

**ENHANCING LANDSLIDE
INVENTORYING, LIDAR HAZARD
ASSESSMENT AND ASSET
MANAGEMENT**

Final Report

SPR 786



Oregon Department of Transportation

ENHANCING LANDSLIDE INVENTORYING, LIDAR HAZARD ASSESSMENT AND ASSET MANAGEMENT

Final Report

PROJECT SPR 786

by

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16. Abstract Landslides are frequent hazards that result in major economic, environmental and social impacts for operation, maintenance and construction of highways. Current landslide databases are limited and often fragmented since they are based on a variety of inventories/geologic maps from various sources, which have been mapped sporadically over time as funding permits. Recent geospatial technologies such as lidar provide detailed geomorphologic information of the topography that significantly improves the accuracy of landslide mapping, particularly in forested terrain where these features can be masked by vegetation. This research significantly modified and improved the Contour Connection Method (CCM), a semi-automated approach to mapping existing landslides from digital elevation models to efficiently produce inventories. Supporting GIS-based tools were developed for straightforward implementation of the research. A special paper documenting workflows to utilize the tool for different applications was produced and will be published by the Department of Geology and Mineral Industries. The report also provides a detailed accuracy assessment of the accuracy and limitations of the CCM approach. The methodology was applied to large sections of several highway corridors that routinely experience landslides including US Routes 36 and 126, 42, and 101. The inventories were then integrated with traffic modeling analyses in a risk-based framework to evaluate economic consequences resulting from damages and closure time from the occurrence of landsliding.		
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°F	Fahrenheit temperature	5(F-32)/9	Celsius temperature	°C					

* SI is the symbol for the International System of Measurement

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1.0 INTRODUCTION

1.1 PROBLEM STATEMENT

Landslides are frequent hazards that result in major economic, environmental and social impacts for operation, maintenance, and construction of Oregon highways. Current databases of landslides in Oregon are limited and fragmented since they are based on a variety of inventories/geologic maps from various sources, which have been mapped sporadically over time. Often, when large landslides occur on Oregon highways, there is no information about whether it is a reactivated existing landslide or a new slope failure without performing detailed, costly investigations. Therefore, up to date inventories of landslides and associated hazards are essential to provide baseline quantity, size, and location information for existing landslides - especially for those of which are ongoing. Such knowledge is crucial to support asset management, especially in the wake of significant rain events or strong seismic activity (e.g., Cascadia subduction zone event).

Despite their impact, maps and inventories of existing landslides are challenging, time-consuming, and expensive to produce. Many current landslide mapping techniques do not have sufficient accuracy, resolution or consistency for inventorying landslide deposits on a landscape scale. Fortunately, recently popularized lidar data may be used to derive digital elevation models (DEMs) that provide sufficient accuracy and detail to start inventorying regions subject to landslides that surround Oregon highways. These high resolution DEMs can reveal the landscape beneath vegetation and other obstructions, highlighting landslide features, including scarps, deposits, and fans. Furthermore, such DEMs are scheduled to be available for the entire state of Oregon in coming years (e.g., USGS 3D Elevation Plan, 3DEP), with critical highways likely to be the first mapped areas. However, use of lidar for landslide inventorying, risk assessment, and management prioritization is primarily reliant on the subjective interpretation of individual geologists. The expertise of geologists certainly may provide improved manual landslide inventories, but it also introduces inconsistency and is limited by a pace that is not sufficient to accommodate ODOT's large network of managed right-of-way traversing a dynamic landscape. In order to improve large-scale asset management strategies in context of unstable slopes, it is desirable that a consistent and automated landslide inventorying approach be developed and employed by ODOT.

1.1.1 Study Area

Because Oregon has high topographic relief, high rainfall, and active tectonics, landslides are scattered across the rugged terrain. Figure 1.1 shows the extents of the study area analyzed in this report, consisting of sections of Oregon Routes 36, 42, and 126 within the Oregon Coast Range, and the segment of U.S. Route 101 in Curry County. These highways are critical to the economic and social well-being of coastal communities, but are often subject to road closures and repeated maintenance due to regular landslide activity, particularly in winter months. Much of this landslide activity stems from particular ongoing slope failures that require frequent maintenance.

However, there are also numerous other historic, active landslides that have a high potential of affecting the function and safety of ODOT's infrastructure. It is essential to not only inventory these past slope failures, but also to investigate their proximity, and possible threats, to infrastructure.

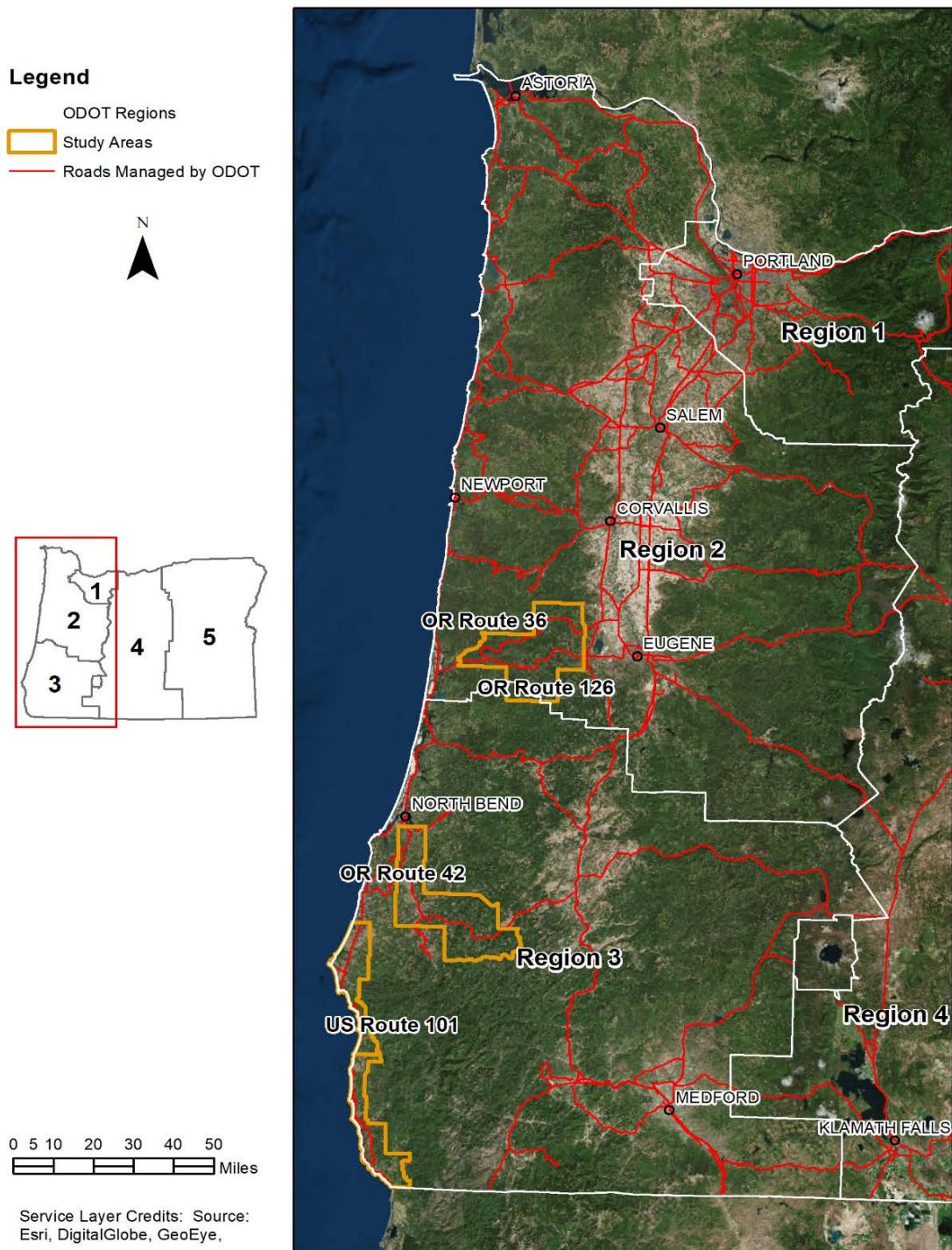


Figure 1.1: Overview of study areas in Western Oregon.

1.2 COMPONENTS OF THIS STUDY

Lidar-derived DEMs play an ever-increasing role in mapping landslides, but a level of automation is necessary to sufficiently and systematically inventory ODOT's large road network for improved allocation of resources, asset management, operations, and construction. This study has developed an advanced risk and hazard mapping framework for prioritizing landslide mitigation and management efforts. The framework expands the Contour Connection Method (CCM, Leshchinsky, Olsen, & Tanyu, 2015) to consistently detect landslide deposits on a landscape scale using publicly-available lidar data. It also considers risk posed by these landslides to adjacent infrastructure as well as economic losses. A variety of deliverables have been developed for efficient, immediate implementation of this framework by ODOT engineers.

The key components of this report and accompanying deliverables include:

A literature review documenting landslide hazards in Oregon, and summarizing existing approaches to landslide inventory, hazard and risk mapping.

Description of modifications made to CCM to improve mapping efficiency and applicability to a wider amount of terrain. The CCM tool is provided with this report.

Assessment of accuracy of the CCM tool in comparison to manual landslide inventories.

Landslide maps for three major ODOT corridors in western Oregon. Geographic Information Systems (GIS)-compatible landslide layers in a geodatabase are provided along with this report.

Spatial analysis of CCM-mapped landslides along ODOT right-of-way.

Description of risk-based approach to assess the impact of landslide reactivation along highway corridors, provided with analyses that provide estimates of closure costs and delays for each preselected ODOT corridor. GIS-compatible risk tools are provided alongside this report.

In addition to these products included with this report, a Special Paper publication (Bunn, 2018) is in production by the Department of Geology and Mineral Industries (DOGAMI) that provides detailed descriptions and workflows to apply the CCM tool to generate various types of landslide inventories to support a wide range of needs.

Key objectives of this report include:

1. Describe advancements made to the CCM algorithm to be more computationally efficient and effective in the mapping of landslide deposits in a variety of terrains.
2. Evaluate the accuracy of the CCM approach compared with manual inventories at select locations.
3. Provide tools that ensure straightforward application of the CCM algorithm.
4. Create and analyze landslide maps along predefined ODOT corridors to provide insight into the potential impacts of landslide reactivation along State right-of-way.

5. Create and describe a risk-centric framework for assessing the potential impacts of landslide reactivation, both in terms of closure times and economic impacts.
Demonstrate applicability across three critical ODOT corridors.
6. Create a DOGAMI Special Publication outlining the application of CCM as a supplement for manual landslide mapping by experts.

1.3 PROJECT SIGNIFICANCE AND LIMITATIONS

This project has resulted in a unique, computationally-efficient tool for landslide mapping on a large scale. This tool has significant utility, particularly when leveraging quality datasets such as high-resolution lidar, as it supplements and expedites the manual landslide mapping process. The landslide maps are particularly useful for assessing potential impacts of landslide reactivation along highway corridors, enabling enhanced planning and prioritization along infrastructure with large spatial extents. However, when landslide inventories are used for regulatory or zoning purposes, it is important that mapped landslides are subject to the expert judgment of trained professionals, regardless of how the mapping was performed.

This project demonstrates, perhaps unsurprisingly, that there are a significant number of landslides on the Oregon Coast and in the Oregon Coast Range, including many that traverse ODOT right-of-way. However, prioritization and planning around such an extensive number of hazards is daunting as there is often limited resources available. A starting point in planning mitigation procedures, however, is first understanding the relative scale of potential hazards. Use of the revised CCM approach provides a means of effectively estimating this relative hazard along ODOT right-of-way, particularly when overlaid with multiple relevant datasets in a GIS framework. Future work may better capture the relative probability of slide reactivation or movement to provide enhanced prioritization, particularly considering the large number of landslides encountered in proximity to state highways.

This project has resulted in the development of a new approach towards assessing the risk towards infrastructure associated with landslide reactivation, including closure costs, soil cut/fill volumes, and rerouting costs – to the authors’ knowledge, this has not been done using landslide maps before. This original approach provides a unique means of using knowledge of the required embankment geometry (stated in the ODOT Geotechnical Design Manual, GDM) leveraged with lidar topographic data and landslide inventories to provide estimates of volumes of soil that must be cut – or filled - to regain highway access in the case of landslide reactivation. These volume estimates can be coupled with (1) estimates of material costs attained from ODOT’s “Unstable Slopes” database or (2) closure costs associated with construction or excavation time (validated with an internal database of landslide closures) to provide direct estimates of economic impacts stemming from landslide reactivation. Of particular interest is the use of ODOT Transportation Planning and Analysis Unit (TPAU) data to estimate the potential financial costs of landslide reactivation from a commerce perspective. This approach is promising as it provides the basic framework for ODOT to begin an assessment of “what-if” scenarios regarding landslide impacts on state highways – valuable for planning purposes and enhancing infrastructure resilience. Future work could further enhance the proposed planning tool by accounting for possible material transport costs/time, creating more robust estimates of how supply-chain networks would be affected by hypothetical landslides, and perhaps most practically, assisting in strategic

allotment of material and equipment stores statewide to enable expedited recovery from landslide closures following an extreme event.

2.0 LITERATURE REVIEW

2.1 OVERVIEW

This literature review evaluates the current state of the art methodologies for landslide inventorying and classification with their associated advantages and disadvantages. These observations were used to further develop the CCM algorithm (Leshchinsky et al., 2015) and develop the risk-based framework. This review also introduces relevant landslide dangers in Oregon.

The review begins with the definition of landslides and landslide types followed by a description of landslide hazards in Oregon. Next, we summarize existing landslide inventorying methodologies as well as a discussion of landslide hazard and risk mapping. Finally, we close with a description of challenges that guided the work in this report.

2.2 INTRODUCTION TO LANDSLIDES

Landslides can occur under a variety of circumstances, including heavy rainfall, the presence of weak surficial soils, ground slope, and seismic loading (Cornforth, 2005). Anthropogenic modifications, such as roadway cuts or the placement of fills, can also contribute to landslide occurrence. Landslides also tend to re-occur at locations where a previous landslide has occurred. Expectedly, any combination of these factors tends to exacerbate landslide hazard through increased occurrence, although the exact influence of these factors is poorly understood.

Cruden (1991) defines landslides as a movement of a mass of rock, earth or debris down a slope. Although simply defined here, this downslope movement is a very complex geohazard that can take many forms. Cruden and Varnes (1996) classify landslides into five types (Table 2.1, Figure 2.1): *Falls, topples, slides, spreads and flows*. These type classifications are based on characteristics of the material, water content, and movement rate.

Table 2.1: Summary of Landslide Movement Types (Modified from Cruden, 1996).

Movement Type	Material	Water Content	Rate	Example in Figure 2.1
Fall	Rock	Dry	Extremely rapid	D, G
Topple	Soil	Moist	Very rapid	E
Slide	Earth	Wet	Rapid	A, B, C
Spread	Debris	Very wet	Moderate	J
Flow	-	-	Slow	F, H, I

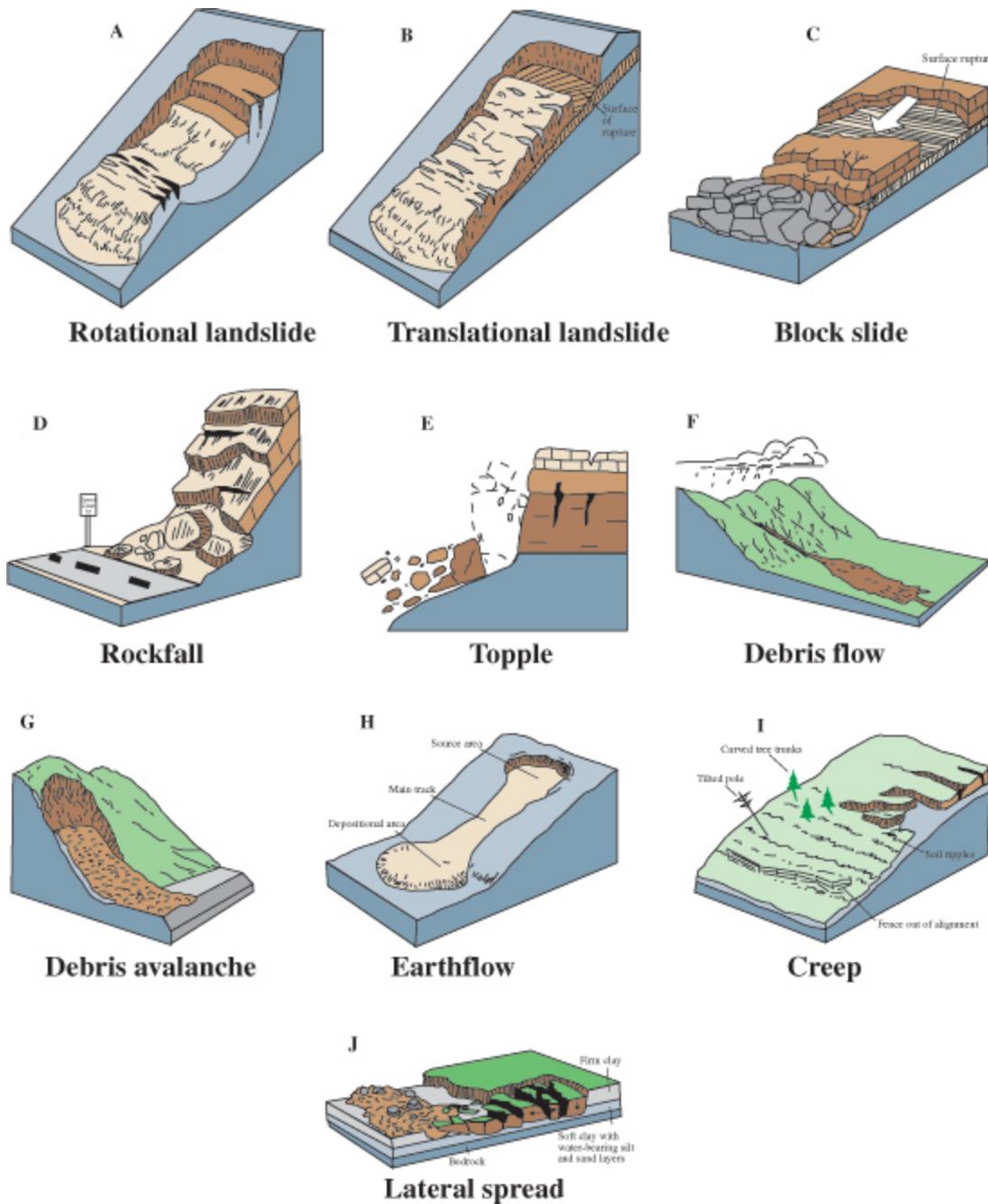


Figure 2.1: Illustrations of various landslide types (from Highland, 2004).

