Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

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**Abstract**

Landslide hazard and its consequences in the transportation network are well-understood, yet current methods of identifying and assessing landslide conditions are inefficient, as they are mostly based on labor-intensive field surveys. This research was performed as a feasibility study, where the potential of airborne LiDAR data for landslide detection was investigated. The primary objective of this pilot study was to develop, implement and validate computer models for automatic detection and assessment of landslides using time-series of airborne LiDAR data. Models have been developed using LiDAR data obtained from SR 666 in Muskingum County (District 5) and independently tested on LiDAR data covering southern Ohio. In this research effort, two techniques, one using single and the other based on multi-temporal surface models, obtained by airborne LiDAR, were proposed, implemented and tested for landslide susceptibility and hazard mapping. Based on a single dataset, 84% of the landslides from the reference inventory map of SR 666 were correctly identified, while using two datasets acquired four years apart, the proposed technique was able to identify 66% of the mapped landslides that are experiencing temporal changes susceptible to slides.
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Disclaimer

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1 INTRODUCTION

Landslides are natural disasters that cause environmental and infrastructure damage worldwide. To reduce future risk posed by such events, effective methods to detect and map their hazards 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 form, semi-automatic or automatic or a combination of them and can be accomplished using different sensors.

Landslide hazard and its consequences in the transportation network are well-understood, yet current methods of identifying and assessing landslide conditions are inefficient, as they are mostly based on labor-intensive field surveys. In addition, many sites are not easily accessible to land crews. Landslides are an ever-present risk to Ohio’s state highway system. The ODOT Office of Geotechnical Engineering (OGE) is currently facing landslide hazards in all of its districts, and some of these districts (e.g., Districts 8, 9, and 10) have several hundred of problem sites. Landslides that are impacting the roadway (e.g., guardrail, shoulders, cracks, sags, displacements) are generally known to county managers and District engineers by way of maintenance crews. On the other hand, landslides that are not yet impacting a highway are more difficult to detect and may pose a future hazard. In order to have better forewarning of these threats and to save on remediation cost in many cases (i.e., generally remediation costs increase as a landslide progresses), the OGE is searching for a means to identify and assess landslides as early as possible. Using field crews to scour every adjacent cut and fill slope for Ohio’s state highway system is completely impractical. Therefore, OGE is interested in developing a method to automatically search for and assess the magnitude of landslides using remote sensing data.

Recent developments in remote sensing have significantly improved the topographic mapping capabilities, resulting in higher spatial resolution and more accurate surface representations. Dense 3D point clouds can be directly obtained by LiDAR or created photogrammetrically, and allow for better exploitation of surface morphology. The potential of extracting spatial features, characteristic to landslides, especially small failures provides new opportunities for mapping at large scale.

Light Detection And Ranging (LiDAR) technology has seen phenomenal developments in the past ten years, and both airborne and terrestrial LiDAR can directly provide accurate surface models. Therefore, this technology is a prime consideration for landslide detection and monitoring, as it is relatively easily available, efficient and can achieve the accuracy needed for detecting surface changes in the cm-level range. Given Ohio’s extensive road infrastructure and its fast rate of deterioration, the research to assess the feasibility of LiDAR for landslide identification is of high urgency. Clearly, LiDAR represents the best opportunity, as the Office of CADD and Mapping Services (Office of Aerial Engineering) is routinely collecting this data, and the incremental cost for landslide detection and assessment would therefore be minimal. This study has been prepared
to address this need in the form of a pilot project, with cooperation between ODOT, The Ohio State University (OSU), and Kent State University (KSU).

2 RESEARCH OBJECTIVES

The research was performed as a feasibility study, where the potential of airborne LiDAR data for landslide detection was investigated. The primary objective of this pilot study was to develop, implement and validate computer models for automatic detection and assessment of landslides using time-series of airborne LiDAR data. Models have been developed using LiDAR data obtained from SR 666 in Muskingum County (District 5) and independently tested on LiDAR data covering southern Ohio. Since the landslide identification is based on change detection, a test area was selected by ODOT where past LiDAR data of good quality are available. While the key aspect of LiDAR data is that it is a remote sensing technology, yet for performance validation and reference, the necessary ground surveys have been conducted in consultation with the OGE staff.

3 GENERAL DESCRIPTION OF RESEARCH

3.1 LiDAR Technology

The introduction of airborne LiDAR (Light Detection and Ranging) in the late nineteen nineties was followed by a quick proliferation of the technology, and LiDAR is now considered the primary surface data extraction technique. This remarkable success of LiDAR technology is mainly due to the fact that LiDAR data are explicit (X, Y, Z point cloud in a selected reference frame) and the processing can be highly automated. Consequently, only limited operator intervention is required, and the turnaround time is very short. The quality of the LiDAR product is excellent, as compared to most of the surface datasets collected in the past. These factors largely contributed to the fast market acceptance of LiDAR technology. ODOT OAE procured a state-of-the-art LiDAR system in 2003 (Toth and Grejner-Brzezinska, 2005) and since then the system has been used to support both planning and, more importantly, design-level (or engineering scale) mapping. Years of experiences confirmed that this technology can provide high accuracy geospatial data not only for transportation corridor mapping but also for several other applications. The achievable vertical accuracy is remarkable, sub-decimeter range, and various methods have been developed in cooperation with ODOT to facilitate QA/QC. First LiDAR-specific ground targets were introduced (Csanyi & Toth, 2007), and most recently pavement marking based ground control has been studied, and is expected to be transferred into production (Toth et al., 2007 and 2008).
3.2 Geotechnical and Geological Component

The hazards of natural disasters occur from processes of the earth and cause damage, devastations, 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). Landslides have consistently damaged human infrastructure and impeded the lives of many. They are the result of a broad range of geologic processes that cause the downward movement of mass over spatial and temporal scales (McKean and Roering 2004). In addition, their effects have a strong dependability on the spatial pattern of incident, rate of recurrence and amount of movement (McKean and Roering 2004).

A “landslide” is defined by types 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 and Roering 2004). However, it describes various types of mass movements and is not restricted to any movement process. The failure of the slope happens when gravity exceeds the strength of the earth materials. Landslides occur due to the instability of a hill or mountain side. Landslides are not individual events, they occur in conjunction with other factors. Factors that can allow gravity to overcome the resistance of earth material are: erosion, addition of moisture, shocks and vibrations, volcanic eruptions, overdevelopment, and deforestation to name a few (Highland 2004). There are various landslide types, such as rock falls, rotational slides, translational slides, and debris flow, to name a few, all having unique characteristics that define them. In addition, they tend to have similar geomorphologic features, yet are still very different. Obviously, the behavior of one type of landslide can be different from other types.

Traditional landslide detection, in general, consists of visual interpretation of aerial and satellite imagery coupled with on-site validation. Note that the field work dominates the geotechnical engineering practice, and thus the process of traditional landslide detection is tedious and time consuming. In order to reduce the risk of active landslides, technologies that can support landslide detection based on remote sensed data is sought. Ideally, an automated landslide detection method should detect early warning signs of potentially hazardous landslides and allow for a better understanding of landslide behavior to help engineers create better measure/designs for preventing landslide movements.

Landslides cause a great distress to both the residents and the state. They are natural disasters that could take the lives of the innocent and impose burdens on those affected. State departments are prompted to respond to the disasters by devoting their resources and time. In order to reduce the cost of repairs and improve the safety among the residents, the localization of potential landslide activity is of high importance. Landslide prevention has been a priority for the State of Ohio, in particular, the Ohio Department of Transportation (ODOT), and this study is devoted to assess the
feasibility of LiDAR-based landslide detection method in order to prevent and/or minimize the likelihood of future events.

The objective of this study is to develop an experimental technique that is able to identify landslide prone regions, and thus, early warning signs of potential landslide activity can be created. In this study, different methodologies have been investigated to understand and model the behavior of landslides, including geomorphic features, geomorphologic shape (profile and shape based) and change detection. The long-term goal is to design a highly automated landslide detection algorithm that will identify potential landslide regions with high probability. The promise is that with the use of high precision airborne LiDAR, the landslide activities can be detected. The implementation of an automated landslide detection algorithm can reduce the need for onsite data collection issue. Therefore, field surveys to identify landslides could be minimized, and thus reducing the cost and time to identify and act upon warning signs of a landslide region.

3.3 Review of Existing Research in Landslide Detection

Hazard mapping for landslide susceptibility is a method for estimating areas suspect to mass movement. 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, Cardinali, Fiorucci, Santangelo & Chang, 2012; Jaboyedoff et al., 2012). Ideally, an automatic or semi-automatic landslide detection method should identify early warning signs of potentially hazardous mass movement and allow for a better understanding of landslide behavior to help create better measures/designs for preventing future events and/or break the progress of the ongoing occurrences.

The existing techniques, mostly manual techniques, are typically based on field inspection, aerial photograph interpretation and contour map analysis (Booth, Roering & Perron, 2009). However, these methods have limitations that reduce the accuracy, completeness and reliability necessary to map small landslides with high confidence level (Booth et al., 2009; Galli, Ardizzone, Cardinali, Guzzetti & Reichenbach, 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, Hodgson, Ghoshal & Latiolais, 2012; Van Den Eeckhaut et al., 2005). For these reasons, traditional methods are not sufficiently effective and new techniques for landslide 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 due to small failures requiring more precise and accurate surface models to increase the detectability of landslide surface features. The spatial resolution of the 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 sought.

Remote sensing technology has seen large advances in the past decade in cost, accuracy and accessibility. One of the major improvements has been the spatial resolution of LiDAR technology. Until recently, only a coarse nominal point spacing (> few meters) was available and the improvement of this technology has allowed for higher spatial resolutions (< 1 meter) (Shan & Toth, 2008). The increase made in spatial resolution provides mapping opportunities at remarkably large scales. 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 susceptibility mapping, for example, the spatial resolution, broad terrain coverage, vegetation penetration. A particular LiDAR technology, capable of overcoming the aforementioned challenges, is airborne LiDAR. This type of instrument is capable of penetrating the vegetation, mapping areas up to thousands of square kilometers (Guzzetti et al., 2012; Shan & Toth, 2008) and providing sub-meter spatial resolutions.

3.4 The Concept of Extracting Landslide Information from LiDAR Data

Landslide hypothesis can be obtained based on analyzing the terrain surface and from change detection between surface data acquired at different times. In the first case, surface features and properties are analyzed to identify parameter values, typical for landslides. The second method is aimed at detecting changes in surface movement and deformation, which are characteristic to landslide developments. In both cases, the performance of the landslide prediction depends a lot on the surface representation in terms of spatial sampling and accuracy. The more detailed and accurate the surface model, the higher the chance to identify landslide suspect areas. Both techniques are important, as there are dormant landslides, where there is no or undetectable surface changes, and actively developing landslides, where surface motion can be observed. Figs. 3.1 and 3.2 show the conceptual workflow for both approaches.
Figure 3.1. The concept of the landslide identification process, based only on one LiDAR data derived surface
Figure 3.2. The concept of the landslide identification process, based on change detection between two LiDAR data derived surfaces
4 TEST AREA

4.1 SR 666

The existing geohazard inventory and evaluation of Muskingum State Route 666 in Zanesville, Ohio, completed in 2006, provides important information about the general locations of landslides affecting the road prism. Therefore, this area seemed to be a good choice to support this study. Besides the geohazard inventory report, LiDAR data was also available from 2008 and 2012. The location of the study area is shown in Fig 4.1; note that the study area along State Route (SR) 666 is highly vegetated, near the riverbanks of the Muskingum River, with a few residential areas. The section begins at Mile Marker (MM) 0.00, which is at the intersection of SR 60 within the city of Zanesville just north of Interstate Route 70 and south of the Muskingum River. The study section ends at MM 14.34 at the intersection of State Route 208 east of the Village of Dresden.

Since the geohazard inventory report was published in 2006, and was based on data collected earlier, the inventory needs to be updated, supplemented, and transformed into a complete and georeferenced map in order to provide the information essential for quantitative landslide modeling. In addition, another reason for this is that although the existing inventory includes information about general landslide problem area locations, it does not provide a detailed map showing the geographic location, type, and extent of each landslide feature described in the report. Additionally, there may exist landslides that have either developed since the inventory was released eight years ago or were not recognized at the time.

While building complete inventory map is not an objective of the project, a GIS-based base map will be created building upon the general locations of problem areas referenced in the SR 666 geohazard inventory. This GIS inventory map that will result from this research will include the boundaries or shapes of landslides identified and surveyed during the course of this project, containing clear delineation of visible diagnostic features, such as landslide scarps and toes; inferences about the state of activity of the observed landslides (e.g., currently active, recently active, dormant); and inferences about the type of landslide (e.g., translational vs. rotational, slide vs. flow, incipient depression vs. fully developed landslide). Collection of this kind of information will allow for the formulation of more complete and potentially more useful predictive models, for example by determining if different kinds of landslides have distinctly different signatures. The inventory map will include information from all available LiDAR datasets so that, for instance, one inventory map will be available for computer model development and the other one will be available for model verification. If there was not substantial landslide movement between the first and second LiDAR flights, the two inventories will in essence represent two snapshots of the same landscape. The proposed work goes beyond simple field verification of model results derived from incomplete data, and will provide the detailed and geologically sound data necessary to develop useful models.
The processing of LiDAR data results in surface shape descriptions, a.k.a. geomorphologic derivative maps, that can be directly used and they do not require supplementary information such as soil properties. Nevertheless, such information is incorporated into the GIS inventory, as it might be useful if it were practical to obtain in typical ODOT applications. Their purpose is to recast the topography in such a way as to accentuate subtle indications of landsliding that may not be apparent from qualitative visual inspection alone. As such, this requires a considerable amount of geologic expertise with the regard to selection of appropriate scales and variables.

**Figure 4.2.** Study area along Route 666
4.2 Independent Test Areas

Six datasets were used in the course of this research with the objective of testing the proposed landslide surface feature extraction algorithm, including the above mentioned dataset from SR 666. The 70 cm spatial resolution Digital Elevation Model (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, 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, 70 cm spatial resolution DEM from ADA-247-1.20 (Approx. Latitude: 38° 43' 02", Longitude: W83° 30' 41"), acquired in November 2012 covering part of Manchester, OH, USA, 120 cm spatial resolution DEM from LAW-93-22.34 (Approx. Latitude: 38° 47' 05", Longitude: W82° 37' 09"), acquired in January 2014 covering part of Washington, OH, USA, 80 cm spatial resolution DEM from LAW-217-2.17 (Approx. Latitude: 38° 32' 58", Longitude: W82° 31' 36"), acquired in March 2014 covering part of Kitts Hill, OH, USA, 90 cm spatial resolution DEM from MRG-266-8.40 (Approx. Latitude: 39° 31' 56", Longitude: W81° 45' 17"), acquired in February 2014 covering part of Stockport, OH, USA, represent a typical mix of terrain topography and landscape, including residential areas, roads, and vegetated areas (see Fig 4.2). All airborne LiDAR datasets were acquired by ODOT, and subsequently used.

Unfortunately, there is no detailed landslide inventory map (reference) available that displays the landslides extents to evaluate the algorithms performance on either dataset; however ODOT has noted for each test area whether a slide has occurred and was repaired in the area. The six areas are described as follows:

1) ADA-247-1.20 Slide repair
2) HAM-75-5.58 Slide repair
3) MRG-266-8.40 Road relocation
4) LAW-217-2.17 Bridge replacement with slide repair
5) TUS-77-1.12 Slide repair
6) LAW-93-22.34 Slide repair
Fig 4.2. (A) Orthophoto of HAM-75-5.58, (B) Orthophoto of TUS-77-1.12, (C) Orthophoto of ADA-247-1.20, (D) Orthophoto of LAW-93-22.34, (E) Orthophoto of LAW-217-2.17, (F) Orthophoto of MRG-266-8.40.
5 LANDSLIDE TYPES

5.1 Landslide Categories and Definitions

The primary regions of landslide incidence and potential are the coastal and mountainous areas (Highland, 2004). Landslides come in various shapes and forms that help define the geomorphologic shape, behavior and type as shown in Fig 5.1. The objective of this research effort is to focus on the types that are typical in Ohio, such as rotational and translational landslides.

Since landslides share similar features, there is a commonly used nomenclature for describing the various landslide parts, as is shown in detail in Fig. 5.2. Although many types of mass movements are included in the general term "landslide," the more restrictive use of the term refers only to mass movements, where there is a distinct zone of weakness that separates the slide material from more stable underlying material (Highland, 2004). The two major types of landslides are the rotational and translational slides. In rotational slides, the surface of rupture is curved concavely upward and the slide movement is roughly rotational about an axis that is parallel to the ground surface and transverse across the slide, see Fig. 5.1A. In contrast, in translational slides, the landslide mass moves along a roughly planar surface with little rotation or backward tilting see Fig. 5.1B. A third frequently type is the block slide is a special case of translational slide in which the moving mass consists of a single unit or a few closely related units that move down slope as a relatively coherent mass, see Fig. 5.1C.
Figure 5.1. Major landslide types (Highland, 2004)
Figure 5.2. Landslide nomenclatures (Highland, 2004)

5.2 Surface Characterization Parameters

The mathematical definition of the geomorphologic features used to describe surfaces and, consequently, landslides, is discussed in detail in Appendix 16.
6 LiDAR DATA

The Light Detection And Ranging (LiDAR) data, was collected by the ODOT Office of CADD and Mapping (formerly Office of Aerial Engineering). The data acquisition system is composed of an Optech ALTM airborne LiDAR sensor with a GPS/INS georeferencing system. The data were collected at different times in order to perform change detection between different datasets that is essential to detect movement and/or deformation differences in the terrain. The LiDAR data was georeferenced to the Ohio State Plane system, South Zone; the georeferencing information is listed in Table 6.1. The details of the LiDAR data campaigns as well as the data collection parameters are listed in Table 6.2.

<table>
<thead>
<tr>
<th>Datum and Coordinate System</th>
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<tr>
<td>Vertical</td>
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<td>Orthometric Height Datum:</td>
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<td>Geoid Model:</td>
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<td>Combined Scale Factor:</td>
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Table 6.1. LiDAR dataset georeferencing
Table 6.2. LiDAR datasets used in the investigation

The SR 666 LiDAR data collections were performed in 2008 and 2012, in winter and the early spring, respectively; there was no dense vegetation to avoid any complications in the data collection, thus providing a clearer view of the bare earth. The primary LiDAR product used in this project is based on the point cloud of the bare earth. The spatial distribution of the LiDAR points is rather uneven; it varies by object distance, scan angle, etc. Generally, computer algorithms work with evenly spaced, gridded, raster data.

### 6.1 LiDAR Data Gridding

There are several options to grid irregularly spaced point data. Methods vary based on the implementation types, such as spatial or frequency domains. One important aspect is that regardless of the selected method some error is introduced in the Z component. Also, the magnitude of the error depends on average point spacing of the irregular data as well as surface complexity. In addition, the irregular data has a non-negligible error budget. Consequently, noise suppression and gridding are interlinked, and based on the selected methods different smoothing can be implemented. For the simplicity, the initial gridding was made by using ArcView software tools and the kriging interpolation method.
6.2 Surface Filtering

In some cases, the unfiltered DEM was processed through a smoothing filter in order to remove noise and anomalies in the data. By processing the DEM through a filter, the DEM will be smoother, as the variability in the terrain will diminish. Consequently, important details may be lost in the DEM, though, in general, it is easier to perform an analysis on the filtered data, as it allows for a better understanding, especially when working on surface profiles.

To smooth the DEMs, the classical method of windowed linear-phase Finite Impulse Response (FIR) digital filter design was applied. The filter was designed as a standard lowpass filter. The Hamming filter was chosen due to its attractive properties and its simple implementation when applying to a gridded dataset; note other filter types are also applicable.

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 lowpass 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:

$$uv^T = \begin{bmatrix} u_1 \\ \vdots \\ u_{16} \end{bmatrix} \begin{bmatrix} v_1 & \cdots & v_{16} \end{bmatrix} = \begin{bmatrix} u_1v_1 & \cdots & u_1v_{16} \\ \vdots & \ddots & \vdots \\ u_{16}v_1 & \cdots & u_{16}v_{16} \end{bmatrix} \quad (6.1)$$

If the window size is not too large, then convolution is used to compute the filtered DEM. Fig. 6.1 shows the parameter values of the 16 x 16 Hamming window.

