i,j)ER_2(i,j)ST(i,j)H(i,j)SO(i,j)SP(i,j)SMV(i,j)]$

SVM classification:

for pts_{i} = 1..row
    for pts_{j} = 1..column
        // Landslide Classification (if classified as landslide = 1, otherwise = 0)
        LM(i,j) = SVMclassifier(SR_{ij})
    end
end

Post-classification filtering:

for pts_{i} = 1..row
    for pts_{j} = 1..column
        // Filter flat terrain
        if $S(i,j) \leq 15^\circ$
            LM(i,j) = 0 ← stable
        end
    end
end

for pts_{i} = 1..row
    for pts_{j} = 1..column
        // Conditional Dilation/Erosion filter
        if $0.60 \leq LW(i,j)$
            LM(i,j) = 1 ← landslide
        else
            LM(i,j) = 0 ← stable
        end
    end
end
Landslide detection:

\[ c_i \leftarrow \text{Clusterize landslide surface points from } LM \]

// Map landslide suspect areas
if \( 150m^2 \leq c_i \)
\[ RLM_i = \text{landslide suspect cluster} \]
else
\[ RLM_i = \text{stable cluster} \]
end

Output: \( RLM \leftarrow \text{Resulting landslide map} \)

<table>
<thead>
<tr>
<th>Variables:</th>
</tr>
</thead>
<tbody>
<tr>
<td>• ( SF_{ij} ): ((i\text{th},j\text{th})) surface features from DEM</td>
</tr>
<tr>
<td>• ( Z_{ij} ): ((i\text{th},j\text{th})) elevation grid point from DEM</td>
</tr>
<tr>
<td>• ( LM_{ij} ): ((i\text{th},j\text{th})) classified grid point from landslide map</td>
</tr>
<tr>
<td>• ( S_{ij} ): ((i\text{th},j\text{th})) slope grid point from DEM</td>
</tr>
<tr>
<td>• ( LW_{ij} ): ((i\text{th},j\text{th})) local window from ( LM_{ij} ) (% of grid points in local window classified as landslide)</td>
</tr>
<tr>
<td>• ( c_i ): (i\text{th}) cluster of landslide surface points</td>
</tr>
<tr>
<td>• ( SVM\text{classifier} ): trained SVM model/classifier</td>
</tr>
<tr>
<td>• ( SoilMap ): soil map from inventory database</td>
</tr>
</tbody>
</table>

Table 19. Algorithm workflow for landslide detection based on surface feature extraction.

4.1.3 Performance Evaluation

The performance of the proposed landslide detection based on surface feature extraction method is assessed using SR 666 (see Figure 3) and two independent test datasets.

4.1.3.1 SR 666 Dataset

The mapped locations vary for each area, reflecting on the variation in the topography (see Figure 31A, B, C and D). Areas that are smooth will go undetected by the proposed algorithm (e.g., SW corner Figure 31B and W section of Figure 31C), while areas that are rough will be mapped as landslide susceptible (e.g., E section of Figure 31A and Figure 31B). The rough areas shown in Figure 31 correspond to those mapped in Figure 32. Additionally, the areas identified as landslide prone by the proposed algorithm tend to
coincide to those mapped locations provided by the reference inventory map, verifying that the proposed SVM model can delineate landslide terrain (see Figure 32).

Figure 31. Topographic variability of segments A – D along SR 666. The surface feature used to depict the topographic variability was roughness. The higher variability the rougher the surface.
In our study area, the proposed algorithm is capable of identifying 84% (67 out of 80) of the inventory mapped landslides (Figure 32A, B, C and D). This confirms that the samples selected for training the classification model were representative of the landslide terrain throughout the study area, and, thus, identifying a high percentage of the landslides. As anticipated earlier, some topographic features display characteristics of stable terrain within a landslide and vice versa. In particular (see Figure 32D), a vast majority of the inventory mapped landslides are incorrectly classified as stable, since the surface roughness is low for this area (see Figure 31D). In order to understand and potentially overcome these limitations, further evaluation is necessary which is beyond the scope of this study.

The algorithm tends to misclassify topographic features with sharp edges or abrupt changes in elevation (e.g., SE and NE corner of Figure 32C and SE corner of Figure 32A, also shown in Figure 33 in detail). Even though, some of the incorrectly classified areas are along these abrupt surface changes, many inventory mapped landslides are also along abrupt changes in elevation, especially, along SR 666. Additionally, natural surface features also express abrupt changes or high surface roughness in the terrain, which include riverbanks (e.g., SW corner of Figure 32C and Figure 31C, also shown in Figure 33 in detail), bluffs, streams, creeks and high elevation changes in a short distance. The increase in surface roughness of these natural features is caused by erosion and geomorphological events, which cause the surface features to mimic those of landslides. In addition, the algorithm also tends to overlook topographic features found within the
boundaries of the inventory mapped landslides due to insufficient surface roughness or
man-made improvements made to the environment.

A GIS database was compiled during the course of this research. The information stored provides important knowledge regarding the geographic location of roads, rivers, creeks, residential development, etc. affecting the local environment of the study area. Results from tests performed (e.g., point-based and profile-based characterization, surface feature extraction algorithms, including landslide classification results) were also stored in the GIS database. The generated data were subsequently used to evaluate potential trends in the data. The GIS database proved to be very valuable as the various layers generated could be analyzed for the same geographic location to characterize landslide morphology. Although the compiled GIS database was available, it was not introduced into the developed algorithm as an additional input. The intent of the algorithm was to evaluate the potential of the surface geometry without the addition of any external information. If a GIS database were to be used it would have been used to filter out misclassified locations along creeks, rivers, streams, roads, residential development, etc. or regions where the potential of a slide is unlikely (e.g. flat terrain).
Figure 32. Resulting landslide classification map. The mapped landslides in red are those mapped by the proposed algorithm and those outlined in black are the landslides mapped in the inventory map. The underlying DEM is a rasterized hillshade DEM and segments A – D are those shown in Figure 31.
In the study area, landslides have a range of ages and activity levels, so the surfaces of various landslides have undergone different degrees of surface deformation and post-failure improvement. The transportation of soil and weathering over time along older and/or inactive slides will cause them to smoothen and make them difficult to identify, if no or minimal mass movement is experienced during long temporal periods. For example, most of the mapped landslides shown in Figure 32D are mapped incorrectly due to the smooth topography. The area is composed of older landslides and the surface features that depict them as slides are no longer exhibited, thus preventing the algorithm from detecting and identifying the mapped landslides in this area.

Figure 33. Resulting landslide classification map, with misclassified topographic features shown in detail. The mapped landslides in red are those mapped by the proposed algorithm and those outlined in black are the landslides mapped in the inventory map. The underlying DEM is a rasterized hillshade DEM and segments A & C are those shown in Figure 31.

The performance of the proposed algorithm assessed how well the mapped areas coincide with the landslide inventory map of the study area. As a reminder it is noted that
landslide experts have different criteria to determine a landslide, resulting in personal bias, and, therefore, the reference cannot be considered absolutely reliable, as there may be some discrepancies amongst experts to characterize the algorithms performance. The proposed algorithm mapped a total of 200 locations throughout the study area. 110 of those identified locations overlapped areas in the landslide inventory map, providing an accuracy of 55% for the algorithm. The accuracy is acceptable as the number of overlooked landslides is minimized without over-classifying the study area; i.e., having less Type II errors or false negatives. For this reason, the accuracy results are satisfactory. Additionally, twenty of the misclassified mapped areas were along rivers and creeks crossing the transportation network, which excludes areas along the Muskingum riverbank West of SR 666, thus, accounting for 10% of the mapped areas. The reason for these areas being consistently mapped can be attributed to the amount of erosion generated which creates high surface roughness. Although some of the mapped areas did not overlap the reference map, they were adjoining to these areas (see Figure 32C). In order to confirm that these areas are landslides, further investigation is necessary to verify that these mapped areas are indeed not new developing landslides or existing landslides that have developed further. Moreover, additional analysis would be beneficial to evaluate why some of the inventory mapped landslides were overlooked by the proposed algorithm. One reason for overlooking inventory mapped landslides may be due to the amount of surface roughness exhibited within the landslides (see SW corner of Figure 32A, W of road for Figure 32B and Figure 32D), which is not sufficient to delineate them from stable terrain. Therefore, these mapped landslides (reference) will go undetected
until enough surface roughness is found in the vicinity. Note that landslide detection is not only dependent upon the morphology, the geologic structure is important as well as underground water flow. Nevertheless, in a geologically homogenous area, the investigation of the geomorphology is beneficial. This information was not used in this study as the focus was on the landslide morphology.