Slides occur when masses of earth displace upon surfaces experiencing high shear strain. The geometry of these sliding surfaces, also referred to as the surface of rupture or failure planes, can usually be broken into one of two groups: rotational or translational. Rotational slides have curved failure surfaces and tend to reach greater depths; whereas, translational slides have planar failure surfaces and tend to be shallow in nature. The upper extent of rotational and some translational slides can be defined by a steep face of undisturbed soil known as a scarp, while the lower extents are typically comprised of displaced and disturbed material known as deposits.

Under certain conditions, it is also possible for slide deposits to transition into flow movements. Any combination of landslide types, such as this example mentioned here, may also be referred to as a *complex landslide*.

It is important to acknowledge that all types of movement included in Table 2.1 significantly affect infrastructure; however, fundamental differences between each type mean that no single engineering solution may be applied to all types. Current engineering methodologies exist for the assessment, and sometimes mapping of, *fall*, *topple*, and *spread* hazards (Pierson, 1991; Pierson, Gullixson, & Chassie, 2001; Youd, Hansen, & Bartlett, 2002), but they are not the focus of SPR-786. The approach undertaken in this research focuses on landsliding associated with *slides* and *flows*.

2.3 LANDSLIDE HAZARDS IN OREGON

The geology and climate of western Oregon are responsible for creating significant landslide hazards, particularly in the Oregon Coast Range. This risk can be explained in large part by the correspondence of high susceptibility (e.g., weak, weathered soils or rock) and high precipitation (e.g., quantity, rate, duration) (Olsen et al., 2015). The Oregon Department of Geology and Mineral Industries (Burns, 2016) recently published a new, statewide landslide susceptibility map (Figure 2.2). When these high to very high susceptibility conditions throughout the Coast Range and Cascades are exposed to substantial volumes of rainfall, the risk of landslides becomes large and results in the frequent occurrence of damaging slides. Landslides often impact highway infrastructure and result in closures for removal of debris and or repair. The major landslides of the winter season of 2015-16 are summarized in Table 2.2.)

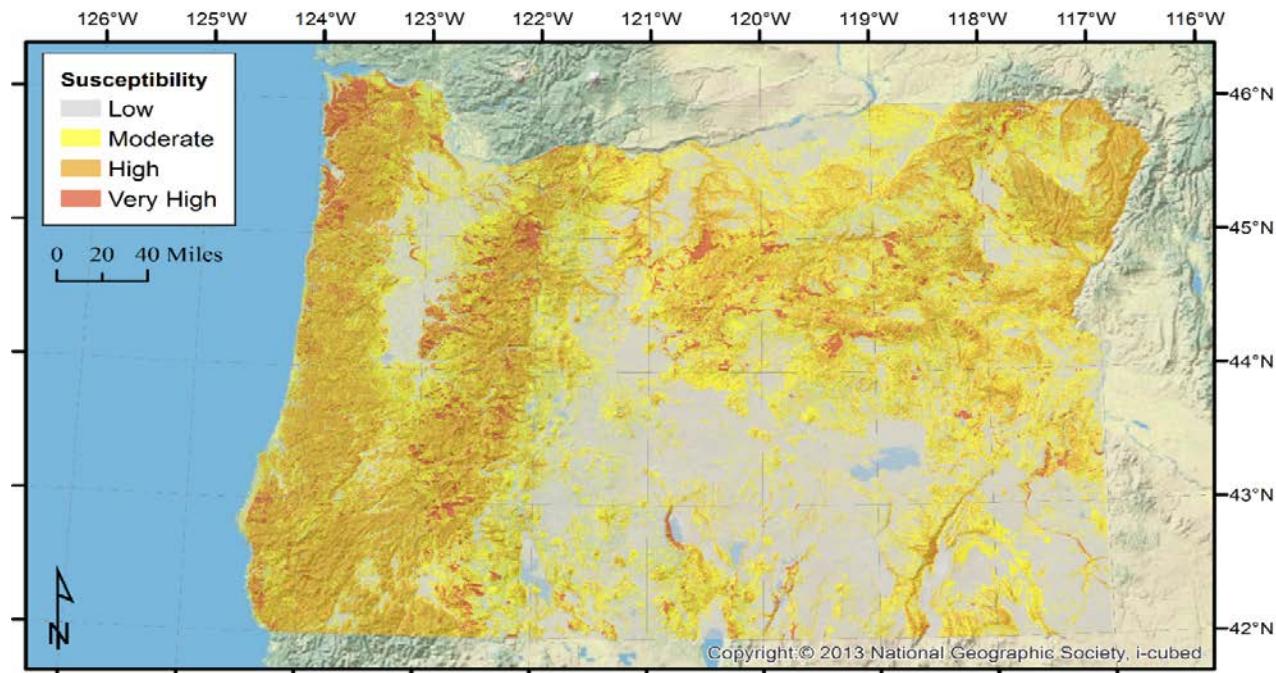


Figure 2.2: Landslide susceptibility map of the state of Oregon (from Burns, 2016)

Table 2.2: Sampling of Major Landslides in Oregon, Winter Season 2015-16.

Date	Location	Description	Reference
12/8/2015	Portland	Landslide causes closure of Cornell Road	Oregonian 2015a
12/8/2015	Portland	Landslide temporarily closes US 30	KPTV 2015
12/18/2015	Florence	Landslide destroys home, killing one person	Oregonian 2015b, 2016a
12/23/2015	Oregon City	Recurring landslides require the evacuation of several apartment units, and water and power shutoff to dozens more	Oregonian 2015c, 2016a
12/23/2015	Douglas and Coos County	Landslide closes Oregon 42 for one month, costs an estimated \$5 million to repair	Oregonian 2015d, 2016a
1/28/2016	Brookings	Landslide and sinkhole destroy US 101	Oregonian 2016b
2/28/2016	Heceta Head	Landslide causes closure of US 101	Oregonian 2016c
3/12/2016	Triangle Lake	Landslide causes closure of Oregon 36	KVAL 2016

Landslide events, such as those in Table 2.2, cost Oregon an average of more than \$10 million annually, with losses from particularly severe winter storms having cost more than \$100 million (Burns, 2009). As an example, in March 2011, winds and heavy rains resulted in nearly \$6 million in damages to state highways (The Curry County Natural Hazards Mitigation Plan (University of Oregon, 2016)).

In recent decades, efforts have been made by government agencies, such as the Oregon Department of Geology and Mineral Industries (DOGAMI) and the Oregon Department of Transportation (ODOT), to reduce these costs. One approach taken by these agencies has been to map (inventory) previously occurring landslides throughout the state. The most current form of these statewide inventories has been compiled by DOGAMI as the Statewide Landslide Information Database for Oregon (SLIDO).

SLIDO is a collection of numerous layers of geospatial and geological data that includes locations of historic landslides, extents of landslide features, landslide photographs, and attributes for many of the landslides. Only parts of the state have been mapped in SLIDO, and Figure 2.3 shows the distribution of mapped landslide features across the state of Oregon. Creation of landslide inventories using lidar within SLIDO is documented by Burns and Madin (2009) in DOGAMI Special Paper 42, and will be discussed further in a later section of this review. Note that lidar-derived landslide mapping has only been completed and included in SLIDO at a limited number of strategic locations. In these locales, the high resolution terrain models have enabled a significant number of landslides to be detected.

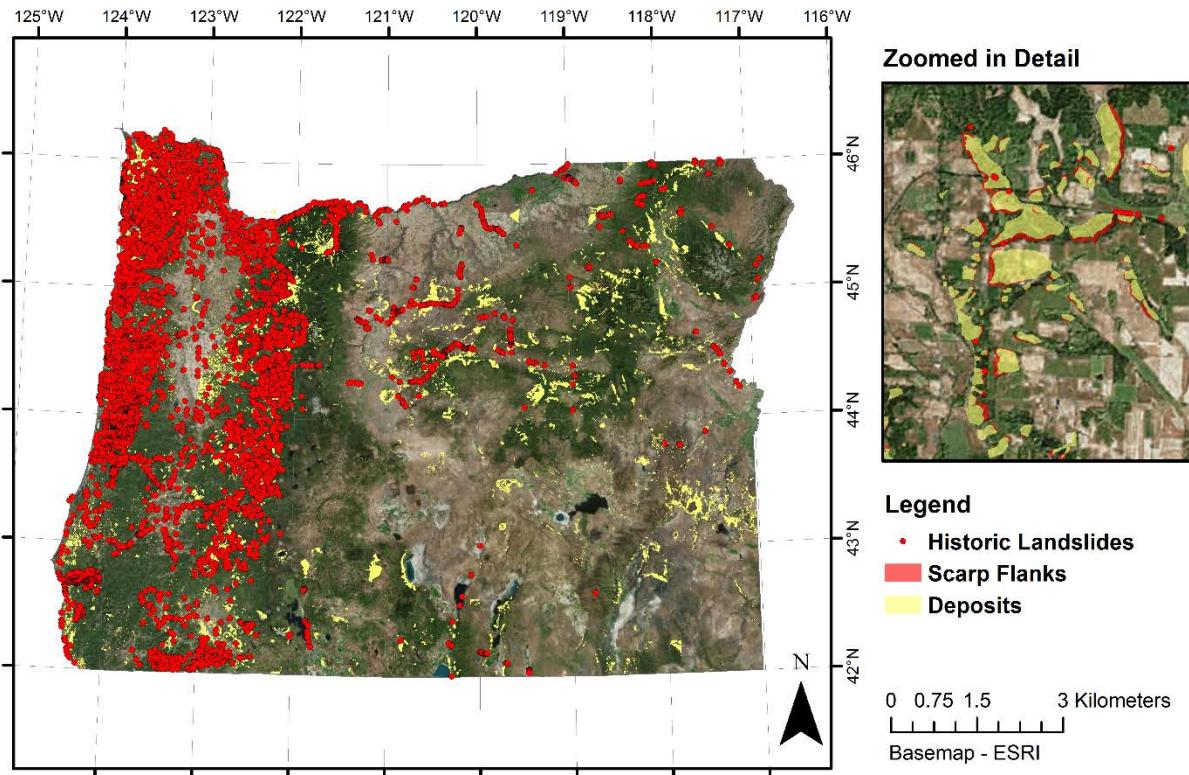


Figure 2.3: Mapped landslide features in SLIDO (version 3.2).

2.4 LANDSLIDE MAPPING

The aforementioned SLIDO database is an example of a landslide inventory map. Landslide maps are created with the purpose of displaying the location of landslide hazards. They are useful for community planning, as well as communicating hazards with the public (Cornforth, 2005). There are four major categories of landslide mapping (Highland & Bobrowsky, 2008). The first is inventory mapping, which identifies the spatial extents of previously occurred landslides. SLIDO is a collection of inventory maps. The second category is susceptibility mapping, which examines the factors behind failures on an inventory map, identifies the factors that contribute most to landsliding, and then maps susceptible areas based on these factors. The final two categories are hazard and risk mapping, which incorporate the findings of both previous categories, sometimes with theoretical models, to predict the severity and extent of landsliding. These can be based on specific scenario events.

2.4.1 Inventory Mapping

Landslide inventory maps are simply the mapped spatial extents of past landslide occurrences. Their purpose is to provide background for landslide hazard and risk assessment, to investigate the distribution, types, and patterns of landslides, and to study landscape evolution (Guzzetti et al., 2012). Despite this simple definition, performing landslide inventories can be a challenging task. Hence, in recent decades, significant research has been oriented toward the improvement of

inventory mapping procedures to utilize advances in technology. This section will review existing landslide inventorying methodologies beginning with manual, non-lidar approaches, continuing through semi-automated non-lidar approaches, and ending with both manual and automated lidar approaches.

2.4.1.1 Manual, Non-Lidar Methods

Wills and McCrink (2002) compared two common landslide inventorying methods of the time, aerial photograph interpretation and topographic map interpretation, with large-scale field mapping. The inventory mapping was performed on a mountainous and heavily forested 7.5 minute quadrangle for the purpose of gaging the effectiveness of either method, given the assumption that field mapping would capture the “true” location of landslides. What they found was that the aerial photograph interpretation identified 58 percent of the landslide area mapped in the field and that the contour map interpretation identified a similar result of 57 percent. Wills and McCrink (2002) primarily attributed the lack of correspondence to the presence of dense forest cover that prevented the identification of landslide features. Further, when landslides identified through either interpretation method did align with those identified during field mapping, the interpretation-based maps lacked the detail to distinguish between landslide features (i.e. scarp and deposits).

In addition to the accuracy of mapping landslides, Wills and McCrink (2002) compared the effort required to produce each type of inventory map. While both interpretation techniques produced results of similar accuracy, the contour map interpretation took approximately one-tenth of the time needed for aerial photo interpretation. Additionally, the field mapping took approximately ten times the amount of time required to perform aerial photo interpretation.

2.4.1.2 Semi-Automated Non-Lidar Methods

As evidenced by Wills and McCrink (2002), the speed at which manual landslide inventorying can be performed is an important limitation. The availability of digital information in the form of multi-spectral satellite imagery has led to the development of a number of automated methods for landslide inventory mapping.

Borghuis, Chang, and Lee (2007) presented two approaches for landslide inventory mapping based on the classification of multi-spectral imagery for a mountainous and forested region in Taiwan. An automated classification was performed using 10 m SPOT-5 multi-spectral satellite images to extract landslide signatures from pixels within the extents of previously mapped landslides. Alternatively, a manual classification was performed that involved the visual interpretation of 2.5 m SPOT-5 supermode imagery and a normalized difference vegetation index (NDVI) layer. Following their study, Borghuis et al. (2007) found that the automated classification identified 63 percent of the landslide area identified manually, and performed far better than the manual classification at identifying the extents of small landslides, but was marred by identifying features such as roadways and riverbeds to also be landslides.

A more complex approach was presented by Martha, Kerle, Jetten, van Westen, and Kumar (2010), who combined 10 m Cartosat-1 digital surface models with 5.8 m resolution multi-spectral imagery from the Indian Remote Sensing Satellite P6 to map landslides in a rugged and mountainous region of India. Landslides were identified from NDVI values indicative of disturbed terrain. False positives were then determined and removed using an object oriented, as opposed to pixel-based, analysis that considered spectral, morphometric, and contextual information regarding each landslide. Landslide class (i.e., shallow translations, flow, etc.) was then determined from the remaining landslides based on topographic shape criteria. The result was that Martha et al. (2010) were able to identify 76.4 percent of landslide areas determined through manual photo interpretation, while also identifying five different landslide classes.

2.4.1.3 Manual Lidar Methods

A limitation of many of the previously mentioned techniques is that they cannot adequately penetrate a dense, forest canopy such that the ground surface can be identified to sufficient detail. Another limitation is the spatial and temporal resolution of the data. Lidar technology overcomes many of these limitations and is ideally suited for landslide inventory processes (Burns, 2009). Furthermore, the previously mentioned techniques only consider two dimensional images, and provide limited information about the shape of landslides. The use of lidar incorporates elevation, allowing for the addition of a third dimension. A detailed discussion of the background of lidar technology, how it works, and an introduction to its applications for landslide identification can be found in the review work of Jaboyedoff et al. (2012).

For the purposes of this document, two example methodologies for identifying past landslides provide sufficient background on how lidar can be effectively utilized for landslide inventories. It should be noted that while these methods can be very accurate at identifying landslide features, they are also highly time consuming and require an experienced practitioner to minimize subjectivity.

Schulz (2004) used a 6 foot lidar-derived DEM to manually identify landslides in highly-vegetated and urban Seattle, Washington. Identification was aided by orthorectified aerial photographs and numerous additional lidar-derivatives, including hillshades of varying sun azimuth, ground slope, and a 2 m contour map. The different forms of data were then evaluated to locate morphological features of interest, including headscarsps, hummocky terrain, and convex and concave slopes, from which landslides were identified. The method correctly identified the locations of recorded historic landslides, while also identifying many landslides that had previously gone unnoticed.

In their documentation of the development of SLIDO, Burns and Madin (2009), or DOGAMI Special Paper 42, discuss a similar methodology to Schulz (2004), while also introducing a framework for tabular data that may accompany mapped features. This supporting data includes the landslide types and other attributes (Table 2.3). The additional information provided by this framework may serve as an important resource for future research, but it is important to understand that not all of the data presented in Table 2.3 has been provided for each landslide mapped in SLIDO. DOGAMI Special

Paper 42 is the standard practice followed in Oregon for landslide inventory mapping and has been adopted by other states.

Another limitation with the use of lidar data is that data are not yet available statewide. The status of lidar data collection in Oregon is presented in Figure 2.6. Note that a current, national initiative, the 3D-Elevation Plan (3DEP) has targeted acquiring continuous lidar data for the conterminous United States. The Oregon Lidar Consortium (OLC), led by DOGAMI, has been coordinating these efforts between agencies in Oregon.

Table 2.3: Examples of Tabular Data Fields Included in the SLIDO Geodatabase (from Burns, 2009).

Field Name	Brief Description
TYPE_MOVE	Type of movement
CONFIDENCE	Confidence of identification
AGE	Estimated age
DATE_MOVE	Date of last known movement
GEOL	Geologic unit
SLOPE	Adjacent slope angle
FAIL_DEPTH	Failure depth, estimated and/or calculated slope normal thickness of failure depth
FAN_HEIGHT	Change in elevation from top to toe of fan
FAN_DEPTH	Estimated and/or calculated fan depth
DEEP_SHAL	Deep or shallow seated
DIRECT	Direction of movement
AREA	Area of landslide deposit
VOL	Volume of landslide deposit

2.4.1.4 Automated Lidar Methods

Manual landslide mapping using lidar data is both expert-based and time consuming. For these reasons, research efforts have aimed to develop computer algorithms that simulate human interpretation to improve the speed and efficiency of the mapping process.