![Figure 6.1. 2D Hamming-window distribution](image)
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 focused on selected areas; so not the entire road section was surveyed. This work was jointly performed with the KSU team.

- Precise boundary surveying of the selected areas based on highly-accurate GPS and total station measurements. The surveying work was done by the OSU team under the guidance of the KSU team, who identified the landslide boundaries to be surveyed.

- Performance validation of the landslide prediction method, including the surveying and geotechnical assessment of areas identified as potential landslide by the developed method but not listed in the inventory database.

- To update the existing inventory data of SR 666 to the extent it is feasible based on all the field work.

7.1 Landslide Inventory Mapping

The KSU team prepared two landslide inventory lists using the available OGE and Consultants’ reports regarding landslide activity along SR 666. These two inventory lists are included as Appendices A and B, respectively. Appendix A shows 38 areas of slope instability. Most of these landslide locations affect the road embankment and have since been remediated. The report uses the general term “slope instability” and, except for a few locations, it does not specify the mode of failure (rotational slide, translational slide, earth flow, mud flow, etc.). We have attempted to highlight in bold whether or not a mode of failure (landslide category) is indicated in the descriptions and, if not, what is the nature of instability described. In a number of cases, the instability is inferred only from the cracking in the pavement or it is a creep type of movement. We verified some of the landslide locations from this inventory list. However, because of time constraints, the entire list of instabilities could not be verified as landslides. Appendix B is a similar inventory of 18 landslide locations based on the Consultants’ report prepared for OGE. These 18 sites were selected as potential sites for the field investigations. The second and the third columns of the table provide the corresponding site numbers from the OGE report and the Consultants’ report, respectively. This inventory table includes the mode of failure as observed in the field, affecting both the embankment and natural hill-slope. Additionally, it lists information about the state of activity, slope angle, slope height, soil type, water conditions, impact on the road, and repair type. The following observations can be drawn from the inventory table in Appendix B:
1. Mode of failure – 12 of the 18 locations are listed as complex slides, 3 as rotational slides, 2 as translational slides, and 1 with no designation. Figures 7.1 and 7.2 are examples of rotational and translational slides, respectively.

2. Embankment/natural slope – 12 of the locations are listed as instabilities affecting the embankment slope, 2 locations affecting the natural slope, and 4 locations listed as affecting both the embankment and natural slopes.

3. State of activity – all 18 locations are designated as active landslides.

4. Slope angle – slope angle ranges from 23° to 42°, with an average value of 30°.

5. Slope height – the slope height is highly variable, ranging from 15 feet to 140 feet, with 11 of the 16 measured slopes being less than 50 feet in height.

6. Soil type – fine sand and silt comprises the landslides affecting the embankment, whereas colluvial soil comprises the landslides affecting the natural slope.

7. Water conditions – poor drainage, indicated by hydrophilic vegetation at several locations, appears to be one of the primary causes of landslide activity.

8. Impact on road – the main impact of landslide activity is cracking of the pavement surface, with varying amounts of horizontal and vertical displacement.

9. Repair type – repairs type consists mostly of repaving or patching of the road surface, except for one instance of retaining wall installation and one instance of drainage realignment.

Figure 7.1. Example of a rotational slide, affecting the embankment, near mile marker 7.3 that has since been stabilized along SR 666
The next step was to prepare a landslide inventory map using the LiDAR data acquired in 2008, and the information gathered from the OGE and Consultants’ reports. This inventory mapping, consisting of 34 sections, is provided as Appendix C. This inventory mapping includes the following features:

1. Location of SR 666.
2. Location of mile markers.
3. Location of 38 sites from the OGE report.
4. Stretches of the road affected by landslide activity along with the OGE site numbers.
5. Polygons indicating the boundaries of potential landslides affecting both the embankment and the natural hill-slope. The information used for delineating these boundaries included: (i) disturbance in the contour patterns, (ii) shaded-relief, (iii) hummocky topography, and (iv) the presence of distinct landslide features, as described in Figure 3.3 of the TRB special report 247, such as steepened contours indicating head scarps and increased elevation indicating zones of accumulation and toe bulges.

The inventory maps in Appendix C indicate 92 potential landslide locations that could be considered for development of the computer model as well as verification of the model. As for the extent of landslide activity, the inventory mapping 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. Out of the 92 total landslides identified on the LiDAR imagery, there are 56 landslides affecting the natural hill-slope, 15 landslides affecting the embankment,
and 21 landslides affecting both the natural slope and the embankment. Many of these locations had not been identified in either the OGE or the Consultants’ reports, both of which focused primarily on the embankment slopes. The inventory maps alone do not indicate the mode of failure or the type of material comprising the failure. However, it can be tentatively stated that rotational landslides can be differentiated from translational landslides by steeper and higher head scarps, as indicated by a series of three or more closely spaced contour lines. Translational slides, on the other hand, have just a few closely spaced contours lines defining the head scarp.

In order to field-check the presence of landslides identified on the inventory maps, we made a few reconnaissance trips to selected locations. These trips indicated that most of the slides identified on the LiDAR imagery were actually present in the field, but some were not. We revised some of the inventory maps to reflect changes, based on field observations, for a small portion of SR 666. These changes included elimination of landslide polygons that could not be verified in the field, as well as modifications of previously established landslide boundaries. It should be noted that field verification of the landslides identified on the LiDAR imagery has been conducted for only select stretches of the road.

7.2 GPS Surveying of Selected Landslides

To support OSU in the collection of accurate GPS data for a selected number of landslides, nine landslide sites were identified by the KSU team, as shown in Appendix D. These sites included four landslides affecting the natural slope, three affecting the embankment, and two affecting both the natural slope and embankment. Appendix D shows that four of these landslides are rotational in nature, two are translational slides, and three are complex slides involving both rotational and translational movement. To facilitate surveying, we identified points along the landslide boundaries in the field which were then used by the OSU team to collect GPS data that were then used to develop the model. The locations of the selected sites are shown in Fig. 7.3, including the environment of the surveyed landslide areas.
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 C are likely to change with time and additional landslides may develop. Considering this, it is imperative to compare the latest LiDAR imagery with the one used in the study to this point.

7.4 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 KSU team has provided and analyzed data regarding bedrock geology, soil type, and hydrogeology (if available). These data will form the basic GIS map layers, developed by KSU; this information is provided in standard shapefile format, and will be subsequently used in the classification process.
7.5 **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 Fig 7.4 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 only 3 were in agreement for all teams. Therefore, it can be concluded that detection and classification of landslide hazards is difficult without reliable references (domain knowledge).

![Diagram](image)

*Figure 3.4. Comparison of geotechnical experts’ evaluations*
8 POINT-BASED LANDSLIDE DETECTION

This investigation aimed at assessing the feasibility of using local surface point characterization to identify likely landslide areas. First, the overall statistics were computed for the surveyed area, which is shown in Table 8.1. Note that surrounding areas, marked by T around the respective sites, are used for control purpose, as non-landslide regions.

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<th>GSD [ft]</th>
</tr>
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</tr>
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Table 8.1. LiDAR point statistics of test sites, including surrounding (non-landslide) areas

8.1 Parameter Analysis

Table 8.2 – Table 8.7 show the parameter statistics for the LiDAR dataset collected in 2012. The parameter evaluation reveals that the landslide and stable areas cannot be delineated from single point surface features. Although, there are some areas that perform well, the overall performance is low; for example, landslide surface features are found in stable terrain and vice versa. Therefore, a clear delineation was unsuccessful.

Since the individual statistical evaluation produced no solution, a rule-based classification that combines all parameters, was proposed to classify each area using the surface features extracted. The constraints were chosen after evaluating each parameter and defining a suitable criterion that would have the ability to potentially delineate the two types of terrain (see Table 8.2 – Table 8.7).
### Statistics of Hillshade

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<th>Max</th>
<th>STD</th>
<th>Pass (%)</th>
<th>Fail (%)</th>
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Table 8.2. Statistical Data of Hillshade

### Statistics of Slope

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Table 8.3. Statistical Data of Slope
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

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<td>81.17</td>
<td>18.83</td>
</tr>
<tr>
<td>Landslide 5</td>
<td>0.99</td>
<td>0.94</td>
<td>0.00</td>
<td>3.03</td>
<td>0.54</td>
<td>87.80</td>
<td>12.20</td>
</tr>
<tr>
<td>Landslide 6</td>
<td>0.78</td>
<td>0.73</td>
<td>0.00</td>
<td>2.99</td>
<td>0.44</td>
<td>80.11</td>
<td>19.89</td>
</tr>
<tr>
<td>Landslide 7</td>
<td>0.50</td>
<td>0.47</td>
<td>0.00</td>
<td>2.36</td>
<td>0.24</td>
<td>73.26</td>
<td>26.74</td>
</tr>
<tr>
<td>Landslide 8</td>
<td>0.50</td>
<td>0.40</td>
<td>0.00</td>
<td>3.77</td>
<td>0.37</td>
<td>82.85</td>
<td>17.15</td>
</tr>
<tr>
<td>Landslide 9</td>
<td>0.46</td>
<td>0.40</td>
<td>0.00</td>
<td>3.41</td>
<td>0.31</td>
<td>80.85</td>
<td>19.15</td>
</tr>
<tr>
<td>T1234</td>
<td>0.61</td>
<td>0.50</td>
<td>0.00</td>
<td>19.27</td>
<td>0.49</td>
<td>86.52</td>
<td>13.48</td>
</tr>
<tr>
<td>T56</td>
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<td>0.47</td>
<td>0.00</td>
<td>11.78</td>
<td>0.57</td>
<td>87.08</td>
<td>12.92</td>
</tr>
<tr>
<td>T7</td>
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<td>0.68</td>
<td>0.00</td>
<td>18.63</td>
<td>0.83</td>
<td>81.01</td>
<td>18.99</td>
</tr>
<tr>
<td>T89</td>
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<td>0.50</td>
<td>0.00</td>
<td>7.59</td>
<td>0.50</td>
<td>85.01</td>
<td>14.99</td>
</tr>
<tr>
<td>Grand Total</td>
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<td>0.53</td>
<td>0.00</td>
<td>19.27</td>
<td>0.50</td>
<td>84.91</td>
<td>15.09</td>
</tr>
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<td>Mean</td>
<td>Median</td>
<td>Min</td>
<td>Max</td>
<td>STD</td>
<td>Pass (%)</td>
<td>Fail (%)</td>
</tr>
<tr>
<td>-------------</td>
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<td>-------</td>
<td>-------</td>
<td>-------</td>
<td>----------</td>
<td>----------</td>
</tr>
<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>45.12</td>
<td>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>42.30</td>
<td>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>44.36</td>
<td>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>43.20</td>
<td>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>44.05</td>
<td>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>35.93</td>
<td>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>36.00</td>
<td>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>35.78</td>
<td>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>37.02</td>
<td>62.98</td>
</tr>
<tr>
<td>T1234</td>
<td>0.06</td>
<td>0.00</td>
<td>-23.95</td>
<td>14.95</td>
<td>0.43</td>
<td>33.90</td>
<td>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>35.13</td>
<td>64.87</td>
</tr>
<tr>
<td>T7</td>
<td>0.10</td>
<td>0.00</td>
<td>-18.85</td>
<td>26.00</td>
<td>0.68</td>
<td>38.33</td>
<td>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>36.90</td>
<td>63.10</td>
</tr>
<tr>
<td>Grand Total</td>
<td>0.07</td>
<td>0.00</td>
<td>-23.95</td>
<td>26.00</td>
<td>0.50</td>
<td>36.57</td>
<td>63.43</td>
</tr>
</tbody>
</table>

Table 8.6. Statistical Data of Plan Curvature

<table>
<thead>
<tr>
<th>Units: None</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>-0.28</td>
<td>-0.14</td>
<td>-17.31</td>
<td>16.89</td>
<td>0.93</td>
<td>43.69</td>
<td>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>39.73</td>
<td>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>44.98</td>
<td>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>39.66</td>
<td>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>46.01</td>
<td>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>35.84</td>
<td>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>25.51</td>
<td>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>29.74</td>
<td>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>29.18</td>
<td>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>30.22</td>
<td>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>30.88</td>
<td>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>34.61</td>
<td>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>32.77</td>
<td>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>32.12</td>
<td>67.88</td>
</tr>
</tbody>
</table>

Table 8.7. Statistical Data of Profile Curvature
Table 8.8. Constraints

<table>
<thead>
<tr>
<th>Topographic Feature</th>
<th>Constraint</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 8.9 list the percentage of the single points meeting all of the constraints shown in Table 8.8. Clearly, the performance is low and the proposed simple rule-based classification was unsuccessful at delineating landslide and stable terrain when all constraints were evaluated simultaneously. Furthermore, the statistics of single parameters show that the performance for each area given the threshold was also not highly successful (see Table 8.2 – Table 8.7), although they are much better than meeting all constraints simultaneously. In summary, the performance is very low for surface classification and demonstrates that point-based landslide detection is unable to delineate landslide and stable terrain.

One of the main factors that causes the point-based characterization to fail is due in part by having surface features found in landslide morphology also in stable terrain and vice versa. This is the case for areas consisting of manmade features and sudden changes in elevation, although it is known that some of these features are not failures, as they have similar features as the landslides. In addition, some of the landslides may be old and the surface features may have smoothened over time, therefore losing the details necessary to differentiate them from stable terrain. For these reasons, it is difficult to conclude that all surface features within a landslide can be differentiated from those of stable terrain and vice versa.
Table 8.9. Percentage of cells meeting all criteria set

<table>
<thead>
<tr>
<th>Percentage of Cells Meeting Criteria</th>
<th>Pass (%)</th>
<th>Fail (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landslide 1</td>
<td>5.16</td>
<td>94.84</td>
</tr>
<tr>
<td>Landslide 2</td>
<td>4.04</td>
<td>95.96</td>
</tr>
<tr>
<td>Landslide 3</td>
<td>6.57</td>
<td>93.43</td>
</tr>
<tr>
<td>Landslide 4</td>
<td>3.64</td>
<td>96.36</td>
</tr>
<tr>
<td>Landslide 5</td>
<td>5.85</td>
<td>94.15</td>
</tr>
<tr>
<td>Landslide 6</td>
<td>2.61</td>
<td>97.39</td>
</tr>
<tr>
<td>Landslide 7</td>
<td>0.94</td>
<td>99.06</td>
</tr>
<tr>
<td>Landslide 8</td>
<td>0.71</td>
<td>99.29</td>
</tr>
<tr>
<td>Landslide 9</td>
<td>0.84</td>
<td>99.16</td>
</tr>
<tr>
<td>T1234</td>
<td>1.48</td>
<td>98.52</td>
</tr>
<tr>
<td>T56</td>
<td>1.72</td>
<td>98.24</td>
</tr>
<tr>
<td>T7</td>
<td>3.09</td>
<td>96.91</td>
</tr>
<tr>
<td>T89</td>
<td>1.45</td>
<td>98.55</td>
</tr>
<tr>
<td>Grand Total</td>
<td>1.94</td>
<td>98.06</td>
</tr>
</tbody>
</table>

8.2 PCA Analysis

Parameters derived from the same observation domain are frequently correlated. To remove this functional correlation, it is important to reduce the parameter space and support better classification performance. Principal Component Analysis (PCA) is a quantitatively 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; in least squares sense. The principal components as a whole form an orthogonal basis, a new space, for the data.

To investigate the potential of the PCA-based parameter space, an evaluation was carried out using thirteen datasets. The data used for this study were the same as those described earlier and shown in Figure 7.3; landslides: 1-9, T1234, T56, T7 and T89. 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, case 1, landslide features only (case 2) and stable features only (case 3). The principal components were computed for all the three data types. Figure 8.1 – Figure 8.4 reveal that PCA analysis for LiDAR dataset from 2012 has shown little or no correlation with most of the test sites. As a result, the PCA decorrelation was unsuccessful due to the similarities between the surface features of both terrain types. Since all surface features are used for each case,
the testing was exhausting, and the results prove that there is no correlation with the two categories, as there is very little distinction between the features.

Figure 8.1. Principal components for Site 1-4
Figure 8.2. Principal components for Site 5-6

Figure 8.3. Principal components for Site 7
Figure 8.4. Principal components for Site 8-9

9 PROFILE-BASED LANDSLIDE DETECTION

Profiles are frequently used for surface analysis and visualization, as they represent an easily imaged one-dimensional data domain. For example, 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.

Fig. 9.1 shows the surveyed area of landslide 1 with five profiles; note the DEM is filtered. The profiles were analyzed, four of them in the four cardinal directions and one along the steepest slope. 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.
Fig. 9.2 shows the profiles, including both profiles derived from filtered and original (unfiltered) DEMs, so the impact of smoothing is also demonstrated. As expected the diagonal directions are somewhat noisier due to the rasterized data, but after smoothing, all the profiles are quite similar. The profiles along the steepest slope and also the NW/SE directions show the typical “S” shape of the rotational landslide.
Figure 9.2. Landslide 1 profiles derived from filtered and unfiltered DEM
9.1 1st and 2nd Derivatives

The derivative evaluation is performed on a profile basis along the 4 cardinal directions. Since the NW/SE direction reveals the typical “S” shape of the rotational landslide, the steepest slope direction was excluded from this evaluation. The investigation of the derivatives revealed that abrupt changes in elevation along the DEM could be identified by analyzing the profile shapes. The profile for the typical “S” shaped rotational slide shown in Fig 9.3 exhibits a higher first and second order derivative than all the other profiles occurring. Note the signal response is strong where the scarp is located. In comparison, the second derivative is clearly better indicator than the first derivative. All other profiles do not exhibit a particular trend or pattern that identify unique surface features.

![Figure 9.3. All profile derivatives for landslide 1](image)

Subsequently, profiles were evaluated for two different cases, shown in Table 9.1, along the areas surveyed. The main difference between the two cases is that case 2 includes more evaluations compared to case 1, thus computationally it is more costly. The parameters given in each case are shown in Table 9.1.

<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 9.1. Parameter selection for landslide classification
From analyzing the typical “S” shaped rotational slide of landslide 1, a criterion was determined to identify scarp-like features. The constraint values selected are shown in Table 9.2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Constraint</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st Derivative (ft/ft)</td>
<td>$\geq 1.00$ (0.30 m/m) or $\leq -1.00$ (-0.30 m/m)</td>
</tr>
<tr>
<td>2nd Derivative (ft/ft$^2$)</td>
<td>$\geq 0.10$ (0.03 m/m$^2$) or $\leq -0.10$ (-0.03 m/m$^2$)</td>
</tr>
</tbody>
</table>

**Table 9.2.** Constraints for landslide classification

The profile shape analysis was designed to investigate any point on the profile, meeting the constraints stated above. If any constraint was met that would flag that profile as having landslide characteristics. Since the derivatives are capable of identifying any abrupt changes in the surface, the performance for landslide classification may be low. If the landslide does not have a scarp-like feature within it, then it will likely go overlooked. In addition, this classifier is restricted to identifying one type of surface feature and all other surface features representative of landslide activity probably 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, as previously mentioned (see Figure 9.4 and Figure 9.5).

![Figure 9.4](image-url)  
*Figure 9.4.* Classification results for area 1 with landslides 1-4, shown are case 1 (A) & case 2 (B)*
9.2 Geomorphological Openness

The geomorphological openness is performed on a profile basis similar to the first and second derivatives. This investigation revealed similar findings to those observed from the derivative approach. Abrupt changes in elevation along the profiles could be identified. The profile in Fig 9.6 along the typical “S” shaped rotational slide has a sharp change in positive openness, which consequently shows its ability to identify scarp like features. However, the negative openness sharp change is not as uniquely defined; nonetheless it still has the ability to identify the scarp surface feature.

Figure 9.5. Classification results for area 4 with landslides 8 and 9, shown are case 1 (A) & case 2 (B)
This investigation produced similar findings to those of the first and second derivative based approach. Consequently, no classification was performed as the results are expected to be similar.

10 SHAPE-BASED LANDSLIDE DETECTION

The surface feature parameters of the shape-based approach are computed similarly to those of single points described earlier. However, we are interested in assessing the variability of a local neighborhood by computing the standard deviation and thus location dependent evaluation can be performed. The variability for every surface point in the areas examined is computed and then distributions are used to develop landslide propositions. 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, though some of them were previously discussed in the single point section.