4.1.3.2 Independent Test Dataset

The test data was prepared based on 2 validation areas, that were not included in the investigation and algorithmic developments. Assuming that both test areas are geologically homogeneous to SR 666, the model developed in the previous section for landslide surface feature extraction can be used without any modification. If the assumption is not true, then the model should be re-trained to have similar morphological features of those to be classified. The only minor change in the model was introduced in the post-filtering step where the conditional dilation/erosion threshold was reduced from 60% to 40%. The reason for this modification was to increase the size and number of the generated landslide clusters, thus making the classifier a little more sensitive. The HAM-75-5.58 DEM shown in Figure 34A shows five landslide suspect areas, identified based on previously known slide activity. In this area, there was a slide repaired as noted by ODOT (private communication), therefore, the identification of these suspect areas indicates that the area is actively prone to mass movement. The four mapped locations (see Figure 34B) exhibit high topographic variability when compared to their neighboring terrain, which demonstrates the algorithms ability to identify suspect areas of mass movement. However, there is one area noted by a black arrow (see Figure
34B), where there seems to have been mass movement, yet the algorithm was not able to identify this location. Note the overall terrain is rather smooth, which signifies that this area may have been remediated in the past. Additionally, one cause for the algorithm’s failure to identify the overlooked landslide suspect area may be due to the landslide cluster size being smaller than the minimum area threshold, which may be lowered if desired. Note that landslide cells may be classified and clustered together only if they do not meet the minimum area criterion, otherwise they will be filtered and removed. In summary, for this test area the algorithm identifies four out of five landslide suspect areas, an 80% success rate clearly illustrates the algorithm’s ability to identify landslides in locations different from SR 666.
Figure 34. HAM-75-5.58 validation area, where (A) is the rasterized hillshade DEM, and (B) is the resulting classified landslide map.
In the test site of TUS-77-1.12, the proposed method identified landslide suspect areas as shown in Figure 35B. In particular, a text book style rotational landslide outlined in black in Figure 35A is shown. The landslide scarp, hummocky topography and toe are clearly visible in the DEM. The ability to map this landslide demonstrates that the algorithm developed has the ability to identify landslides in independent test sites. Amongst the rest of the test area of TUS-77-1.12, there is no potential landslide activity visible from the DEM or noted by ODOT. However, the algorithm incorrectly classifies areas along the creek crossing the test area, which is a problem found and discussed in the previous section of our algorithm as streams and river channeling display similar features as those found in failures. In addition, there is a potential landslide identified in the SW corner of Figure 35B that was not noted as a landslide by ODOT (private communication). To ensure that this mapped area is not a landslide, future field inspection is needed to evaluate the classified area. In summary, the algorithm is capable of identifying the lone landslide that was noted by ODOT and some misclassified areas that can be easily filtered since they are along stream and river channeling.
Figure 35. TUS-77-1.12 validation area, where (A) is the rasterized hillshade DEM, and (B) is the resulting classified landslide map.
4.2 Landslide Detection Based on Temporal Changes

So far, C2C and DoD change detection techniques were examined on experimental data and it was confirmed that both approaches are suitable and capable of detecting surface changes. However, the two methods approach the task differently and consider different components to do so. C2C propagated uncertainties are lower, which is an advantage since it does not consider those introduced by interpolation as does the DoD approach. In complex surfaces, however, the C2C algorithm identifies most complex surfaces as high probability change because the point density is low, which is a limitation to this approach. Obviously, if the spatial resolution was infinite then the C2C approach would be more suitable as the uncertainty introduced is lower. In complex surfaces, the DoD method is more conservative due to the uncertainty introduced from interpolation, which results in a higher uncertainty level. Therefore, not all surface changes will be considered real surface deformations. Since a higher spatial resolution relevant to the surface changes and features is not available in our test datasets, the conservative approach was considered. Since the methods are similar, they can be easily modified to fit both techniques if a high spatial resolution data were available in a future study. The workflow of the proposed landslide detection is based on state-of-the-art change detection and surface feature extraction. The outline of the method is:

1) Filter the airborne LiDAR point cloud to contain bare-earth points only.

2) Rasterize the bare-earth point cloud using kriging interpolation method.

3) Perform surface feature extraction to characterize landslide morphology.

4) Classify the LiDAR-derived DEM using SVM.
5) Evaluate the propagated uncertainties in the DoD.

6) Perform change detection using DoD approach (cell-by-cell).

7) Evaluate probabilistically the surface changes using the non-parametric signed rank test.

8) Map temporal changes susceptible to landslide activity that have highly probable surface changes and landslide surface features.

The change detection algorithm used is described and tested in the DoD based approach in sections 3.3.2 and 3.3.3. In the following sections, this method for landslide detection based on temporal changes is introduced in greater detail.

4.2.1 Introduction

Topographic changes can be detected using the proper remote sensing technology that provides the spatial resolution and accuracy needed to monitor temporal changes, yet determining the source of temporal changes (e.g., erosion, deposition, subsidence, uplift, noise) is complex (James et al., 2012). Typically, the source of the change is known, which removes the process of identifying the cause. However, when the source is unknown, field investigation is required to confirm the cause of the topographic change. To mitigate field investigation for the detection of landslide susceptible temporal changes, we propose a technique based on multi-temporal airborne LiDAR-derived DEMs.
4.2.2 Methodology

The proposed methodology using multi-temporal surface models to characterize and detect landslide hazards is described in the following sections.

4.2.2.1 Surface Feature Extraction

With respect to the previous section (see section 4.1.1), the focus of the proposed landslide surface feature extractor will be the topographic variability. To quantify and map the amount of surface roughness observed in landslide morphology, the variability (standard deviation) in slope (see section 2.2.1.5) of the local topography was analyzed from small sampling windows of a fixed size ($9 \times 9$). This results in a feature vector for each observation or DEM grid cell. The 2012 LiDAR dataset was chosen for this evaluation as it represented the latest surface topography. Subsequently, SVM is used to train the model and characterize landslide morphology. SVM was used for its advantages described in section 4.1.2.1. The kernel function used to map the data into the kernel space was Multilayer Perceptron as described in section 4.1.2.1, and the scales for the kernel function were $P_1 = 1$ and $P_2 = -1$, determined after testing and evaluating the performance of the classifier on a sample dataset of the OH SR 666 2012 dataset. The area selected as a training sample is described in section 2.2.3.5 and shown in Figure 22. Once training is complete, the algorithm can be tested to detect landslide morphology.

4.2.2.2 Landslide Hazard Detection

To generate the landslide map, cells having a probability of vertical change detected greater than a desired threshold (see Chapter 3 for more details of the DoD approach) and
being classified as a landslide surface feature (see section 4.2.2.1 for more details) are retained in the DEM. Subsequently, clusters are generated by combining adjoining retained cells. Finally, a threshold is chosen as a cutoff for the smallest cluster area to be mapped as a landslide.

4.2.2.3 Algorithm

To mitigate the amount of field investigation necessary to detect temporal changes caused by landslides over broad swaths of terrain under land cover, we propose a technique that fuses change detection and supervised classification for landslide hazard mapping. The algorithmic steps can be described as follows: first, the method computes cell-by-cell vertical differences between two airborne LiDAR-derived DEMs. Next, the changes observed are evaluated probabilistically by employing the non-parametric signed rank test to determine the probability of the changes being real. Then, geomorphological surface feature extraction is performed to analyze the variability of slope for each DEM grid cell. Subsequently, the algorithm uses the supervised classification of SVM to quantify and map the topographic signatures of landslides by employing the slope variability to classify the LiDAR-derived DEM by the trained SVM model. In our case, the 2012 dataset was used for SVM training, as it was the newest data. After that, DEM grid cells experiencing both high probability change and exhibiting landslide topographic signatures are retained as landslide cells, followed by the clusterization of the adjoining retained landslide cells. Finally, clusters of a minimum area are mapped as landslide hazards. To assess the performance of the proposed landslide hazard mapping technique, a comparison is performed to quantify new and existing landslides with respect to the
provided landslide inventory map of the area. Algorithm implementation details are provided in Table 20.
Algorithm 2: Landslide detection based on temporal changes

Inputs: $DEM_1, DEM_2, SVMclassifier_1$

Change Detection:

// Compute elevation differences/changes over time
$DoD = DEM_2 - DEM_1$

Probabilistic Change Detection:

// The signed rank test evaluates the null hypothesis of a local neighborhood ($w \times w$ cells)
$H_0: \theta \geq M$ vs. $H_1: \theta < M$

$ProbMap \leftarrow$ Probability map of changes detected

Geomorphological surface feature extraction:

// Extract the following surface features for each DEM grid point $Z_{ij}$
1. Slope $= SP_{ij}$

// Each DEM grid point is now one dimensional, two if DEM elevation is included
$SF_{ij} = [SP(i,j)]$

SVM classification:

for $pts_i = 1..row$
    for $pts_j = 1..column$
        // Landslide Classification (if classified as landslide = 1, otherwise = 0)
        $LM(i,j) = SVMclassifier_1(SF_{ij})$
    end
end

Landslide classification and probabilistic change detection fusion:

for $pts_i = 1..row$
    for $pts_j = 1..column$
        // Data Fusion
        if $LM(i,j) = $ Landslide & $0.90 \leq ProbMap(i,j)$
            $PLM(i,j) = 1 \leftarrow$ landslide
        else
            $PLM(i,j) = 0 \leftarrow$ stable
        end
    end
end
Landslide hazard detection:

\[ c_i \leftarrow \text{Clusterize landslide surface points from PLM} \]

// Map landslide suspect areas
if \( 25m^2 \leq c_i \)
\( RLM_i = \text{landslide suspect cluster} \)
else
\( RLM_i = \text{stable cluster} \)
end

Output: \( RLM \leftarrow \text{Resulting landslide map} \)

Variables:
- \( SF_{ij} \): (ith, jth) surface features from DEM
- \( Z_{ij} \): (ith, jth) elevation grid point from DEM
- \( LM_{ij} \): (ith, jth) classified grid point from landslide map
- \( c_i \): ith cluster of landslide surface points
- \( PLM \): preliminary landslide map
- \( w \): window size
- \( M \): propagated uncertainty (uncertainty in DoD)
- \( \theta \): the treatment effect (vertical changes from DoD)
- \( SVM_{classifier} \): trained SVM model/classifier

Table 20. Algorithm workflow to detect and map landslide temporal changes.