Automated methods using lidar typically come in one of two forms, pixel-based or object based. Pixel-based classifies individual pixels of a lidar DEM, while object-based group pixels together, typically through image segmentation, to form objects that are then classified.

Using lidar data from much of the area studied by Schulz (2004) in Seattle, Washington, and additional data for the Tualatin Mountains, near Portland, Oregon, Booth, Roering, and Perron (2009) developed a pixel-based identification technique using the roughness of deep-seated landslides based on two-dimensional discrete Fourier transforms and two-dimensional continuous wavelet transforms, both spectral, performed on a lidar DEM. The purpose of both transforms was to determine wavelengths that could then be

compared with topographic wavelengths empirically determined to be representative of landslide features.

Another pixel-based approach, focused on roughness, came from Berti, Corsini, and Daehne (2013). They identified six geomorphologic units in their terrain, each with unique roughness characteristics, and implemented an approach similar to what Booth et al. (2009) applied to a single DEM, but for their six geomorphologic units.

An object-based alternative was presented by Van Den Eeckhaut, Kerle, Poesen, and Hervás (2012). The area considered consisted of vegetated hills in the Flemish Ardennes of Belgium. Landslides were mapped through the segmentation and classification of a lidar DEM. Segmentation was performed by implementing region grow and image binarization algorithms to identify and group cells of similar texture and to locate abrupt terrain changes. Segmented features were then classified as landslide scarps or bodies based their ground roughness, slope, plan view curvature, and several other variables.

A similar approach to Van Den Eeckhaut et al. (2012) was presented by Li, Cheng, Chen, Chen, and Liu (2015), who utilized similar machine learning techniques, but this time to study rugged, mountainous terrain. Acknowledging that mountainous terrain serves to disrupt traditional landslide signatures, Li et al. (2015) departed from Van Den Eeckhaut et al. (2012) by allowing greater scaling of landslide objects during segmentation and using a probabilistic approach for grouping nearby objects rather than the Van Den Eeckhaut et al. (2012) reliance on adjacency of like classes.

Another object-based lidar approach came from Leshchinsky et al. (2015), who presented the Contour Connection Method (CCM), which uses the shape of topographic features to locate past landslides. Full resolution of most lidar-derived DEMs is typically unnecessary, making CCM less influenced by noise in the scan itself or defects in the DEM. CCM first identifies landslide scarps based on an upper slope threshold, then moves downslope until a lower slope threshold is reached. Computational speed is improved by reducing high resolution DEMs into a mesh of contours with regularly spaced nodes that are connected when acceptable slopes between nodes are achieved. After the algorithm has been implemented, information pertaining to the number of connections to each node and the slope of each connecting line can then be analyzed to reveal distinct signatures for the type of slide that has been mapped.

Table 2.4: Overview of Landslide Inventory Methodologies.

Method	Description	Strengths	Weaknesses	Reference
Lidar				
Manual/ SP42	Landslides are mapped based on the visual interpretation of trained geologists.	-Highly accurate for large features. -Identifies landslide features (<i>i.e.</i> scarps and deposits)	-Time consuming, labor intensive -Requires the work of a trained geologist	Burns (2009); Schulz (2004)
Spectral	Identifies topographic signatures corresponding with manually mapped landslides and locates the same signatures in unmapped terrain.	-Quickly performs mapping - Identifies landslide features with topographic signatures	-Cannot distinguish between overlapping landslides -Requires minimal calibration using manual inventory -Only meant for large, deep landslides -Sensitive to anthropogenic land features (<i>i.e.</i> road cuts, borrow pits)	Berti et al. (2013); Booth et al. (2009)
Object Oriented	Segments map and classifies each segment based on its topographic signature.	-Identifies landslide features (<i>i.e.</i> scarps and deposits) -Quickly performs mapping	-Computationally complex -Requires calibration using manual inventory -Only meant for large, deep landslides	Van Den Eeckhaut et al. (2012)
CCM	A digital elevation model is broken into contours and nodes. Nodes on adjacent contours are connected, and the slope of these connections is identified as belonging to a landslide or not.	-Computationally simple -Identifies landslide features (<i>i.e.</i> scarps and deposits) -Quickly performs mapping -Provides a topographic signature that may be useful for age classification	-Requires calibration using manual inventory -Dependent on the successful identification of landslide scarps -Sensitive to anthropogenic land features (<i>i.e.</i> road cuts, borrow pits)	Leshchinsky et al. (2015)

Satellite Imaging				
Multi-Spectral	<p>Spectral signatures corresponding with manually mapped landslides are identified and used to identify landslides in other similar terrain.</p>	<ul style="list-style-type: none"> -Data is relatively inexpensive and frequently acquired -Quickly performs mapping 	<ul style="list-style-type: none"> -Subject to cloud cover and inconsistent lighting -Requires calibration using manual inventory -Vegetation may have a significant influence on results -Cannot distinguish between overlapping landslides -Only meant for large, deep landslides due to low spatial resolution 	Borghuis et al. (2007); Martha et al. (2010)

2.4.2 Hazard Mapping

Hazard mapping of landslides aims to predict the extents of hazard exposure and the associated characteristics of a given hazard. In its deterministic form, hazard mapping seeks to estimate magnitude of potential displacements, estimate a factor of safety against failure, or provide an index of hazard, and may be adjusted to be probabilistic. Table 2.5 summarizes statistical approaches that have been used to determine the probability of a specific quantified hazard being exceeded. These approaches require a priori knowledge to identify and separate parameter values associated with landslide occurrence from those associated with non-occurrence. The statistics associated with occurrence for each parameter are then generalized to produce a probability for the entire system.

An example of probabilistic, seismically-induced landslide hazard mapping in Oregon comes from SPR-740 by Olsen et al. (2015), who applied a framework similar to the Saygili and Rathje (2008) landslide hazard framework (Figure 2.4). Olsen et al. (2015) developed probability distributions for input parameters, and incorporated them into a Newmark (1965) physical model. While knowledge of the occurrence or non-occurrence of landslides (i.e. inventory maps) is not used directly, it is necessary for developing the probability distributions and back analyzing material strength. Alternatively, Pradhan and Lee (2010) used a logistic regression analysis to produce rainfall-induced landslide hazard maps. Their approach lacks a physical model and directly incorporates the occurrence/non-occurrence to develop a weighted equation for probability.

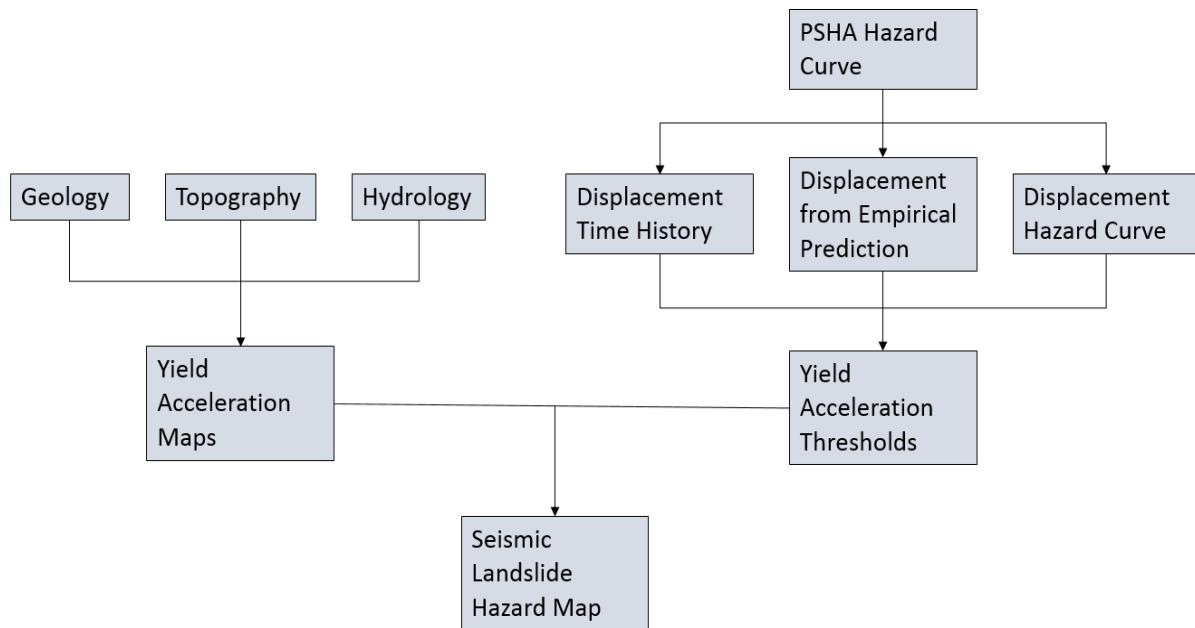


Figure 2.4: Landslide hazard framework of Saygili and Rathje (2008).

Table 2.5: Summary of Probabilistic Approaches Used in Landslide Hazard Mapping.

Method	Type	Short Description	Reference
Monte Carlo simulation	Numerical Analysis	Given a probability distribution of input variables, values are randomly selected and analyzed until a probability distribution of outputs has been developed.	Luzi, Pergalani, and Terlien (2000); Refice and Capolongo (2002); Soeters (1996); Zhou, Esaki, Mitani, Xie, and Mori (2003)
Bayesian theory	Regression	Multiple independent variables are assigned a weight-of-evidence based on prior knowledge.	Lee, Choi, and Min (2002)
Fuzzy gamma techniques	Regression	Spatially located objects are given weights ranging from 0 to 1, called membership values. Membership values of multiple object types are then brought together using one of several geoprocessing techniques to develop a final set of weights.	(Lee & Sambath, 2006); Pradhan, Lee, and Buchroithner (2009)
Artificial Neural Networks	Machine Learning	A set of nodes, each representing an independent variable, are tied together using weighted connections. Weights of each connection are optimized through training with existing data.	Pradhan and Lee (2010)
Multivariate	Regression	Multiple independent variables (e.g. slope, curvature, and lithology) are divided into landslide and non-landslide groups using a linear function. The mean values and variance and covariance matrices of each group are then used to compute a coefficient vector to weight each variable. In cases interested in the occurrence/non-occurrence of landslides, logistic multivariate regressions tend to be used.	Erener and Düzgün (2008); Lee et al. (2008)

2.4.3 Risk Mapping

In the case of hazard mapping, landslide severity is identified over the entire region based on the mechanisms behind landsliding, and not by what might be damaged. Risk mapping goes a step further and considers the costs, economic, social or environmental, sustained by landslide occurrence. In this way, a risk map is not necessarily sensitive to a landslide in a remote setting. Corominas et al. (2014) define landslide risk as the product of landslide hazard, the exposure of elements at risk, and their vulnerability. By this definition, hazard is the same as described previously, and elements at risk tend to be the human infrastructure that stands to be damaged when a landslide occurs. Exposure refers to the spatial correspondence of landslide hazard and

the location of elements at risk, while vulnerability refers to the resilience of the elements at risk. Examples of vulnerability are the potential lifeline closure time, importance of access, or resilience of exposed infrastructure. Van Westen, Van Asch, and Soeters (2006) presented a procedure for a multi-hazard assessment of risk, which is presented schematically in Figure 2.5.

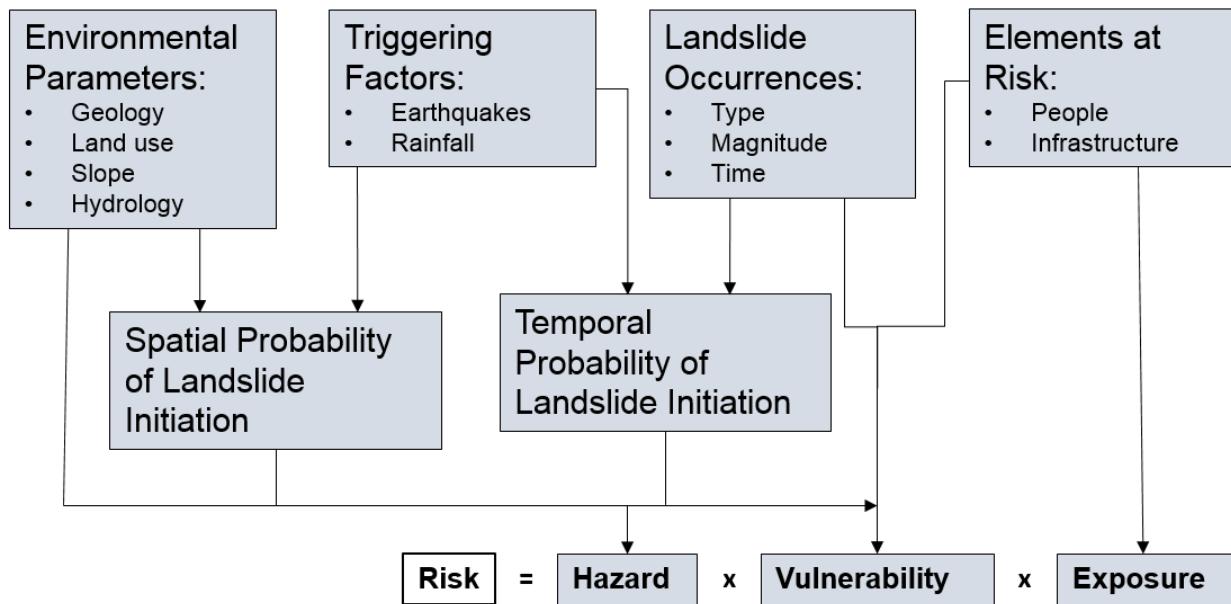


Figure 2.5: Schematic of a multi-hazard risk assessment (modified from Van Westen et al., 2006).

2.4.4 Challenges and Future Opportunities

Two primary challenges exist regarding landslide mapping in Oregon. First, the state does not have a complete inventory, and second, once a complete inventory exists, it is an ongoing challenge to update it since landslides frequently occur. Other reasons for why these challenges exist include application requirements and subjectivity for each inventorying method, natural variability, and landscape evolution.

Requirements for the application of any inventorying method play a major role in what is ultimately mapped. In the case of inventory mapping in Oregon, the availability of lidar data is an important limitation. Currently, only a portion of the state has been covered with lidar data (Figure 2.6). One hindrance to complete statewide coverage is the cost and time required to perform airborne laser scans is accompanied by difficulties in storage and organization of large datasets. In spite of this challenge in data acquisition, major efforts are being made to continue collecting lidar data, adding optimism to the use of lidar-based inventorying methods. The USGS 3D Elevation Program (Sugarbaker et al., 2014) aims to accelerate the collection of lidar data nationwide, and the state of North Carolina has already been covered, with many areas now being covered for a second time (North Carolina Floodplain Mapping Program ("North Carolina Floodplain Mapping Program, 2014 LiDAR Collection," 2014)).

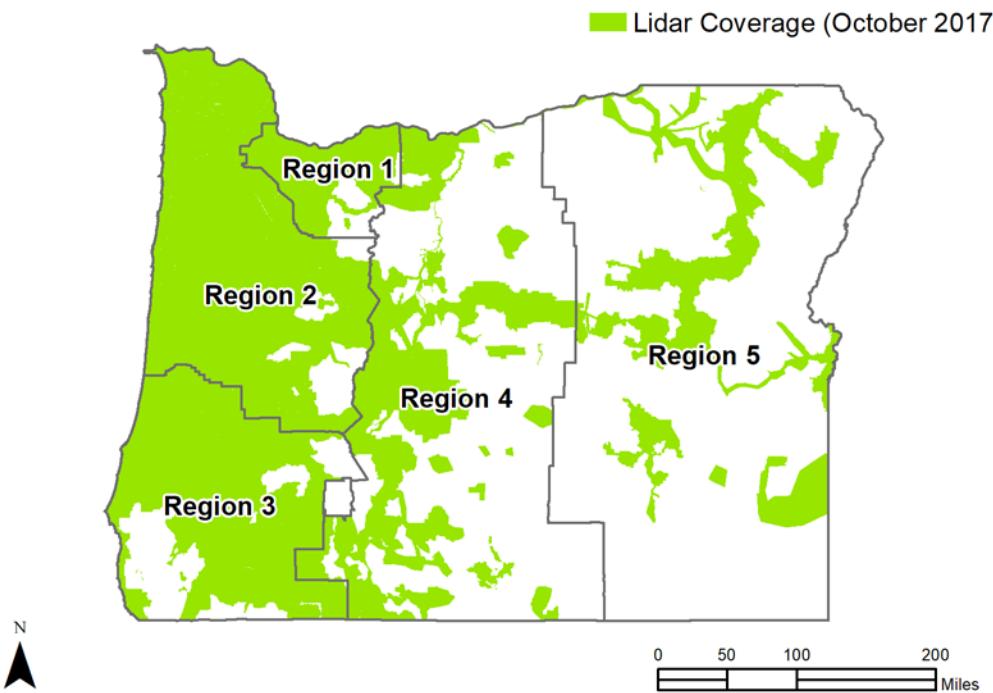


Figure 2.6. Status of lidar data collection in Oregon as of October 2017.

Natural variations in factors such as geology, precipitation, and anthropogenic alteration, mean that inventorying methods requiring calibration that cannot necessarily be applied systematically over a large area. This limitation is exacerbated by inconsistent levels of detail and quality for complementary, relevant datasets throughout the state. Many important data sources are missing, however, lidar shows promise as a critical and consistent starting point to infer other necessary factors. Additional gains may also be made by incorporating inputs relative to site geology, soil conditions, climate, and other factors that may influence the topography of past landslides into semi-automated inventorying methods.

The ever-changing evolution of our landscape presents a second challenge towards maintaining up-to-date landslide inventories. As time passes, erosion and landslides continue to occur, particularly in coastal or fluvial regions subject to the forces of moving water. Changes to topography and new landslide initiations cause existing inventories to become outdated. This limitation is an important reason why automated inventorying methods and multi-temporal lidar datasets may provide improved management decisions in consideration of hazards. The opportunities presented by serial lidar are very promising as it enables better understanding of landslide hazards and their behavior. However, these changes over time have limited meaning without a starting inventory of landslides.