10.1 Performance Evaluation

Fixed sampling window of size (9 x 9) was defined as a neighborhood and then the selected windows were used to evaluate the direction cosine eigenvalue ratios and the length of the orientation vectors. The statistical measure of the standard deviation is evaluated from all sampling windows to define the local topographic variability parameters of aspect, hillshade, roughness, slope, resultant length of orientation vectors and customized Sobel operator. Areas experiencing higher degrees of surface deformation will exhibit higher topographic variability, thus delineating rough and smooth terrain.

To determine characteristics of landslide surface features in the study area, we first selected a representative patch of a mapped landslide and stable terrain. Having learned the difficulties of analyzing all data points in a mapped landslide through the point-based and profile-based approach, we decided to use a section of 450 m north of mile marker 9 as representative patches.
(see Fig 10.1). The size of the representative area was 30 x 40 m (1,200 observations) for stable and 60 x 25 m (1,500 observations) for landslide terrain (which is a section of the surveyed landslide 8). The representative terrain selected was less than 1% of the entire study area. Next, we computed the surface features for each terrain patch. Fig 10.2 shows the distribution of the samples selected for each surface feature. The topographic variability is higher for landslide than stable terrain. These patterns indicate that the landslide surface in our study area tends to experience higher amounts of surface deformation, meaning it is rougher in texture. Earth processes that can generate such behavior are those of mass movement found in landslides.

Figure 10.1. LiDAR-derived hillshade map of SR 666, Zanesville, Ohio study area with the entire selected sample 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 are shown in Fig 10.2 and can be described as follows: the central mark in each box is the median (Q2), the limits of the box are the 25th (Q1) and 75th (Q3) percentiles of the samples, the interquartile range (IQR) is equal to Q3 − Q1, the dashed line (whiskers) extend to the typically used Q1 - 1.5(IQR) and Q3 + 1.5(IQR) range which is about +/−
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

2.7σ and 99.3 percent of the data, provided the data are normally distributed. The remaining samples not lying within these limits are considered outliers (not plotted). It is expected to observe some 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.

![Box plots of various features](image)

**Figure 10.2.** Distribution of samples before being normalized between [-1 1], where, stable and landslide terrain are represented on the left and right, respectively, for each surface feature extracted.
The representative patches demonstrate that 75% or more of the samples are linearly separable for all surface features (Fig 10.2). It was found that the eigenvalue ratios (see Table 10.1) 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 (see Table 10.1) 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 of all surface features (Fig 10.2). This behavior is expected as stable terrain will experience lower rates of mass movement; therefore, most stable surface features are expected to express the same behavior.

<table>
<thead>
<tr>
<th>Surface Feature</th>
<th>Stable</th>
<th>Landslide</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$Q_1$</td>
<td>$Q_2$</td>
</tr>
<tr>
<td>Eigenvalue Ratios $\ln(\lambda_1/\lambda_2)$</td>
<td>1.15</td>
<td>1.30</td>
</tr>
<tr>
<td>Eigenvalue Ratios $\ln(\lambda_1/\lambda_3)$</td>
<td>2.32</td>
<td>2.47</td>
</tr>
<tr>
<td>Roughness (m)</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>Customized Sobel Operator (m)</td>
<td>0.68</td>
<td>0.85</td>
</tr>
<tr>
<td>Aspect (°)</td>
<td>11.53</td>
<td>13.42</td>
</tr>
<tr>
<td>Hillshade</td>
<td>0.05</td>
<td>0.06</td>
</tr>
<tr>
<td>Slope (°)</td>
<td>3.45</td>
<td>4.02</td>
</tr>
<tr>
<td>Resultant Length of Orientation Vectors</td>
<td>0.35</td>
<td>0.49</td>
</tr>
</tbody>
</table>

**Table 10.1.** Percentiles of distribution samples

### 11 PROBABILISTIC CHANGE-BASED LANDSLIDE DETECTION

Temporal changes can be determined from analyzing the terrain surface. Change detection techniques and properties are analyzed to identify proper methods to detect surface changes. This procedure may be performed in two different forms by characterizing temporal changes from a cloud-to-cloud (C2C) and DEM-to-DEM approach. The performance of the change detection prediction 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 identify temporal changes. Fig 3.2 shows the conceptual workflow of the change detection-based identification of landslides.

Detecting changes between two surface datasets, acquired at two reasonable different times, gives the best potential to identify changes in surfaces, including motion and deformation. This investigation aimed at assessing the feasibility of using change detection to identify likely landslide areas.
11.1 Evaluating Uncertainty

Characterizing uncertainty found in the data is an important factor that helps determine real surface deformation from changes that may be due to other factors, such as noise, errors. In order to perform change detection with high confidence, it is necessary to evaluate the uncertainties found in the data sources and 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.

11.1.1 LiDAR measurement uncertainty

The uncertainty found in LiDAR measurements can be separated into horizontal and vertical components. The positional error in the horizontal component, being larger in magnitude than the vertical component for LiDAR point cloud, has an effect on the observed vertical differences, especially in sloped areas. However, LiDAR is rarely characterized by horizontal errors, and therefore only the vertical component is analyzed, though the impact of horizontal errors on the vertical component may not be negligible. Our interest is to analyze the vertical changes between two surfaces, and therefore the vertical uncertainties are of high interest. The vertical positional error ($\delta z$) can be associated with the true vertical component ($Z_{Actual}$) as follows:

$$Z_{Actual} = Z_{DEM} + \delta z$$

(11.1)

where $Z_{DEM}$ is the observed vertical component. Many approximations, ranging from manufacturer instrument precision specification to error budget analysis, have been proposed to evaluate $\delta z$ (Lichti, Gordon and Tipdecho 2005). Nonetheless, there are many components that affect $\delta z$ other than manufacturer instrument precision, including measurement errors, spatial sampling pattern and interpolation methods (Wheaton, Brasington, et al. 2010a). Furthermore, error budget analysis requires data collection and testing techniques that go beyond conventional surveying methods, which are dominated by the collection of specific 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, root mean square error (RMSE) and standard deviation requires more information than can be provided in the topographic data (Wheaton, Brasington, et al. 2010a).

11.1.2 Interpolation uncertainty

Once the DEMs are generated using the bare-earth filtered LiDAR data, sloped segments distributed evenly 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 is either lower or higher with
respective to the surface representation. For these reasons, it is important to evaluate the uncertainties in such complex terrain. For both DEMs, the vertical differences were computed for every point in the corroboration data by following the equation used in Bater and Coops (2009):

\[
\delta E_i = M_i - P_i
\]  

(11.2)

where, \( \delta E_i \) is the vertical difference at location \( i \), \( M_i \) is the LiDAR measured value from the corroboration data at location \( i \) and \( P_i \) 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 must be incorrectly assumed to be constant (Bater and Coops 2009). 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.

### 11.1.3 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/or the LiDAR and the DEMs as follows:

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

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

(11.3)

where \( \delta u_{C2C} \) is the propagated error in the C2C change detection, \( \delta u_{DoD} \) is the propagated error in the DEM of Difference (DoD), \( \delta z_2 \) and \( \delta z_1 \) are the errors between the LiDAR and ground control in DEM2 and DEM1, respectively, and \( \delta E_2 \) and \( \delta E_1 \) are the errors between the LiDAR and DEM2 and DEM1, respectively. However, a limiting factor not considered on the data quality is the spatial resolution (Wang, Sawada and Moriguchi 2013). The uncertainty introduced by the spatial resolution is not considered, although it is an important factor that needs to be addressed to model surfaces precisely. The assumption made is that the errors in each cell 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 that are coherent and predictable in spatial variability (Wheaton,
Brasington, et al. 2010a). In our approach we have accounted for the most complex terrain, which leads to a conservative assessment of the propagated uncertainties. The conservative approach is not ideal for terrains that are less complex (e.g. flat terrain), however, our interest is identifying topographic changes susceptible to landslide activity which generally occur in complex terrain. For these reasons, the conservative approach is appropriate.

11.1.3.1 Evaluating propagated uncertainty

The propagated uncertainties in the surface models were evaluated in two steps: 1) the adjusted LiDAR point cloud was compared to the hard surface ground control and 2) the interpolated DEM was compared to the adjusted LiDAR point cloud. In the C2C approach only the uncertainties in step 1 are considered, while in the DoD approach both error sources are considered (see Eq. 11.3).

The error sources show approximately a normal distribution for 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 along 6 segments distributed along the study area (see Fig 11.1, Table 11.1 and Table 11.2) and show an RMSE and standard deviation of 0.11 m (see Fig 11.1 and Table 11.1) for the 2008 DEM and an RMSE and standard deviation of 0.10 m (see Fig 11.1 and Table 11.2) for the 2012 DEM. The uncertainties of the DoD were propagated using Eq. 11.3 to 0.17 m given 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 were real.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Mean</th>
<th>Median</th>
<th>Min (m)</th>
<th>Max (m)</th>
<th>STD (m)</th>
<th>RMSE</th>
<th>No. Pts</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.05</td>
<td>0.03</td>
<td>0.00</td>
<td>0.82</td>
<td>0.12</td>
<td>0.12</td>
<td>4,241</td>
</tr>
<tr>
<td>2</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
<td>0.84</td>
<td>0.14</td>
<td>0.14</td>
<td>3,181</td>
</tr>
<tr>
<td>3</td>
<td>0.06</td>
<td>0.04</td>
<td>0.00</td>
<td>0.58</td>
<td>0.09</td>
<td>0.11</td>
<td>7,589</td>
</tr>
<tr>
<td>4</td>
<td>-0.03</td>
<td>-0.03</td>
<td>0.00</td>
<td>0.32</td>
<td>0.08</td>
<td>0.08</td>
<td>4,610</td>
</tr>
<tr>
<td>5</td>
<td>-0.02</td>
<td>-0.03</td>
<td>0.00</td>
<td>0.72</td>
<td>0.13</td>
<td>0.13</td>
<td>4,564</td>
</tr>
<tr>
<td>6</td>
<td>0.04</td>
<td>0.04</td>
<td>0.00</td>
<td>0.67</td>
<td>0.08</td>
<td>0.09</td>
<td>4,866</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>0.02</strong></td>
<td><strong>0.02</strong></td>
<td><strong>0.00</strong></td>
<td><strong>0.84</strong></td>
<td><strong>0.11</strong></td>
<td><strong>0.11</strong></td>
<td><strong>29,051</strong></td>
</tr>
</tbody>
</table>

**Table 11.1.** Accuracy assessment of 2008 DEM
11.1.4 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, there have been questions 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 (δuC2C, δuDOD) will be used to characterize change map. The importance of the propagated uncertainty (δuC2C, δuDOD) is that it helps define the probability that the observed changes in the change map are real.

11.2 Change Detection Methodology

11.2.1 C2C

Assuming that the 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 using the nearest neighbor approach. 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 \( z = ax + by + cx^2 + dy^2 + exy \)).

All models were tested and produced similar results, which may be due to the modest spatial resolution of the LiDAR data. Note the distances can be compared in the X, Y and Z components.

11.2.2 DoD

In order to perform DoD accurately, it is important that the registration and acquisition of the data be prepared consistently between dates (as in the C2C approach), to avoid discrepancies and maintain the data quality. Then, the DEMs can be simply subtracted by using a cell-by-cell approach, to obtain 1D elevation changes.

11.2.3 Probabilistic Change Detection

Surface changes are important to detect, but knowing the probability of the change detected being real or not is as equally vital. In this section we will evaluate a probabilistic approach to determine the probability of the change detected being real. In summary, the higher the probability, the higher
the chance of the change detected being a real surface deformation. Subsequently, the lower probability changes can be filtered.

11.2.3.1 Non-Parametric signed rank test (Wilcoxon)

A probabilistic signed rank test is proposed to evaluate local neighborhoods of vertical differences. 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 form that the distribution is not dependent of any parent distribution nor of its parameters. The signed rank test evaluates the null hypothesis ($H_0: \theta \geq M$) that the observations in the local neighborhood ($w \times w$ cells for the DoD approach and nearest neighbors for the C2C approach) come from a continuous distribution with a median greater than $M$ (Hollander and Wolfe 1999), where $\theta$ is the treatment effect (in our case vertical changes). For this assessment, we computed $P$, where $P$ is 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:

$$H_0: \theta \geq M \text{ vs. } H_1: \theta < M \ (11.4)$$

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

11.3 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 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, however 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, see Fig 11.2. The changes between the two methods display similarities where the highest topographic change occurs in complex (rougher) and 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 produce the highest uncertainty due to the data interpolation in sparse areas. Nonetheless, the C2C approach produces larger vertical differences, which may be caused by the greater spatial extents between the data points.

![Figure 1.2](image1.png)

**Figure 1.2.** (A) DoD map, absolute values, (B) C2C changes

The statistics for the segment studied were computed and evaluated to compare the two methods described is shown in Table 11.3. The average change observed was 0.09 and 0.06 m for the DoD and C2C approach, respectively. Therefore, the mean change was below the propagated uncertainty level, hence changes were unreliable. However, 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. Therefore, the spatial resolution is critical, as it could limit the accuracy of the proposed approach in complex surfaces, which are typically the areas of interest.

<table>
<thead>
<tr>
<th>Method</th>
<th>Mean (m)</th>
<th>Median (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 11.3.** Statistics of Vertical Differences. Absolute Values
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 ($3m \times 3m$) 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 was enough to estimate the probability. It was 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 and 0.08 m, respectively; computed using Eq. 11.3, which is outside the uncertainty level, therefore corresponding to the fact that the local neighborhood does indeed experience surface deformation with high-probability.

The probability map generated using the signed rank test displays various magnitudes and locations of probable topographic change, shown in Fig 11.3. The map exhibits similarities between the vertical changes observed in Fig 11.2, 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 area capable of identifying high-probable changes in the area.

The surface along the riverbank for both approaches (West end of DEM shown in Fig 11.3) experiences similar high probability changes. This behavior is clearly visible along the western extents of the DEM. The C2C seems to classify most complex surfaces as high-probable change compared to the DoD approach, which seems to be more conservative. However, 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.
CLASSIFICATION PERFORMANCE ANALYSIS

Classification is the step, when based on extracted parameters, landslide hypotheses can be formed. There is a variety of methods available depending on reference data availability, such as supervised classification, or if not then identifying clusters in the parameter domain, called unsupervised classification.

During this study, several classification tasks have been tested, including rule-based and support vector machine methods. As more data are becoming available, the parameter space will be extended and the classification approach is refined.

12.1 Surface Feature Extraction Method

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 profiles found in landslide surfaces. Subsequently, the profiles are matched throughout the DEM. However, the profile-based approach is not robust and can only identify slides that have evident scarps, thus limiting this approach to one surface feature, which is not always evident in all cases. Fortunately, the shape-based approach was capable of delineating landslide and stable surface features as shown in section 10. In our novel method, the shape-based surface feature extraction is further modified to resolve the problems mentioned in previous sections and provides robust identification of landslide surface features.
The objective of the 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 modern approach compared to existing techniques. The process to identify landslide surface features 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 neighborhood-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 10. In the following sections, this novel method for landslide surface feature extraction is introduced in greater detail.

12.1.1 Introduction

The effects of mass movement are important and greatly dependent on their spatial pattern of occurrence, frequency and amount of activity (McKean and 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 landslide suspect areas. This technique is focused on examining and evaluating single surface models and the developed method can serve as a tool to filter landslide suspect areas. Landslides are known to have rougher surfaces than neighboring unfailed terrain. This is due to the mechanics, subsidence and surface deformation experienced. The surface roughness of failed (bottom) terrain experiences higher topographic variability than unfailed (top) terrain as illustrated in Fig 12.1. 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 unfailed terrain. For these reasons, the surface roughness will be added to other surface feature parameters in the proposed algorithm.
12.1.2 Components of Classification Methodology

Extracting landslide surface features is the core step in landslide susceptibility mapping. To quantify topographic roughness, it is necessary to understand and delineate the characteristics found in landslide morphology. Therefore, a sample set representing these distinct features is necessary. Support Vector Machine (SVM) is a supervised classification method that is well established and known to produce acceptable results in landslide susceptibility mapping (Samui 2008, Yao, Tham and Dai. 2008, Marjanović, et al. 2011, Micheletti 2011, Ballabio and Sterlacchini 2012, Tien Bui, et al. 2012). 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 single observations with nine dimensions (surface features described earlier plus soil type) to determine if the observation is representative of landslide activity for each cell in the DEM. If it is, then it is mapped as landslide susceptible, otherwise, it is mapped as unfailed. Each cell in the DEM provides a nine-dimensional observation to the classifier. SVM is known to perform well with small training samples, high dimensional spaces and it employs a subset of the training samples in the decision function. For these reasons, it was the prime consideration for classification.
12.1.2.1 Support Vector Machine

SVM was developed by Vladimir Vapnik (2000). The idea of SVM is to determine the optimal hyperplane for linearly separable patterns, see Fig 12.2. If the patterns are not linear then, the data is 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, thus, lying closest to the decision surface (Tien Bui, et al. 2012).

![Small Margin and Large Margin with Support Vectors](image)

Figure 12.2. The rectangles and ovals represent the data points, the solid line is the (hyperplane) selected to divide the two classes and the dashed lines define the distance between the hyperplane line and the support vectors (Sherrod 2008)

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 a small sample available for training. In general, the SVM algorithm is trained through a sample set of two classes enclosing all features desired. The two classes are failed and unfailed terrain and the aforementioned surface feature vector is used in our tests. After training is complete, the algorithm is tested on independent datasets to evaluate its performance, a LiDAR-derived DEM in our case.

12.1.2.2 Flat Terrain Filtering

Landslides have shown to occur more often on steeper slopes (Gomez and Kavzoglu 2005). 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 12.1 illustrates unstable slopes for various types of mass movement taken from Soeters and van Westen (1996).
#### Table 12.1. Slope instability for mass movement type

<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>

Given the ranges of slope instabilities in Table 12.1 and those found in our study area, it was determined that slopes (≤ 15°) would be considered stable and are excluded from processing.

**12.1.2.3 Conditional Dilation/Erosion Filter**

Mathematical morphology is a method used to extract useful features found within an image that characterize shapes of objects (Gonzalez and Woods 2002). Furthermore, it is helpful in filtering, which is our interest. Two common morphological operations are dilation and erosion. Dilation expands the shapes found within an image, while erosion removes 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 size threshold (Shapiro and 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. 12.1

\[
\frac{\text{# of failed cells}}{\text{# of total cells in window}} \geq \text{Threshold} \tag{12.1}
\]

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 potential thresholds, the most suitable window size and threshold found were 11×11 (5m x 5m) and 60%, respectively. This particular window size and threshold did not distort the information produced from the classification algorithm, as it only dilated and eroded the classification results as intended. For these reasons, the threshold and window size selected were subsequently used.
12.1.2.4 Noise Suppression

The analysis of clusters is a vital component of feature extraction. The importance of this step is to analyze clusters and suppress noise. Small regions that are lesser than a desired threshold do not provide useful information; therefore, they are not of interest and are ignored. The importance of determining a good threshold is so that the noise level is minimized and useful information is not lost. In our approach clusters of cells classified as failed terrain are analyzed and evaluated to determine if the cluster will be classified as failed or unfailed given the following criterion:

\[ \text{Cluster Area} \geq \text{Minimum Area Threshold} \]  

The minimum area to be considered landslide susceptible was tested and evaluated by having varying areas of 50 – 250 m². This range was selected after evaluating the minimum size of the mapped landslides provided by the reference inventory map, which was 200 m². After evaluating potential thresholds, it was determined that 150 m², was the most appropriate threshold, for this reason, all clusters less than 150 m² were ignored and considered as noise. The criterion selected will allow for clusters of said size to be mapped as landslide susceptible, additionally, minimizing the probability of small landslides being overlooked.