4.2.3 Performance Evaluation

The performance of the proposed landslide detection method is assessed using the dataset of SR 666 study area (see Figure 3).

4.2.3.1 DoD Evaluation

The vertical changes in a DoD map may show a wide range of magnitudes, locations and patterns of mass movement that can be difficult to characterize for large areas. Therefore, to mitigate the analysis of mass movement and to reduce computation time, we offer a method that can be run on large datasets without issues by analyzing surface patches. The testing areas selected are general representations of the landforms found in the study area.
that characterize the typical mass movement behavior described in the landslide inventory map.

Shown in Figure 36 is the distribution of three test sites along the study area labeled TAI, TAIi and TAIii. Figure 37A, B and C display DoD maps with areas that experience noticeable vertical change depicted by a black arrow. Figure 37D, E and F show bare-earth shaded relief maps made from DEMs at 0.50 m spatial resolution acquired by the 2012 LiDAR survey, where the shaded relief maps exhibit various surface features; for example, rough surface textures that may indicate mass movement. Figure 37G, H and I display the slope map for each testing area. Although, there is vegetation in the study area, detailed surface features are still visible in the DEM. Statistically the changes observed in the study area can be modeled by a mean and standard deviation of 0.00 m and 0.18 m, respectively. This means that approximately 1 sigma of the changes are within the uncertainty level of 0.17 m, which will define approximately 68% of the detected vertical changes. Therefore, there are sufficient samples to test (~32%) and determine if the changes detected are above the uncertainty level. In addition, the 0.00 mean indicates that the mass around the study area is balanced; in other words, if an area experiences loss in mass another will gain the mass and help maintain a balance.
The proposed DoD method detects vertical changes within the landslide inventory map (Figure 37A and G) and areas not previously mapped as landslides (Figure 37D), signifying that new landslides may be developing. The statistics, for the changes observed for the testing areas displayed in Figure 37A, B and C, and listed in Table 21, illustrate that the small mean for TAI has a balanced mass, while TAII experiences more uplift or gain in mass, and TAIll experiences more subsidence in mass. In addition, the standard deviation of TAIll is significantly higher than the uncertainty level of 0.17m, which is not the case for TAI and II, where they are similar and below the uncertainty level, respectively.
TAI (Figure 37D) demonstrates areas with high topographic variability compared to their respective neighboring regions. These rough textured areas include an inventory mapped landslide that is of particular interest as it appears to experience uplift as shown in the DoD map. Moreover, the DEM boundary on the western end of TAI is along the
riverbank of the Muskingum River, therefore as natural processes occur, mainly caused by rainfall, the mass will erode into the Muskingum River. For this reason, along the riverbank the DoD map displays subsidence. In TAI, the sloped terrain experiences higher amounts of uplift than subsidence, while flat terrain differences seem to vary as some areas experience small amounts of uplift and others show nearly no change. The sloped area along TAI is not within a mapped landslide from the reference inventory map and it is of interest as it may be a newly developing landslide. TAI is an interesting section because large amounts of mass movement are clearly represented from the DoD map (Figure 37C). The vertical differences, where large (> ± 0.50 m) magnitudes of mass movement occur, are noticeably visible and clustered together (Figure 37C). Furthermore, the northern section is along the riverbank, thus, displaying erosion. Since a landslide has occurred between the surveys, it may indicate that more frequent surveys with shorter time periods between them are necessary to better detect and monitor landslide hazards.

<table>
<thead>
<tr>
<th>Testing Areas</th>
<th>Mean (m)</th>
<th>Median (m)</th>
<th>STD (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TAI</td>
<td>0.01</td>
<td>0.01</td>
<td>0.18</td>
</tr>
<tr>
<td>TAI1</td>
<td>0.07</td>
<td>0.05</td>
<td>0.12</td>
</tr>
<tr>
<td>TAI11</td>
<td>-0.03</td>
<td>0.00</td>
<td>0.29</td>
</tr>
</tbody>
</table>

Table 21. Statistics of DoD maps (vertical changes) for TAI, TAI1, and TAI11 shown in Figure 37.

In summary, various surface changes (see Table 21) on a wide variety of surface topography (see Figure 37) are detected using multi-temporal surface models. Therefore, characterization of these surface changes is needed.
4.2.3.2 Probabilistic Change Detection

Before computing the probability map, the effect of the sample size was tested and evaluated by having varying window widths between 3 and 11 cells, resulting in the window size of $7 \times 7$ cells ($3m \times 3m$) selected, which appeared to provide enough samples to determine if the local neighborhood exhibited high-probability surface change. It was also observed that the sample size did affect the size of the high-probability clusters but did not change their location. Consequently, as the sample size increased, the cluster size decreased as expected.

After assessing the vertical differences, the probability that each vertical difference was above the uncertainty level was evaluated using the Wilcoxon signed ranked test, which evaluates the null hypothesis ($H_0: \Delta \geq M$), as described in Chapter 3. The probabilistic non-parametric signed rank test generates a probability map, shown in Figure 38A, B and C. The results for the non-parametric signed rank test are similar to the DoD maps shown in Figure 37A, B and C. It is observed for both maps that local neighborhoods having the highest amount of vertical differences also have the highest probability of the vertical change being above the uncertainty level. One limitation of the probability map, however, is that it does not differentiate between uplift and subsidence; obviously, it can easily be compared to the DoD map to determine the change type.

The results demonstrate that the probabilities computed from the proposed method are either low or high for most cases, which is advantageous as it simplifies the detectability of highly probable changes. Additionally, the method properly clusters the high
probability changes, which is needed to identify surface patches suspect to temporal changes.

The results generated from the signed rank test show that TAI, TAIi and TAIII in Figure 38 exhibit surface deformations with high-probability. In TAI, the changes detected coincide with the mapped landslide outlined in Figure 37D. Furthermore, it is noted that high-probability clusters are also observed along the western edge of the road, suggesting that these may be newly developing landslides and/or that the already mapped landslide from the ground truth (reference) has developed further. These locations are shown with black arrows in Figure 38A. The riverbank is also mapped with high-probability clusters, suggesting erosion in the area.

The algorithm also identifies highly probable changes in TAIi (Figure 38B). In particular, small areas along the road bank on the western side of the road experiences high-probability vertical change, which are shown with black arrows. Since, the area along the slope is not mapped as a landslide in the reference inventory, the high-probability changes suggest that this may be an area prone to landslide activity, as changes observed could lead to a future landslide hazard.

TAIII (see Figure 38C and Figure 37F) has inventory mapped landslides on the northern and southern side of the road revealing highly probable changes. A landslide seems to have occurred during the span of the surveys as a large cluster of high-probability changes is depicted in Figure 38C. This figure shows (see green arrow) that the signed rank test generates a nicely outlined high-probability cluster that illustrates the shape of the potential slide, as expected, as there were high vertical changes ($> \pm 0.50$ m) detected
at this location. The northern side of the road demonstrates higher topographic variability in the hillshade map than the southern side of the road, which may be the reason why there is less vertical change there, and only small clusters are created that may be suppressed as noise (see black arrows). Since the northern end is along the riverbank, high-probability changes are expected along this area. Overall, this area presents a unique scenario, as the changes observed were after the potential sliding occurred and before it was repaired. The approach proposed appears to work well as it clearly identifies the highly probable temporal changes.

In summary, the results demonstrate that the probabilities computed from the proposed method are either low or high for most cases, which is advantageous as it simplifies the detectability of highly probable changes. Additionally, the method clusters the high probability changes, needed to identify surface patches suspect to temporal changes.
Figure 38. Illustrated in (A, B and C) are the probabilities (signed rank test) for TAI, TAIi and TAIii, respectively, that the surface deformations are real given a local neighborhood of $7 \times 7$ cells and $M = 0.17$ m. Areas experiencing highly probable changes are depicted by arrows.
4.2.3.3 Surface Feature Extraction

The classified locations by the proposed morphology based algorithm coincide with the areas experiencing high topographic variability for all three testing areas. The algorithm has performed properly as it was able to delineate rough and smooth topography as shown in Figure 39. The reference mapped landslides exhibit high topographic variability and the surface feature extraction algorithm is capable of identifying and classifying these surface features as landslide surface features. However, the algorithm tends to overclassify landslide surface features, especially those mapped in the landslide inventory map (see black arrows in Figure 39).
Figure 39. Illustrated in (A, B and C) are the surface roughness maps for TAI, TAIi and TAIii, respectively. Shown in (D, E and F) are the classified maps from the proposed landslide surface feature extractor. Overclassified areas are depicted by black arrows.
4.2.3.4 Landslide Hazard Detection

The last step of the proposed approach was to identify areas classified as having landslide surface features and experiencing high probability change. To generate the landslide map from the proposed algorithm, the effect of the cluster size and probability threshold was tested. The thresholds were evaluated by having varying cluster sizes between 25 and 150 m$^2$ and the probability threshold for the signed rank test was between 0.70 and 0.99 for cells classified as landslide prone. These ranges were selected after evaluating the minimum size of the mapped landslides provided by the reference inventory map, which was 200 m$^2$, and aiming to have only high-probability changes, classified as landslide surface features. In addition, not all surface locations will exhibit mass movement simultaneously. The surface changes will occur in surface patches, consequently impacting the neighboring topography. For this reason, smaller cluster sizes than the minimum mapped landslide were evaluated. After evaluating potential cluster sizes and probability thresholds, it was determined that 25 m$^2$ and 0.90, were the most appropriate thresholds for the test dataset. The criteria selected will allow for clusters of said size and probability to be mapped as high-probability surface changes, and, additionally, suppressing potential noise.