While major challenges do exist for landslide mapping in Oregon, the potential to overcome or mitigate them also exists, particularly when utilizing computational tools to expedite and improve the process. Enhancing the CCM algorithm to incorporate information other than solely topography will enable a starting point of landslide inventories – critical to not only making

management decisions about existing hazards, but the behavior of existing hazards and possible future hazards. Furthermore, it presents an opportunity to streamline and supplement the current, manual landslide inventorying process in a framework that would potentially be less subjective, more repeatable and more expedient. Furthermore, there is potential to better classify various landslide types based on associated data from application of the algorithm. That is, it is possible that characteristics like activity, failure mechanism and runout distance may be inferred in a consistent analysis.

The overlap of the aforementioned hazard mapping with data layers like state highway right-of-way, associated traffic data, maintenance costs presents a means to evaluate risk, an important aspect of making management decisions. There are quantifiable metrics, including cost of repair, cost of closure, traffic counts and access to alternative roadways that may help inform the impact of a given hazard. With knowledge of hazard proximity, impact and subsequent risk, a generalized means to evaluate landslide risk may be developed – a critical tool for informed asset management. Enhancing CCM to better inventory landslides, process landslide data into a quantifiable metric, and overlap hazards with agency-relevant metrics presents promise for better asset management and DOT decision-making.

3.0 METHODOLOGY

3.1 SEMI-AUTOMATIC LANDSLIDE INVENTORY MAPPING

3.1.1 Overview

The semi-automated landslide inventory method described in this report is a modification of the Contour Connection Method (CCM) developed by Leshchinsky et al. (2015). While the new procedure holds numerous similarities to the original, its implementation is considerably different and has been significantly developed through this research. Notably, the new approach has changed the initiation of CCM from a user-defined slope threshold to a scarp line. As a result, the new approach is comprised of two primary steps, 1) the identification of scarp lines (SI), and 2) running CCM to delineate deposits. Together, the two steps are referred to as Scarp Identification and Contour Connection Method (SICCM). The details behind the performance of either step are dictated by the desired results, the existence of nearby manual landslide inventories, and available time. A detailed, step-by-step procedure for how to implement this methodology may be found in Appendix E, and related source code may be found in Appendix G. This section will provide the background needed for successful implementation.

3.1.2 Base Data Acquisition and Processing

All landslide inventory approaches presented in this report begin with a DEM, which may be derived from lidar or other remotely sensed data. No DEM is automatically disqualified from being mapped using this methodology, but the resolution and quality directly influence the size of landslide that may be mapped. The user must first examine the hillshade, or other DEM-derived layer of their choice and decide if landslides are visible. If the user cannot see landslides, the computer likely will have difficulty identifying the features as well. If the user can see landslides, the focus then shifts to how confident they are in the landslides that they see. Confidence is often dictated by the quality of the DEM. Quality, in this sense, refers to the amount of noise present in a DEM. Noise may be the result of processing, such as incomplete vegetation removal from lidar data (Figure 3.1A), or spatial interpolation, such as the generation of a triangular irregular network (TIN) with lidar (Figure 3.1B) or commonly available contour-derived surfaces (Figure 3.1C). While these forms of noise may be present at the DEM's native resolution, we assume that when reduced to some working resolution, the noise will be muted. Nonetheless, if the scarp features exist at the same scale as the noise, then the working resolution will mute those features as well.

In this report, selection of a working resolution is a qualitative endeavor, although significant testing of lidar data prepared to Oregon Lidar Consortium standards (Watershed Sciences Inc., 2010) has shown that resampling of 3 foot native resolution DEMs to a 20 foot working resolution can be reasonably effective. Practitioners interested in optimizing the working resolution for a specific dataset should resample their DEM to several different resolutions and

compute slope from each resampled DEM. The optimal resolution is the smallest raster cell-size that eliminates unwanted artifacts and anthropogenic features (i.e., roads and building foundations). This process is illustrated in Figure 3.2, where an originally 3 foot resolution DEM was resampled to 10, 20, and 30 foot resolutions. Roughness from artifacts is evident at A and B for the 3 and 10 foot examples, while roughness from landslide topography is evident at C in all but the 30 foot example. Notice how artifacts are still present in the 10 foot hillshade, but not in the 20 and 30 foot hillshade. The 20 foot DEM would be considered better than the 30 foot DEM because it has eliminated most of the artifacts while sacrificing less detail of the original DEM.

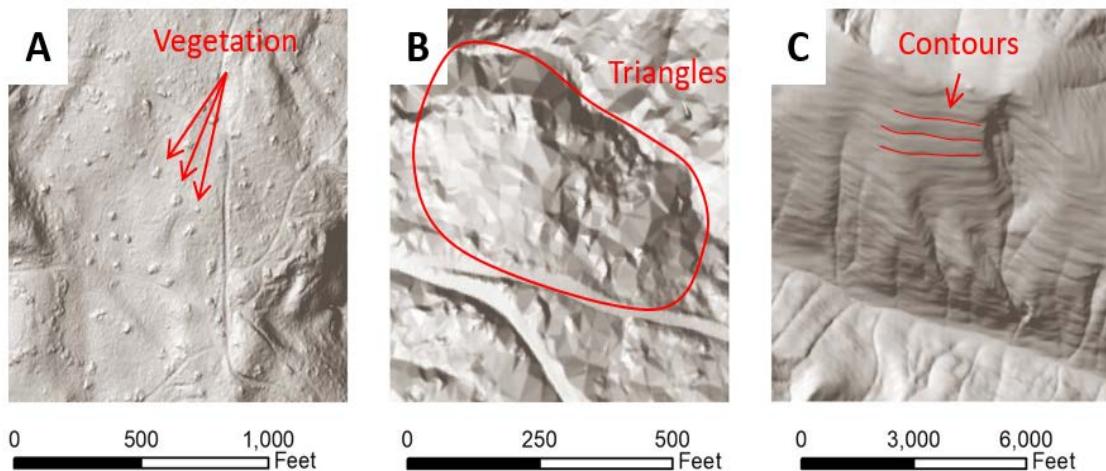


Figure 3.1: Common examples of noise in DEMs through examination of hillshades. The scale at which noise exists can vary significantly depending on how a DEM was produced.

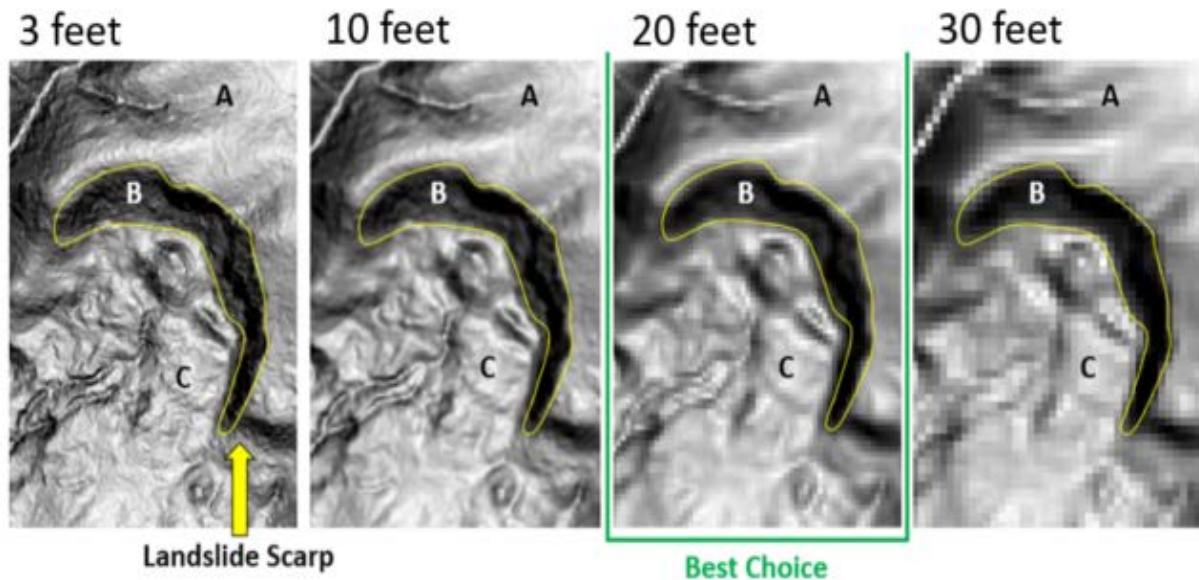


Figure 3.2: Illustration of original DEM and three resampled versions. The 20 foot resolution is considered optimal because it eliminates the artifacts while retaining as much of the original DEM's detail.

While the 20 foot resolution works well for the example in Figure 3.2 and serves as an excellent starting point for all lidar-derived DEMs prepared to OLC standards, practitioners should understand that some landslide scarps do exist at other scales. If these other scarps are very important to the work being performed, then it is recommended that the scarp identification procedure be completed at multiple resolutions and all resulting scarp lines combined into a single shapefile in GIS before running the CCM algorithm.

3.1.3 Scarp Identification Procedure

Landslide scarps are the location of vertical displacement that marks the uppermost boundary of a landslide's extent. At the base of the scarp, a hummock is where displaced material has come to rest. Where the scarp and the hummock meet, there is a topographic trough where the terrain briefly curves upward. For the purposes of this methodology, scarp lines may be defined as either the crest of the scarp or upward curving trough (Figure 3.3).

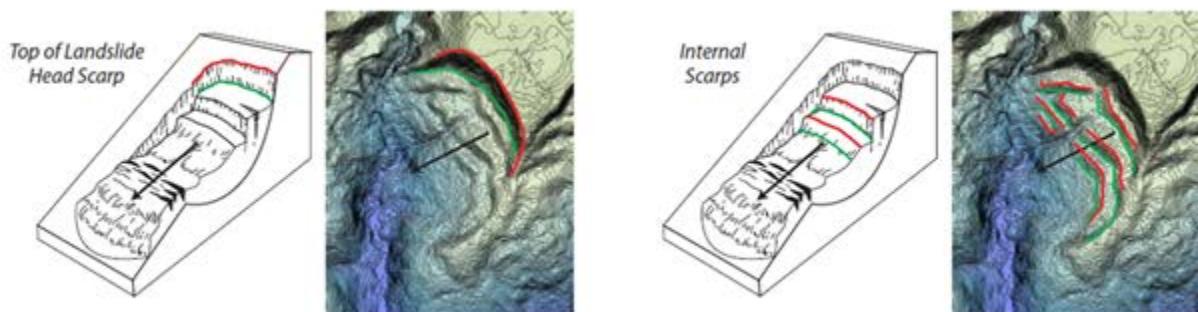


Figure 3.3: Acceptable CCM input scarp locations (adapted from SP 42, Burns, 2009).

This methodology section will discuss two scenarios that exist for scarp identification: manual digitization of scarp lines, and semi-automatic digitization of scarp lines. The semi-automatic digitization can be further broken down based on whether or not a nearby, or geologically similar, manually mapped landslide inventory exists. Manual mapping by an expert is considered to be the most accurate yet most time consuming approach; whereas, semi-automatic mapping requires less time, and in some cases, less experience from the practitioner. The performance of each scenario will be detailed in the sections below.

The semi-automatic scarp line identification procedure is performed in three steps: segmentation, classification, and formation of scarp line features (Figure 3.4). Strategically placed among these three steps are several points of **intervention** that allow an experienced practitioner to manually influence the process, if desired. Each intervention is meant as a brief period in time (several minutes, or less) when the practitioner may review the entire study area and make minor changes to numerical thresholds or the size of objects being mapped. The time involved in intervention is a function of scale or the level of correction desired; however, after several minutes to an hour, the returns tend become diminished.

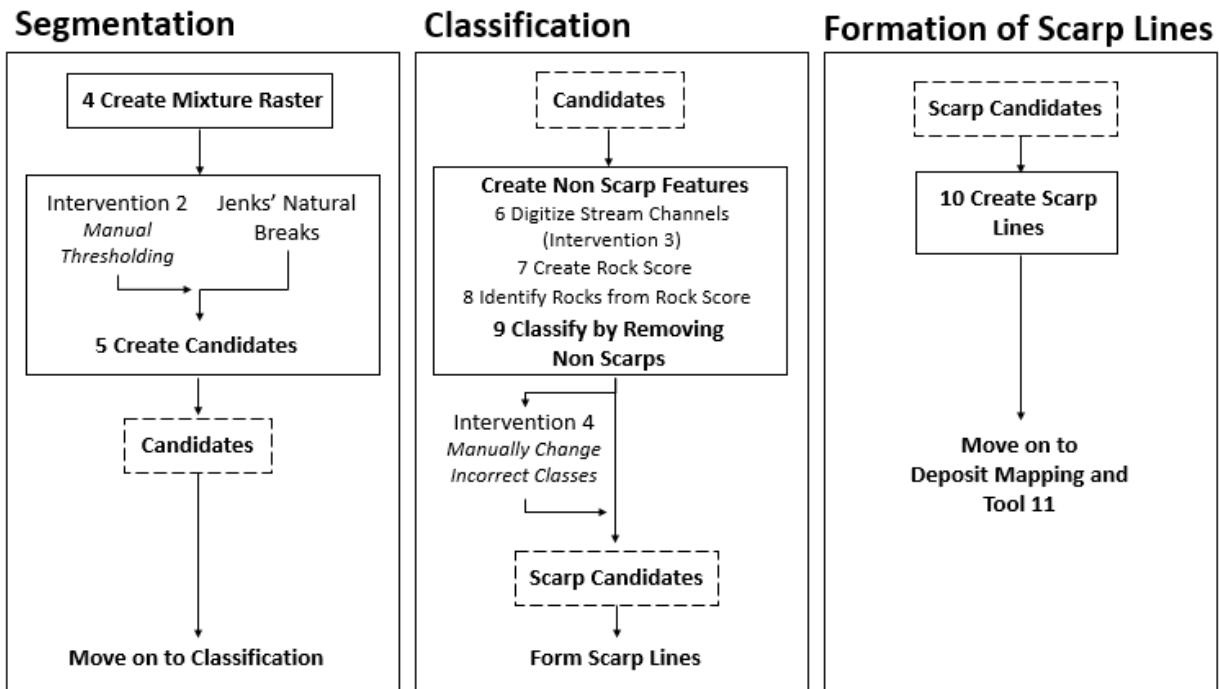


Figure 3.4: Flowchart of semi-automatic scarp line mapping procedure. Numbered items represent tools within the SICCM toolbox.

3.1.3.1 Segmentation

Prepare Mixture Raster

The first group of tasks illustrated in Figure 3.4 are collectively titled segmentation. The purpose of the segmentation process is to create the mixture raster. The mixture raster is produced through pixel-by-pixel multiplication between two digital elevation model (DEM) derivatives - slope and profile curvature - which results in cell values that represent the terrain's concavity or convexity. It exaggerates scarp crests (convex topographical features) and troughs (concave topographical features). These exaggerations can then be visualized on a given DEM to highlight scarp-like features.

Setting the Mixture Threshold

Once the mixture raster is created, a user should apply Jenks Natural Breaks optimization (de Smith, 2015) to create three classes, each representing similar cell values. The lowest-valued class will represent areas of convexity in the terrain, which includes scarp crests and ridgelines. The highest-valued class will represent areas of concavity in the terrain, which includes troughs and stream channels. The mixture threshold is the class break between the highest-value class and the lower-value classes (Figure 3.5).

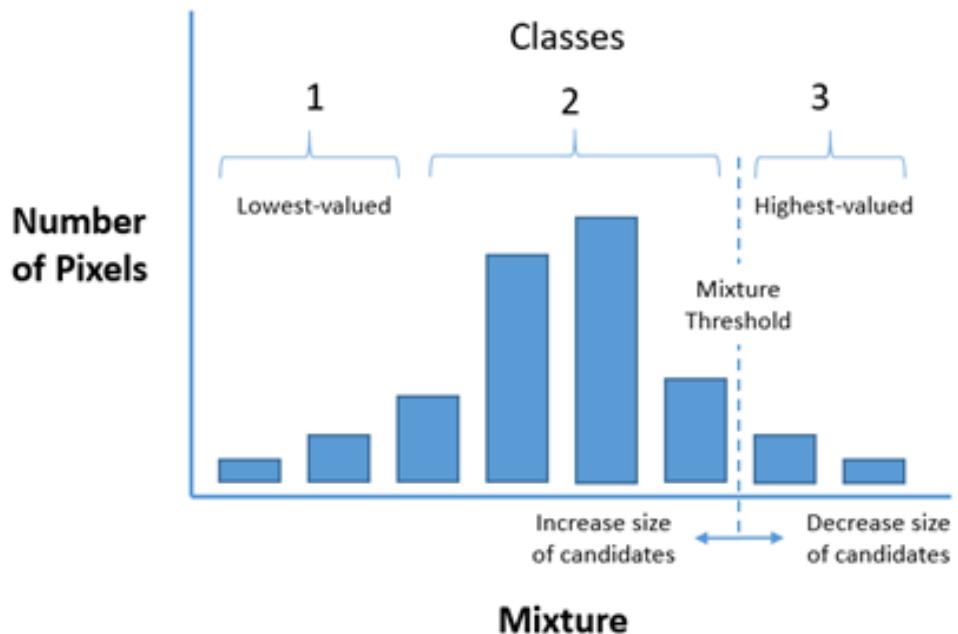


Figure 3.5: Histogram produced from pixels of the Mixture raster.

Separating scarp crests from ridgelines is challenging due to their topographic similarities (Figure 3.6), and failure to do so results in significant landslide over-prediction. Because of this challenge, the semi-automatic procedure attempts to map the scarp troughs instead. Nonetheless, a user may elect to use scarp crests as well, but should be cautious about over-prediction. The values that represent the scarp troughs in the mixture raster are found in the highest class. The mixture raster is then re-classified so that you exclude all but the highest class, which is representative of troughs.



Figure 3.6: Common sources of convex and concave topography in a typical mapped region.

The values of the highest class are converted from clusters of cells to polygons called scarp candidates. Each scarp candidate represents an area that may be a scarp trough, but may also be streams, roads, and other topography with concavity, as displayed in Figure 3.6.