12.1.3 Performance Evaluation

12.1.3.1 SR 666

The mapped locations will vary for each area, which reflects the variation in the topography, see Figs 12.3A, B, C and D. Areas that are smooth will go undetected by the proposed algorithm, SW corner Fig 12.3B and W section of Fig 12.3C, while areas that are rough will be mapped as landslide susceptible, E section of Fig 12.3A and Fig 12.3B. The rough areas shown in Fig 12.3 tend to correspond to those mapped in Fig 12.4. Additionally, the areas identified as landslide susceptible 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 Fig 12.4.
Figure 12.3. Topographic variability of segments. 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% of the inventory mapped landslides, see Fig 12.4A, B, C and D. This confirms that the training samples selected for training the classification model were representative of the landslide terrain throughout the study area, thus, identifying a high percentage of the landslides. As anticipated earlier, some topographic features display characteristics of unfailed terrain within a landslide and vice versa. In particular, in Fig 12.4D, a vast majority of the inventory mapped landslides are incorrectly classified as unfailed, and it is expected to classify incorrectly as the surface roughness is low for this area, see Fig 12.3D. In order to understand and potentially overcome the 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, see SE and NE corner of Fig 12.4C and SE corner of Fig 12.4A. 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 at the SW corner of Fig 12.4C and Fig 12.3C, bluffs, streams, creeks and high elevation changes in a short distance. These natural features increase the surface roughness due to erosion and geomorphological events, which cause surface features to mimic those of landslides. Nonetheless, the algorithm also tends to overlook topographic features found within the boundaries of inventory mapped landslides due to insufficient surface roughness or man-made improvements made to the environment. Although, a GIS database was available and can be used to minimize misclassifications generated by the proposed algorithm it was only used to store geographic information of roads, rivers, creeks, residential development, etc., and the results generated by the algorithm.
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 Fig 12.4D are mapped incorrectly due to the smooth topography from an older landslide. The removal of landslide features prevents the algorithm from detecting and identifying the mapped landslides in this area.
The performance of the proposed algorithm was assessed by how well the mapped areas coincide with the mapped landslides (reference) in the study area. The proposed algorithm was able to map a total of 200 locations throughout the study area. One hundred and ten of those identified areas overlapped mapped landslides (reference), providing an accuracy of 55% for the algorithm. Additionally, twenty of the misclassified mapped areas were along rivers and creeks crossing the transportation network, which does not include areas along the Muskingum riverbank that is 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, creating high surface roughness. Nonetheless, the algorithm was able to identify 67 out of 80 mapped landslides in the inventory map. Although some of the mapped areas did not overlap the reference map, they were adjacent to these areas, see Fig 12.4C. In order to confirm that these mapped 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 is required to evaluate why some of the inventory mapped landslides were overlooked by the proposed algorithm. One reason for overlooking mapped landslides (reference) may be due to the amount of surface roughness exhibited within the landslides, see SW corner of Fig 12.4A, W of road for Fig 12.4B and Fig 12.4D. The amount of surface roughness is not sufficient to delineate them from unfailed terrain. Therefore, these mapped landslides (reference) will go undetected, until enough surface roughness is displayed from experienced mass movement. However, landslide susceptibility is not only dependent upon the morphology, the geologic structure is important as well as underground water flow. Nevertheless, in a geologic homogenous area the investigation of the geomorphology is beneficial.

12.1.3.2 Independent Test Datasets

The test data was prepared based on the airborne LiDAR data introduced in section 6. Assuming that all six test areas are geologically homogeneous and similar to SR 666, the model developed in the previous section for landslide surface feature extraction can be used without or with minor modification. The change in the model was performed in the post-filtering step where the conditional dilation/erosion threshold was changed from 60% to 40%, to increase the size and number of the generated landslide clusters.

The HAM-75-5.58 DEM shown in Fig 12.5A illustrates that five landslide suspect areas identified based on visual inspection and previously known slide activity. In this area, there was a slide repaired as noted by ODOT, therefore, the identification of these suspect areas indicates that the area is actively prone to mass movement. The four mapped locations, see Fig 12.5B, exhibit high topographic variability when compared to their neighboring terrain, which demonstrates the algorithm’s ability to identify suspect areas of mass movement. However, there is one area outlined in black in Fig 12.5B, where there seems to have been mass movement, yet the algorithm was not able to identify this location. Although, there seems to be some mass movement, the overall terrain is rather smooth, which signifies that this area may have been remediated in the past. Additionally,
one cause for the algorithms failure to identify the overlooked the landslide suspect area may be due to the landslide cluster size being smaller than the minimum area threshold. Therefore, although landslide cells may be classified and clustered together, if they do not meet the minimum area criterion, they will be filtered and removed. In summary, for this test area the algorithm identifies four out of five landslide suspect areas, which illustrates the algorithms ability to identify landslides in locations other than SR 666.

**Figure 12.5.** HAM-75-5.58 Pair (A) rasterized DEM (B) Classified landslide map.

In the test site of TUS-77-1.12 the proposed method identified landslide suspect areas as shown in Fig 12.6B. In particular, a text book style rotational landslide outlined in black in Fig 12.6A 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. Among 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 Fig 12.6B that was not noted as landslide hazardous by ODOT. To ensure that this mapped area is not a landslide, field inspection is needed to evaluate the classified area. For this test area, 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.
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Figure 12.6. TUS-77-1.12 Pair (A) rasterized DEM (B) Classified landslide map.

Test site ADA-247-1.20 demonstrates an area outlined in black as having landslide activity as noted by ODOT, see Fig 12.7A. The algorithm was able to identify two landslide locations within the outlined area. This shows that the proposed algorithm can correctly identify mass movement. In addition, it does not misclassify or over-classify around the remaining test area. This is clearly an advantage that the algorithm shows for this particular area as it has the ability to pinpoint with high confidence areas of mass movement precisely and accurately in this test site. Therefore, it can be concluded that our proposed algorithm works with high confidence in detecting landslide hazards.
Shown in Fig 12.8B for LAW-93-22.34 are many classified landslide locations by our proposed method. Outlined in black is an area noted by ODOT as having mass movement as shown in Fig 12.8A. This area is correctly classified by the proposed algorithm. In addition, there are misclassified locations along abrupt changes in elevations near the road embankments that were not noted as landslide hazards by ODOT. Moreover, our algorithm as noted before misclassifies streams and creeks. However, there are some classified locations along areas not typical to misclassification. These areas are landslide suspect and should be investigated further to determine if they are prone to mass movement as they may have been overlooked by ODOT.

**Figure 12.7.** ADA-247-1.20 Pair (A) rasterized DEM (B) Classified landslide map.
For the test area of LAW-217-2.17, Fig 12.9, ODOT noted that there was a bridge replacement with slide repair in the area. However, no details were given of the exact location of the slide repair and ODOT did note that they did not anticipate a slide to be visible from the DEM. However, the proposed method does identify landslide activity along the test area. Since, a slide previously occurred, it is recommended to inspect it in the field and verify if the identified locations are landslide hazards. Note some of the classified locations occur along abrupt changes in elevation and may be misclassified locations, since it is one of the issues with the proposed algorithm. Nevertheless, the area should be inspected to confirm mass movement, as ODOT did not anticipate any landslides.
The test area shown in Fig 12.10 (MRG-266-8.40) is quite an interesting area. For this particular area ODOT did not note any landslide activity, however, they have future plans for a road relocation. Therefore, it is essential for them to locate potential landslide hazards to avoid them in their road relocation design. For this particular area, there are many misclassified areas around streams and river channels. However, there are other areas that are classified not typical to misclassification. These areas might be landslide hazardous and should be evaluated further. Clearly, the algorithm will give ODOT an idea of which areas to avoid in their design, since they are prone to landslides. This area is difficult to evaluate from the DEM solely and based on the algorithms performance so far for previous test areas, the algorithm has shown its potential to identify landslide hazards.

![Figure 12.10. MRG-266-8.40 Pair (A) rasterized DEM (B) Classified landslide map.](image)

### 12.2 Change Detection and Feature Fusion Technique

So far, we have tested C2C and DoD change detection techniques on our data and learned lessons from those methods. Both approaches are suitable and capable of identifying 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 the C2C algorithm identifies most complex surfaces as high probability change because the point density is low, which is a limitation to this approach, as presented earlier. Nonetheless, if the spatial resolution was infinite, then the C2C approach would be ideal. In complex surfaces the DoD method is more conservative due to the interpolation and higher uncertainty level. Therefore, not all surface changes will be considered real surface deformations. Spatial resolution plays an important role in change detection, especially in complex surfaces which are the main areas of interest. Since an ideal spatial resolution is not available, the conservative approach was considered. Fortunately, the methods are similar and can be easily modified accordingly to fit each technique if a desirable
spatial resolution was available in a future study. The workflow is based on the change detection strategy inspired by state-of-the-art methods. To summarize, the outline of the new 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 using the neighborhood-based approach.
4) Classify the LiDAR-derived DEM.
5) Evaluate the propagated uncertainties.
6) Perform change detection using DoD approach (cell-by-cell).
7) Evaluate probabilistically the surface changes.
8) Map temporal changes susceptible to landslide activity.

The change detection algorithm used is that described and tested in the DoD based approach in section 11. In the following sections, this novel method for landslide susceptible temporal changes is introduced in greater detail.

12.2.1 Introduction

Topographic changes can be detected using the proper remote-sensing technology, though determining the source of temporal changes, such as erosion, deposition, subsidence, uplift, noise, is complex (James, et al. 2012). Typically, the source of the change is known, and could be a combination of several processes. In general, when the source is unknown, field investigation is required to confirm the cause of the topographic change. A workflow diagram of the proposed approach to landslide susceptibility and hazard mapping utilizing multi-temporal airborne LiDAR data is shown in Fig 12.11. The methods introduced in the workflow diagram are discussed in the following sections in greater detail.
12.2.2 Methodology

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

12.2.2.1 Surface Feature Extraction

With respect to the previous section, 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 in slope of the local topography was analyzed. To measure the variability in the terrain, a statistic measure of the standard deviation is evaluated from small sampling windows with a fixed size of $(9 \times 9)$. It is expected to observe higher topographic variability in areas experiencing higher degrees of surface deformation than stable/inactive terrain. To quantify and map the topographic signatures of landslides, it is necessary to characterize the attributes in landslide morphology. For this reason, a sample set representative of landslide and stable terrain is necessary. The area selected as a training sample was a pre-determined section 450 m north of MM 9.00, as described in the previous section, see Fig 10.2. Additionally, SVM was used as the classification algorithm.

The SVM classification model is trained in our case using a sample set of representative landslide and stable terrain that has been characterized by the topographic variability of slope. Once training is complete, the algorithm can be tested to assess its performance.
12.2.2.2 Susceptibility Mapping

To generate the landslide susceptibility map, DEM cells having a probability greater than a desired threshold and being classified as a landslide feature are retained. Next, local neighborhoods (clusters) are generated of the retained cells. Then, a threshold is set for the minimum area of the generated clusters to be considered susceptible to landslides. The landslides are mapped using a convex hull, which is the smallest convex polygon that can contain the cluster. The minimum area criterion will help suppress noise, while minimizing the loss of valuable information. Finally, all clusters meeting said criterion are mapped and considered landslide susceptible.

12.2.3 Performance Evaluation

In this chapter, the performance of the proposed landslide susceptibility mapping method is assessed using the dataset of SR 666.

12.2.3.1 DoD Evaluation

The DoD map provides amounts of vertical changes. The differences provide a wide range of magnitudes, locations and patterns of mass movement that can be difficult to distinguish when analyzing a large area. For this reason, it is necessary to evaluate local neighborhoods/surface patches of mass movement.

Fig 12.12A, D and G display DoD maps for three segments in the study area labeled I, II and II, respectively. Fig 12.12B, E and H show bare-earth shaded relief maps made from DEMs at 0.50 m spatial resolution acquired by the 2012 survey. Fig 12.12C, F and I display the slope map for each segment. Although, there is vegetation in the study area, detailed surface features are visible in the DEM. The segments selected are general representations of the landforms found in the study area and characterize the mass movement behavior expected. It is noted that areas along sloped surfaces tend to experience higher amounts of surface changes than flatter surfaces, see Fig 12.12. The magnitude of changes observed in the entire study area ranges from a maximum of 5.75 m and 5.50 m, for subsidence and uplift, respectively. Statistically the changes observed can be modeled by a mean and standard deviation of 0.00 m and 0.18 m, respectively.
The shaded relief maps exhibit various surface features, for example, smooth and rough surface textures (see Fig 12.12B, E and H). The changes detected along rough surfaces may be due to the complexity of the surface, which plays an important role as it increases the noise level due to the uncertainties introduced. Yet, the proposed DoD method displays its robustness as it is able to detect changes along various surface complexities, including those within the inventory mapped landslides. This exemplifies the algorithms ability to overcome potential problems that may be encountered due to the lack of data quality. Additionally, changes are detected in areas not previously mapped, signifying that new developing landslides may be emerging.
The statistics for the changes observed for the segments displayed in Fig 12.12A, D and G are listed in Table 12.2. The statistics show that the standard deviation is higher than the uncertainty level for Segments I and III, while it is the opposite for Segment II. Although, Segment II has the lowest standard deviation, it has the highest mean vertical change. It can be said that the statistical evaluation supports the fact that vertical changes are occurring throughout the three segments and that a vast amount of those changes are above the uncertainty level.

To model complex surfaces precisely and reduce the noise level introduced by them a dataset with higher spatial resolution than the one used in this study is required.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Mean (m)</th>
<th>STD (m)</th>
<th>Max Uplift (m)</th>
<th>Max Subsidence (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0.01</td>
<td>0.18</td>
<td>1.70</td>
<td>2.47</td>
</tr>
<tr>
<td>II</td>
<td>0.07</td>
<td>0.12</td>
<td>1.38</td>
<td>1.35</td>
</tr>
<tr>
<td>III</td>
<td>-0.03</td>
<td>0.29</td>
<td>2.72</td>
<td>2.70</td>
</tr>
</tbody>
</table>

Table 12.2. Statistics of DoD map

Segment I (see Fig 12.12B) demonstrates areas with high topographic variability compared to their respective neighboring regions. These rough textured areas include a mapped landslide that is of particular interest as it appears to experience uplift as shown in the DoD map. Moreover, the limit on the western side of Segment I is along the riverbank of the Muskingum River, and therefore, it consistently displays subsidence/erosion along it, as expected. In Segment II, the sloped terrain experiences higher amounts of uplift than subsidence within it, while flat terrain differences seem to vary as areas experience small amounts of uplift and others show no change. The sloped area is not within a mapped landslide in the reference inventory map and for this reason, it is of interest as it may be a newly developing landslide. The last Segment III is an interesting section of the study area as large amounts of mass movement are clearly represented in the DoD map. The vertical differences where large (> ± 0.50 m) amounts of mass movement occur are noticeably visible and clustered together. Furthermore, the northern section is along the riverbank, thus, displaying erosion along it, as expected. Since a potential landslide has occurred between the surveys, it may indicate that more frequent surveys are necessary to detect and prevent landslide hazards.

In summary, the change detection algorithm proves that it has the ability to identify various surface changes on a wide variety of surface topography using multi-temporal surface models, which is an important attribute of the proposed method.

12.2.3.2 Probabilistic Change Detection

After assessing the vertical differences, the probability that each difference was real and not noise was evaluated using the Wilcoxon signed ranked test, which evaluates the null hypothesis \( H_0: \theta \geq M \) as described in section 11.2.3. The probabilistic non-parametric signed rank test generates a
probability map as shown in Fig 12.13A, B and C. The results for the non-parametric signed rank test are similar to the DoD maps shown in Fig 12.12A, C and E, as expected. It is observed for both maps that local neighborhoods having the highest amount of vertical differences also have the highest probability, as expected. Obviously, there is a relationship between the vertical changes and probabilities. One limitation of the probability map is that it does not differentiate between uplift and subsidence, but it can easily be compared to the DoD map to determine the type of the change.

![Figure 12.13.](image)

\textbf{Figure 12.13.} Illustrated in (A,B and C) are the probabilities (signed rank test) for segment I, II and III, respectively, that the surface deformations are real given a local neighborhood of $7 \times 7$ cells and $M = 0.17 \text{ m}$

The results generated from the signed rank test show in Fig 12.13 that Segments I, II and II exhibit surface deformations with high-probability, as expected. In Segment I, the changes detected coincide with the mapped landslide outlined in Fig 12.12B. 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 (reference) has developed further. The riverbanks are also mapped with high-probability clusters, which suggest that erosion is experienced, as expected.

The algorithm also identifies high probable changes in Segment II (Fig 12.13B). In particular, small areas along the road bank on the western side of the road experiences high-probability vertical change. 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 are observed that could lead to a future landslide hazard.

Segment III, see Fig 12.13C, which was mapped for having slope instabilities on the northern and southern side of the road reveals highly probable changes. A landslide hazard seems to have occurred during the span of the surveys. The potential landslide in Fig 12.13C shows that the signed rank test generates a nicely outlined high-probability cluster that illustrates the shape of the potential slide, which was expected as there were high vertical changes ($> \pm 0.50 \text{ m}$) detected in
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 and only small clusters are created that may be suppressed as noise. Since the northern end is along the riverbank water body, high-probability changes are expected along this area. This area presents a unique scenario, as the changes observed were after the potential sliding occurred and before it was repaired, which is uncommon.

In general, the probabilities are either low or high, although there is a minimal amount of medium scale probability changes. This is an advantage of the proposed algorithm as it simplifies the identification of changes detected by making them noticeable. Additionally, the method clusters the high probability changes, which is needed to identify surface patches that are suspect to temporal changes. Overall, the approach can be said to work well as it clearly defines the high probable temporal changes identified.

12.2.3.3 Surface Feature Extraction

The classified locations by the proposed algorithm coincide with the areas experiencing high topographic variability for all three segments. The algorithm has performed properly as it was able to delineate rough and smooth topography as shown in Fig 12.14. 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 susceptible. However, the algorithm tends to overclassify landslide suspect areas, especially those mapped in the landslide inventory map. With that being said, the performance of the proposed algorithm achieves good results that are necessary to differentiate high topographic variability from smooth undisturbed terrain.
Figure 12.14. Illustrated in (A, C and E) are the surface roughness maps for segment I, II and III, respectively. Shown in (B, D and F) are the classified maps from the proposed landslide surface feature extractor.

12.2.3.4 Susceptibility and Hazard Mapping

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 susceptibility map from the proposed algorithm the impact of the cluster size and probability threshold was tested. The thresholds were evaluated by having varying cluster sizes between 25 and 150 m² and a probability threshold from the signed rank test between 0.70 and 0.99 for cells classified as landslide prone. This range was selected after evaluating the minimum size of the mapped landslides provided by the reference inventory map, which was 200 m² and aiming to have only high-probability changes that were classified as having landslide prone features. After evaluating potential cluster sizes and probability thresholds, it was determined that 25 m² and 0.90, were the most suitable thresholds. The criterion selected will allow for clusters of said size and probability to be mapped as high-probability surface changes, additionally, suppressing potential noise.
The mapped landslides in Fig 12.15 from our proposed algorithm coincide with the mapped landslide from the inventory map and those areas experiencing high topographic variability for Segment I. The mapped landslides in Segment II from our proposed algorithm suggest that these may be new developing slides, as there are no slides provided from the reference inventory in this area. Segment III clearly maps a potential landslide, which displayed a high probability change and surface roughness. The mean change observed for this particular potential landslide is above the normal within its proximity, suggesting that more frequent surveys are necessary to prevent these events. Although, the hazard event has already occurred the proposed approach demonstrates its ability to identify sliding that occurs between the LiDAR surveys that have yet to be corrected or stabilized or being left in the natural landslide form. This suggests that the algorithm can also be used as a post-failure rapid mapping technique, if pre-failure data is available.

![Figure 12.15: Mapped slides with underlying DEM for segments I (A), II (B) and III (C)](image)

The three segments 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, which proves its robustness. One limitation that is observed to be affecting the algorithms true potential is the LiDAR data spatial resolution. The spatial resolution has a great effect on the ability to detect changes; note that the LiDAR vertical accuracy also has an impact. Despite the lack of data quality, the method was able to identify 66% of the mapped landslides from the inventory map as either experiencing landslide susceptible changes within or adjacent to them. There were a few instances where it was observed that flat terrain was mapped. To verify that the flat terrain mapped locations are correct, further analysis is necessary, including, field investigation. The mapped slides in the reference inventory that did not display high probable surface changes between the surveys are potentially changing at a lower rate, therefore either
continuous monitoring or higher spatial resolution data are needed to detect those changes; since we are working with small failures the latter seems to be the most appropriate.