The mapped landslides (see Figure 40) by the proposed algorithm mostly coincide with the mapped landslides from the inventory map and include additional areas experiencing high topographic variability for TAI. The mapped landslides in TAI suggest that these may be new developing slides, as there are no slides provided from the reference inventory in this area. TAIII clearly maps an unknown landslide, which displays a high
probability change and surface roughness, suggesting that more frequent surveys are necessary to prevent these events. Clearly, the algorithm can also be used as a post-failure rapid mapping technique, if pre-failure data is available.
Figure 40. Mapped slides with underlying DEM for TAI (A), TAIi (B) and TAIii (C).
The three testing areas illustrate different scenarios that can potentially occur, which are: 1) monitoring of existing slides, 2) identifying newly developing slides, and 3) identifying slides that occurred and were not repaired between surveys. The proposed algorithm works well in all three cases, indicating robustness. One limitation observed is the LiDAR data spatial resolution that seems to greatly impact the algorithm’s potential performance. Note that the vertical accuracy also has an impact on performance. For the medium data quality test dataset, the method was able to identify 66% of the mapped landslides from the inventory landslide map of SR 666 as either experiencing landslide changes within or adjoining to them. The accuracy of the identified areas was 27% for the proposed approach when compared to the correctly detected areas mapped in the landslide inventory map. This does not necessarily define that the algorithm’s performance was poor as many of the detected landslides were within a close proximity of the inventory mapped landslides and could be new or existing developing landslides. Of course, to confirm that they are not new developing landslides or landslides that were overlooked during the inventory map generation, field investigation is required to confirm the cause of the detection.

One limitation of the proposed algorithm is that it can’t differentiate between landslide and erosion along water bodies. For the test dataset, 25% of the total mapped areas were along rivers, streams, and creeks, and, in addition, 13% of them were along the riverbank. These areas are known to mimic landslide surface features and experience temporal changes through deposition and erosion. Therefore, it is obvious that they will be detected in most cases. To improve the classification algorithm, a GIS database may be
used to filter out these misclassified locations by removing these detected areas, where deposition and erosion is known to occur. It was also observed that flat terrain was mapped by the proposed approach at some locations along the study area. Reference inventory mapped slides that were not detected by the proposed approach are potentially experiencing slower rates of mass movement. The statistics of the changes observed within the inventory mapped landslides (reference) and those identified by the algorithm within the inventory mapped landslides are listed in Table 22. The evaluation of the two areas was performed as follows: shown in Figure 41 is an example of an area mapped as a landslide. Outlined in black is the total area of the inventory mapped landslide, and in red is the area mapped by the algorithm. The statistics of the inventory mapped landslide area will evaluate everything within the outlined solid black line. The algorithm mapped areas will only consider the area in red that is within the inventory mapped landslide outlined in black, thus excluding anything mapped by the algorithm lying outside the solid black line and not mapped within the inventory mapped landslide. Note that reference landslide inventory has also uncertainty, which may be significant in some cases.

<table>
<thead>
<tr>
<th>Changes Detected (Units: m)</th>
<th>Mean</th>
<th>Median</th>
<th>STD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inventory mapped slides (A)</td>
<td>0.01</td>
<td>0.02</td>
<td>0.17</td>
</tr>
<tr>
<td>Algorithm mapped w/in inventory slides (B)</td>
<td>0.02</td>
<td>0.18</td>
<td>0.48</td>
</tr>
</tbody>
</table>

Table 22. Statistics of vertical changes detected; (A): vertical changes detected within the inventory mapped landslides (reference), and (B): vertical changes detected by the algorithm within the inventory mapped landslides
The mean changes observed between the two areas analyzed (inventory mapped areas and algorithm mapped w/in inventory slides) are similar and close to a balanced deposition and erosion of mass. However, the variation is higher for the mapped areas by the algorithm within the landslide inventory locations. This may be due to the algorithm’s ability to classify only local neighborhoods susceptible to changes greater than the uncertainty level of 0.17 m with a high degree of probability; consequently, having high surface deformation in either subsidence or uplift. Meanwhile, the inventory mapped slides consider all changes, even those with a low degree of probability of the changes being real, e.g., those experiencing no change or below the uncertainty level causing the variation to decrease. The variation of the changes detected within the entire inventory mapped landslides is similar to that of the uncertainty level. The distribution shown in Figure 42A illustrates a normal distribution for the changes detected in the entire inventory of mapped landslides, while those detected by the algorithm within the inventory of mapped landslides (Figure 42B) do not reveal a normal distribution and appear as a bimodal Gaussian distribution. The peak shown in Figure 42A is around 0 m,
while the peaks shown in Figure 42B are above the propagated uncertainty level of ±0.17 m. The changes detected, in theory, are expected to indicate a loss in material at higher elevations of the slope and a gain at the lower elevations due to erosion and deposition. However, this is not the case for all changes detected because they vary at each location and there is no clear pattern observed between them in the DoD maps (see Figure 37). The only location displaying this pattern is shown in Figure 37C where a major landslide has occurred.

Figure 42. Distribution of vertical changes observed between the 2012 and 2008 DEMs. (A): vertical changes observed within the inventory mapped landslides, and (B): vertical changes mapped by the proposed approach within the inventory mapped landslides.
4.3 Summary and Discussion

In this section, two techniques, one based on single and the other one based on multi-temporal surface models, were proposed for landslide detection and monitoring. Both methods were limited by the LiDAR data spatial resolution and if higher spatial resolution is provided, both methods may be improved. For this reason, an evaluation is necessary to determine the impact of spatial resolution on landslide detection. Additionally, as mentioned in Chapter 1 the reference inventory map is not 100% accurate and there may be discrepancies between the evaluations of different landslide experts. Despite the limitations found, the performance of the proposed algorithms was good.

In the first approach, surface features are extracted and quantified to characterize landslide areas. Then, the trained SVM is used to classify the data into two classes, landslide and stable. The training data plays an important role in classification and needs to be representative of the landslide morphology of the data to be tested. For training, we used a sample less than 1% of the data from OH SR 666. Subsequently, the estimation performance of the method is tested on a surface model having a known reference (SR 666) and two independent test datasets that were noted as having slide repairs by ODOT. Next, the results from the classification are filtered and noise is suppressed. In the final step, suspect areas are mapped as landslides, resulting in a landslide map.

To summarize the morphology based approach, when using surface feature extraction, the proposed method was able to identify 84% of the mapped landslides from the reference inventory map of SR 666 and 5 out of 6 areas mapped as landslide suspect in
the validation datasets. Using the information provided by ODOT it was observed that the algorithm was capable of identifying landslide suspect activity from both test datasets. Important to this procedure is to use areas representative of most landslide surface features for training. When this assumption is false, the proposed method becomes data dependent and may fail for other areas. For our limited data, the proposed method achieved promising landslide detection results.

In the second approach, surface features are extracted and fused with temporal changes to characterize landslide areas. First, temporal changes are evaluated probabilistically to delineate real surface deformations from uncertainties. Then, just like the previous method, surface features are extracted and quantified to characterize landslide areas using a trained SVM model. Subsequently, areas experiencing high probability change and depicting landslide surface features are mapped as landslides. All other areas not susceptible to landslide hazards will be filtered. Estimation performance of the technique is tested on a surface model having a known reference. Next, the results from the fused model are filtered and noise is suppressed. Finally, suspect areas are mapped as detected landslides. The result of the approach is a landslide map.

To summarize this approach, when using multi-temporal surface models, the proposed technique was able to identify 66% of the mapped landslides experiencing temporal changes susceptible to slides when compared to the reference inventory map. Important to this procedure is to use areas representative of most landslide surface features for training the surface feature extractor as described earlier, but also to use a spatial resolution pertinent to the morphological features found in the landslides. This is a vital
component necessary to maximize the performance of any landslide detection algorithm. When this assumption is false, the proposed method is likely to perform poorly. However, if a good spatial resolution is used, the algorithm’s chances of being successful increase.
Chapter 5 The Effects of Spatial Resolution

Since the introduction of airborne LiDAR data for landslide detection, few studies have evaluated the effects of spatial resolution, especially amongst small landslides. In this chapter, we analyze the importance of spatial resolution for landslide classification and the characterization of landslide surface features. From the evaluation, we observe that spatial resolution plays an important role in landslide surface feature extraction as the performance is strongly dependent of the spatial resolution. It should be noted that the spatial resolution is primarily dependent on the sensors mapping abilities and the platform used for data acquisition.