3.1.3.2 Classification

Once scarp candidates have been produced, the task is to identify which polygons are scarp troughs. For this step, called classification, the practitioner may choose to eliminate non-trough features using varying approaches or to use a logistic regression classifier to filter scarp candidates based on training data sets, like manually mapped landslide inventories with digitized headscarsps. DOGAMI currently maps landslide features with digitized headscarsps. In either case, the outcome is that all candidates are assigned a class of scarp or non-scarp.

Elimination of Non-Scarp Topography

Scarp troughs, roads, streams, and rock outcrops all have topography that may cause them to be mapped as a scarp candidate. If most non-scarp trough topography is associated with streams, roads, or rocks, then it is possible to eliminate these features using digitized road, stream, or rock layers. Candidates that intersect (simple intersection, no buffer) road or stream lines, or rock polygons, may simply be removed and the remaining candidates are assumed to be scarp troughs.

This methodology comes with an approach for mapping rock outcrops on the working resolution DEM. First, the working resolution DEM is resampled to a lower resolution to create a smoother form of the topography. The smoothed DEM is then subtracted from the working resolution DEM, effectively computing the volume difference between the DEMs. Pixels with the greatest volume difference are considered to be rock outcrops, and are converted into polygons, which can then be used in the elimination process.

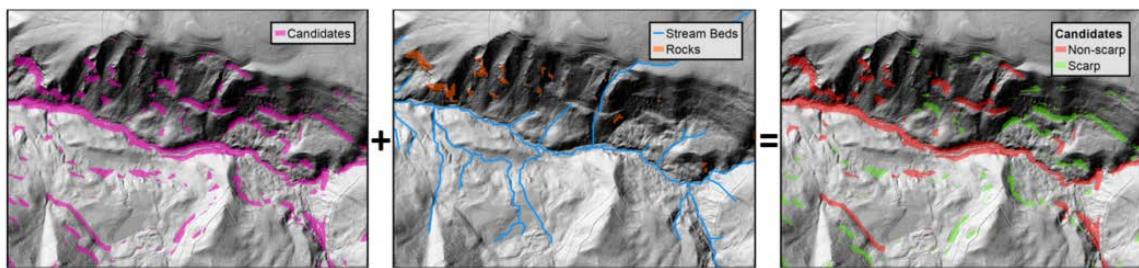


Figure 3.7: Elimination of Non-Scarp Topography using stream beds and rock outcrops as non-scarps to classify candidates.

Logistic Regression Classifier

Logistic regression is a statistical technique used to differentiate between two groups. The classifier “learns” from an existing landslide inventory and uses the information to classify candidates as scarp troughs, or non-scarp troughs. If a manually produced

landslide inventory exists nearby, or has similar landslide geomorphology to the area being mapped, then the logistic regression presents a simple and rapid way for a practitioner to perform this classification with more confidence. In order to operate the logistic regression classifier, candidates must also be produced for the area mapped in the existing manual inventory. Candidates that lie within the extents of inventoried deposits are called scarp troughs and all other candidates are called non-scarp troughs.

The logistic regression is driven by topographic variables describing each candidate and outputs a label of scarp or non-scarp. Each variable is a statistic (i.e., mean, standard deviation, range, etc.) computed from the raster cells of elevation derivatives underlying each candidate polygon.

3.1.3.3 Formation of Scarp Lines

Once the candidates have been classified as scarp troughs, then they may be thinned into scarp lines (Figure 3.8). The candidate represent an “area” where the scarp trough is located. The CCM model requires polyline inputs; therefore, the candidates must be converted from raster pixels to polylines.

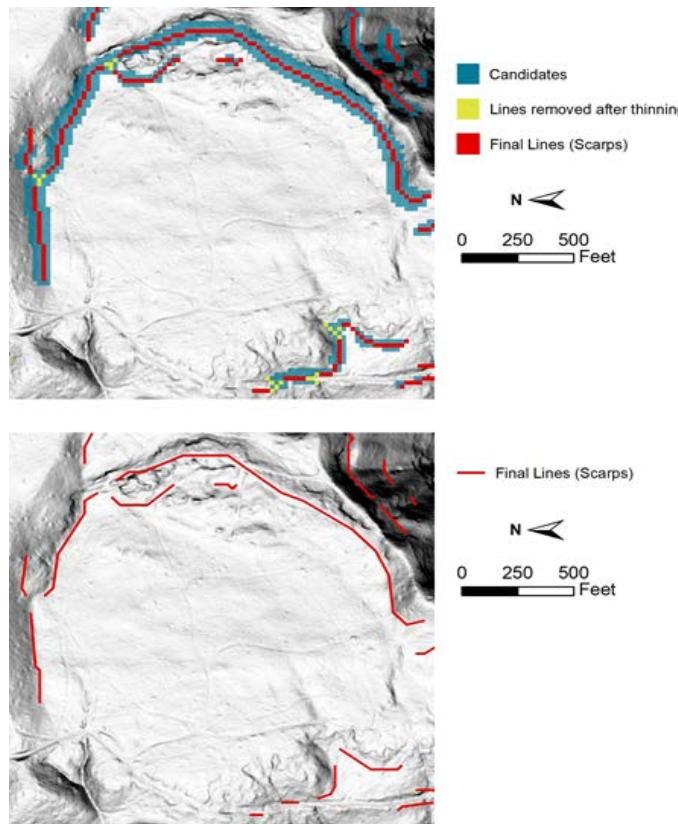


Figure 3.8: Blue candidates are thinned into green scarp lines during the thinning process. Red lines are removed to prevent intersecting scarp lines.

3.1.3.4 Interventions

Intervention 1: Finding a Cell Size for Mapping

Choice of a good mapping cell size will result in the best candidate shapes with the least amount of noise. Selection is made by producing slope rasters at several cell sizes and interpreting which one does the best at eliminating noise from the original DEM. Noise has been eliminated when slopes are smooth surfaces with no small dimples or visible triangular planes.

Intervention 2: Manual Mixture Thresholding

Although Jenk's Natural Breaks is an acceptable method towards identifying the mixture threshold, minor manual adjustments in the threshold value can lead to improved results in the majority of cases. These adjustments include either increasing or decreasing the threshold that divides the classes. Increasing the threshold decreases the number of candidates. This may exclude some real scarp lines while removing false scarp lines. Decreasing the threshold will increase the number of candidates. While this will increase the capture of actual scarp lines, it may also include many false scarp lines (Figure 3.9).

In order to determine how to adjust the threshold, the user should review candidate scarp lines overlain on the DEM. If there are many candidates that do not represent actual scarp lines, increase the threshold. If there are actual scarp lines missing or excluded from candidates, decrease the threshold.

Proper intervention requires that the practitioner understands the appearance of scarp candidates and how it is influenced by the threshold. Figure 3.9 gives an example of what to look for during manual thresholding of the mixture raster. Good scarp lines rely on simple, continuous candidates, but removal of intersections means that some complex shapes may still be reasonable. Procedurally, manual thresholding should begin at the second and third class threshold defined by Jenk's Natural Breaks.

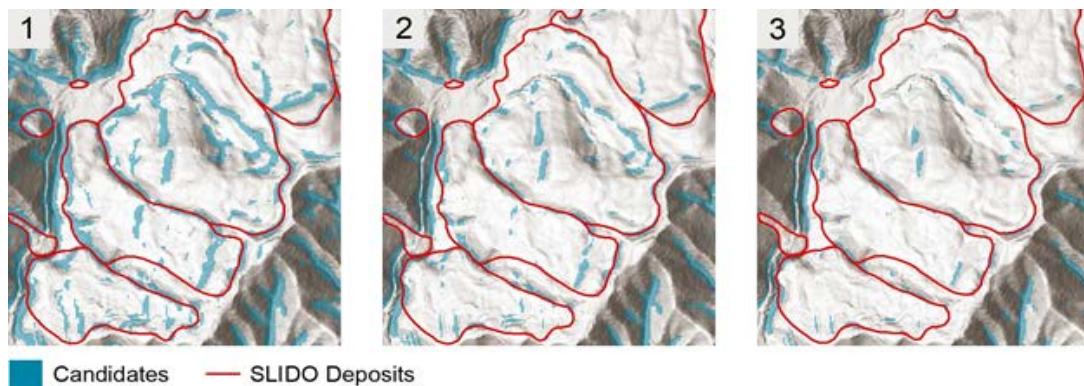


Figure 3.9: Three examples of mixture thresholds and their effect on candidate formation.
Note that the threshold values are unique to the DEM depicted, and values will likely be different for other DEMs.

Intervention 3: Selecting the Best Stream Channels

The stream channels used in non-scarp identification are meant to represent any topographic channels or gullies associated with streams, and are not necessarily where surface water is flowing. In many cases, existing stream databases, such as the National Hydrography Dataset (NHD) may provide adequate features for SICCM. Despite this available data, producing a stream channel network is relatively easy, and Intervention 4 is an iterative process that tests various flow accumulated areas for the initiation of stream lines.

Intervention 4: Manually Change Incorrect Classes

There will likely be instances where the chosen classification method incorrectly decides between scarp and non-scarp. If time allows, practitioners should spend several minutes to an hour looking over the mapped area and using judgement to manually change incorrect classes.

Once classes of scarp and non-scarp have been assigned to candidates, they are ready to be thinned into scarp lines. This methodology performs the steps illustrated in Figure 3.8, which provides the practitioner with scarp line features. At this point, the scarp lines are now ready for input into the modified Contour Connection Method for mapping the landslide deposits below each scarp.

3.1.4 Mapping Landslide Deposits

3.1.4.1 Overview of the Contour Connection Method

Landslide deposits are mapped using an adaptation of the Contour Connection Method (CCM, Leshchinsky et al., 2015). Required inputs include the scarp lines identified in Section 3.1.3.3 and the parameters listed in Table 3.1.

Table 3.1: Definitions of Parameters Used by the Modified Contour Connection Method. Notation follows that of Leshchinsky et al. (2015).

Parameter	Name	Definition	Recommended Values
Δ_{active}	Active slope	Minimum gradient for active slide region	0.03, 0.05 (rise/run)
ΔE_z	Contour interval	A fixed vertical distance between X-Y contour layers for a given range Z	10, 20, 30 feet
L_n	Nodal spacing	A fixed length between contour node assignments	10, 20, 30 feet
B_n	Branch parameter	A branching connection parameter.	3, 5

The steps implemented (automatically) by the modified Contour Connection Method are as follows (Figure 3.10).

- A DEM is input. To prevent any ill effects of noise, it is recommended that the DEM has been resampled to the working resolution, as described in section 3.1.2.
- A collection of scarp lines is input, derived manually or from automated approaches described in Section 3.1.3.
- Based on dimensions of each individual scarp line, the algorithm draws a square region of interest around a hypothetical inscribed circular landslide downslope of the scarp. The diameter of the circle is set to 1.4 times the scarp line length.
- The DEM is clipped to the region of interest in order to reduce the time required for analysis.
- Elevation contours are drawn at the user-specified contour interval.
- Nodes are drawn at the user-defined nodal spacing along each contour.
- Nodes are connected to downslope nodes that exist on an adjacent contour of lower elevation. The connection between given nodes will occur at the steepest gradient possible. The number of connections must be less than, or equal to, the user-specified branch parameter. Connections may only be drawn if their slope exceeds the user-specified active slope.
- A polygon is drawn around the edges of the connected nodes. This polygon represents the potential extents of a landslide feature.

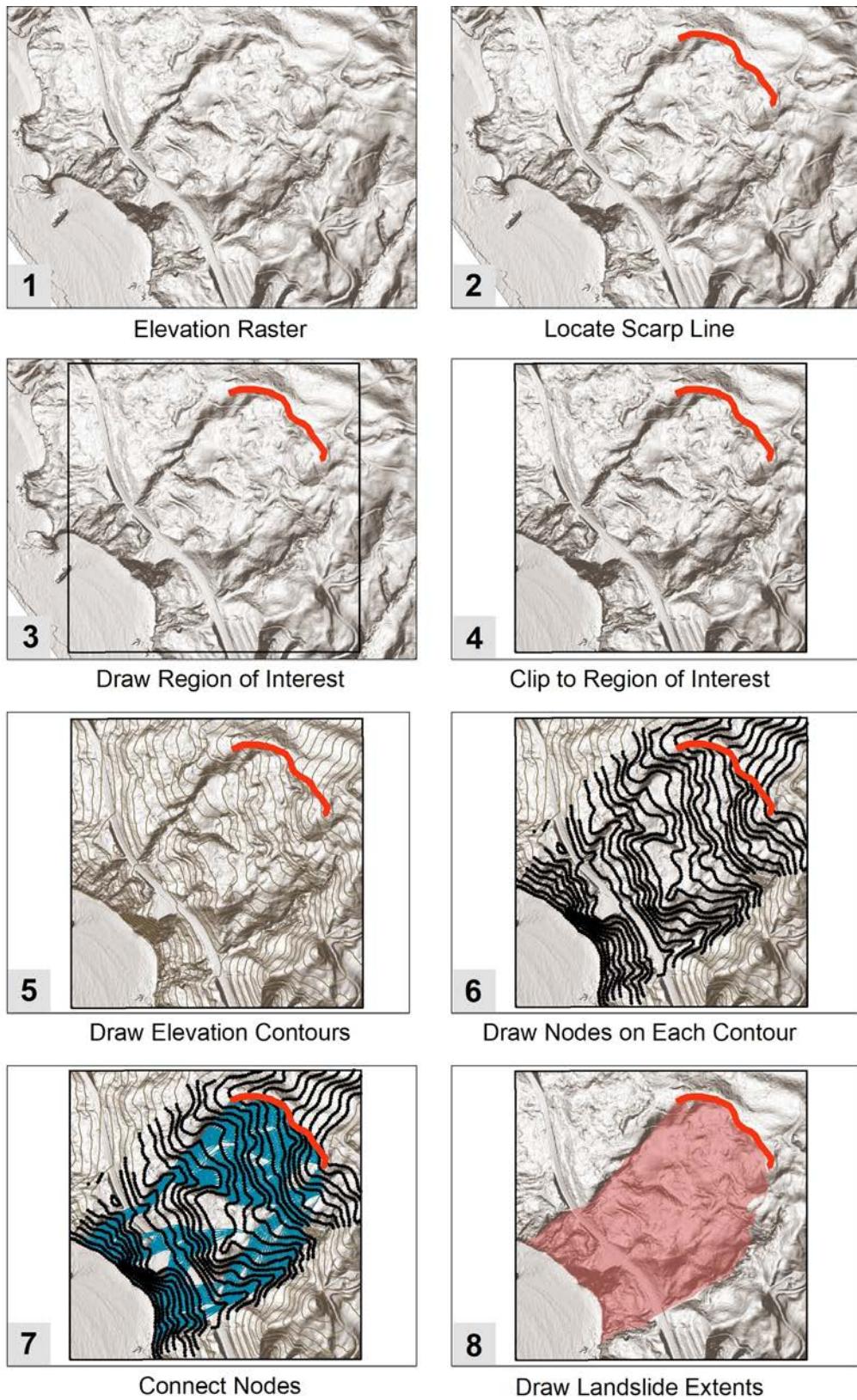


Figure 3.10: Operations of the modified Contour Connection Method.

Operation of the modified CCM algorithm can take on two forms: use of recommended CCM parameters (Table 3.1) or use of manually-selected CCM parameters. Practitioners with little experience operating the algorithm or limited time should choose the recommended parameters. The recommended parameters are not perfect for all landslides, but perform well on terrain with a variety of landslide types (e.g., the Oregon Coast Range).

Manually selecting appropriate CCM parameters requires some prior knowledge of the relative influence of each parameter. Practitioners should always begin with the recommended parameters, and then use the results to decide which parameters to vary. Figures 3.11 through 3.15 are provided with the purpose of giving the practitioner some basic experience with the sensitivity of each parameter. Landslide extents are shown with transparent red polygons and the CCM connections that comprise them are shown as blue lines. Below each figure is a description of how each parameter influenced mapping.

3.1.4.2 Effect of Varying the Active Slope

Active slope controls the termination of the CCM process. The basic idea is that landslides occurring in steep terrain will follow steep active slopes, while landslides occurring in gradual terrain will follow shallow, active slopes. In selecting an active slope, the practitioner will want to choose a value that is steep enough to prevent connections from traversing hillslopes, but shallow enough to allow connections to form over and around landslide hummocks. In Figure 3.11, right image, the active slope was too steep, which resulted in the landslide on the right being undermapped from a premature termination of connections.

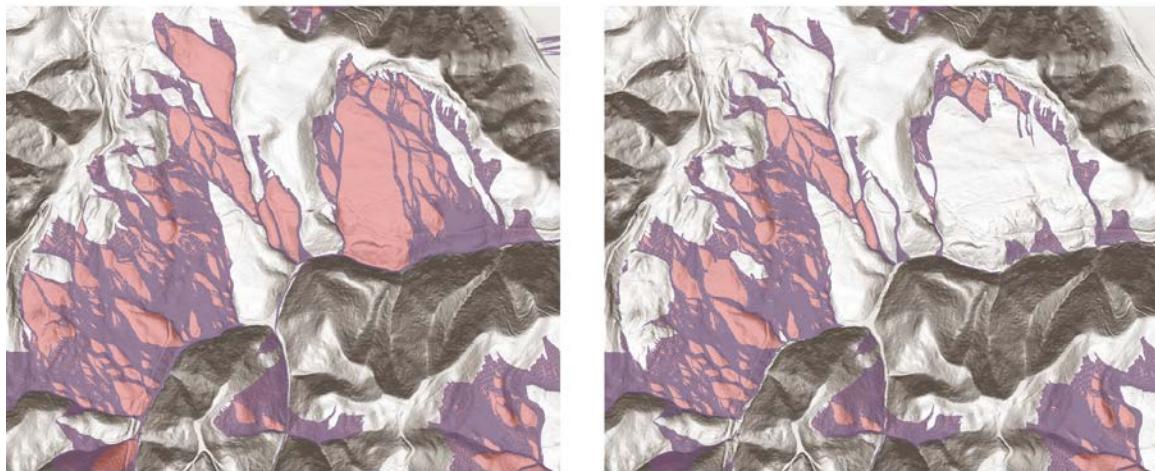


Figure 3.11: Effect of varying the active slope. The left image was mapped using recommended parameters (contour interval and nodal spacing of 10 feet, active slope of 0.05, and branch parameter of 3) and the right image was mapped using the recommended parameters and an active slope of 0.08.