The statistics of the changes observed within the entire inventory mapped landslides (reference) and those identified by the algorithm with a high degree of probability within all of the inventory mapped landslides are tabulated in Table 12.3 and their respective distributions are displayed in Fig 12.16. The mean changes observed between them are similar and close to a balanced deposition and erosion, as expected. However, the variation is higher for the algorithms mapped areas within the landslide inventory locations. This may be due to the algorithms ability to classify only local neighborhoods susceptible to changes greater than 0.17 m with a high degree of probability, and 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. Note that the variation of the changes detected within the entire inventory mapped landslides was not expected to be similar to that of the uncertainty level. The distribution shown in Fig 12.16 illustrates a normal distribution for the changes detected in the entire inventory mapped landslides (A), while those detected by the algorithm within the inventory mapped landslides (B) reveals a bimodal (normal) distribution. The peak shown in Fig 12.16A is around 0.00 cm, while the peaks shown in Fig 12.16B are above the propagated uncertainty level. The changes detected, in theory, are expected to have a loss in material in the upper part of the slope and a gain in the lower part due to erosion and deposition. However, this is not the case for all changes detected, as they vary at each location and there is no clear pattern observed between them in the DoD maps, see 12.12. The only location displaying this pattern is shown in Figure 12G where the potential landslide has occurred.

<table>
<thead>
<tr>
<th>Changes Detected</th>
<th>Mean</th>
<th>STD</th>
<th>Max Uplift</th>
<th>Max Subsidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entire Inventory Mapped</td>
<td>0.01</td>
<td>0.17</td>
<td>2.90</td>
<td>3.22</td>
</tr>
<tr>
<td>Algorithm Mapped w/in</td>
<td>0.02</td>
<td>0.48</td>
<td>2.41</td>
<td>3.22</td>
</tr>
</tbody>
</table>

*Table 12.3. Statistics of Vertical Changes in Inventory Mapped Landslides*
Figure 12.16. Distribution of vertical changes observed between the 2012 and 2008 DEMs. The top figure (A) displays the vertical changes observed within the entire inventory mapped landslides. The bottom figure (B) shows the vertical changes mapped by the proposed approach within the inventory mapped landslides.

13 SIMULATION ANALYSIS

Since LiDAR data can come at varying spatial densities (average density), its spatial resolving power, in terms of surface details, consequently ranges over a broad range. Some landslide features can be relatively small, such as less than a foot, so a spacing of 1-2 feet, typical for LiDAR data acquired for topographic mapping, is not adequate to identify those smaller features. Obviously, the spatial resolution of LiDAR data cannot be increased infinitely, as it has cost impact and sensor limitations. Yet, the trend in the LiDAR technology is that the spatial resolution is steadily growing while cost holds or slightly declining. Therefore, it is essential to proactively assess the potential of higher resolution data with respect to identifying landslide features.
The simulation work is an important effort, as it has serious implications concerning the recommendation developed at the final stage of the project. Based on real data used in our investigation, a simulation tool is developed to simulate varying data sampling densities to verify the limitations of the spatial scope of the landslide that can be detected as a function of data point density.

The simulation tool will be essential in planning any future LiDAR mission that will target landslide detection and monitoring.

13.1 Introduction

Spatial resolution is one of the fundamental characteristics of remote sensing (Chen, Stow and Gong 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 (> few meters) to fine (< 1 dm) scales depending on the capabilities of the remote sensing sensor used for mapping, such as spaceborne and airborne imagery, airborne and terrestrial LiDAR. 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, Stow and Gong 2004). Spatial resolution of a DEM limits the identification of surface features and pattern details. Improper choice of spatial resolution may lead to misinterpretation 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, Zhu and Gold 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, Stow and Gong 2004). For these reasons, evaluating the effects of spatial resolution is complex. In this report, the impact of spatial resolution, measured in DEM grid size on processing performance is investigated.

Spatial resolution is an important component of landslide susceptibility mapping, especially when landslides are small and the dimensions of slope instability vary. The spatial resolution needs to be relevant to the scale apparent in the landslide morphology as it affects all stages of landslide susceptibility mapping from surface feature extraction to the classification of a DEM grid cell. However, landslide susceptibility is not only dependent upon the morphology, the geologic structure is important as well as underground water flow. Nevertheless, in a geologically homogeneous area the investigation is useful.

In this section we will analyze a test dataset and resample the base airborne LiDAR-derived DEM to generate coarser DEMs. Next, the proposed landslide surface feature extraction algorithm described in section 12.1 will be applied to all DEMs. Finally, an evaluation will be performed and the findings will be discussed.

### 13.2 Methodology

The methods used to evaluate the effects of spatial resolution are discussed in this section. First, we discuss the generation of coarse DEMs from base data. Then, we classify each DEM using the developed SVM classification method described in section 12.1. Finally, the classification results at each spatial resolution are examined using a performance evaluation method to determine how spatial resolution affects landslide surface feature extraction.

#### 13.2.1 Simulated Data

The base high-resolution surface model is formed based on a generalized rotational landslide extracted from the test area (landslide 1) and the overall surface of the test area. A 10 x 10 cm grid with 11 landslides of various scales and orientations are inserted into the surface. DEM’s of various spatial resolutions, simulated to 20, 40, 80, 160 cm are created in six segments.

#### 13.2.2 Surface Feature Extraction

The feature extraction algorithm used is described in detail in the previous chapters. For the 10, 20, 40, 80 and 160 cm spatial resolution the following parameters were adjusted compared to the original algorithm. The customized Sobel operator used a fixed sampling window of size \((31 \times 31)\), the inter-cell difference (roughness) used a fixed sampling window of \((11 \times 11)\), while fixed sampling windows of size \((41 \times 41)\) were used for the direction cosine eigenvalue ratios, length of orientation vectors and for the statistic measure of the standard deviation (variability) of aspect, hillshade, roughness, slope, resultant length of orientation vectors and customized Sobel operator.

#### 13.2.3 Performance Evaluation

The performance evaluation was assessed by analyzing the resulting landslide susceptibility map to the independently compiled landslide inventory map. A common form to evaluate the performance of a landslide susceptibility model is to use a confusion matrix (Frattini, Crosta and
Carrara 2010). The model performance is analyzed by assessing the correctly and incorrectly classified landslide and stable areas. Since, the algorithms 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 13.1: 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, Crosta and Carrara 2010). Table 13.1 represents a two-class confusion matrix, as the one used.

<table>
<thead>
<tr>
<th>Actual Class</th>
<th>Predicted Class</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Landslide</td>
<td>Stable</td>
</tr>
<tr>
<td>Landslide</td>
<td>True Positive (+</td>
<td>+), Error Type II</td>
</tr>
<tr>
<td>Stable</td>
<td>False Positive (+</td>
<td>-), Error Type I</td>
</tr>
</tbody>
</table>

Table 13.1. Confusion matrix used for performance evaluation

13.3 Simulated Data Evaluation

The details in the DEM are lost as the spatial resolution decreases, as is visibly noticed in Fig 13.1, meaning the surface features are no longer distinct in the DEM. One particular feature that is lost is the transportation corridor. In the base (10 cm) DEM the corridor is easily depicted, but as the DEM becomes coarser it is no longer noticeably apparent, thus illustrating that surface features are lost as the spatial resolution decreases.
The classified landslide susceptibility maps generated at varying spatial resolutions are shown in Fig 13.1 and the performance evaluation was tabulated in Table 13.2. The accuracy statistics in Table 13.1 reveal that the algorithms 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 57.28 to 0.00 %. This pattern signifies that the algorithm becomes incapable of distinguishing landslide and stable features due to the loss of detail in the terrain representation. The lower resolution of 160 cm has the worst performance as no landslide features are classified correctly and the highest resolution of 10 cm has the utmost performance. Although the 40 cm spatial resolution did not have the best performance, it did have the best precision. This is clearly due to the preservation of landslide features when resampling the DEM.
Table 13.2. Accuracy statistics of the supervised classification algorithm

<table>
<thead>
<tr>
<th>Units: %</th>
<th>10 cm</th>
<th>20 cm</th>
<th>40 cm</th>
<th>80 cm</th>
<th>160 cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>93.53</td>
<td>96.79</td>
<td>97.99</td>
<td>98.02</td>
<td>98.06</td>
</tr>
<tr>
<td>True Positive Rate</td>
<td>57.28</td>
<td>25.97</td>
<td>14.97</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>False Positive Rate</td>
<td>5.75</td>
<td>1.81</td>
<td>0.38</td>
<td>0.04</td>
<td>0.01</td>
</tr>
<tr>
<td>False Negative Rate</td>
<td>42.72</td>
<td>74.03</td>
<td>85.03</td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Precision</td>
<td>16.43</td>
<td>22.03</td>
<td>44.05</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

The performance of the classifier demonstrates a strong dependency between the scale of the landslide surface features and the spatial resolution used to generate each DEM. For this reason, for any landslide susceptibility model to maximize performance, a spatial resolution performance evaluation is needed to determine a spatial resolution relevant to the surface features found in the landslide morphology. The proposed evaluation will minimize any issues pertaining to spatial resolution.

14 CONCLUSION, FUTURE RECOMMENDATION

14.1 Research results

Landslide susceptibility and hazard mapping is a challenging and interesting research topic. Many attempts to solve this problem have incorporated various remote-sensing technologies from various platforms, such as spaceborne, airborne and terrestrial. Every remote-sensing technology and platform, however, has limitations that reduce the accuracy necessary to map slides with high confidence; particularly, mapping small landslides under vegetation is difficult. For these reasons, it is critical to select a remote-sensing technology and platform suitable for the application needs to map small landslide hazards as those are affecting most of the transportation corridors in the state of Ohio.

The last decade has seen remarkable improvements in remote sensing technologies, resulting in higher accuracy and better spatial resolution. Now airborne LiDAR systems acquire data at a ten times higher rate than a decade ago, and the vertical accuracy has also improved. Large-format digital cameras can provide GSD down to a few cm with comparable georeferencing accuracy. Both sensor data can be used for surface extraction at excellent accuracy. With respect to mapping smaller landslides in highly vegetated areas, clearly, airborne LiDAR more advantages due to high vertical accuracy and good canopy penetration capabilities, and, undoubtedly, the optimal sensor available for inexpensive landslide detection at the moment.

In this report, two techniques, one using single and the other multi-temporal surface models were proposed for landslide susceptibility and hazard mapping. The performance of both methods
depends on the spatial resolution LiDAR data. The higher the resolution, the better the detection rate. Note that some parameter adjustment may be required if the resolution is measurably different from the data sets that were used in this study. Additionally, there is an aspect of human subjectivity in judging landslides, so consequently, reference landslide inventories have non-negligible uncertainties.

In the first approach, surface features are extracted and quantified to characterize landslide areas. Then, SVM is used to train the classification model of the two class problem (landslide and stable terrain). 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 of about 1% of the data from SR 666. The estimation performance of the method is tested on a surface model having a known reference (SR 666) and six independent test datasets with known landslides in the proximity. In this approach, the results from the trained model are filtered and noise is suppressed. In the final step, suspect areas are mapped as landslide hazards.

To numerically evaluate this approach, using surface feature extraction, the proposed method was able to identify 84% of the mapped landslides from the reference inventory map of SR 666. For the independent data sets, there was no landslide inventory available, only geotechnical experts provided an assessment. Based on that, it was observed that the algorithm was capable of identifying landslide suspect activity from the HAM-75-5.58 dataset, while in the TUS-77-1.12, a clearly defined landslide was overlooked. Since using areas representative of most landslide surface features for training is important, when this assumption fails, the proposed method is likely to fail. However, if good surface features are used the algorithms chances of being successful increase. That being said, at least for our limited data, the proposed method achieved promising landslide hazard mapping performance.

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 hazardous to 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 landslide hazards.

To judge the performance of the multi-temporal surface model based approach in numbers, 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. Obviously, this approach is also dependent on the training data. Also, the using a spatial resolution pertinent to the morphological features found in landslides is essential to achieve good performance. This is a vital
component necessary to maximize the performance of any landslide susceptibility mapping algorithm. When this assumption is false, the proposed method is likely to perform poorly. However, if a sufficiently high spatial resolution is used, the algorithm’s chances of being successful increase. That being said, at least for our limited data, the proposed method achieved promising landslide hazard mapping results.

Both proposed techniques were implemented, coded and executed on a desktop computer using Matlab Version R2014a (The MathWorks, Inc.), and provided to ODOT. Note an earlier version of the program was tested at ODOT OGE. The Manual of the software is in Appendix F.

14.2 Recommendation for ODOT OGE

The proposed methods are only as accurate as the remote-sensing technology used to map surface models. However, by selecting an appropriate technology many limitations and problems can be overcome (e.g. spatial resolution, accuracy, terrain coverage). Our methods employ many independent processes and with the incorporation of more advanced techniques, further improvements are possible. For example, other change detection techniques could be considered or different surface feature extraction methods can be applied that may include 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 with respect to the spatial variability, instead of assuming a conservative uncertainty level for all areas in the change detection approach. Work that could extend the proposed change detection algorithm further 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. The rate of change is an important component and should be used to classify landslide hazards.

If landslide identification is to be improved, a spatial resolution similar to the morphological features found in small failures should be obtained with high accuracy. Based on our study it is recommended that future airborne LiDAR acquisitions be acquired having a point spacing of 20 – 30 cm. This will not only improve the landslide surface feature extraction by having a spatial resolution relevant to the features of the landslides, but also the probabilistic change detection. In addition, more time-series should be acquired to analyze and identify relevant patterns found in landslide surface changes with high confidence. Both of these recommendations are important and should be considered in future studies and data acquisitions. Nonetheless, given the modest point spacing and high accuracy of the airborne LiDAR datasets provided, it is shown that landslide detection and monitoring is feasible.

Finally, the use of UAS technology for landslide detection and monitoring is highly recommended. This inexpensive platform has an enormous potential in acquiring data at high spatial and good temporal resolution with excellent accuracy. LiDAR manufacturers are rolling out new small yet
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

powerful sensors for UAS platforms. Compared to airborne platforms, UAS can follow more or less any road pattern and map an evenly split swath along the centerline. Some of these sensors feature 0.5M points per second data acquisition rate, which combined with slower platform motion, can provide high spatial resolution surface data. Since UAS operations are affordable, 2-4 surveys per year can be easily implemented, ultimately resulting in temporal sampling that is comparable to most landslide growth rate.
15 REFERENCES


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16 APPENDIX

16.1 Appendix A: MUS-666-0.00 Geohazard Inventory Summary, November 13, 2006

<table>
<thead>
<tr>
<th>Mile Marker</th>
<th>Mode of Failure/Past Stabilization/Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MM 1.35-MM 1.47</td>
<td><strong>No mode of failure stated.</strong> Southbound embankment slope shows signs of instability; several head scarps noted; over-steepened slope; slope instability not impacting roadway (Fig. 13).</td>
</tr>
<tr>
<td>MM 1.47-MM 1.55</td>
<td>Two H-pile post and panel retaining walls; wall A (southern wall) is 175’ long and wall B (northern wall), 100’ from wall A, is 150’ long. A rotational failure identified prior to wall construction (Fig. 2). Material dropped 3’-5’ after wall construction; <strong>tension cracks noted near the southern end of wall B.</strong></td>
</tr>
<tr>
<td>MM 1.58-MM 1.77</td>
<td><strong>No mode of failure stated.</strong> A row of pipe piles, 1/3 of the way up the slope. No instability noted.</td>
</tr>
<tr>
<td>MM 1.77-MM 1.97</td>
<td><strong>Minor creep</strong> affecting the over-steepened southbound embankment slope. Slight undulation and cracking of the roadway (Figure 20); hummocky topography.</td>
</tr>
<tr>
<td>MM 2.15-MM 2.30</td>
<td>Wash out areas within a steep (0.75H:1V–1H:1V) rail embankment above the roadway. <strong>Evidence of general instability</strong> (Fig. 25).</td>
</tr>
</tbody>
</table>
6. MM 2.31-MM 2.40  No mode of failure stated. An old rail-bed/bike path located to the west of the road. Cracks in the roadway (Fig. 26) suggest instability affecting the slope between the road and the bike path; no well-defined toe bulge; the slope is 6’-10’ high with an avg. slope angle of 45°; poor drainage conditions noted along the northbound lane, resulting in water seeps near the embankment toe and impacting the bike path (Fig. 28).

**Study Area C**

*(MM 2.7-MM 5.7)*

7. MM 2.78-MM 2.96  No mode of failure stated. Cracking of pavement in both lanes (Fig. 33) indicates instability within the western embankment; triggered by steepness (1H:1V) of slope (6’-18’ high) and poor drainage of the toe area due to raised, abandoned, rail bed.

8. MM 2.86  Mudflow/debris flow from slope above the road (Fig. 34). Slope angle 1H:1V; sparsely vegetated.

9. MM 3.0-MM 3.2  No mode of failure stated. Historically unstable area; paved in 2005; embankment slope wet (day lilies).

10. MM 3.27-MM 3.41  “Translational creep (?)”, resulting in pavement cracking (Fig. 36); over-steepened southbound embankment slope (6’-10’ high).

11. MM 3.41-MM 3.52  Minor “translational creep”, resulting in minor pavement cracking. Western embankment slope (2’-6” high) is over-steepened.

12. MM 3.81-MM 3.99  No evidence of current instability except minor pavement cracking. Western embankment slope (8” high) is constructed over wet farmland.

13. MM 4.07  A toe bulge (12’ high) within the northbound ditch due to slope instability above the road (Fig. 38); scarp ~ 50’ above the road. Roadway not impacted.
14. MM 4.79-MM 4.82  
No mode of failure stated. Slope above the roadway shows instability (100’ upslope) and encroaches upon the ditch line (Fig. 39). Roadway not impacted; no sign of instability below the roadway.

15. MM 5.16-MM 5.47  
No mode of failure stated. Very active section of roadway with severe undulations; dip and cracking between MM 5.21 and MM 5.25; saturated embankment with heavy growth of lilies (Fig. 40).

16. MM 5.41-MM 5.69  
No mode of failure stated. Slope above the roadway shows instability; several toe bulges evident above the ditch line (Fig. 41). Numerous tilted trees; roadway paved in 2005.

17. MM 5.47-MM 5.70  
No mode of failure stated. A large toe bulge of rail embankment, extending into camp ground noted at MM 5.55. A 2005 FEMA overlay from MM 5.5 to MM 5.7 shows undulations, displacement, and cracking (1” wide, ½” dip) (Figs. 42 and 43).

Study Area D  
No slope stability issues in this area; it is the State Nursery area and is flat.

MM 5.7- MM 6.9  

Study Area E  

MM 6.9-MM 7.8  

18. MM 7.17-MM 7.24  
No mode of failure stated. The remediation work at MM 1.7 consisted of removing potentially unstable material from a steep slope along the northbound lane, re-grading the embankment, and providing drainage. At MM 7.24 (or 7.25?), previous work shows a picture of a bent guard rail (Fig. 67). The remediation work at this location included construction of a stabilization berm, covered with riprap, removal of the berm after slope movement, and construction of a shear key and a wider berm (Figs. 68-71). No slope instability
problems are listed at this site. Currently, the reconstructed embankment is well vegetated and is performing well.

19. MM 7.25-MM 7.29  **No mode of failure stated.** The remediation work at MM 7.29 included replacement of weak, saturated, unstable embankment under the southbound lane and incorporation of internal drainage. This repair is experiencing new instability problems, with guard rail losing support (Fig. 85).

20. MM 7.29-MM 7.37  **No mode of failure stated.** The remediation project at this location (MM 7.4 according to the report), below the southbound lane and directly above the Ellis Lock and Dam, involved installation of H-piles adjacent to the road, construction of a sheared key (1.5’ deep, 8’ wide) following additional movement, provision of drainage, and reconstruction of the embankment (Figs. 72-78). This is where a new landslide, not included in the LiDAR coverage, is currently being remediated. This failure was anticipated as the repaired slope showed signs of instability according to the 2006 report.

21. MM 7.34  **A mudflow** occurred along the hillside. A landslide occurred on this slope, about 80’ above the roadway, and the failed material, upon saturation, resulted in mudflow (Fig. 88).

22. MM 7.37-MM 7.50  **No mode of failure stated.** The southbound lane here has a high terrace bench and a very steep slope above and below the bench. Pipe piles and H-piles are present (Figures 89 and 90). Several areas around the piles show movement. Bench stability is affected. Piling with guard rail sections installed in 2006 (Figures 91 and 92), but the site shows instability (Figure 93).