5.1 Introduction

Spatial resolution is one of the fundamental characteristics of remote sensing (Chen et al., 2004; Vander Jagt et al., 2013). The spatial resolution defines the smallest scale at which surface features may be extracted, identified and mapped from remote sensing technology. The spatial resolution may range from coarse (>10 meters) to fine (< 1 cm) scales depending on the capabilities of the remote sensing technology used for mapping (e.g., spaceborne and airborne imagery, airborne and terrestrial LiDAR), including platform. Spatial resolution may refer to the ground sampling distance in an image, the grid size in a DEM or point density in LiDAR, etc. The information in a DEM is dependent on the spatial resolution (Chen et al., 2004), as it defines the size of the
smallest surface feature that can be represented in a DEM. Improper choice of spatial resolution may lead to misrepresentation of the surface features; for example, coarse spatial resolutions will overlook fine scale surface features. For this reason, selecting an appropriate spatial resolution requires understanding the spatial scales of the surface features mapped.

An appropriate spatial resolution depends on surface complexity (Li et al., 2005), information desired and methods used to extract such information. To determine the appropriate spatial resolution, the scale of the available data, techniques for analysis, environmental settings and objectives should be considered (Chen et al., 2004). For these reasons, evaluating the effects of spatial resolution is complex. In this dissertation, the impact of spatial resolution, measured in DEM grid size, on processing performance is investigated.

Many studies using remote sensing technology have explored the effects of spatial resolution (Atkinson & Curran, 1995; Benson & MacKenzie, 1995; Chen et al., 2004; Claessens et al., 2005; Irons et al., 1985; Lee et al., 2004; Pax-Lenney & Woodcock, 1997; Qi & Wu, 1996; Razak et al., 2011; Schoorl et al., 2000; Turner et al., 1989; Vander Jagt et al., 2013; Wang et al., 2013) to analyze landscape pattern (Qi & Wu, 1996; Turner et al., 1989) and landslide susceptibility mapping (Claessens et al., 2005; Lee et al., 2004; Razak et al., 2011; Wang et al., 2013). Although there have been studies focused on the effects of spatial resolution for landslide susceptibility mapping (Claessens et al., 2005; Lee et al., 2004; Razak et al., 2011; Wang et al., 2013), to the best of our knowledge, none have focused on small failures. The improvements made in
spatial resolution and accuracy of LiDAR technology and new emerging platforms, such as UAS, provide new alternatives to acquire high resolution LiDAR data with the spatial resolution and accuracy necessary to map the surface representation of small failures.

In this chapter we will analyze a section of the test data and resample the base airborne LiDAR-derived DEM to generate coarser DEMs. Next, the proposed landslide surface feature extraction algorithm described in Chapter 4 will be applied to all DEMs. Finally, an evaluation will be performed and the findings will be discussed.

5.2 Methodology

5.2.1 Base to Coarse DEM Generation

The coarse 100, 200 and 400 cm spatial resolution DEMs were built by resampling the base 50 cm DEM. The resampled DEMs were determined without interpolation due to the fact that the points are lying at the very same locations of the base DEM and, thus, no interpolation is required (Li et al., 2005). This technique is regarded as the simplest resampling method (decimation). The effects of resampling are shown in Figure 43 along a portion of OH SR 666. To make comparisons easier, the inventory map is also resampled similarly to each spatial resolution.
Figure 43. Portion of SR 666 displaying the impact of resampling in 3D. (A) original 50 cm DEM, (B) 4 times resampled 200 cm DEM, and (C) 8 times resampled 400 cm DEM.

5.2.1.1 Effects of Decimation

The effects of decimation are shown as an example in Figure 44 along a surface profile. Clearly, the small variations along the surface, which provide the detail that is needed to
map geomorphological features of landslides, are lost as the terrain representation smoothens (decimation increases). Although, this effect is clearly visible, the impact varies by the surface characteristics.

Figure 44. Example of the impact of decimation along a profile. (A) Original profile, (B) 2 times decimated profile, and (C) 4 times decimated profile.
5.2.2 Surface Feature Extraction

The feature extraction algorithm used is described in detail in section 4.1. The operators/window sizes are fixed and the same parametrization are used for all spatial resolutions.

5.2.3 Performance Evaluation

The performance evaluation was assessed by analyzing the resulting landslide map with respect to the independently compiled landslide inventory map. A common form to evaluate the performance of a landslide detection model is to use a confusion matrix (Frattini et al., 2010). The model performance is analyzed by assessing the correctly and incorrectly classified landslide and stable areas. Since, the algorithm’s output is a cluster, cluster overlap based on a cell count is used. There are two types of errors involved in this type of accuracy assessment (see Table 23): Type I and Type II. Type I error is associated with the incorrect rejection of a true null hypothesis, while a Type II error is the failure to reject a false null hypothesis. The costs related to Type II error are usually larger than those of Type I (Frattini et al., 2010). Table 23 represents a two-class confusion matrix used here.

<table>
<thead>
<tr>
<th>Actual Class</th>
<th>Predicted Class</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Landslide</td>
</tr>
<tr>
<td>Landslide</td>
<td>True Positive (+</td>
</tr>
<tr>
<td>Stable</td>
<td>False Positive (+</td>
</tr>
</tbody>
</table>

Table 23. Confusion matrix used for performance evaluation.
5.3 Test Data Evaluation

Figure 45 shows the four DEMs where the details are visibly lost as the spatial resolution decreases, meaning the surface features may be no longer distinct in the DEM. One particular feature that loses detail is the transportation corridor. In the base (50 cm) DEM, the corridor is clearly visible, but as the DEM becomes coarser it is no longer noticeably apparent, illustrating that surface features are lost as the spatial resolution decreases. In this section, the term surface roughness refers to the topographic variability of the surface.

A few of the surface feature extractors are tabulated statistically in Table 24 - Table 26 to illustrate the impact of spatial resolution. Although, only a few are listed, all were used for classification. Since the classification algorithm determines that flat terrain that is safe from landsliding should be filtered as stable (slope ≤ 15°), it was decided that analyzing the surface features in two parts, where slopes > 15° are in one group and slopes ≤ 15° are in another, would be appropriate.

Topographic variability maps shown in Figure 46 were made using the roughness surface feature extractor. The topographic variability is shown to be the same along sloped and flat surfaces as the spatial resolution decreases (see Figure 46). The effect caused by the decreasing spatial resolution is as expected and described in section 0.
Figure 45. Generated DEMs with 50 (A), 100 (B), 200 (C) and 400 (D) cm spatial resolution. The surface details are lost with coarser spatial resolutions.
The roughness surface feature extractor results are tabulated in Table 24. The landslide terrain is shown to be rougher than stable terrain for slopes $\leq 15^\circ$, except for the 400 cm spatial resolution where the surface roughness is comparable for both terrain types. For slopes $> 15^\circ$ the surface roughness is similar for stable and landslide cells. However, the variation is higher for stable cells. The landslide terrain mean ranges from 6 to 11 cm for slopes $\leq 15^\circ$ and 9 to 12 cm for slopes $> 15^\circ$, while the stable terrain increases from 3 to 11 cm for slopes $\leq 15^\circ$ and 9 to 12 cm for slopes $> 15^\circ$, as the spatial resolution decreases.

<table>
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<tr>
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<th>Stable Cells (Slope &gt; 15°)</th>
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<td></td>
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<td>.50 m 1m 2m 4m</td>
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<td>Mean</td>
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<td>0.09 0.11 0.12 0.12</td>
</tr>
<tr>
<td>Med</td>
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<td>0.08 0.10 0.11 0.11</td>
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<td>0.03 0.04 0.08 0.11</td>
</tr>
<tr>
<td>Med</td>
<td>0.05 0.08 0.12 0.12</td>
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<tr>
<td>Max</td>
<td>0.22 0.23 0.22 0.16</td>
<td>0.62 0.54 0.36 0.21</td>
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</tbody>
</table>

Table 24. Statistics [m] of roughness surface feature for each slope and terrain type.
Figure 46. The impact of spatial resolution on the geomorphological surface feature Roughness is shown with the underlying DEM at 50 (A), 100 (B), 200 (C) and 400 (D) cm spatial resolution.
The influence of spatial resolution on aspect is shown in Table 25. The pattern observed between sloping terrain > 15° for both terrain types is similar with coarser DEM. Sloping terrain > 15° for both terrain types also become smoother with decreasing spatial resolution. The surface roughness of sloping terrain ≤ 15° is higher than sloping terrain > 15°, which is due to higher sensitivity of slope calculation caused by subtle variations in flat terrain.

<table>
<thead>
<tr>
<th>Cell size:</th>
<th>Landslide Cells (Slope &gt; 15°)</th>
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<td>Mean</td>
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<td>Med</td>
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<tr>
<td>Max</td>
<td>146.61</td>
<td>66.42</td>
</tr>
</tbody>
</table>

Table 25. Statistics [°] of aspect surface feature for each slope and terrain type.
Hillshade feature statistics are shown in Table 26. As the DEM becomes coarser, the surface features become smoother as shown by the statistical mean and median. It is also observed that the landslide terrain is similar in surface roughness for both slope categories at each spatial resolution and the surface roughness decreases insignificantly with decreasing spatial resolution. Stable cells with slopes $> 15^\circ$ are noticeably rougher than cells with slopes $\leq 15^\circ$. The variations are smaller for landslide cells than stable cells for both slope types.