3.1.4.3 Effect of Varying the Branch Parameter

The branch parameter controls the ability of connections to spread laterally as the process moves downslope. Larger branch parameters may be good for cases where the landslides being mapped are broad, low-sloping, or hummocky, where connections need to flow around objects. Use of too large of a branch parameter can lead to overmapped regions (i.e. ridgelines such as shown in the center of Figure 3.12, right image) as well as major increases in computation time. Recommended branch parameter values are between 2-5.

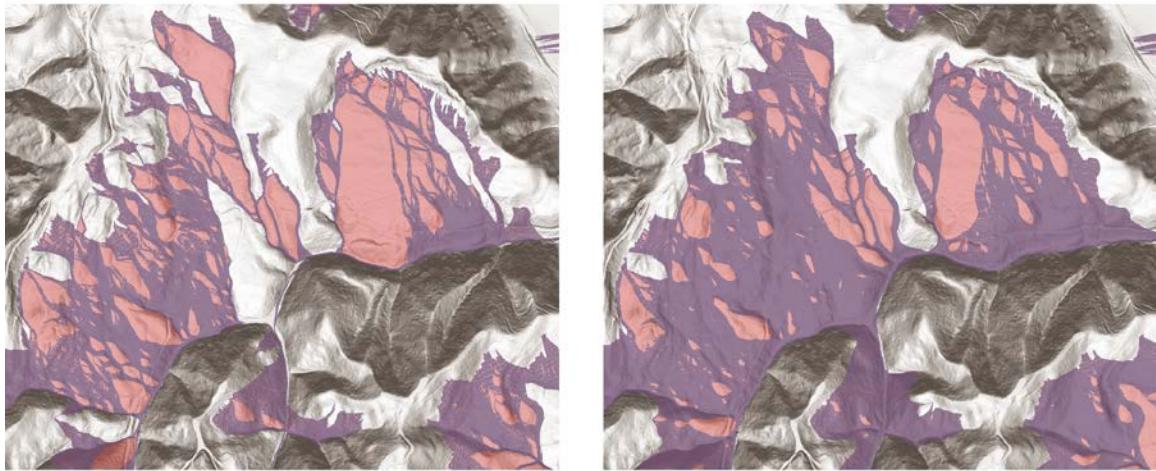


Figure 3.12: Effect of varying the branch parameter. The left image was mapped using recommended parameters (contour interval and nodal spacing of 10 feet, active slope of 0.05, and branch parameter of 3) and the right image was mapped using the recommended parameters and a branch parameter of 5.

3.1.4.4 Effect of Varying the Nodal Spacing

Nodal spacing controls the lateral resolution of the contour connection procedure, which has a significant influence on the distance used to compute connection slope (Figure 3.13). As nodal spacing increases, there is an increase in the slope distance and no change in the slope rise. The result is similar to increasing the branch parameter, but at the same time reducing computation time.

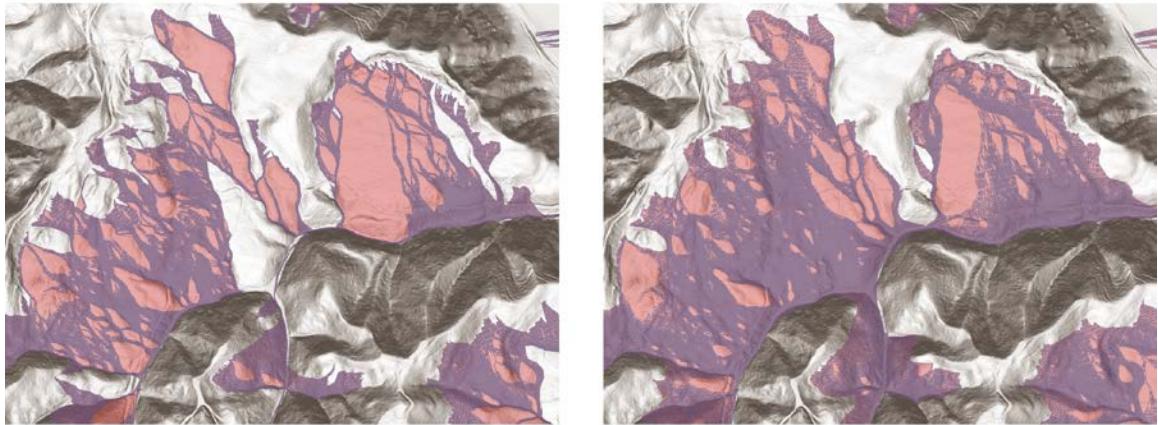


Figure 3.13: Effect of varying nodal spacing. The left image was mapped using recommended parameters (contour interval and nodal spacing of 10 feet, active slope of 0.05, and branch parameter of 3) and the right image was mapped using the recommended parameters and nodal spacing of 20 feet.

3.1.4.5 Effect of Varying the Contour Interval

Contour interval controls the vertical resolution of the contour connection procedure. Increasing the contour interval can be a useful technique to overcome small features that cause early termination (Figure 3.14, right image), without producing major changes to results obtained using the recommended parameters. In all cases, the contour interval should be chosen based on the dimensions of the smallest landslide being mapped as well as considering the resolution of the corresponding DEM.

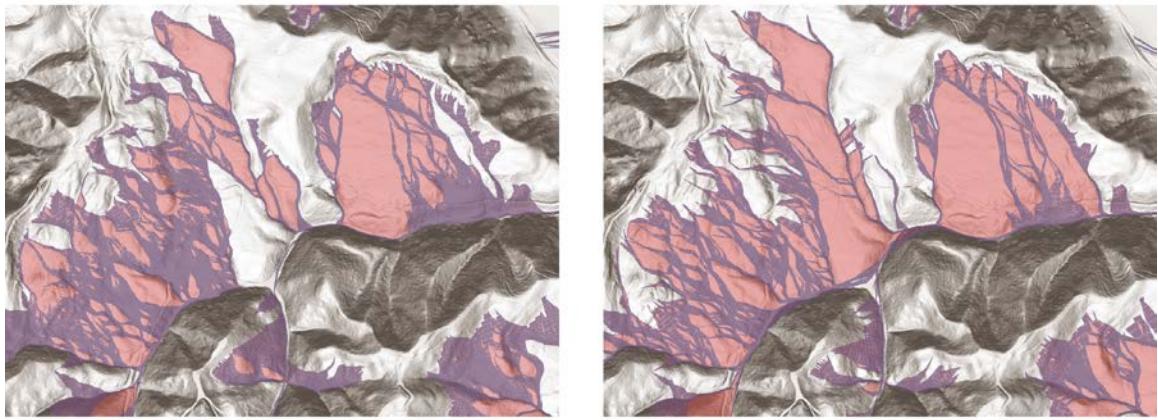


Figure 3.14: Effect of varying contour interval. The left image was mapped using recommended parameters (contour interval and nodal spacing of 10 feet, active slope of 0.05, and branch parameter of 3) and the right image was mapped using the recommended parameters and contour interval of 20 feet.

3.1.4.6 Combined Effect of Varying the Contour Interval and Node Spacing

Increasing nodal spacing and contour interval together is generally the best way to reduce the influence of the roughness of large hummocks that might prevent the algorithm from moving downslope. The results are generally similar to those obtained using the recommended parameters (Figure 3.15), and they should be used in situations where the practitioner is limited by time.

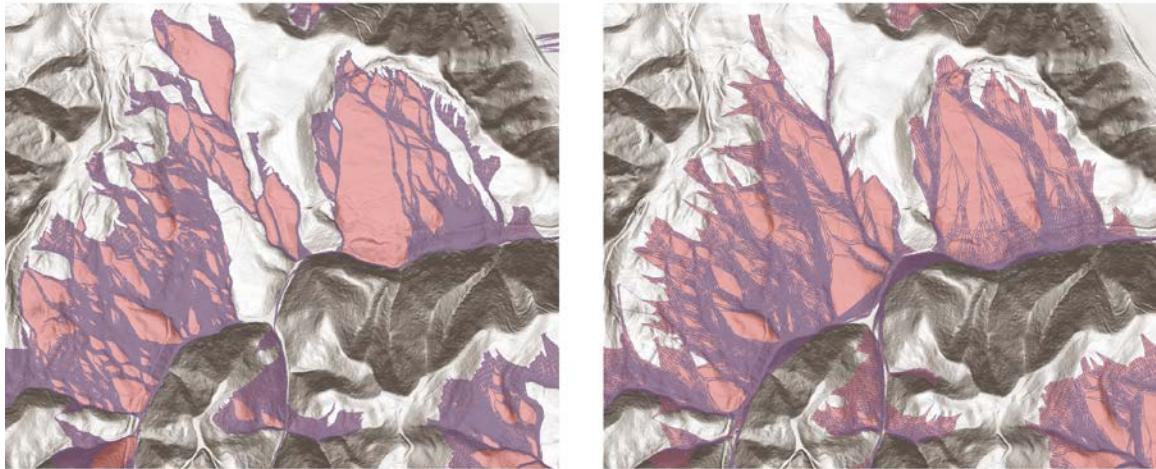


Figure 3.15: Combined effect of contour interval and node spacing. The left image was mapped using recommended parameters (contour interval and nodal spacing of 10 feet, active slope of 0.05, and branch parameter of 3) and the right image was mapped using the recommended parameters and contour interval and node spacing of 30 feet.

3.1.4.7 Computational Considerations for Running SICCM

Computation times for SICCM are dictated by the size of area being mapped and the value of deposit mapping parameters. Time required to produce candidates and scarp lines is a function of map size, and increases in time generally increase linearly with area. Deposit mapping parameters behave differently, as increases in parameter values typically result in larger increases to computation time. For example, a change in branch parameter from three to five will result in an increase in computation time by a factor of four, or even more.

Designing a set of deposit mapping parameters should not only be based on desired results, but also the amount of time available. Changes in branch parameter will always lead to the most significant increase in computation time, followed by contour interval and nodal spacing, and then active slope. In many cases, changing the active slope will result in very small increases in computation time.

Measured computation times for the SICCM inventories associated with this report ranged from 15 to 45 minutes for scarp identification and 20 minutes to 3.5 hours for deposit mapping over large extents (i.e. >100 sq. mi.). These times are unique to the computers that performed the mapping, and times are expected to vary for other

computers. Most users will likely see that the procedure requires more time to perform, but the increase in time is not expected to be significant.

3.1.4.8 Advantages and Disadvantages versus Manual and other Automated Approaches

SICCM has been designed to be simple to understand, quick to implement, applicable to a large variety of terrain, and capable of producing accurate results. Other automated or semi-automated landslide inventorying methods presented in the literature will likely satisfy one or two of those criteria, but not all four. Appendix B includes a listing of accuracies reported in the literature, and SICCM is on par with each of the methods. SICCM has also been applied to a greater variety of terrain than other methods. Furthermore, SICCM has been designed to operate without the need for software other than ArcGIS™. All other approaches require the use of at least of MATLAB® or eCognition®, which may incur additional licensing costs.

3.2 RISK MAPPING WITH CCM LANDSLIDE INVENTORIES

3.2.1 Overview

Chapter 2 established that a landslide risk map is the synthesis of landslide hazard and infrastructure exposure and vulnerability. Hazard has previously been considered as the likelihood of some event, typically heavy precipitation or an earthquake, triggering landslides. Because the goal of this report is to evaluate risk using a detailed landslide inventory, a new approach was developed (Table 3.2).

Table 3.2: Incorporation of Landslide Inventory and Highway.

Risk Component	Treatment
Hazard	<ul style="list-style-type: none">The deposits of deep-seated landslides are unstable and represent a likely setting for shallow landslidesDeep-seated landslides may reactivate during a wet winter season or during a large earthquake
Exposure	<ul style="list-style-type: none">The spatial correspondence of landslide extents with highway infrastructure
Vulnerability	<ul style="list-style-type: none">The cost of and time required to rebuild highwayThe economic loss due to reroutes and delays within the transportation network

3.2.2 Hazard Component

Landslide hazard is visible in the context of a landslide inventory as either shallow landsliding of unstable topography within the deposits of a deep-seated landslide or as movement of the entire deep-seated landslide. The first hazard is more common as landslide-prone terrain often experiences small slope failures from differential movements, settlement of loose landslide material or relatively steep, weak topography deposited in vulnerable dynamic terrain (e.g.,

streams, creeks, marine environments, etc.). These failures frequently occur after heavy rainfall, and result in the deposition of soil and debris on infrastructure. The second hazard – large, catastrophic movement of slopes - is rarer, but its occurrence can result in the total loss of infrastructure and the ground it was built upon. Note that both hazards are likely to occur during a major earthquake.

Despite potential differences in cause and frequency of these hazards, they may be modeled as the same unstable block (Figure 3.16). This similarity exists because of a worst-case assumption that the violent reactivation of a deep-seated landslide would lead to failure of a roadway embankment. The difference in hazards is accounted for by defining that shallow landslides will fall onto the roadway, which may be repaired using excavation, and that the deep-seated landslides may fail with a total loss of roadway, which requires the roadway to be rebuilt for that section.

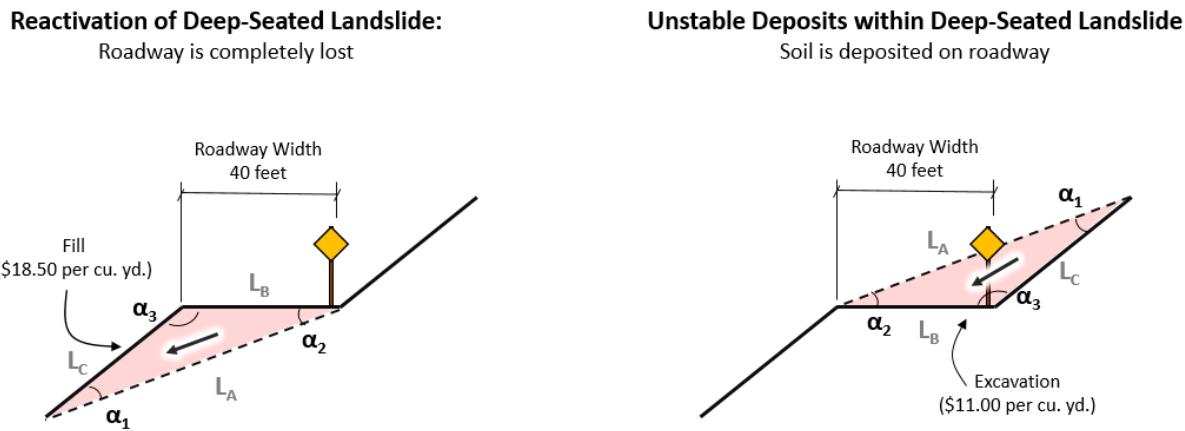


Figure 3.16: Example geometry of unstable blocks modeled for deep-seated and shallow landslides.

3.2.3 Exposure Component

Unstable blocks are identified by considering the slopes within the extents of a landslide mapped by SICCM. Slopes that are steeper than the mean slope within landslide deposits are assumed to be unstable, as the deposits tend to be weak, unconsolidated soils. Any time that there are landslide deposits with a steeper slope than the mean slope, there must also be an adjacent slope that is less steep than the mean slope. This less steep slope is uniquely associated with a single unstable mass, whereas the steeper slope may link several unstable masses. For this reason, the less steep slopes are used to identify the horizontal surface of an unstable mass (LB in Figure 3.16).

The hazard considered for each unstable block, deep-seated versus shallow, is determined by the spatial relationship between the block and infrastructure. If the block intersects the road line,

then it is treated as the deep-seated case (Figure 3.17). All other blocks are treated as the shallow landslide case.

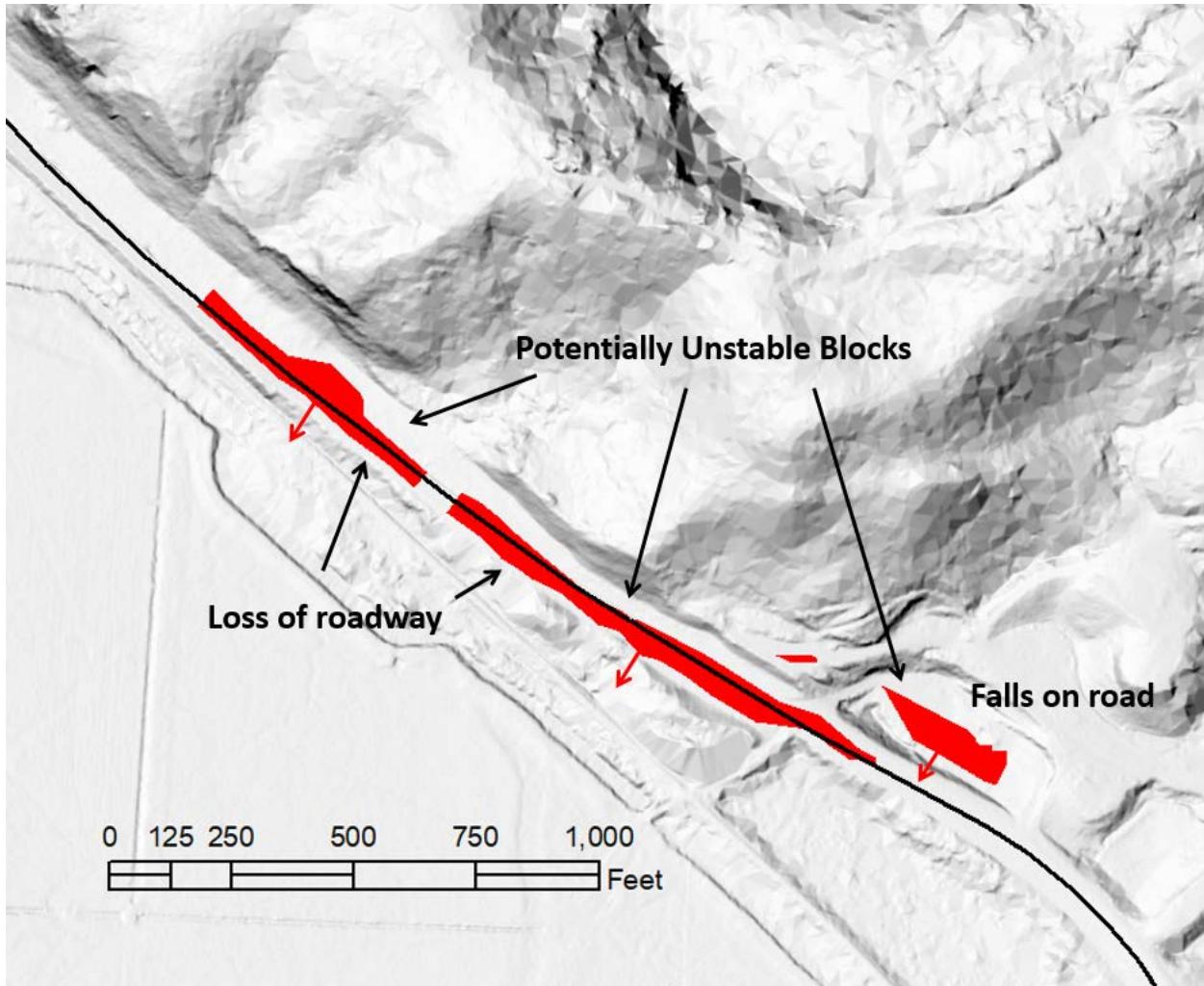


Figure 3.17: Illustration of the two types of block failure and their interaction with the roadway.