23. MM 7.48  **A mudflow** on the slope above the road; saturated conditions.

24. MM 7.50  Reconstructed embankment; **no signs of additional instability.**

25. MM 7.62-MM 7.64  **No mode of failure stated.** The remediation project at this location consisted of installing a new culvert and a drainage blanket under the embankment, in a deep valley, because of slope instability problems prior to remediation (Fig. 96). A concrete gutter was installed later on. CHECK OUT CURRENT STABILITY.
26. MM 7.74-MM 7.77  **No mode of failure stated.** Instability of the embankment slope below the southbound lane, prior to corrective measures, was indicated by tension cracks and a tilted fence (Fig. 80). The remediation consisted of embankment reconstruction involving installation of a shear key, a drainage blanket, and a berm (Fig. 81). Currently, the embankment is performing well (Fig. 97).

**Study Area F**

**MM 7.8-MM 11.2**

27. MM 8.55-MM 8.60  **No signs of slope instability;** embankment reconstructed in 2004 with a subsurface drainage blanket.

28. MM 8.75-MM 8.80  **No signs of slope instability;** the embankment, reconstructed in 2004 with a shear key and a subsurface drainage blanket, and is performing well (Fig. 113).

29. MM 8.80-MM 9.45  **No mode of failure stated.** Unstable slope above the road; hummocky topography, small toe bulges, old scarps, poor drainage, and leaning trees (Fig. 114).

30. MM 8.80-MM 9.00  **Minor cracking** in the southbound Lane; embankment slope (32°) is 5’-8’ high (Fig. 115).

31. MM 9.00-MM 9.31  **Cracking and minor displacement** of the southbound lane; slope above the road is hummocky and has toe bulges (Fig. 116).

32. MM 9.32-MM 9.41  **No mode of failure stated.** Severe cracking and displacement across both lanes of the roadway; slopes above and below the road are subject to instability; embankment slope is over-steepened, extending to the bench with homes on it (Figs. 117 and 118). Pavement is undulated with up to 6” of displacement.
33. MM 9.45-MM 9.57 Minor stability problems affect slopes both above and below the roadway. A rock-lined drainage ditch was installed in the slope above the road in 2004 (Fig. 119).

34. MM 9.92-MM 9.96 Potential for erosion of northbound embankment slope by the cutting side of the Symmes Creek meander (Fig. 121).

35. MM 10.07-MM 10.17 Evidence of a rotational failure, with a toe bulge, located within MM 10.12 and MM 10.17 of the northbound lane of the valley-fill embankment (Fig.122). Northbound embankment slope is saturated and southbound slope is over-steepened (45°).

36. MM 10.58-MM 10.64 No mode of failure stated. Instability indicated by the cracking of the southbound lane of the valley-fill embankment. Both embankment slopes are saturated (Fig. 123).

Study Area G

MM 11.2-MM 14.3

37. MM 12.83-MM 13.15 No mode of failure stated. Slope above the road shows evidence of instability in the form of toe bulges, scarps, and leaning trees (Fig. 129); road not impacted.

38. MM 13.60-MM 13.76 Severe cracking of the road; natural slope along the southbound lane is over-steepened.
16.2 Appendix B: Landslide Inventory List Based on Consultants’ Report
<table>
<thead>
<tr>
<th>Site #</th>
<th>OGE2006 Site #</th>
<th>Consult. Site #</th>
<th>From M.M.</th>
<th>To M.M.</th>
<th>Mode of Failure / Description</th>
<th>Active / Inactive (A/I)</th>
<th>Natural / Embankment Slope (N/E)</th>
<th>Slope Angle (deg)</th>
<th>Slope Height (feet)</th>
<th>Soil Type</th>
<th>Water Conditions</th>
<th>Impact on Road</th>
<th>Repair Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6</td>
<td>12A</td>
<td>2.328</td>
<td>2.390</td>
<td>Rotational slide; hummocky topography</td>
<td>A</td>
<td>E</td>
<td>30</td>
<td>17</td>
<td>Fine sand to silt</td>
<td>Poor drainage conditions</td>
<td>Yes; cracks evident; 1&quot; HD, 2&quot; VD</td>
<td>Road patchwork</td>
</tr>
<tr>
<td>2</td>
<td>7, 8, 9</td>
<td>14A</td>
<td>2.894</td>
<td>3.037</td>
<td>Complex slide; hummocky topography</td>
<td>A</td>
<td>Both</td>
<td>30</td>
<td>23</td>
<td>Fine sand to silt</td>
<td>Poor drainage of toe area due to raised RR embankment</td>
<td>Yes; cracks evident; 1&quot; HD, 3&quot; VD</td>
<td>Road patchwork</td>
</tr>
<tr>
<td>3</td>
<td>9, 10</td>
<td>19A</td>
<td>3.112</td>
<td>3.424</td>
<td>Complex slide; hummocky topography</td>
<td>A</td>
<td>Both; natural slope may not be potential site</td>
<td>29</td>
<td>24</td>
<td>Fine sand to silt</td>
<td>Poor drainage; hydrophilic vegetation</td>
<td>Yes; cracks evident; 2&quot; HD, 1&quot; VD</td>
<td>Road repaved</td>
</tr>
<tr>
<td>4</td>
<td>None</td>
<td>22</td>
<td>3.405</td>
<td>3.419</td>
<td>Rotational slide / earthflow</td>
<td>A</td>
<td>N</td>
<td>~30</td>
<td>~20</td>
<td>Colluvial soil</td>
<td>Unknown</td>
<td>Not evident</td>
<td>None</td>
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<tr>
<td>5</td>
<td>12</td>
<td>none</td>
<td>3.940</td>
<td></td>
<td></td>
<td>A</td>
<td>E</td>
<td></td>
<td></td>
<td>Embankment constructed on wet farmland</td>
<td>Yes; cracks evident</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>15</td>
<td>26A</td>
<td>5.176</td>
<td>5.271</td>
<td>Complex slide; hummocky topography</td>
<td>A</td>
<td>E</td>
<td>23</td>
<td>59</td>
<td>Fine sand to silt</td>
<td>Poor drainage; hydrophilic vegetation</td>
<td>Yes; cracks evident; 1&quot; HD, 2&quot; VD</td>
<td>Road repaved</td>
</tr>
<tr>
<td>7</td>
<td>15</td>
<td>28</td>
<td>5.300</td>
<td>5.360</td>
<td>Complex slide; hummocky topography</td>
<td>A</td>
<td>E</td>
<td>25</td>
<td>72</td>
<td>Fine sand to silt</td>
<td>Poor drainage; hydrophilic vegetation</td>
<td>-</td>
<td>Road repaved</td>
</tr>
<tr>
<td>8</td>
<td>16</td>
<td>33</td>
<td>5.616</td>
<td>5.669</td>
<td>Rotational slide; several toe bulges</td>
<td>A</td>
<td>N</td>
<td>Unknown</td>
<td>Unknown</td>
<td>Colluvial soil</td>
<td>Unknown</td>
<td>Unknown</td>
<td>Road repaved</td>
</tr>
<tr>
<td>9</td>
<td>17</td>
<td>29A</td>
<td>5.512</td>
<td>5.634</td>
<td>Complex slide; hummocky topography</td>
<td>A</td>
<td>E</td>
<td>31</td>
<td>39</td>
<td>Fine sand to silt</td>
<td>Poor drainage conditions</td>
<td>Yes; cracks evident; 1&quot; HD, 3&quot; VD</td>
<td>Road repaved</td>
</tr>
</tbody>
</table>
## ODOT MU666 Potential Field Sites for LiDAR Study

<table>
<thead>
<tr>
<th>Site #</th>
<th>OGE2006 Site #</th>
<th>Consult. Site #</th>
<th>From M.M.</th>
<th>To M.M.</th>
<th>Mode of Failure / Description</th>
<th>Active / Inactive (A/I)</th>
<th>Natural / Embankment Slope (N/E)</th>
<th>Slope Angle (deg)</th>
<th>Slope Height (feet)</th>
<th>Soil Type</th>
<th>Water Conditions</th>
<th>Impact on Road</th>
<th>Repair Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>19, 20, 22</td>
<td>37A</td>
<td>7.241</td>
<td>7.532</td>
<td>Complex slide; hummocky topography; erosion of toe by river</td>
<td>A</td>
<td>E</td>
<td>29</td>
<td>81</td>
<td>Fine sand to silt</td>
<td>Poor drainage prior to remediation</td>
<td>Yes; cracks evident; 0.5&quot; HD, 4&quot; VD</td>
<td>Retaining structures; internal drainage installed; internal slope reinforcement; road repaved</td>
</tr>
<tr>
<td>11</td>
<td>30</td>
<td>53A</td>
<td>8.829</td>
<td>8.976</td>
<td>Complex slide; hummocky topography</td>
<td>A</td>
<td>E</td>
<td>31</td>
<td>21</td>
<td>Fine sand to silt</td>
<td>Poor drainage conditions</td>
<td>Yes; cracks evident; 1&quot; HD, 1&quot; VD</td>
<td>Road repaved</td>
</tr>
<tr>
<td>12</td>
<td>31</td>
<td>59, 60</td>
<td>9.145</td>
<td>9.272</td>
<td>Complex slide; hummocky topography</td>
<td>A</td>
<td>Both</td>
<td>29</td>
<td>140</td>
<td>Fine sand to silt</td>
<td>Poor drainage conditions</td>
<td>Yes; cracks evident</td>
<td>Road repaved</td>
</tr>
<tr>
<td>13</td>
<td>32</td>
<td>61</td>
<td>9.303</td>
<td>9.327</td>
<td>Complex slide; hummocky topography</td>
<td>A</td>
<td>Both</td>
<td>28</td>
<td>75</td>
<td>Fine sand to silt</td>
<td>Poor drainage conditions</td>
<td>Yes; cracks evident; 1&quot; HD, 2&quot; VD</td>
<td>Road repaved</td>
</tr>
<tr>
<td>14</td>
<td>None</td>
<td>65</td>
<td>9.649</td>
<td>9.664</td>
<td>Complex slide; hummocky topography; erosion of toe by river</td>
<td>A</td>
<td>E</td>
<td>36</td>
<td>41</td>
<td>Fine sand to silt</td>
<td>Unknown</td>
<td>Yes; cracks evident; 0.5&quot; HD, 0.5&quot; VD</td>
<td>None</td>
</tr>
<tr>
<td>15</td>
<td>35</td>
<td>66</td>
<td>10.069</td>
<td>10.095</td>
<td>Translational slide; Rotational slide</td>
<td>A</td>
<td>E</td>
<td>39</td>
<td>33</td>
<td>Fine sand to silt</td>
<td>Poor drainage conditions</td>
<td>Yes; cracks evident; 3&quot; HD, 2&quot; VD</td>
<td>None</td>
</tr>
<tr>
<td>16</td>
<td>38</td>
<td>67</td>
<td>13.620</td>
<td>13.666</td>
<td>Complex slide; hummocky topography; erosion of toe by river</td>
<td>A</td>
<td>E</td>
<td>37</td>
<td>27</td>
<td>Fine sand to silt</td>
<td>Unknown</td>
<td>Yes; cracks evident; 2&quot; HD, 2&quot; VD</td>
<td>Road repaved</td>
</tr>
<tr>
<td>17</td>
<td>38</td>
<td>69</td>
<td>13.690</td>
<td>13.726</td>
<td>Translational slide; hummocky topography; erosion of toe by creek</td>
<td>A</td>
<td>E</td>
<td>42</td>
<td>15</td>
<td>Fine sand to silt</td>
<td>Poor drainage prior to remediation</td>
<td>Yes; cracks evident; 4&quot; HD, 2&quot; VD</td>
<td>Drainage relocated</td>
</tr>
<tr>
<td>18</td>
<td>38</td>
<td>68</td>
<td>13.700</td>
<td>13.722</td>
<td>Complex slide; hummocky topography; erosion of toe by creek</td>
<td>A</td>
<td>E</td>
<td>41</td>
<td>18</td>
<td>Fine sand to silt</td>
<td>Poor drainage prior to remediation</td>
<td>Yes; cracks evident; 3&quot; HD, 2&quot; VD</td>
<td>Drainage relocated; Retaining wall</td>
</tr>
</tbody>
</table>
16.3 Appendix C: Landslide Inventory Mapping Using LiDAR Imagery

Mile marker 1.25 to 1.60
Mile marker 1.60 to 2.00
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 2.00 to 2.40
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 2.40 to 2.80
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 2.80 to 3.20
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 3.20 to 3.55
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 3.85 to 4.20
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 4.55 to 4.85
Mile marker 4.85 to 5.20
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 5.20 to 5.55
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 5.55 to 5.90
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 5.90 to 6.25
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 6.25 to 6.60
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 6.60 to 6.95
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 6.95 to 7.35
Mile marker 7.35 to 7.75
Mile marker 7.75 to 8.15
Mile marker 8.15 to 8.55
Mile marker 8.55 to 8.97
Mile marker 8.97 to 9.35
Mile marker 9.35 to 9.75
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 9.75 to 10.20
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 10.60 to 10.95
Mile marker 10.95 to 11.55
Mile marker 11.55 to 12.08
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 12.45 to 12.75
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 12.75 to 13.08
Mile marker 13.08 to 13.45
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 13.45 to 13.80
Mile marker 13.80 to 14.18
16.4 APPENDIX D: Landslide Locations Selected for GPS Data Collection

Mile marker 2.80 to 3.20
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 3.20 to 3.55

mm 3.20 to mm 3.55

Rotational slide #1 - GPS measurements taken
Rotational slide #2 - GPS measurements taken
Erosional channel (not a slide)
Rotational slide #3 - GPS measurements taken
Rotational slide #4 - GPS measurements taken

500 feet
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Mile marker 6.95 to 7.35

Large complex landslide surveyed on June 29, 2012
Probabilistic Use of LiDAR Data to Detect and Characterize Landslides

Large complex landslide surveyed July 13, 2012

Mile marker 8.97 to 9.35
Large complex landslide surveyed on July 13, 2012

Mile marker 9.35 to 9.75
16.5 APPENDIX E: Surface Characterization Parameters

The geomorphologic features used to describe landslides, and, in general, land formations, can be parameterized by various numbers derived from surface models. The parameters, discussed below and subsequently used in this project, were chosen based on previous landslide studies performed that demonstrated these characteristics having unique features depicting landslide as well as stable areas; see, e.g., McKean and Roering, 2004; Glenn, et al., 2006; Booth, et al., 2009. In general, the parameters are computed for every surface point in the areas investigated, and then statistical analysis and classification 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 parameters is discussed in the following subsections. The computation of the parameters is rather straightforward as well as 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); consequently, there is a not always negligible error introduced in the computation.

16.5.1 Aspect

Aspect is the slope orientation of each point or cell in the DEM, the compass direction that a land surface faces, expressed as an angle. It is calculated from the two directional surface normals. Basically, it identifies the steepest slope direction, and can be interpreted as the slope direction.

\[
\theta = \arctan \left( \frac{n_x}{n_y} \right)
\]  (5.1)

Where \(n_x\) and \(n_y\) are the derivatives in the X and Y directions, respectively. To evaluate the aspect for a DEM grid point \(z_9\) (see Eq. 5.2) of a \((3 \times 3)\) local neighborhood, the surface normals, \(N_x\) and \(N_y\) need to be computed in the east-west and north-south direction (see Eq. 5.10), respectively.

16.5.2 Curvature

Curvature, in general, is the second derivative of the surface. Profile curvature is defined as the curvature along the steepest downward gradient and plan curvature is the curvature perpendicular to the downward gradient. Obviously, the profile curvature is measured in the direction determined by the aspect parameter.

The simplest implementation of curvature computation for rasterized surface, DEM, is described below. The indexing of an 8-connected neighborhood for a point in a grid is defined as
The first-order derivatives along the X and Y axes can be estimated as

\[
\hat{z}_x = \frac{\Delta z}{\Delta x} = \frac{z_2 - z_6}{2h}
\]
\[
\hat{z}_y = \frac{\Delta z}{\Delta y} = \frac{z_8 - z_4}{2h}
\]  

where, \( h \) is the grid spacing of the DEM. Then, the second-order and mixed derivatives are similarly derived as

\[
\hat{z}_{xx} = \frac{\Delta^2 z}{\Delta x} = \frac{z_2 - 2z_9 + z_6}{h^2}
\]
\[
\hat{z}_{yy} = \frac{\Delta^2 z}{\Delta y} = \frac{z_{28} - 2z_9 + z_{46}}{h^2}
\]
\[
\hat{z}_{xy} = \frac{\Delta^2 z}{\Delta x\Delta y} = \frac{-z_7 + z_4 + z_5 - z_3}{h^2}
\]

And introducing two terms as

\[
p = \left(\hat{z}_x\right)^2 + \left(\hat{z}_y\right)^2
\]
\[
p = p + 1
\]  

The profile and plan curvatures are defined as

\[
K_c = \frac{\hat{z}_{xx}\left(\hat{z}_y\right)^2 - 2\hat{z}_{xy}\hat{z}_x\hat{z}_y + \hat{z}_{yy}\left(\hat{z}_x\right)^2}{q^{3/2}}
\]  

\[
K_p = \frac{\hat{z}_{xx}\left(\hat{z}_x\right)^2 - 2\hat{z}_{xy}\hat{z}_x\hat{z}_y + \hat{z}_{yy}\left(\hat{z}_y\right)^2}{pq^{3/2}}
\]
16.5.3 Slope

Slope parameter at any point is defined as the steepest downward gradient of the surface. In a basic raster implementation using the notation of (5.2), it is approximated as

\[ S_{DB} = \max_{i=1-8} \left[ \frac{Z_9 - Z_i}{h \phi(i)} \right] \]  

(5.9)

Where \( \phi(i) = 1 \) for the cardinal (north, south, east and west) neighbors \( (i=2,4,6 \text{ and } 8) \) and \( \phi(i) = \sqrt{2} \) for the diagonal neighbors \( (i=1,3,5,7) \) to account for the extra distance to those cells.

16.5.4 Hillshade

Hillshading is a very powerful tool for relief representation; the hillshade parameter calculates a shaded relief for a digital elevation model based on the angle between the surface and the incoming light beam. The hillshading algorithm follows the logarithmic approach to shaded relief representation of Katzil and Doytsher (2003).

For the simplest gridded surface representation, using the notation of (5.2), first the surface normals are computed

\[ \hat{\delta}_E \frac{\Delta z}{\Delta x} = \frac{(z_1 + 2z_8 + z_7) - (z_3 + 2z_4 + z_5)}{8h} \]  

\[ \hat{\delta}_N \frac{\Delta z}{\Delta y} = \frac{(z_1 + 2z_2 + z_3) - (z_7 + 2z_6 + z_5)}{8h} \]  

(5.10)

Then introducing a few intermediate terms

\[ A' = \frac{A_s \hat{\delta}_E + A_c \hat{\delta}_N}{\sqrt{A_s^2 + A_c^2}} \]  

(5.11)

where parameters \( A_s \) and \( A_c \) reflect the direction of illumination

\[ A_s = \sin(\text{azimuth of light}) \]  

\[ A_c = \cos(\text{azimuth of light}) \]  

(5.12)

Finally, the shading function is expressed as

\[ SR(\hat{\delta}_E, \hat{\delta}_N) = \frac{1}{2} + \frac{1}{2} (A' + a) \frac{1}{b} \]  

(5.13)
16.5.5 Roughness

Roughness, metric used to quantify deviations of a surface, is defined as the maximum difference between any two points in a surface patch. In DEM representation, it is simply the largest inter-cell difference between the central pixel and its surrounding cells.

\[ R = \max_{i=1-8} [Z_i - Z_9] \]  

(5.14)

16.5.6 Direction Cosine Eigenvalue Ratios

The eigenvalue ratios express the amount of roughness in three-dimensional surfaces (Kasai, et al. 2009). The vectors are defined by their direction cosines: \( x_i = \sin \theta_i \cos \phi_i \), \( y_i = \sin \theta_i \sin \phi_i \) and \( z_i = \cos \theta_i \), where \( \theta_i \) is the colatitude and \( \phi_i \) is the longitude 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 (5.15) 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 and Roering 2004). Lower eigenvalue ratios indicate that the unit orientation vector of the cells will have higher degrees of surface roughness (Woodcock 1977, McKean and Roering 2004).