<table>
<thead>
<tr>
<th></th>
<th>Cell size:</th>
<th>Landslide Cells (Slope $&gt; 15^\circ$)</th>
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<tr>
<td>Mean</td>
<td>0.08</td>
<td>0.04</td>
<td>0.02</td>
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<tr>
<td>Med</td>
<td>0.08</td>
<td>0.04</td>
<td>0.02</td>
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<td>0.02</td>
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<td>0.01</td>
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<tr>
<td>Max</td>
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<td>0.02</td>
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<td>0.01</td>
<td>0.01</td>
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<tr>
<td>Min</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Max</td>
<td>0.18</td>
<td>0.08</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Table 26. Statistics [unitless] of hillshade surface feature for each slope and terrain type.

Analyzing the surface features extracted can help determine trends caused by spatial resolution. From the statistical evaluations, it was observed that the surface features displayed similar patterns as a function of decreasing spatial resolutions. Most surface features behaved similarly as the spatial resolution decreased.
The classified landslide maps generated at varying spatial resolutions are shown in Figure 47 and the corresponding performance results are tabulated in Table 27. The accuracy statistics in Table 27 reveal that the algorithmic performance decreases with respect to the spatial resolution. The performance of the true positive statistic, signifying the landslide features that were classified correctly, decreases from 35.71 to 0.00%. This pattern indicates that the algorithm becomes incapable of distinguishing landslide and stable features due to the loss of detail in the terrain. The lower resolution of 400 cm has the worst performance, as no landslide features are classified correctly, and the highest resolution of 50 cm has the best performance.

<table>
<thead>
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<th>.50 m</th>
<th>1m</th>
<th>2 m</th>
<th>4 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy (%)</td>
<td>78.66</td>
<td>77.86</td>
<td>81.41</td>
<td>80.17</td>
</tr>
<tr>
<td>True Positive Rate (%)</td>
<td>35.71</td>
<td>17.42</td>
<td>13.86</td>
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</tr>
<tr>
<td>False Positive Rate (%)</td>
<td>10.54</td>
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<tr>
<td>True Negative Rate (%)</td>
<td>89.46</td>
<td>93.04</td>
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<tr>
<td>False Negative Rate (%)</td>
<td>64.29</td>
<td>82.58</td>
<td>86.14</td>
<td>100.00</td>
</tr>
<tr>
<td>Precision (%)</td>
<td>45.98</td>
<td>38.61</td>
<td>67.72</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 27. Accuracy statistics of the landslide surface feature extraction algorithm described in section 4.1. The performance was tested at varying spatial resolutions.

These tests have confirmed that the performance of the classifier strongly depends on the relationship between the size of the landslide surface features and the spatial resolution used to generate each DEM. The smallest size of surface feature expected to be determined is a function of the available DEM resolutions.
Figure 47. Classification results of the landslide surface feature extraction algorithm described in section 4.1 with 50 (A), 100 (B), 200 (C) and 400 (D) cm spatial resolution.
5.4 Summary and Discussion

In this chapter, four different spatial resolution DEMs ranging from 50 to 400 cm were generated using SR 666 airborne LiDAR dataset. The objective was to assess the impact of spatial resolution on both surface feature extraction and small landslide detection with varying spatial resolution. The discussion in this chapter shows an approximately linear relationship between the landslide detectability and DEM spatial resolution for the small test data. It should be noted that in order to map the required size of surface features, the spatial resolution of the DEM should be determined prior to the LiDAR data acquisition. The resulting DEM is a function of sensor type and settings, and flight planning.

As LiDAR technology improves in spatial resolution and accuracy, and new emerging platforms, such as UAS become more accessible and affordable, the ability to detect and map small failures with high confidence is becoming more realistic.

In summary, the DEM spatial resolution is a crucial component of small landslide detection, as shown throughout this study. When generating DEMs for landslide detection, it is important to know and understand the scale of the landslide morphology in order to maximize the performance of the classifier. If an insufficient spatial resolution is selected, the success rate of the classifier will decrease.
Chapter 6 Conclusions and Recommendations

This chapter summarizes the course of the research for the proposed landslide detection techniques. Next, the proposed methods are discussed in terms of their contribution to the landslide detection, their performance and suitability for this application. Finally, some conclusions are offered on applying these landslide mapping techniques to improving the performance of the existing techniques.

6.1 Research Agenda

In the early stages of this research, a comprehensive literature review of the landslide surface feature extraction and change detection methods was carried out. These state-of-the-art feature extraction and change detection methods provided the initial thoughts on how to detect landslide hazards based on surface morphology. Next, the candidate methods for surface feature extraction including the point-based, profile-based and shape-based methods were identified tested on the available datasets. Additionally, two candidate techniques for change detection, the C2C and DoD methods were analyzed and tested using the available reference datasets. These experiments led to a conclusion that no single existing method could solve the problem completely and reliably, although, some showed a promise that could be developed further to improve the state-of-the-art in landslide detection mapping methods.
Subsequently, the complex task was divided into two parts: (1) performing the surface feature extraction from the single surface models and (2) to fuse the temporal changes with the surface feature extraction from the multi-temporal surface models. At this stage, several methods were tested to improve each component of the proposed algorithms, and eventually a workable landslide mapping method for each approach was developed. To evaluate the algorithmic performance, a portion of the dataset from OH SR 666 was used as a test bed, and encouraging landslide detection results were obtained. At the final stage of this research, the proposed methods were applied to the entire 23 km section of SR 666 and two independent test datasets separated in time were used. Although the results were noticeably limited by the LiDAR data quality, in particular by the low spatial resolution, satisfactory results were achieved. It should be noted that the horizontal point spacing of LiDAR can impact the vertical accuracy. For example, complex surfaces (high topographic variability) can be occluded in low spatial resolution datasets, that may lead to a loss of the surface details. In addition to the development of the two techniques, the impact of the spatial resolution on landslide surface extraction was evaluated. The analysis confirmed that the spatial resolution has significant impact on the landslide classification performance. Reviewing the course of this research in its entirety and analyzing the test results using the proposed techniques of landslide mapping provide new knowledge and more detailed insights to the landslide mapping field.

6.2 Research Contribution
The main contribution of this work was the development of two approaches to landslide detection. The two methods introduced provide promising results to characterize and
detect landslide morphology/surface geometry. The first method implements a technique to extract, identify and map surface features found in the landslide morphology using a single surface model. The second method is based on combining a shape-based surface feature extraction technique and a change detection method using multi-temporal surface models. The detailed algorithms, presented in Chapters 2, 3 and 4 use the landslide mapping strategy that is based on characterizing landslide morphology. Both methods work as an objective and effective approach, as compared to the most commonly used visual inspection, which is subjective to personal bias and interpretation.

6.2.1 Landslide Detection Based on Surface Features

In the first approach, single surface models are used to identify surface features typical for landslides. Initially, surface features are extracted to quantify landslide areas based on the known reference. Next, training samples are used to tune the SVM model. Subsequently, the trained model is used to classify airborne LiDAR-derived DEMs. Then, filtering is performed to suppress the noise. Finally, the detected landslide areas are mapped, resulting in a landslide map.

The algorithm’s performance of the first approach is rigorously evaluated in Section 4.1.3. Using a dataset from OH SR 666, the estimation performance of the landslide surface feature extraction method was tested and it was found that it, generally, achieved good results. Quantitatively, the algorithm was able to successfully map 84% (67 out of 80) of the landslides from the reference landslide inventory map of SR 666. It is noted that reliable landslide inventory maps are essential in evaluating the performance of any new algorithm. It should be noted, though, that there may be a personal biases among the
experts when compiling detailed landslide inventory maps, as the criteria to determine a landslide may vary amongst experts. Consequently, the reference data may be inconsistent and biased, rendering the validation of any new, automated algorithm difficult. To evaluate the algorithm’s robustness and performance on data that wasn’t used during the developments, the entire processing was run on two LiDAR datasets, acquired in the southern part of Ohio. The algorithm identified five landslide-suspect areas and the results were presented to geotech experts, who performed a visual evaluation of the area based on the LiDAR data. This investigation concluded that there were six landslide-suspect areas in that datasets, and five out of them were correctly identified by the algorithm. This suggests that the algorithm may perform well in other areas, independent from the area used to develop the model. However, this is not to suggest that the proposed algorithm is without limitations. The algorithm had limited data for training, and, therefore, may be too data dependent, necessitating more training samples to adapt to other areas. Having a large amount of training data is vital and may influence the robustness of the algorithm. For this reason, a larger training sample is desired to train the SVM model and is proposed as future work. Additionally, abrupt changes in elevation mimic the surface geometry of landslides, which include man-made features. To minimize misclassification of landslide remediation and known stable surfaces a compiled GIS database may be integrated to the proposed technique to filter the detected landslide hazards and is proposed as future work. The GIS database will embed layers, such as roads, tributuaries, development class, soil type, water content and other readily available data that may be useful in not only filtering but also landslide
classification. To determine which layers are beneficial tests should be performed and evaluated accordingly.

6.2.2 Landslide Detection Based on Combining Surface Changes and Surface Features

In the second approach, the multi-temporal surface models are used to identify temporal changes suspect to landslide activity. First, temporal changes are probabilistically analyzed to evaluate if the surface deformations are above the uncertainty level. Then, similarly to the first approach, the surface features are extracted to quantify landslide areas based on a known reference (training step). After that, the training samples are used to calibrate the SVM model for classification. Subsequently, temporal changes and the trained SVM model classification results are fused to identify the landslide suspect areas. Next, filtering is performed to suppress the noise. Finally, a landslide map is generated.