3.2.4 Vulnerability Component

3.2.4.1 Measurement of risk

Risk is ultimately expressed as (1) a volume of soil needing to be filled or excavated, (2) an expected duration of road closure, (3) a dollar amount reflecting economic losses, or (4) a dollar amount reflecting repair costs. This inventory-based approach exploits landslide and infrastructure geometry to compute volumes, which can then be linked to the other risk measures (Figure 3.18). Links between measures have been developed through various sources, and the rest of this section will describe each source.

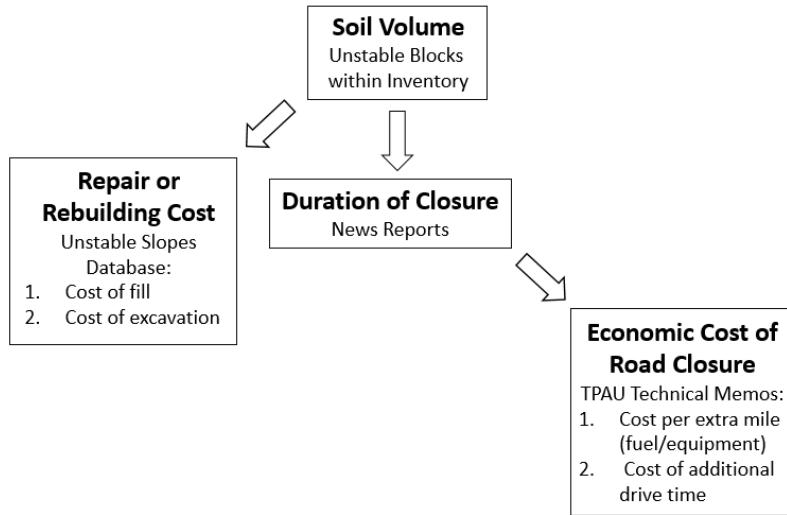


Figure 3.18: Relationship between different risk measures and a description of the method used to compute each measure.

3.2.4.2 Cost required to rebuild or repair highway

Rebuilding or repairing a highway is a complex process with many different costs, many of which vary significantly. This method uses the available construction and repair costs (Table 3.3) found in the ODOT Unstable Slopes Database to convert the volume of unstable blocks into a dollar value. General excavation is used in the case that unstable material falls onto the roadway and needs to be excavated, and stone embankment is used in the case that the roadway fails and needs to be filled. This analysis used average values, despite the fact that all study areas were located in either ODOT Region 2 or 3, because the volatility of prices in the Unstable Slopes Database was interpreted as a reflection of inconsistent estimating practices and not regional costs. Custom ArcGIS® tools have been provided in the event that ODOT engineers choose to perform an analysis with alternative values.

Table 3.3: Average Costs to Repair or Reconstruct Roadway Listed by ODOT Region (from Unstable Slopes Database).

ODOT Region	General Excavation (Cost per m ³)	Stone Embankment (Cost per m ³)
1	\$22.44	\$34.61
2	\$10.97	\$20.66
3	\$15.16	\$30.69
4	\$11.85	\$16.65
5	\$9.57	\$17.50
Average	\$14.40 (~\$11.00 per cu. yd.)	\$24.02 (~\$18.50 per cu. yd.)

3.2.4.3 Impact to commerce and economic cost of highway closure

Aside from highway repair, a road-closing landslide may also incur economic costs. These costs are indirect, and are due to fuel expenses and time losses from reroutes in the highway network. The magnitude of lost commerce and economic delays is a function of time, and its calculation requires knowledge of the duration of a road closure.

The duration of a highway closure is equivalent to the time required to repair the highway. While repair times may be related to the time it takes to excavate or fill a certain amount of material, there are still many uncertainties. In an attempt to capture these uncertainties, a database of landslide repairs was compiled and used to relate volume of soil to time of closure (Table 3.4). The repair rate was determined as 250 cubic yards per day, which is an approximate average of the values computed from this database (Table 3.4).

Table 3.4: Landslides from Winter 2016-2017 Having Both Time of Road Closure and Volume of Material Excavated Reported in the News.

Road Affected	Nearest City	Date Closed	Date Opened	Days Closed	Material Volume (yd ³)
OR 36	Triangle Lake	1/18/2016	1/27/2016	9	100
River Road	Salem	2/21/2017	2/21/2017	1	200
US 20	Toledo	1/5/2017	1/6/2017	1	4000
W Burnside Road	Portland	1/18/2017	1/20/2017	2	200
OR 36	Triangle Lake	1/18/2017	1/23/2017	5	1400
OR 36	Triangle Lake	1/23/2017	1/27/2017	4	1200
W Burnside Road	Portland	3/15/2017	3/24/2017	9	300

Once the duration of closure has been determined, daily closure costs (Table 3.5) prepared by the Transportation Planning Analysis Unit (TPAU; Knudson and Dudich, 2017 and 2018, in Appendix D) can be multiplied by the estimated duration of closure to compute a total closure cost for each unstable block.

Table 3.5: Range of Potential Daily Costs Due to a Landslide Closure on Route 126 (From Appendix D).

Location	Time Costs	Vehicle Operating Costs	Range of Total Costs
OR 126 Tiernan	\$102,000 – \$143,000	\$38,000 - \$53,000	\$140,000 - \$196,000
OR 126 Walton	\$ 21,000 - \$33,000	\$ 7,500 - \$12,000	\$ 28,500 - \$45,000
US101	\$96,471 - \$192,865	\$70,013 - \$139,969	\$166,484 - \$332,834
OR42 East of Remote	\$29,028 - \$72,497	\$7,048 - \$17,601	\$36,075 - \$90,098
OR42 South of Myrtle Point	\$188,021 - \$375,892	\$47,393 - \$94,749	\$235,414 - \$470,640
OR42 At Norway	\$26,303 - \$52,596	\$5,391 - \$10,780	\$31,695 - \$63,376
OR42 North of Cedar Point	\$39,277 - \$78,538	\$6,988 - \$13,973	\$46,265 - \$92,511
OR36 at Alderwood State Wayside	\$2,167 - \$5,412	\$6 - \$16	\$2,173 - \$5,428

4.0 ACCURACY ASSESSMENT

4.1 SEMI-AUTOMATIC LANDSLIDE INVENTORY MAPPING

The purpose of an accuracy assessment for the SICCM landslide inventorying procedure is twofold. First, the assessment identifies values of deposit mapping parameters that produce the best results. Second, the assessment is necessary to convey the quality of maps produced using the procedure. The content of this section will describe the performance SICCM, as described in Chapter 3, and will not discuss the performance of earlier iterations of the methodology. Development of the SICCM methodology saw several changes to both scarp identification and deposit mapping procedures, and accuracy assessments were performed following some of these changes. These initial accuracy assessments have contributed to the design of SICCM and their results have been included in Appendix B.

In order to identify appropriate deposit mapping parameters, a parametric analysis (Table 4.1) was performed by comparing the results of several parameter combinations with manual inventories derived by the Special Paper 42 methodology in Big Elk Creek (Burns, 2012a), Gales Creek (Burns, 2012b), and Dixie Mountain (Burns, 2012c). The inventories are all located in western Oregon (Figure 4.1), and are considered to represent a significant range of landslide geomorphology and sizes. The result of this analysis is a single set of deposit mapping parameters (Table 4.2) that were qualitatively deemed to have a good combination of precision, recall, and accuracy on all three inventories.

Table 4.1 presents several accuracy measures that warrant further explanation. Each measure is computed by converting both the manual inventory and SICCM inventory to rasters and then comparing the rasters on a pixel-to-pixel basis. A simple illustration is provided in Figure 4.2.

- **Landslide Percent of Map:** the ratio of landslide area, based on the manual inventory, to the area of terrain that was mapped. The measure is independent of SICCM results. It is important because it highlights the challenge of appropriately mapping (neither overmapping nor undermapping) landslides in a given terrain.
- **Accuracy:** the percentage of area mapped by SICCM in agreement with the manual inventory. The accuracy computation considers both landslide and non-landslide area, pixel by pixel. This value represents an overall assessment of SICCM's ability to accurately map the extents of landslides.
- **Recall (Percent of Manual):** the ratio of manual inventory landslide pixels to the pixels mapped as landslide by SICCM. Low values represent under mapping by SICCM. While high values are typically better, the measure does not account for area not mapped as landslide by the manual inventory. This value represents SICCM's ability to directly replicate the shape of manually drawn landslides.

- **Precision (Percent Correct):** the ratio of SICCM landslide pixels that correspond with landslide pixels of the manual inventory to the total number of SICCM landslide pixels. Low values tend to reflect over mapping.

Table 4.1 Results of Parametric Study on SICCM Deposit Mapping Parameters.

ID	Site	Contour Interval	Nodal Spacing	Active Slope	Branch Parameter	TP	TN	FN	FP	ACC	LS% MAP	Recall	Precision
1	Gales Creek	10	10	0.05	3	7716	122856	16053	5731	0.86	0.16	0.32	0.57
2	Gales Creek	30	30	0.05	3	9172	121100	14608	7010	0.86	0.16	0.39	0.57
3	Gales Creek	10	10	0.05	5	11113	118046	12663	10534	0.85	0.16	0.47	0.51
4	Gales Creek	30	30	0.03	5	12975	114084	10823	14474	0.83	0.16	0.55	0.47
5	Gales Creek	10	10	0.03	5	12205	116737	11571	11843	0.85	0.16	0.51	0.51
6	Gales Creek	20	20	0.05	3	8791	121671	14973	6455	0.86	0.16	0.37	0.58
7	Gales Creek	20	20	0.05	5	12397	117535	11387	11037	0.85	0.16	0.52	0.53
8	Gales Creek	30	30	0.03	3	9507	119988	14277	8118	0.85	0.16	0.40	0.54
9	Gales Creek	30	30	0.05	5	12722	116010	11072	12552	0.84	0.16	0.53	0.50
10	Gales Creek	10	10	0.03	3	8427	122007	15343	6579	0.86	0.16	0.35	0.56
11	Gales Creek	20	20	0.03	3	9193	121585	14571	7939	0.85	0.16	0.39	0.54
12	Gales Creek	20	20	0.03	5	12705	116456	11077	13050	0.84	0.16	0.53	0.49

1	Dixie Mountain	10	10	0.05	3	17183	70702	36987	4984	0.68	0.42	0.32	0.78
2	Dixie Mountain	30	30	0.05	3	12348	72301	41804	3070	0.65	0.42	0.23	0.80
3	Dixie Mountain	10	10	0.05	5	13453	71772	40790	4124	0.65	0.42	0.25	0.77
4	Dixie Mountain	30	30	0.03	5	22694	68704	31494	6886	0.70	0.42	0.42	0.77
5	Dixie Mountain	10	10	0.03	5	8878	73384	45449	2407	0.63	0.42	0.16	0.79
6	Dixie Mountain	20	20	0.05	3	10831	73027	43438	2748	0.64	0.42	0.20	0.80
7	Dixie Mountain	20	20	0.05	5	17089	71146	37161	4660	0.68	0.42	0.32	0.79
8	Dixie Mountain	30	30	0.03	3	15628	71410	38591	4198	0.67	0.42	0.29	0.79
9	Dixie Mountain	30	30	0.05	5	18816	70020	35330	5279	0.69	0.42	0.35	0.78
10	Dixie Mountain	10	10	0.03	3	12027	72461	42189	3160	0.65	0.42	0.22	0.79
11	Dixie Mountain	20	20	0.03	3	13605	71948	40604	3596	0.66	0.42	0.25	0.79
12	Dixie Mountain	20	20	0.03	5	19864	69769	34379	5720	0.69	0.42	0.37	0.78
12	Big Elk Creek	20	20	0.03	5	61757	140713	19654	24560	0.82	0.33	0.76	0.72
8	Big Elk Creek	30	30	0.03	3	44108	154564	32279	10733	0.82	0.32	0.58	0.80
9	Big Elk Creek	30	30	0.05	5	60563	141296	20819	23938	0.82	0.33	0.74	0.72

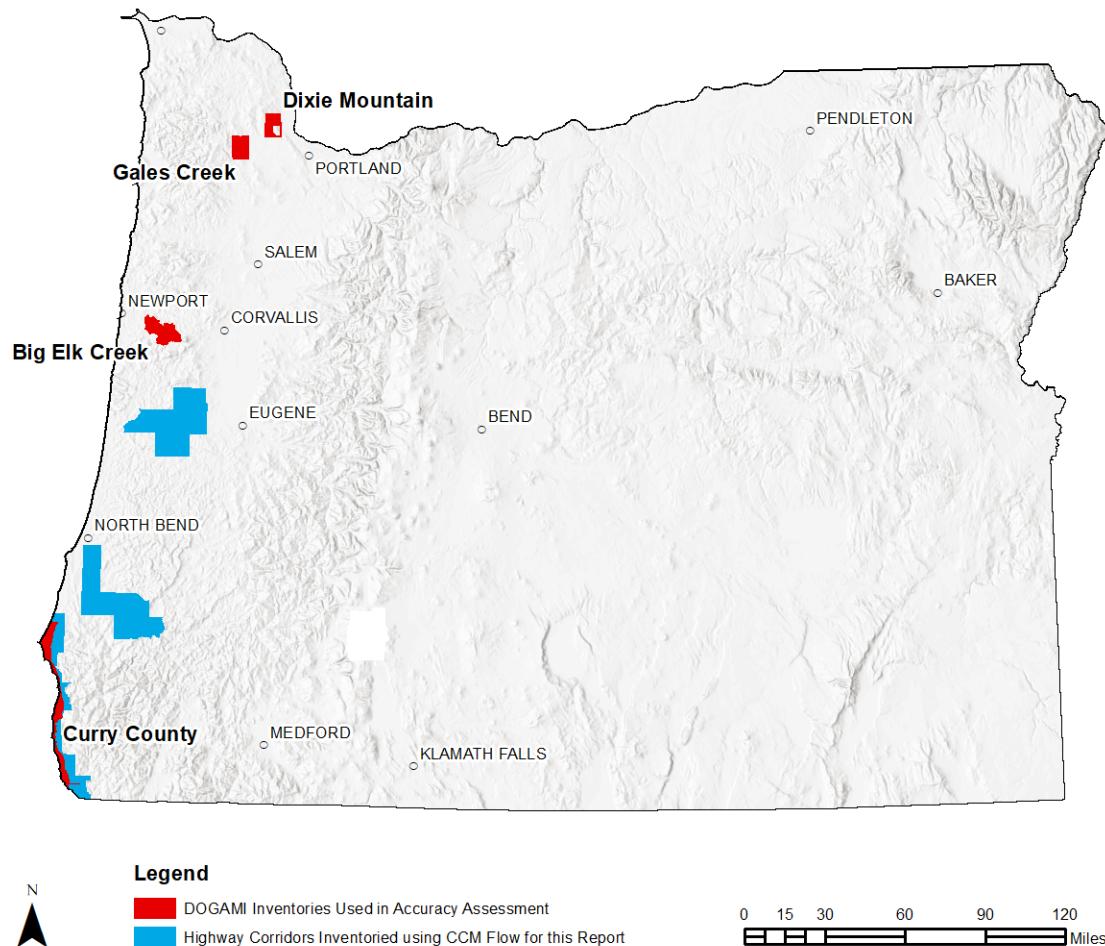
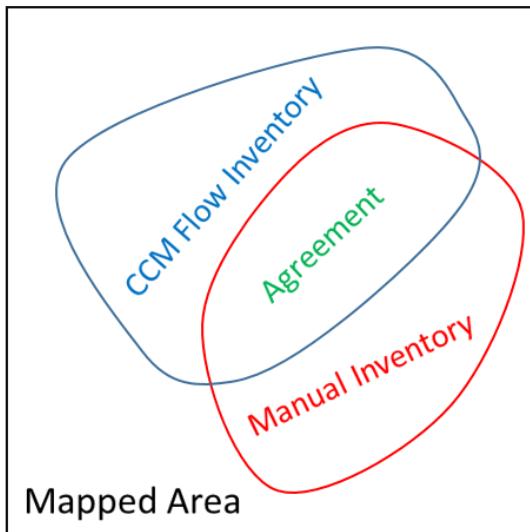


Figure 4.1: Location of manual inventories used in the accuracy assessment and the highway corridors mapped by SICCM.

Table 4.2: Recommended Values Based on the Parametric Study.

Parameter	Value
Contour interval	20 feet
Nodal spacing	20 feet
Active slope	0.03
Branch parameter	5



Landslide Percent of Map	$= \frac{\text{Blue Area}}{\text{Black Square}}$
Precision	$= \frac{\text{Blue and Red Area}}{\text{Blue Area}}$
Accuracy	$= \frac{\text{Black Square} - \text{Red Area}}{\text{Black Square}}$
Recall	$= \frac{\text{Blue and Red Area}}{\text{Red Area}}$

Figure 4.2: Illustration of the accuracy measures presented in Table 4.1. Solid colors, represent the portion of each inventory used in calculations, and a solid black square represents the entire mapped area.