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

(5.15)

16.5.7 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. This measure can be used to define surface roughness, as variations within local neighborhoods will be coincident for smooth topography and greater variations will be displayed for rough topography (McKean and Roering 2004).

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16.5.8 Customized Sobel Operator

The Sobel operator computes an approximation of the gradient of the image intensity function. 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 and Woods 2002). Since a DEM surface representation is an image, the Sobel operator can be directly applied to it.

Various kernels were evaluated, yet none of those tested provided unique characteristics depicting landslide morphology. However, the kernels selected did extract distinctive features, and, thus, could enhance those found in landslides. The chosen kernels of the connected neighborhood cells are as follows:

$$
\begin{bmatrix}
2 & 0 & -2 \\
2 & 0 & -2 \\
2 & 0 & -2 \\
2 & 0 & -2 \\
2 & 0 & -2 \\
2 & 0 & -2 \\
\end{bmatrix}
$$

(A)

$$
\begin{bmatrix}
2 & 2 & 2 & 2 & 2 & 2 \\
0 & 0 & 0 & 0 & 0 & 0 \\
-2 & -2 & -2 & -2 & -2 & -2 \\
\end{bmatrix}
$$

(B)

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. 5.16A, Eq. 5.16B, Eq. 5.16C and Eq. 5.16D, respectively. The magnitude of the gradient was computed by modifying the typically used form illustrated in Gonzalez and Woods (2002) to include all directions:

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

(5.17)
16.5.9 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, Shirasawa and Pike 2002). The two cases, positive and negative openness, are shown in Fig 5.3.

![Figure 5.3](image)

**Figure 5.3.** Positive (left) and negative (right) openness from (Yokoyama, Shirasawa and Pike 2002)

The algorithm described in Yokoyama, Shirasawa and Pike (2002) was implemented in order to determine the geomorphologic feature of openness. The algorithm is described as follows:

1. for each azimuth direction $D$ ($D = 0^\circ, 45^\circ, 90^\circ, 135^\circ, 180^\circ, 225^\circ, 270^\circ$ and $315^\circ$), calculate the elevation angles along the profile from point A (double circle in Figure 5.4A and big black dot in Figure 5.4B) out to length scale $L$. In Figure 5.4B, there is an elevation angle for each grid point along the profile represented by the small black dot. 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 $\mathcal{D} S_L$ for each azimuth direction $D$.
2. calculate maximum elevation angle; $\phi_L = \max(\mathcal{D} S_L)$;
3. calculate minimum elevation angle; $\psi_L = \min(\mathcal{D} S_L)$;
4. calculate zenith angle: $\phi_L = 90^\circ - \phi_L$;
5. calculate nadir angle: $\psi_L = 90^\circ - \psi_L$;
6. obtain positive openness: $\phi_L = \frac{(0 + 45 + \ldots + 315\phi_L)}{8}$
7. obtain negative openness: $\psi_L = \frac{(0 + 45 + \ldots + 315\psi_L)}{8}$

During these processing steps, profiles are computed in eight directions as shown in Figure 5.4A. A profile view along an azimuth is given in Figure 5.4B. Here, the surface is smoothed but not detrended before processing.
16.5.10 Detrending surfaces/profiles

The dominant surface trend, practically average slope, can be easily removed and, therefore, make surface profile comparisons easy. 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 removed by removing the best straight-line fit (in a least-squares sense) from the equation of a straight line \( y = mx + b \). Depending on the approach applied, either a single number or two numbers form this parameter for profiles or surface shapes, respectively.

16.5.11 1st and 2nd Derivatives

The derivatives described here differ from those evaluated using the parameter curvature in the surface point-based section. Here we evaluate the derivatives along profiles, while in the parameter curvature an 8-connected neighborhood is used. Therefore, the methods are similar but applied to different data types. The first derivative is computed from a total of \( n \) elements:

\[
\hat{Z}_x = \frac{\Delta Z}{\Delta x} = \frac{Z_i - Z_{i-1}}{X_i - X_{i-1}}, \quad n - 1 \text{ elements left}
\]  

(5.18)

Then the second derivative is computed using the results of the first derivative:

\[
\hat{Z}_{xx} = \frac{\Delta^2 Z}{\Delta x^2} = \frac{Z_i - Z_{i-1}}{X_i - X_{i-1}}, \quad n - 2 \text{ elements left}
\]  

(5.19)
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.
16.6 APPENDIX E: Publications

Peer-Reviewed Journal Articles (in press)


Dissertation (draft submitted)

Mora, O. E. (2014). Predicting Landslide Hazards Based on Airborne LiDAR Data (doctoral dissertation). The Ohio State University, Columbus, OH.

Peer-Reviewed Proceedings (in press)


Proceedings


16.7 APPENDIX F: Photogrammetric Engineering and Remote Sensing journal paper
Small Landslide Susceptibility and Hazard Assessment Based on Airborne Lidar Data

Omar E. Mora, Jung-kuan Liu, M. Gabriela Lenzano, Charles K. Toth, and Dorota A. Grejner-Brzezinska

Abstract
Landslides are natural disasters that cause environmental and infrastructure damage worldwide. To prevent future risk posed by such events, effective methods to detect and map their hazards are needed. Traditional landslide susceptibility mapping techniques, based on field inspection, aerial photograph interpretation, and contour map analysis are often subjective, tedious, difficult to implement, and may not have the spatial resolution and temporal frequency necessary to map small slides, which is the focus of this investigation. We present a methodology that is based on a Support Vector Machine (SVM) that utilizes a lidar-derived Digital Elevation Model (DEM) to quantify and map the topographic signatures of landslides. The algorithm employs several geomorphological features to calibrate the model and delineate between landslide and stable terrain. To evaluate the performance of the proposed algorithm, a road corridor in Zanesville, Ohio, was used for testing. The resulting landslide susceptibility map was validated to correctly identify 67 of the 80 mapped landslides in the independently compiled landslide inventory map of the area. These results suggest that the proposed landslide surface feature extraction method and airborne lidar data can be used as efficient tools for small landslide susceptibility and hazard mapping.

Introduction
The hazards of natural disasters occur from processes of the earth and cause damage, devastations, loss of life, and environmental change. One particular natural hazard of interest known to cause economic, human and environmental damage worldwide are landslides (Glenn et al., 2006). Landslides have consistently damaged human infrastructure and have impeded the daily lives of many. They have a broad range of geologic processes that cause the downward movement of mass over spatial and temporal scales (McKean and Roering, 2004). In addition, their effects have a strong dependency on their spatial pattern of incident, rate of recurrence, and amount of movement (McKean and Roering, 2004). Their hazards are well-understood, yet current methods of identifying and assessing their conditions are inefficient, and are difficult to predict. Existing techniques are typically based on field inspection, aerial photograph interpretation, and contour map analysis (Booth et al., 2009). However, these methods have limitations that reduce the accuracy, completeness and reliability necessary to map landslides with high probability, especially, small failures where mass movement rates are slower (Booth et al., 2009; Galli et al., 2008). Additionally, many sites are not easily accessed for field inspections. Highly vegetated areas present difficulties for both on-site inspections and aerial photographic interpretation. Historical contour maps do not have the resolution necessary to map small landslides in highly vegetated areas where conventional remote-sensing methods cannot penetrate the land cover (Van Den Eeckhaut et al., 2005; Booth et al., 2009; James et al., 2012). For these reasons, traditional methods are not cost-effective and a new approach to landslide susceptibility and hazard mapping is necessary.

Remote-sensing technology has seen large advances in the past decade, in cost, accuracy, and accessibility. One of the major improvements has been the spatial resolution of Light Detection and Ranging (lidar) technology. In earlier stages only coarse nominal point spacing (>10 meters) was available. Improvement of this technology has allowed for higher spatial resolutions (<1 meter). The increase made in spatial resolution provides mapping opportunities at remarkable scales. This tool provides the accuracy necessary to map surface models precisely (Shan and Toth, 2008; Jaboyedoff et al., 2012). Furthermore, it has the potential to overcome many challenges faced in landslide susceptibility mapping, for example, the spatial resolution, broad terrain coverage and accuracy necessary to map precise surface models. A particular lidar technology capable of overcoming the aforementioned challenges is airborne lidar. This instrument is capable of penetrating vegetation, mapping areas up to thousands of square kilometers (Shan and Toth, 2008; Guzzetti et al., 2012), and providing sub-meter spatial resolutions. For these reasons, it is a prime consideration.

Previous landslide susceptibility mapping techniques revealed the potential that remote-sensing technology presented to identify and map the geomorphic features related to landslide morphology (McKean and Roering, 2004; Glenn et al., 2006; Booth et al., 2009). However, their focus has been on mapping large landslides in hilly terrain and mountainous regions, along coastal bluffs, and river basins (e.g., Van Den Eeckhaut et al., 2005; Booth et al., 2009; Ballabio and Sterlacchini, 2012; Tien Bui et al., 2012). Less attention has been paid to map small failures, which impact our transportation networks. Small failures have been overlooked in previous
studies, potentially due to their impact being less severe compared to large landslides. Furthermore, 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 small landslide morphology (Glenn et al., 2006). To our best knowledge, small landslide susceptibility mapping has not been addressed in the literature and an evaluation is necessary to understand and propose a means of hazard assessment for the prevention of future events.

This paper presents a novel approach for small landslide susceptibility mapping utilizing an airborne lidar-derived Digital Elevation Model (DEM). The approach employs several geomorphologic features to analyze the local topography, specifically: 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. A sample set extracted from the data is used as observations of landslide and stable terrain to calibrate the supervised classification algorithm of Support Vector Machine (SVM). The calibrated 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. 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 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.

**Study Area and Data**

**Study Area**

The study area selected 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 (23 km). The extent of the project coverage is 23 kilometers in length along SR-666 with a varying width of 75 to 180 meters and approximately 3.0 km². The area is characterized by high vegetation densities, stream and river channeling, and some residential development. The study area was chosen due to the availability of an airborne lidar-derived DEM, 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. Along the road seven separate sections damaged by landslides were corrected as a result of these storm events. Figure 1 presents an overview map of the study area.

**Data**

The lidar data was acquired in the spring of 2012 and has a point density of 5 pts/m². The vertical accuracy of the points was assessed after the lidar was adjusted to the hard surface control. The vertical accuracy of the points was assessed by the root mean square error (RMSE), which was 9 cm for soft surfaces and 5 cm for hard surfaces. Additionally, the vertical accuracy was evaluated by the standard deviation, which was 6 cm and 5 cm for soft and hard surfaces, respectively. The bare earth, filtered from the lidar data, was subsequently used for this investigation. The lidar point cloud was bare earth filtered, and then was interpolated to a spatial resolution of 50 cm using Kriging, after evaluating the nominal point spacing to be 45 cm. The statistical results demonstrated that Kriging provided the minimum error between the interpolated surface (DEM) and the bare-earth filtered lidar point cloud. For this reason, it was selected as the prime interpolation method.

For the project area a geo-hazard inventory and evaluation of mass movement affecting the transportation network was completed in 2006 by the Ohio Department of Transportation.
200 m² to 27,000 m² in area. The soil map used for this study limitation found in the reference map is that it only provides we can evaluate the performance of our proposed approach. A inventory map is that it provides a reference against which important information about the general locations of landslides ages per the historical documents. The importance of the 45°; additionally, the landslides described have a range of 18° to 80°, in which the most frequently slope observed was typical landslides affecting the road prism. An updated landslide inventory map was compiled by a team of experts from Kent State University affect the road prism. An updated landslide inventory map was The updated landslide inventory was used 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 areas of instability range from 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 will be the focus of the proposed algorithm.

The objective of the approach is to identify surface features indicative of landslide activity and map their locations in the study area. The process to identify landslide surface features is as follows: (a) filter airborne lidar point cloud to contain bare-earth points only, (b) rasterize the bare-earth point cloud using Kriging interpolation method, (c) perform surface feature extraction, (d) classify lidar-derived DEM, (e) perform post-classification filtering, and lastly (f) map areas experiencing landslide activity. The feature extraction algorithms used are described in the following sections.

**Feature Extraction**

To extract and quantify the amount of surface roughness observed in the terrain, the following eight geomorphological features were utilized: aspect, hillshade, roughness, slope, eigenvalue ratios ($\lambda_1/\lambda_2$ and $\lambda_2/\lambda_3$), customized Sobel operator, and the resultant length of orientation vectors. The selected feature extraction methods are further discussed below. Some of the surface feature extraction methods selected have been used to expose various topographic patterns (e.g., McKean and Roering, 2004; Glenn et al., 2006) and were therefore prime considerations. The standard algorithms available in the MATLAB TopoToolbox by Schwanghart and Kuhn (2010) were used for the evaluation of aspect, hillshade, roughness, and slope. Fixed sampling windows of size (9 × 9) were used to evaluate the direction cosine eigenvalue ratios and length of orientation vectors. Furthermore, a statistic measure of the standard deviation is evaluated from small sampling windows of a fixed size (9 × 9) 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 will illustrate higher topographic variability, thus, delineating rough and smooth terrain.

**Aspect**

Slope orientation is the compass direction a land surface faces. To evaluate the slope orientation, also known as aspect, for a DEM grid point of a (3×3) local neighborhood, $Z_{ij}$, shown in Equation 1, the surface normals need to be computed. Subsequently, the mapping system needs to be 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:

$$\text{ASPECT} = \frac{\theta}{\pi} \times 180^\circ + 180^\circ.$$  

(1)

**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 the illumination...
from a single direction for the shading of the terrain relief. Hillshading is typically used to display shaded relief images, however, it was observed that this feature provided important information regarding topographic variability found in landslide morphology, for this reason, hillshading was included. The shaded relief images used throughout this paper and surface feature extractor follow the approach described in Katzil and Doytsher (2003).

**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 rough. Roughness can be evaluated by computing the largest inter-cell difference of a central pixel and its surrounding cells using Equation 1, \( R = \max(Z_{ij} - Z_{11}) \), where \( i = 0-2, j = 0-2 \).

**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 Equation 1, \( S_{lm} = \max\bigg[\frac{Z_{ij} - Z_{kl}}{h \phi(ii)}\bigg] \)

\( i = 0-2, j = 0-2 \). Where \( \phi(ii) = 1 \) for the cardinal (north, south, east, and west) and \( \phi(jj) = \sqrt{2} \) for the diagonal neighbors.

**Direction Cosine Eigenvalue Ratios**
The eigenvalue ratios express the amount of roughness in three-dimensional surfaces (Kasai et al., 2009). The vectors are defined by their direction cosines: \( x_i = \sin \theta_i \cos \phi_i, y_i = \sin \theta_i \sin \phi_i, \) and \( z_i = \cos \theta_i \), where \( \theta_i \) is the colatitude, and \( \phi_i \) is the longitude of a unit orientation vector as described in McKean and Roering (2004). When considering \( (x_i, y_i, z_i) \ldots (x_n, y_n, z_n) \) as a set of \( n \) unit vectors perpendicular to each cell in the DEM, the orientation matrix, \( T \), may be constructed, see Equation 2. Next, the eigenvalues are computed for \( T \), consequently, \( \ln(\lambda_i/\lambda_j) \) and \( \ln(\lambda_i/\lambda_k) \) are evaluated, where \( \lambda_i \) 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 and Roering, 2004). Lower eigenvalue ratios indicate that the unit orientation vector of the cells will have higher degrees of surface roughness (Woodcock, 1977; McKean and Roering, 2004).

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

(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. This measure can be used to define surface roughness as variations within local neighborhoods will be coincident for smooth topography, and greater variations will be displayed for rough topography (McKean and Roering, 2004).

**Customized Sobel Operator**
The Sobel operator computes an approximation of the gradient of the image intensity function. 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 and Woods, 2002).

Various kernels were evaluated, yet none of those tested provided unique characteristics depicting landslide morphology. However, the kernels selected did extract distinctive features, thus, enhancing those found in landslides. The kernels of the connected neighborhood cells are as follows:

![Kernels for Sobel Operator](image)

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 Equation (3A), (3B), (3C), and (3D), respectively. The magnitude of the gradient was computed by modifying the typically used form illustrated in Gonzalez and Woods (2002) to include all directions:

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

(4)

**Soil Types**
Soils have been widely considered in landslide susceptibility mapping studies (e.g., Wieczorek et al., 1996; Gomez and Kavzoglu, 2005). The six primary soil types found within 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 and it is common to see unstable slopes in this soil type, 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 surface feature to map landslides.

**Landslide Classification**
Extracting landslide surface features is the core step in landslide susceptibility mapping. To quantify topographic roughness it is necessary to understand and delineate the characteristics found in landslide morphology. Therefore, a sample set representing these distinct features is necessary. SVM is a supervised classification method that is well established, and known to produce acceptable results in landslide susceptibility mapping (Samui, 2008; Yao, et al., 2008; Marjanovi, et al., 2011; Micheletti, et al., 2011; Ballabio and Sterlacchini, 2012; Tien Bui et al., 2012). 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 single observations with nine dimensions (surface features described earlier) to determine if the observation is representative of landslide activity for each cell in the DEM. If it is, then it is mapped as landslide susceptible, otherwise, it is mapped as stable. Each cell in the DEM is considered a nine-dimensional observation.

Support Vector Machine
SVM was developed by Vladimir Vapnik (1995). The idea of SVM is to determine the optimal hyperplane for linearly separable patterns (see Figure 3). If the patterns are not linear then, the data is 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, thus, lying closest to the decision surface (Tien Bui et al., 2012).

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 a small sample available for training. For these reasons, it was the prime consideration for classification. In general, the SVM algorithm is calibrated through a sample set of two classes enclosing all features desired. The two classes are landslide and stable terrain, and the aforementioned surface features are those used in our case. After calibration is complete, the algorithm is tested on an independent data set to evaluate its performance, a lidar-derived DEM in our case.

Flat Terrain Filtering
Landslides have shown to occur more often on steeper slopes (Gomez and Kavzoglu, 2005). 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 1 illustrates unstable slopes for various types of mass movement taken from Soeters and van Westen (1996).

Given the ranges of slope instabilities in Table 1 and those found in our study area, it was determined that slopes (15° ≥) would be stable.

Conditional Dilation/Erosion Filter
Mathematical morphology is a method used to extract useful features found within an image that characterize shapes of objects (Gonzalez and Woods, 2002). Furthermore, it is helpful in filtering, which is our interest. Two common morphological operations are dilation and erosion. Dilation expands the shapes found within an image, while erosion removes 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 size threshold (Shapiro and Stockman, 2000). 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, see Equation 5:

\[
\frac{\# \text{ of failed cells}}{\# \text{ of total cells in window}} \geq \text{Threshold} \tag{5}
\]

The effect of the window size and threshold were tested and evaluated by having varying window widths between 3 and 21 cells and varying thresholds between 50 percent and 100 percent. After assessing potential thresholds, the most suitable window size and threshold found was 11 × 11 (5 m × 5m) and 60 percent, respectively. 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.

Noise Suppression
The analysis of clusters is a vital component of feature extraction. The importance of this step is to analyze clusters and suppress noise. Small regions do not provide useful information; therefore, they are not of interest and are ignored. The importance of determining a good threshold is so that the noise level 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 landslide or stable given the following criterion:

\[
\text{Cluster Area} \geq \text{Minimum Area Threshold} \tag{6}
\]

The minimum area to be considered landslide susceptible was tested and evaluated by having varying areas of 50 to 250 m². This range was selected after evaluating the minimum size of the mapped landslides provided by the reference inventory map, which was 200 m². After evaluating potential thresholds, it was determined that 150 m² was the most appropriate threshold, for this reason, all clusters less than 150 m² were ignored and considered as noise. The criterion selected will allow for clusters of said size to be mapped as landslide susceptible, additionally, minimizing the probability of small landslides being overlooked.

### Table 1. Slope Instability for Mass Movement Type

<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>
Results

Training Sample Evaluation
To determine characteristics of landslide surface features in the study area, we first select a representative patch of a mapped landslide and stable terrain. We use a section 450 m north of MM9 as representative patches (see Figure 4). The size of the representative patch was 30 × 40 m (1,200 observations) for stable and 60 × 25 m (1,500 observations) for landslide terrain. The representative terrain elected was less than 1 percent of the entire study area. Next, we compute the surface features for each patch of terrain. Figure 5 shows the distribution of the samples elected for each surface feature.