The change detection technique’s performance using the dataset from OH SR 666 is comprehensively analyzed in Section 4.2.3, indicating a satisfactory performance level. The algorithm performed the landslide detection effectively on the limited available dataset by identifying landslide related changes on 66% of the mapped landslides from the reference landslide inventory map. In addition, the algorithm was able to identify the newly developing landslides (not listed in the inventory map). The assessment of whether the 66% of the inventory mapped landslides detected as land slides is correct is not possible at the moment with high certainty, since the only existing reference inventory was acquired long before the LiDAR data acquisition. Therefore, field investigation should be performed to confirm that the mapped locations are indeed experiencing landslide susceptible changes.
A few limitations were found with respect to the proposed technique. For the study data, it was observed that the propagated uncertainties significantly impact the detectability of vertical changes. Since the uncertainty of the DoD was propagated to be ±0.17m, the method may not be able to detect subtle changes below this uncertainty level. In addition, the detection results were limited by the spatial resolution, as it limited the scale of the surface features that could be extracted. Therefore, in order to maximize the algorithm’s performance, the spatial resolution needs to be relevant to the size of the morphological features of the landslides.

6.2.3 The Impact of Spatial Resolution

Chapter 5 presents the evaluation of the impacts of the spatial resolution on the accuracy and reliability of the landslide detection. The objective is to evaluate, based on simulated data, how spatial resolution directly impacts the performance of the proposed landslide surface feature extraction algorithm of single surface models. The idea is to establish an adequate spatial resolution, relevant to the size of the morphological features found in small landslides. This should provide optimal results, as the spatial resolution adequate to the landslide surface features can be determined while planning the airborne mission parameters and selecting the data collection settings. It was validated that small landslide detection can be performed more accurately with higher spatial resolution, which is not surprising, and we should emphasize that the performance is strongly dependent on the scale of the landslide morphology. As mentioned earlier, the spatial resolution for landslide detection and mapping is determined by considering the vertical accuracy of the
spatial resolution, amount of data that can be acquired, and the scale of the landslide surface features.

6.2.4 Benefits of the Proposed Methods

3D data, such as point clouds or surfaces were exploited in landslide detection. The developed methods provide an efficient way to extract landslide features based on the surface morphology. The potential of extracting spatial features characteristic to landslides, especially small failures provides an opportunity to advance landslide research. By monitoring landslide suspect areas over time, the prevention of landslides could be potentially improved, as previously undetected areas may now be identified, and prevention and remediation can be initiated. Transportation corridors are regularly surveyed by LiDAR to obtain engineering scale data for the road structure, so by using the proposed methods, the same LiDAR data can be further exploited to scan for landslide suspect areas around the road.

6.2.5 Tools Developed

Both techniques proposed in this dissertation were implemented, coded and tested on a desktop computer using Matlab Version R2014a (The MathWorks, Inc.), so the methods should be accessible to the research community. The tools were extensively used for tests and computational performance evaluation. Example codes of the algorithms are available in Appendices C and D. If a copy of any of the software developed is desired, please contact the author.
6.2.6 LiDAR Technology

The early airborne scanning sensors did not have the capabilities to provide the spatial resolution and accuracy necessary to capture the surface models that are needed for small landslide mapping. The continuing improvements in LiDAR sensor technology provide the increasing spatial resolution and more accurate surface representations that will advance the topographic mapping capabilities. Dense 3D point clouds obtained by LiDAR technology clearly allow for better exploitation of the surface morphology. The new, emerging platforms, such as UAS, offer better economy to acquire data, and are readily deployable for surface mapping, as compared to the traditional platforms. As new platforms improve and become more accessible and affordable, the ability to extract spatial features, characteristic to landslides, especially small failures will be achieved with increasing confidence.

6.3 Future Research

As discussed earlier, the proposed methods can only be as accurate as the surface models used for landslide detection. Since the methods employ many independent processes, the incorporation of more advanced techniques may result in further improvements. For example, other change detection techniques (e.g. those described in section 3.3) could be considered, or different surface feature extraction methods could be applied that may include additional data, such as water tables or water entering the landslide area, the angle of internal friction of the landslide material and the configuration of the landslide itself. In addition, adaptive uncertainty estimation can be incorporated that adjusts to the spatial variability, instead of assuming a conservative uncertainty level for all areas in the
change detection approach. Moreover, improved, more exhaustive algorithm training may be adopted to incorporate other environments and increase the robustness of the landslide surface feature extraction method. Since GIS databases are commonly available, they may be used to filter misclassifications generated by the proposed techniques. In addition, individual layers in the database may be integrated as inputs into SVM model of the proposed methods. These layers include: roads, tributaries, development class, soil type, water content, etc.

A particular example that could further extend the proposed change detection algorithm may include the development of an early warning system. The early warning system should categorize the hazards into different risk levels depending on the rate of change.

Beyond the landslide detection, the proposed method has the potential for the development of new applications, such as morphological sediment budgeting in rivers, which normally includes DEMs. However, none of them use the non-parametric probability estimation to identify surface changes; typically, parametric estimation is used to identify surface changes. Note that the probabilistic estimation of the surface change works for any distribution. The main challenge is to distinguish changes due to geomorphic processes from those due to noise and uncertainty inherent in the DEMs. The non-parametric approach introduced in this research could be used to estimate the probability that the observed change is not the noise or the uncertainty. Finally, if volume estimation is desired for areas experiencing real changes, it can be easily added to the detection algorithm. This approach may provide changes due to geomorphic processes of erosion and deposition from the repeated topographic surveys. In addition, this could lead
to a new approach for non-parametric change detection for morphological sediment budgeting in tributaries.
References


and Hazard Mapping. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XL-1.* Denver, CO.


Appendix A: Landslide Inventory Mapping Using LiDAR Imagery

Figure 48. Landslide inventory map along SR 66 MM 1.25 to 1.60.
Figure 49. Landslide inventory map along SR 66 MM 1.60 to 2.00.
Figure 50. Landslide inventory map along SR 66 MM 2.00 to 2.40.
Figure 51. Landslide inventory map along SR 66 MM 2.40 to 2.80.
Figure 52. Landslide inventory map along SR 66 MM 2.80 to 3.20.
Figure 53. Landslide inventory map along SR 66 MM 3.20 to 3.55.
Figure 54. Landslide inventory map along SR 66 MM 3.55 to 3.85.
Figure 55. Landslide inventory map along SR 66 MM 3.85 to 4.20.
Figure 56. Landslide inventory map along SR 66 MM 4.20 to 4.55.
Figure 57. Landslide inventory map along SR 66 MM 4.55 to 4.85.
Figure 58. Landslide inventory map along SR 66 MM 4.85 to 5.20.
Figure 59. Landslide inventory map along SR 66 MM 5.20 to 5.55.
Figure 60. Landslide inventory map along SR 66 MM 5.55 to 5.90.
Figure 61. Landslide inventory map along SR 66 MM 5.90 to 6.25.
Figure 62. Landslide inventory map along SR 66 MM 6.25 to 6.60.
Figure 63. Landslide inventory map along SR 66 MM 6.60 to 6.95.
Figure 64. Landslide inventory map along SR 66 MM 6.95 to 7.35.
Figure 65. Landslide inventory map along SR 66 MM 7.35 to 7.75.
Figure 66. Landslide inventory map along SR 66 MM 7.75 to 8.15.
Figure 67. Landslide inventory map along SR 66 MM 8.15 to 8.55.
Figure 68. Landslide inventory map along SR 66 MM 8.55 to 9.00.

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Figure 69. Landslide inventory map along SR 66 MM 9.00 to 9.35.
Figure 70. Landslide inventory map along SR 66 MM 9.35 to 9.75.
Figure 71. Landslide inventory map along SR 66 MM 9.75 to 10.20.
Figure 72. Landslide inventory map along SR 66 MM 10.20 to 10.60.
Figure 73. Landslide inventory map along SR 66 MM 10.60 to 10.95.
Figure 74. Landslide inventory map along SR 66 MM 10.95 to 11.55.

Figure 75. Landslide inventory map along SR 66 MM 11.55 to 12.08.
Figure 76. Landslide inventory map along SR 66 MM 12.08 to 12.45.
Figure 77. Landslide inventory map along SR 66 MM 12.45 to 12.75.
Figure 78. Landslide inventory map along SR 66 MM 12.75 to 13.08.
Figure 79. Landslide inventory map along SR 66 MM 13.08 to 13.45.
Figure 80. Landslide inventory map along SR 66 MM 13.45 to 13.80.
Figure 81. Landslide inventory map along SR 66 MM 13.80 to 14.18.
Appendix B: Landslide Locations Selected for GPS Data Collection

Figure 82. GPS surveyed landslides along SR 66 MM 2.80 to 3.20.
Figure 83. GPS surveyed landslides along SR 66 MM 3.20 to 3.55.
Figure 84. GPS surveyed landslides along SR 66 MM 6.95 to 7.35.
Figure 85. GPS surveyed landslides along SR 66 MM 8.97 to 9.35.
Figure 86. GPS surveyed landslides along SR 66 MM 9.35 to 9.75.
%% Automated Landslide Identification Algorithm
% This software will identify landslides given the proper inputs.
% Input:
% file1 - Digital Elevation Model (DEM) to classify (esri ascii gridded format)
% file2 - Soil file corresponding to DEM to classify (esri ascii gridded format)
% gs - Grid spacing of input DEM in US survey feet
% units - Units of DEM to classify (US survey feet)
% zone - US state plane coordinates zone (ohio north or ohio south)
% Output:
% File - Text file containing Easting, and Northing locations of flagged landslides in US survey feet
% Image - Figure of flagged landslide locations with levels of susceptibility (low, moderate, high)
% Clear Previous Information
clc; clear filename1 filename2; close all;

%% Input Parameters
gs = 1.64; % Grid spacing of input DEM in US survey feet
units = 'survey feet'; % Units of DEM to classify (US survey feet)
zone = 'ohio south'; % US state plane coordinates zone (ohio north or ohio south)

%% Input Files
[filename1, pathname1] = uigetfile('*.txt*');
if filename1 == 0;
    disp('Did not select a DEM file. Program will now EXIT');
    return
end
file1 = strcat(pathname1,'\',filename1); % directory of DEM
[filename2, pathname2] = uigetfile('*.txt*');
if filename2 == 0;
    disp('Did not select a soil map file. Program will now EXIT');
    return
end
file2 = strcat(pathname2,'\',filename2); % directory of Soil Map

%% Check Inputs
fprintf('The entered grid spacing is: %5.3f\n',gs); % Check grid spacing
fprintf('The entered units are in: %s\n',units); % Check for units
fprintf('The entered US state plane coordinate zone is: %s\n',zone);

Check for zone

disp('Enter 1 to continue with the entered grid spacing, units and zone');
disp('or enter any other integer to exit the program and re-enter the grid spacing, units and zone');
c = input('Enter your choice here: ');
if c~=1
    disp('Re-enter grid spacing, units and/or zone and re-run the program');
    return;
end

%% Classification Algorithm
svm_classifier_ODOT(file1,file2,gs,units,zone);

Listing of the main MATLAB routines used in the algorithm:

- **Main.m**: Main software file where the proper inputs need to be given and confirmed.
- **svm_classifier_ODOT.m**: Algorithm where landslide classification is performed using Support Vector Machine. In this routine the geomorphological surface feature extraction, SVM classification, post-classification filtering and landslide detection are performed.
Appendix D: Example Code for Surface Change Detection Method

%% Probabilistic Change Detection Algorithm
% This software will identify landslide susceptible areas given the proper inputs.
% Input:
% file1 - Digital Elevation Model (DEM) to classify (esri ascii gridded format)
% file2 - Digital Elevation Model (DEM) of Difference (DoD) to classify (esri ascii gridded format)
% gs - Grid spacing of input DEM in US survey feet
% units - Units of DoD to classify (US survey feet)
% zone - US state plane coordinates zone (ohio north or ohio south)
% Error - Error sources in LiDAR and those introduced by interpolation
% Output:
% File - Text file containing Easting, and Northing locations of flagged landslides in US survey feet
% Image - Figure of flagged landslide locations

%% Clear Previous Information
clc; clear filename1 filename2; close all;
%% Input Files
[filename1, pathname1] = uigetfile('*.*\', '*.*');
if filename1 == 0;
    disp('Did not select a DEM file. Program will now EXIT');
    return
end
file1 = strcat(pathname1, '\', filename1); % directory of DEM
[filename2, pathname2] = uigetfile('*.*\', '*.*');
if filename2 == 0;
    disp('Did not select a DoD map file. Program will now EXIT');
    return
end
file2 = strcat(pathname2, '\', filename2); % directory of DoD Map

%% Parameters
th = 0.90; % Probability threshold for clustering landslide susceptible areas
Area = 25; % Minimum area of cluster to be considered landslide susceptible in meters
gs = 1.64; % Grid spacing of DEM, units in ussft
dx2m = gs*1200/3937; % Grid spacing of DEM, units in meters
units = 'survey feet'; % Units of DEM to classify (US survey feet)
zone = 'ohio south'; % US state plane coordinates zone (ohio north or
ohio south)
%
% Error Sources in LiDAR
sig1 = .20; % std or rms in ussf (DEM1)
sig2 = .20; % std or rms in ussf (DEM2)
%
% Error introduced by interpolation
sig3 = .36; % std or rms in ussf (DEM1)
sig4 = .33; % std or rms in ussf (DEM2)
%
% Propagated Uncertainty
sig_DoD = sqrt(sig1^2+sig2^2+sig3^2+sig4^2); % propagated uncertainty
into DoD
%
% Input Parameters (signed rank test)
w = 7; % window size (w x w)
MS = sig_DoD; % data in x are observations from a distribution with
median M
ALPHAS = 0.05; % significance level
METHOD = 'exact'; % compute p-value using exact algorithm for non-
parametric approach
TAILS = 'left'; % alternative hypothesis specified by TAIL
%
% Check Inputs
fprintf('The entered grid spacing is: %5.3f\n',gs); % Check grid
spacing
fprintf('The entered units are in: %s\n',units); % Check for units
fprintf('The entered US state plane coordinate zone is: %s\n',zone); %
Check for zone
fprintf('The entered error sources in LiDAR: %5.3f\n',[sig1, sig2]); %
Check for error sources
fprintf('The entered error sources introduced by interpolation:
%5.3f\n',[sig3, sig4]); % Check for error sources
fprintf('The entered minimum area of cluster to be considered landslide
susceptible in meters: %5.2f\n',Area); % Check for error sources
fprintf('The entered probability threshold for clustering landslide
susceptible areas: %5.2f\n',th); % Check for error sources
disp('Enter 1 to continue with the entered grid spacing, units and
zone');
disp('or enter any other integer to exit the program and re-enter the
grid spacing, units and zone');
c = input('Enter your choice here: ');
if c~=1
    disp('Re-enter grid spacing, units and/or zone and re-run the
program');
    return;
end
if 1 == strcmp(units,'meters')
    disp('All units need to be in US survey feet to run the program,
including input files');
    return;
end
%
% Begin Main Algorithm
file_out1 = strcat(file2,'_Flagged_Locations','.txt'); % Output Easting
and Northing locations of flagged areas
file_out2 = strcat(file2,'_Flagged_Locations','.png'); % Output figure
of classification results
[demd,Xd,Yd] = rasterread(strcat(file2)); % DoD Map (Raw Observed Changes)
[demP,XP,YP] = rasterread(strcat(file1)); % DEM Map
demd = abs(demd); % absolute value conversion
[m,n] = size(demd); % size of DEM map
Pre_Map = zeros(m,n); % Empty Map
[Class] = svm_classifier(file1,gs); % Classification
[Prob_Map] = prob_signrank(demd,MS,ALPHAS,METHOD,TAILS,w); % Perform signed rank test
Pre_Map(Prob_Map >= th & Class == 1) = 1; % Replace values above cut-off threshold with 1's
[L,~] = bwlabel(Pre_Map,8); % Compute connected components for binary images
STATS = regionprops(L,'Area','PixelList','Centroid','ConvexHull'); % Measures a set of properties for each connected component (object)
FinalXY = []; % Empty matrices
k = 1; % Initialize
for i = 1:size(STATS,1);
    if STATS(i).Area*(dx2m^2) >= Area % contraint for cluster size
        FinalXY(k,:) = [XP(1,round(STATS(i).Centroid(1))),YP(round(STATS(i).Centroid(2)),1)]; % Flagged Landslide locations
        k = k + 1;
    end
end
%% Plot classification given threshold or SVM
figure; imageschs(XP,YP,demP,demP,5); title('DEM');
grid on; axis equal tight; colormap('gray'); colorbar('off'); shading interp; camlight;
xlabel('Easting (Feet)'); ylabel('Northing (Feet)'); zlabel('Height (Feet)'); drawnow
% Plot Flagged Areas In Categories
if isempty(FinalXY) == 0;
    hold on; plot(FinalXY(:,1),FinalXY(:,2),'b+','linewidth',2);
end
% Plot Boundaries of Flagged Slides
for i = 1:size(STATS,1);
    if STATS(i).Area*(dx2m^2) >= Area % contraint for cluster size
        hold on;
        plot(XP(1,round(STATS(i).ConvexHull(:,1))),YP(round(STATS(i).ConvexHull(:,2)),1),'k-','linewidth',2); % Plot Convex Hull
    end
end
saveas(gcf,file_out2);
%% Write flagged landslide locations to txt file
if isempty(FinalXY) == 0
    FID = fopen(file_out1,'wt');
    for i = 1:size(FinalXY,1)
        fprintf(FID,'%12.3f %12.3f %s\n',FinalXY(i,1),FinalXY(i,2),cell2mat(cellstr('')));
    end
    fclose(FID);
end
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Listing of MATLAB routines:

- *Main.m*: Main software file where the proper inputs need to be given and confirmed. Algorithm where landslide susceptible areas are detected. In this file the geomorphological surface feature extraction, SVM classification, probabilistic change detection and landslide detection are performed.

- *svm_classifier.m*: Algorithm where classification is performed using Support Vector Machine. In this file the geomorphological surface feature extraction and classification are performed.

- *prob_signrank.m*: Probabilistic approach to quantify that the observed vertical differences of the DoD surpass an uncertainty level for a local area using the non-parametric signed rank test.