The topographic variability is higher for landslide than stable terrain. These patterns indicate that the landslide surface in our study area tends to experience higher amounts of surface deformation, meaning, it is rougher in texture. Earth processes that can generate such behavior are those of mass movement found in landslides.

The distributions in Figure 5 can be described as follows: the central mark in each box is the median (Q2), the limits of the box are the 25th (Q1) and 75th (Q3) percentiles of the samples, the interquartile range (IQR) is equal to Q3 - Q1, the dashed line (whiskers) extend to the typically used Q1 - 1.5(IQR) and Q3 + 1.5(IQR) range which is about ±2.7 and 99.3 percent of the data, if the data are normally distributed. The remaining samples not lying within these limits are considered outliers (are 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 percent or more of the training samples are linearly separable for all surface features (see Figure 5). It was found that the eigenvalues ratio (see Table 2) 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 (see Table 2) for landslide terrain as described in McKeans 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 5). This behavior is expected as stable terrain will experience lower rates of mass movement, therefore, most stable surface features are expected to express the same behavior.

Classification Performance Evaluation
The mapped locations will vary for each area, which reflects the variation in the topography (see Figure 6A, 6B, 6C, and 6D). Areas that are smooth will go undetected by the proposed algorithm (SW corner Figure 6B, and West section of Figure 6C), while areas that are rough will be mapped as landslide susceptible (East section of Figure 6A, and Figure 6B). The rough areas shown in Figure 6 tend to correspond to those mapped in Figure 7. Additionally, the areas identified as landslide susceptible 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 7).

In our study area, the proposed algorithm is capable of identifying 84 percent of the inventory map landslides (Figure 7A, 7B, 7C, and 7D). This defines that the training samples elected for calibrating the classification model were representative of the landslide terrain throughout the study area, 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 (Figure 7D), a vast majority of the inventory mapped landslides are incorrectly
classified as stable, it is expected to classify incorrectly as the surface roughness is low for this area (see Figure 6D). In order to understand and potentially overcome the limitations further evaluation is necessary beyond the scope of this study.

The algorithm tends to misclassify topographic features with sharp edges or abrupt changes in elevation (SE and NE corner of Figure 7C and SE corner of Figure 7A). 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 (SW corner of Figure 7C, and Figure 6C), bluffs, streams, creeks, and high elevation changes in a short distance. These natural features increase in surface roughness due to erosion and geomorphological events, which cause surface features to mimic those of landslides. Nonetheless, the algorithm also tends to overlook topographic features found within the boundaries of inventory mapped landslides due to insufficient surface roughness or man-made improvements made to the environment. Although, a GIS database was available and can be used to minimize misclassifications generated by the proposed algorithm, it was only used to store geographic information of roads, rivers, creeks, residential development, etc, and the results generated by the algorithm.

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 slides will cause them to smoothen and make them difficult to identify. For example, most of the mapped landslides shown in Figure 7D are mapped incorrectly due to the smooth topography from an older landslide. The removal of landslide features prevents the algorithm from detecting and identifying the mapped landslides in this area.

The performance of the proposed algorithm assessed how well the mapped areas coincide with the mapped landslides (reference) in the study area. The proposed algorithm was able to map a total of 200 locations throughout the study area. One hundred and ten of those identified areas overlapped mapped locations.

### Table 2. Percentiles of Distribution Samples

<table>
<thead>
<tr>
<th>Surface Feature</th>
<th>Stable</th>
<th></th>
<th></th>
<th>Landslide</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q₁</td>
<td>Q₂</td>
<td>Q₃</td>
<td>Q₁</td>
<td>Q₂</td>
<td>Q₃</td>
</tr>
<tr>
<td>Eigenvalues Ratio ln(λ₁/λ₂)</td>
<td>1.15</td>
<td>1.30</td>
<td>1.45</td>
<td>0.38</td>
<td>0.60</td>
<td>0.85</td>
</tr>
<tr>
<td>Eigenvalues Ratio ln(λ₁/λ₃)</td>
<td>2.32</td>
<td>2.47</td>
<td>2.61</td>
<td>1.57</td>
<td>1.80</td>
<td>1.99</td>
</tr>
<tr>
<td>Roughness (m)</td>
<td>0.03</td>
<td>0.04</td>
<td>0.05</td>
<td>0.07</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>Customized Sobel Operator (m)</td>
<td>0.68</td>
<td>0.85</td>
<td>1.17</td>
<td>1.82</td>
<td>2.43</td>
<td>3.29</td>
</tr>
<tr>
<td>Aspect (°)</td>
<td>11.53</td>
<td>13.42</td>
<td>15.75</td>
<td>23.76</td>
<td>40.57</td>
<td>66.51</td>
</tr>
<tr>
<td>Hillshade</td>
<td>0.05</td>
<td>0.06</td>
<td>0.07</td>
<td>0.09</td>
<td>0.10</td>
<td>0.12</td>
</tr>
<tr>
<td>Slope (°)</td>
<td>3.45</td>
<td>4.02</td>
<td>4.79</td>
<td>5.51</td>
<td>6.74</td>
<td>8.47</td>
</tr>
<tr>
<td>Resultant Length of Orientation Vectors</td>
<td>0.35</td>
<td>0.49</td>
<td>0.69</td>
<td>3.91</td>
<td>6.54</td>
<td>10.56</td>
</tr>
</tbody>
</table>

Figure 4. Lidar-derived hillshade map of SR-666, Zanesville, Ohio study area with the entire training sample used to calibrate the SVM algorithm outlined on top, and bottom, for stable and landslide terrain, respectively. The map is displayed in US survey feet for the State Plane Coordinate System, Ohio South Zone.
landslides (reference), providing an accuracy of 55 percent for the algorithm. Additionally, twenty of the misclassified mapped areas were along rivers and creeks crossing the transportation network, which does not include areas along the Muskingum riverbank, thus, accounting for 10 percent of the mapped areas. The reason for these areas being consistently mapped can be attributed to the amount of erosion generated, in turn, creating high surface roughness. Nonetheless, the algorithm was able to identify 67 out of 80 mapped landslides in the inventory map, illustrating that 84 percent of the mapped landslides from the reference were identified. Although some of the mapped areas did not overlap the reference map, they were adjacent to these areas (see Figure 7C). Further analysis is necessary to verify that these mapped areas are indeed not new developing landslides or existing landslides that have developed further. Moreover, additional analysis is required to evaluate why some of the inventory mapped landslides were overlooked by the proposed algorithm. One reason for overlooking mapped landslides (reference) is the amount of surface roughness exhibited within the landslides (see SW corner of Figure 7A, West of road for Figure 7B and Figure 7D). The amount of surface roughness is not sufficient to delineate them from stable terrain. Therefore, these mapped landslides (reference) will go undetected, until enough surface roughness is displayed from experienced mass movement.

Conclusions

Landslide susceptibility mapping using remote-sensing techniques may never completely replace traditional mapping methods of field inspection, aerial photograph interpretation, and contour map analysis. Moreover, the mapping methods presented in this and other studies often rely on objective topographic data that relies on the morphologic expressions in the area studied, and often cannot differentiate between adjacent landslides. However, as the spatial resolution, accuracy, and availability of remote-sensing technology increases, new landslide susceptibility mapping methods will provide efficient tools that can assist traditional methods. The proposed approach quantifies and identifies landslide surface features producing results that can potentially become useful in the prevention of future hazardous events.

Although, the generation of landslide maps remains a subjective and time consuming task, airborne lidar provides new opportunities for mapping the topographic features found in small landslides. Lidar technology has become both more accessible and affordable, and the advancements in airborne lidar have allowed for a new method to map landforms, including landslides, over broad swaths of terrain at higher spatial resolutions and accuracy. To our best knowledge, the literature has not capitalized on airborne lidar-derived DEMs to investigate small landslide susceptibility mapping at sub-meter scales over large
swaths of terrain under land cover. Previous landslide susceptibility mapping investigations have focused on geotechnical mapping evaluations over large landslides (e.g., Van Den Eeckhaut et al., 2005; Booth et al., 2009; Ballabio and Sterlacchini, 2012; Tien Bui et al., 2012). Our study presents a new opportunity to map small failures utilizing airborne lidar-derived DEMs.

This proposed algorithm provides a means to evaluate each cell in the DEM to identify patterns of slope instability over the study area, which covers an area of approximately 3.0 square kilometers. The outputs of the algorithm were tested and compared to an independently compiled landslide inventory map to assess the classification performance. Assuming, that the landslide inventory is complete and accurate, our algorithm was able to identify 84 percent of the landslides in the study area. The findings of this study demonstrate that various types, scales, and deformations of landslide surface features (such as hummocky terrain, scars and displaced blocks of material) can be extracted through the proposed approach and a surface model generated from sub-meter spatial resolution. Although, the local topographic roughness can be exploited through the geomorphological features described, an adequate sample representative of the study area is necessary to train the supervised classification algorithm. It is not foreseen for new landslide susceptibility mapping techniques to replace traditional mapping methods; however, new opportunities can improve the efficiency of landslide susceptibility mapping. Future studies may include; 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 order to quantify the amount of activity observed between landslides, careful monitoring is necessary. It is clear that there are different scales and degrees of surface deformation observed within the landslides throughout the study site. To monitor and quantify the temporal changes, further research is necessary to investigate more quantitative patterns of the surface deformation observed, between the different landslides. However, this task is not time and cost-effective, although, it can be highly effective; it is dependent on the needs to monitor mass movement. The proposed approach allows for a semi-automated, fast, objective surface feature extraction of small landslide topography.

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References

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16.8 APPENDIX F: Manual of the software
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2 Introduction

This software is implemented in MATLAB and provides a complete solution for automated landslide detection. Users can use this software to produce a map that demonstrates identified landslide locations.

For automated landslide detection, we provide users a black box solution. The black box solution is in the form of an input and output format. An overview of the software structure is presented in Table 1. The workflow demonstrated in Figure 1 is controlled by the ArcMap and MATLAB routines described below, e.g. creating the project, initializing parameters/paths, pre-processing and so on.

Table 1: Software Product List

<table>
<thead>
<tr>
<th>Software</th>
<th>Main Tasks</th>
<th>Development Environment and Libraries</th>
</tr>
</thead>
<tbody>
<tr>
<td>ArcGIS data preparation</td>
<td>+ Digital Elevation Model (DEM) generation + Soil map generation</td>
<td>ArcMap 10.2 Required Toolboxes: 3D Analyst Tools Data Management Tools Conversion Tools</td>
</tr>
<tr>
<td>MATLAB data processing</td>
<td>+ Automated landslide detection</td>
<td>MATLAB R2013a Required Toolboxes: Image Processing Statistics Topo</td>
</tr>
</tbody>
</table>

![Figure 1: Workflow](image)

3 Overview of Software Components

All routines/programs of the software are listed in Table 2 based on the order of the workflow.
Table 2: Software List – Automated Landslide Detection

<table>
<thead>
<tr>
<th>Module</th>
<th>Routines/Programs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-processing</td>
<td>ArcMap (DEM &amp; soil map generation)</td>
</tr>
<tr>
<td>M-0 Classification Main.m (mandatory)</td>
<td>svm_classifier_ODOT.m</td>
</tr>
<tr>
<td></td>
<td>rasterread.m</td>
</tr>
<tr>
<td></td>
<td>mspherMc.m</td>
</tr>
<tr>
<td></td>
<td>aspect.m</td>
</tr>
<tr>
<td></td>
<td>roughness.m</td>
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<tr>
<td></td>
<td>hillshade.m</td>
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<tr>
<td></td>
<td>GSobel.m</td>
</tr>
<tr>
<td></td>
<td>gradient8.m</td>
</tr>
<tr>
<td></td>
<td>match_soil_extents.m</td>
</tr>
<tr>
<td></td>
<td>Spatial_Filter.m</td>
</tr>
<tr>
<td></td>
<td>Imageschs.m</td>
</tr>
<tr>
<td></td>
<td>Input_Parameters.mat</td>
</tr>
</tbody>
</table>

4 Software Manual

**Note:** Familiarity on how to set up a project or have a project available is necessary. In the following link is a basic introduction tutorial to ArcMap:
http://www.youtube.com/watch?v=hqHCJUudPvs

4.1 Pre-processing

**ArcMap**

In ArcMap we perform two main functions: The first is to generate a DEM from the point cloud and the second is to generate a soil map. The soil map may be generated from the Ohio Department of Natural Resources (ODNR), Division of Soil and Water Resources (http://www.dnr.state.oh.us/tabid/9073/default.aspx). The steps to generate a DEM and soil map are described in detail in sections 4.1.1 and 4.1.2. Make sure to open ArcMap before proceeding further.

4.1.1 DEM Generation

Given a **bare earth** LiDAR point cloud in X, Y, Z format and in text file format we can generate a DEM as follows:

*Step 1. Connect to directory*

1. Go to the File menu, select Add Data from the File dropdown menu and select Add Data from the Add Data dropdown menu.
2. Go to Connect to Folder as shown below and connect to the directory containing the LiDAR point cloud and soil map.
**Step 2. Import Point Cloud**

1. Go to the File menu, select Add Data from the File dropdown menu and select Add XY Data from the Add Data dropdown menu.
2. Select the folder icon (outlined in red below), then navigate to the point cloud file you would like to load.
3. Select correct file fields for X, Y, and Z, respectively. Typically, field 1 = X, field 2 = Y, and field 3 = Z. Check input file format before adding point cloud.
4. Select OK and the point cloud will load into ArcMap.

**Step 3. Boundary Polygon Generation**

1. Go to the Customize menu, select Extensions from the Customize dropdown menu and turn all extensions on.
2. Go to the Geoprocessing menu, select ArcToolbox from the Geoprocessing dropdown menu, this will open ArcToolbox.
3. Go to the ArcToolbox menu, right-click on ArcToolbox, select Add Toolbox…
4. Navigate to the lastools folder and double-click, double-click on the ArcGIS_toolbox folder to open, select LAStools.tbx, and select open. This will load the LAStools toolbox into the ArcToolbox menu.
5. Go to the ArcToolbox menu, select LAStools, and select lasboundary.
6. Click on the folder in the option input file, and then navigate to the desired point cloud to create a boundary. This file is the point cloud loaded previously in step 1.
7. Since all points are bare earth, use (optional) can be set to all_points.
8. Select output format (optional) to be .shp
9. Select output file (optional) and name file to be output.
10. Select output directory (optional) to save file.
11. Select output appendix (optional) to save file.
12. Once all options are chosen select OK.
13. Go to the File menu, select Add Data from the File dropdown menu and select Add Data… from the Add Data dropdown menu.
14. Navigate to the boundary file created and load into the database.

**Step 4. DEM Generation**

1. Go to the ArcToolbox menu, select 3D Analyst Tools, followed by Raster Interpolation, and finally select Kriging. Kriging will be the interpolation method used to interpolate the irregular point cloud into a gridded DEM.

2. Select the Input point features drop down menu with the LiDAR data to interpolate (same as the one used to create the boundary).
3. Select the Z value field of the point features file
4. Select or create an Output surface raster. This will direct you to enter the path\file to save the output raster as.
5. Input the Output cell size *(The cell size should be approximately the average spatial resolution of the bare earth LiDAR point cloud).*
6. Select OK
7. Please stand by as the DEM is generated.
Step 5. Clip Raster File to Match Boundary Extents

1. Go to the ArcToolbox menu, select Data Management Tools, followed by Raster Processing, and finally select Clip.

2. Select Input Raster (raster file to clip)
3. Select Output Extent (optional) and navigate to boundary file
4. Select Use Input Features for Clipping Geometry (optional). This will clip the DEM to the extents of your boundary.
5. Select Output Raster Dataset (select location and file name of output file)
6. **Select OK**

**Step 6. Output Raster in ESRI ASCII Gridded Format**

1. Go to the ArcToolbox menu, select Conversion Tools, followed by From Raster, and finally select Raster to ASCII.

2. Select Input raster (raster file to convert)

3. Select Output ASCII raster file (select location and file name of output file)
4. Select OK.

DEM in ESRI ASCII gridded file format has been generated and is ready for MATLAB input.

4.1.2 Soil Map Generation

Note: Need to create a soil map or have a soil map available for your site. The assumption is that the soil map is a polygon feature type.

Step 1. Load soil map shape file into the database (If it is not loaded already)

1. Go to the File menu, select Add Data from the File dropdown menu and select Add Data… from the Add Data dropdown menu.
2. Navigate to soil map to load into the database.
3. Select OK.

Step 2. Format Soil Map

1. Go to the Table of Contents, select the soil layer to format, right-click the soil layer to format, and open the Attribute Table.
2. Select the option circled in red below.
3. Select Add Field from the dropdown menu
4. Type in a Name and leave Type as Short Integer.
5. Once the field is added go back to the soil layer in the table of contents (table of contents outlined in red) and right click, select Edit Features, then select Start Editing.

6. In the Start Editing window select the soil layer to edit and select Continue (Depending on the version of ArcMap, this may not pop up).

7. Go back to the Table of Contents and Open Attribute Table. Label "1" for "Bkf" soil type and assign arbitrary numbers for all non "Bkf" soil type, meaning each non “Bkf” soil type will get its own arbitrary number. This will be performed to the new field added.

8. Once you are done labeling then go to the Editor toolbar and select Editor, then select Stop Editing.

Step 3. Convert polygon to raster

1. Go to the ArcToolbox menu, select Conversion Tools, followed by To Raster, and finally select Polygon to Raster.
2. Select Input Features (Soil map polygon)
3. Select Value field (field of labeled soil types). This should be the field you created in step 2
4. Select Output Raster Dataset (select location and file name of output file)
5. Select Cellsize (optional) (this needs to match cell size of the generated DEM)

Step 4. Clip Raster File to Match Boundary Extents

1. Follow the procedure of step 4 in section 4.1.1 up to step 5.
2. Select Environments…, followed by Processing Extent, and finally Extent.
3. Select the corresponding DEM file to the soil map. This will match the extents of the DEM and soil map.
4. Select OK
5. Select OK
Step 5. Output Raster in ESRI ASCII Gridded Format

1. Follow the same procedure as step 5 in section 4.1.1.

Soil map in ESRI ASCII gridded file format has been generated and is ready for MATLAB input.

4.2 Module 0 – Classification

Main.m

1. Navigate to the MATLAB software and open by selecting and/or double clicking. Once MATLAB is open, go to the Home menu, select Open from the Home dropdown menu. Then navigate to the Main.m file and open.

2. Go to the Home menu, and select Set Path from the Home dropdown menu. The Set Path pop up window will be displayed as shown below.

3. Select Add with Subfolders, and navigate to topotoolbox folder and select folder, finally Select Save to add folder. The functions in the topotoolbox can be used now.

4. The user will then need to set up 4 inputs to perform the classification.
There are two inputs that need to be entered manually into the Main.m file; the grid spacing and units of the DEM. The inputs are outlined in red above.

gs = 1, then 1 unit is the sampling space of the DEM and soil map
units = ‘feet’, then US survey feet is the unit of the DEM and soil map to classify.

5. After entering the inputs manually go to the EDITOR menu, select RUN from the EDITOR dropdown menu.
6. If the directory is not set, MATLAB will ask if you would like it to set the directory to where Main.m file is located. Select Change Folder as shown below.

7. There will be two popup windows requesting Select File to Open:
a. In the first pop up window, one will select the DEM file. Navigate to that file and select the DEM to load.

b. In the second pop up window, one will select the soil map file. Navigate to that file and select the soil map to load.

8. Please make sure to follow the prompts in the Command Window (outlined in red above). There will be a question to answer and/or any errors shown.

9. Output files will be saved in the same root directory containing the source files. The classification will be performed and two output files will be generated:
   a. This text file will contain the easting and northing coordinates of flagged landslides. The name will be the same as the DEM file name, but with an added extension of “_Flagged_Locations.txt”.
   b. This figure will contain an image of the flagged landslides. The name will be the same as the DEM file name, but with an added extension of “_Flagged_Locations.png”.

The text file containing the horizontal locations of the identified landslides can be uploaded to ArcMap by performing the procedure in step 1 of section 4.1.1.

5 Summary

1. Pre-processing
   a. DEM Generation
   b. Soil Map Generation

2. Module 0 - Classification
   a. Main.m

6 Software Guide

Project root folder must contain all source files to run this project.