The deposit mapping parameters in Table 4.2 used to produce SICCM inventory maps for the highway corridors discussed in the next chapter. To provide a sense of the quality of the corridor landslide inventories, Table 4.3 includes the accuracy measures computed based on the Table 4.2 parameters for all three manual inventories, and an additional manual inventory for coastal Curry County (Burns, 2014). The Curry County inventory overlaps with much of the US Route 101 corridor, and provides a good representation of the quality of maps produced for this report.

Table 4.3 also includes a new measure, Percent of Slides Mapped > 50%, inspired by Van Den Eeckhaut et al. (2012), to measure how well the SICCM inventories capture individual landslides from a manual inventory. Unlike the other measures, 50% of Manual is computed by looking at each manually mapped landslide and counting those whose extents have been at least 50 percent mapped by SICCM. This measure does not completely describe accuracy, as it does not consider over-prediction, but it does add another perspective to the accuracy assessment.

Table 4.3: Results of Accuracy Evaluation for Selected Deposit Mapping Parameters.

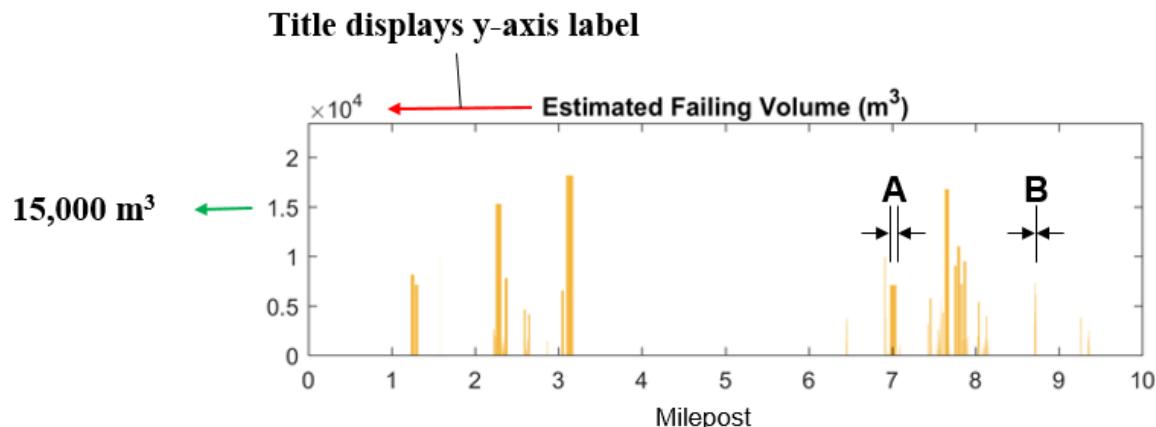
Location	Area Mapped (Square Miles)	Landslide Percent of Map (%)	Accuracy (%)	Recall (%)	Precision (%)	Percent of Slides Mapped > 50% (%)
Gales Creek	55	16	84	53	49	48
Dixie Mountain	47	42	69	37	78	31
Big Elk	88	33	82	76	72	70
101 South of Otter Point	74	21	69	75	37	63
101 North of Otter Point	83	13	86	54	49	36

5.0 RESULTS AND DISCUSSION

5.1 OVERVIEW

There are a number of outputs associated with this report, which include landslide inventory maps and risk assessments for four ODOT-managed highways, but also the entire methodology of Chapter 3, corresponding digital GIS data and the SICCM toolbox. This chapter will focus on presentation and discussion of the inventory maps and risk assessments, and the digital data and methodology are included with the report as geodatabases, an ArcGIS™ toolbox, and standalone software. A list of these included files can be found in Appendix A, and step-by-step instructions for how to use the methodology may be found in Appendix E.

Risk assessments have been presented as plots of risk measure (volume of soil, duration of closure, etc.) versus milepost. Each unstable block is represented by a bar on the plot, with the height corresponding to the total value for the block (not per unit length) and the length corresponding to the length of highway that intersects the block. Figure 5.1 has been included to assist in the interpretation of these plots.



Observations about landslides A and B:

- A affects the road for a greater length than B because its bar is wider
- A and B have similar failing volumes because their height is similar
- Since failing volume is similar, the landslides will also have similar durations of closure

Figure 5.1: Guide to interpreting risk plots presented in this chapter.

The four ODOT-managed highways discussed in this section are Oregon Routes 36, 42, and 126, and US Route 101 (Figure 5.2). Each highway serves a unique purpose in the Oregon

transportation network, and all have been previously impacted by landslide activity. The following sections will introduce each highway corridor, and then present landslide inventory maps produced using SICCM and risk analyses based on the inventories.

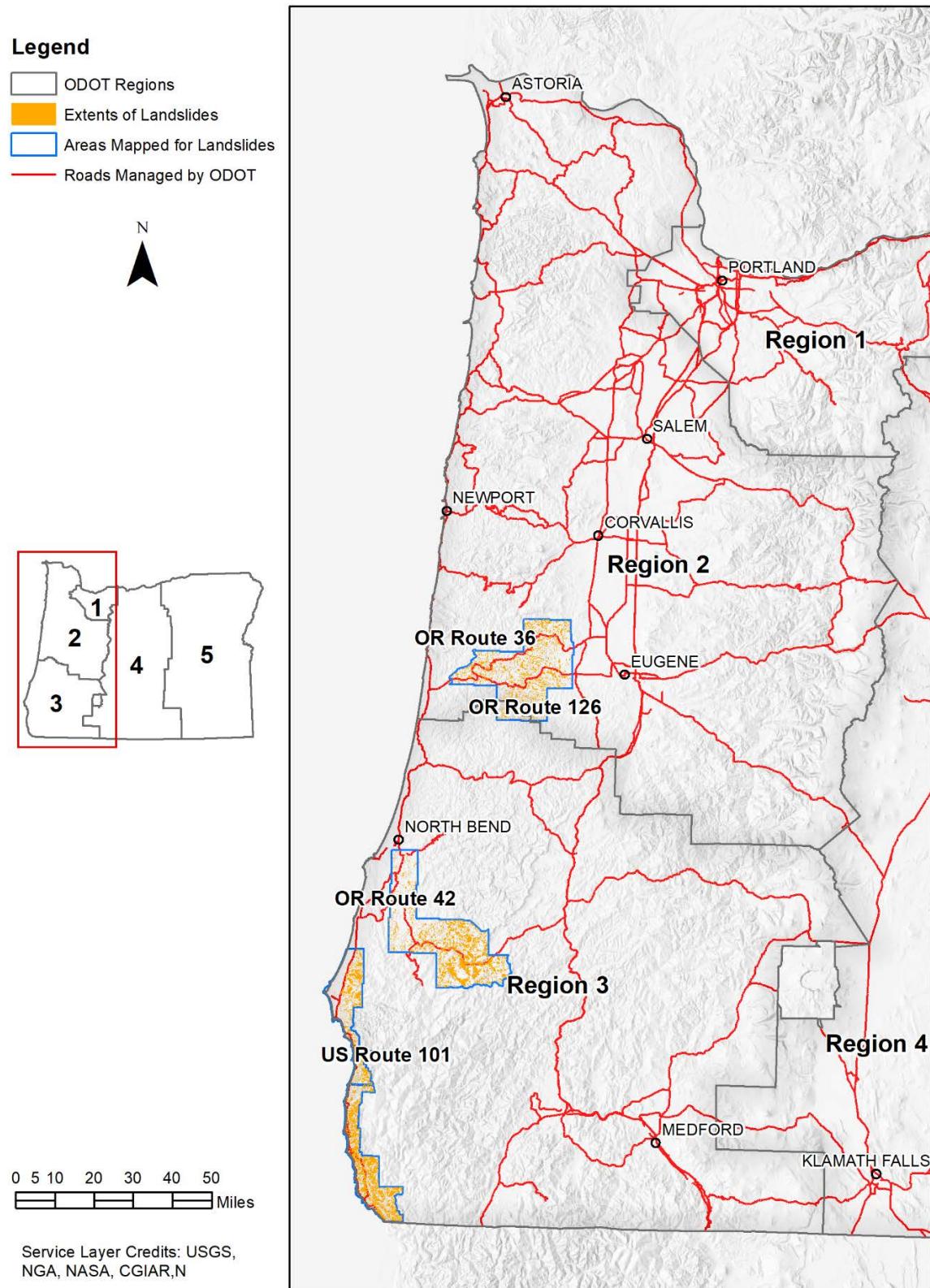


Figure 5.2: Location of the four study corridors within Western Oregon (ODOT Regions 2 and 3).

5.2 OREGON ROUTES 36 AND 126

5.2.1 Route 36 and 126 Overview

Oregon Routes 36 and 126 traverse the Oregon Coast Range between the southern Willamette Valley and Florence. Although both are two lane highways passing through similar geology, the purpose of each route is quite different. Route 36 services a number of small communities, and sees annual average daily traffic (AADT) ranging from less than 500 west of Triangle Lake to 1,500 where it enters the Willamette Valley. Route 126 serves as a primary link between the southern Willamette Valley and the Oregon Coast and sees AADT of approximately 4,000 to 6,000 for its entire course. Geology alongside most routes is entirely comprised of Tyee Formation, with the exception of short alluvial segments when crossing floodplains. Landslide activity along both routes is characterized by deep slides occurring at weak bedding interfaces, and areas of high activity typically exists in places where bedrock dips steeply (Roering, Kirchner, & Dietrich, 2005). The loosely deposited soils resulting from these deep landslides also leads to small instabilities that routinely cause short road closures. This process has been most visible in several multi-day closures of Route 36 during the 2015-16 and 2016-17 winters.

5.2.2 Route 36 and 126 Inventory Map

The SICCM methodology was used to map 466 square miles surrounding more than 80 miles of Routes 36 and 126. A full-resolution landslide inventory map has been included with this report, but a reduced size version can be found in Figure 5.3. A quantitative summary of the corridor is presented in Table 5.1.

Table 5.1: Quantitative Summary of the Oregon Route 36 and 126 Landslide Inventory.

Quantity	Route 36	Route 126
Area Mapped	466 sq. mi.	
Number of Mapped Landslide Features	8,493	
Number of Landslide Features that Intersect Highway	63	48
Length of Highway	42.1 mi.	39.1 mi.
Length of Highway Crossing Landslide Deposits	6.1 mi.	5.9 mi.
Percent of Highway Length that Crosses Landslide Deposits	14 %	15 %

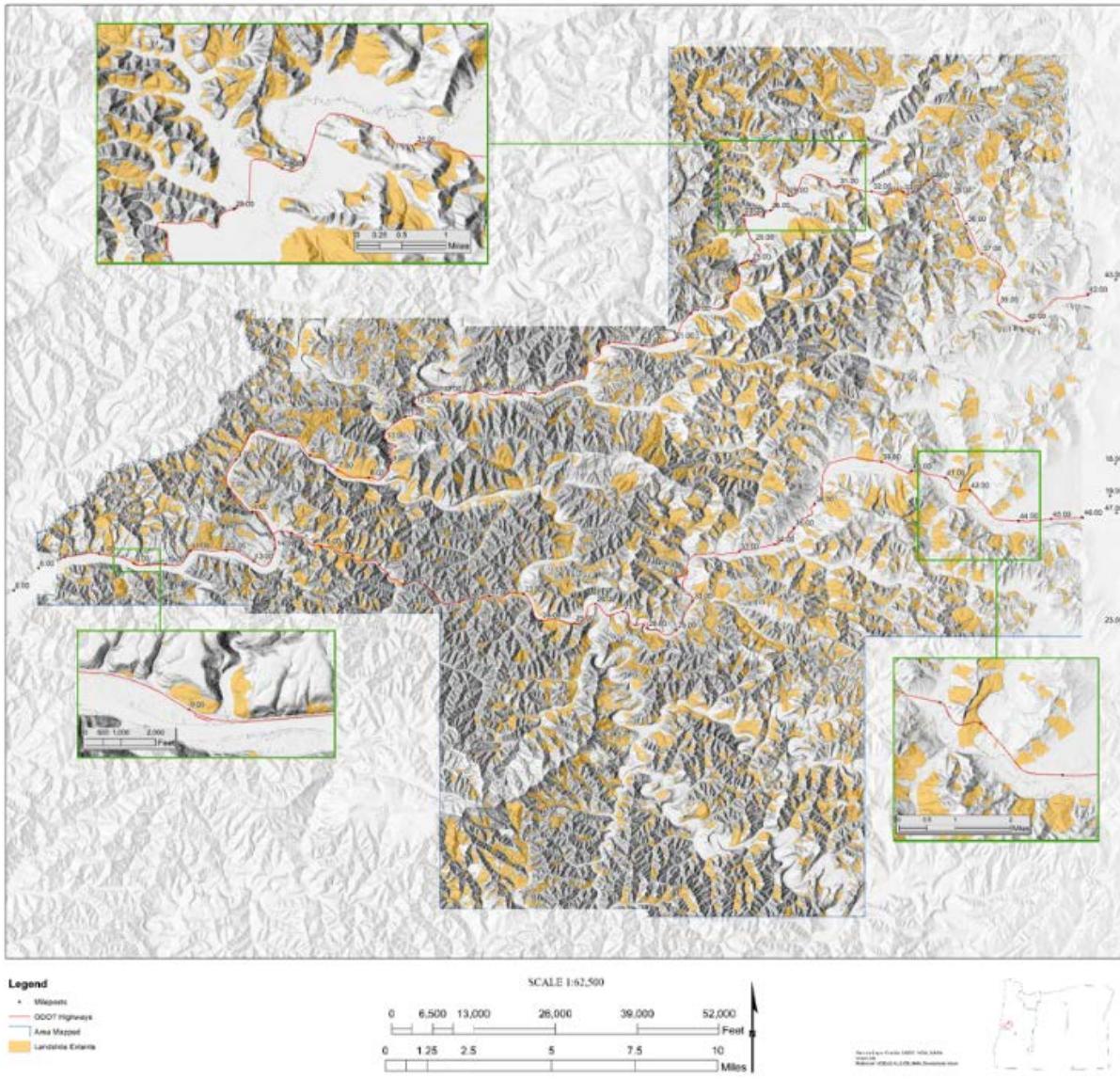


Figure 5.3: Landslide deposit inventory map for the Oregon Route 36 and 126 corridor of the Oregon Coast Range. Inset maps have been provided to add detail in locations where the highways pass through predicted areas of high landslide activity.

The landslide inventory map shows a region dominated by landslide activity. Toward the west, landslides occur on steeper slopes and at all aspects, and toward the east, landslides occur at shallow slopes and appear on slopes of similar aspect. While landslide deposits are widespread in the region, the highways were typically constructed on flat ground, near rivers and away from landslides. The two settings where landslides appear to be a hazard are where the river forces the highway against a canyon wall (Route 36: MP 1-5, MP 23-25; Route 126: MP 7-12, MP 15-18) and where the highway crosses a pass from one river drainage to another (Route 36: MP 32-35; Route 126: MP 19-23).

The aforementioned observations - that highways tend to be built on flat ground and away from landslides - does not provide a sense of how far the two are apart. A look into how landslide features are distributed within 1,000 feet of either highway (Figure 5.4) shows that a larger number of landslides are located within 100 feet of Route 36 than Route 126; information not obvious from Table 5.1 or from a quick glance at the inventory map. The close proximity of landslides to Route 36 implies that it may be subject to more future landslides than Route 126. Note that landslide features in Figure 5.4 are referred to as “new” because a given histogram value does not reflect any values from histogram bars closer to the road. For example, the histogram count of 200 to 300 feet does not reflect the count of 100 to 200 feet.

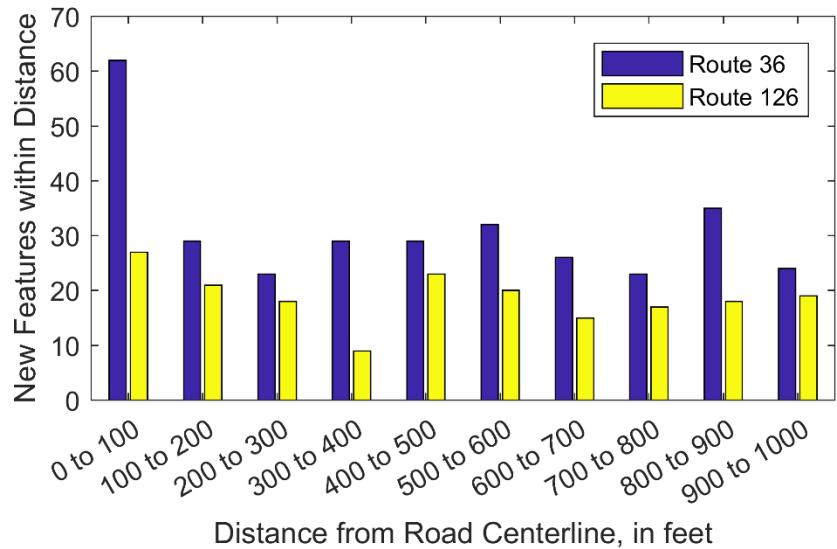


Figure 5.4: Distribution of landslide features within 1,000 feet of Oregon Routes 36 and 126. Note that the figure does not include landslides that intersect highway.

5.2.3 Route 36 and 126 Risk Analysis

A risk analysis was performed to gain more information about the potential dangers from landslide hazards along Routes 36 (Figures 5.5 – 5.9) and 126 (Figures 5.11 – 5.15). Refer to Chapter 3.2 of this report for detail on how the plots were created.

Figures 5.5 through 5.9 tend to agree with the previous observation that landslide risk is the greatest when the highway crosses mountain passes (MP 34 – 39) or is confined by a river and

hillslope (MP 2 and 14). Unfortunately, the plots do not indicate significant risk from mileposts 24 to 25, where recent landslide activity has been indicated by news reports. The omission is due to SICCM's failure to map the ancient Triangle Lake landslide and its deposits (Figure 5.10).

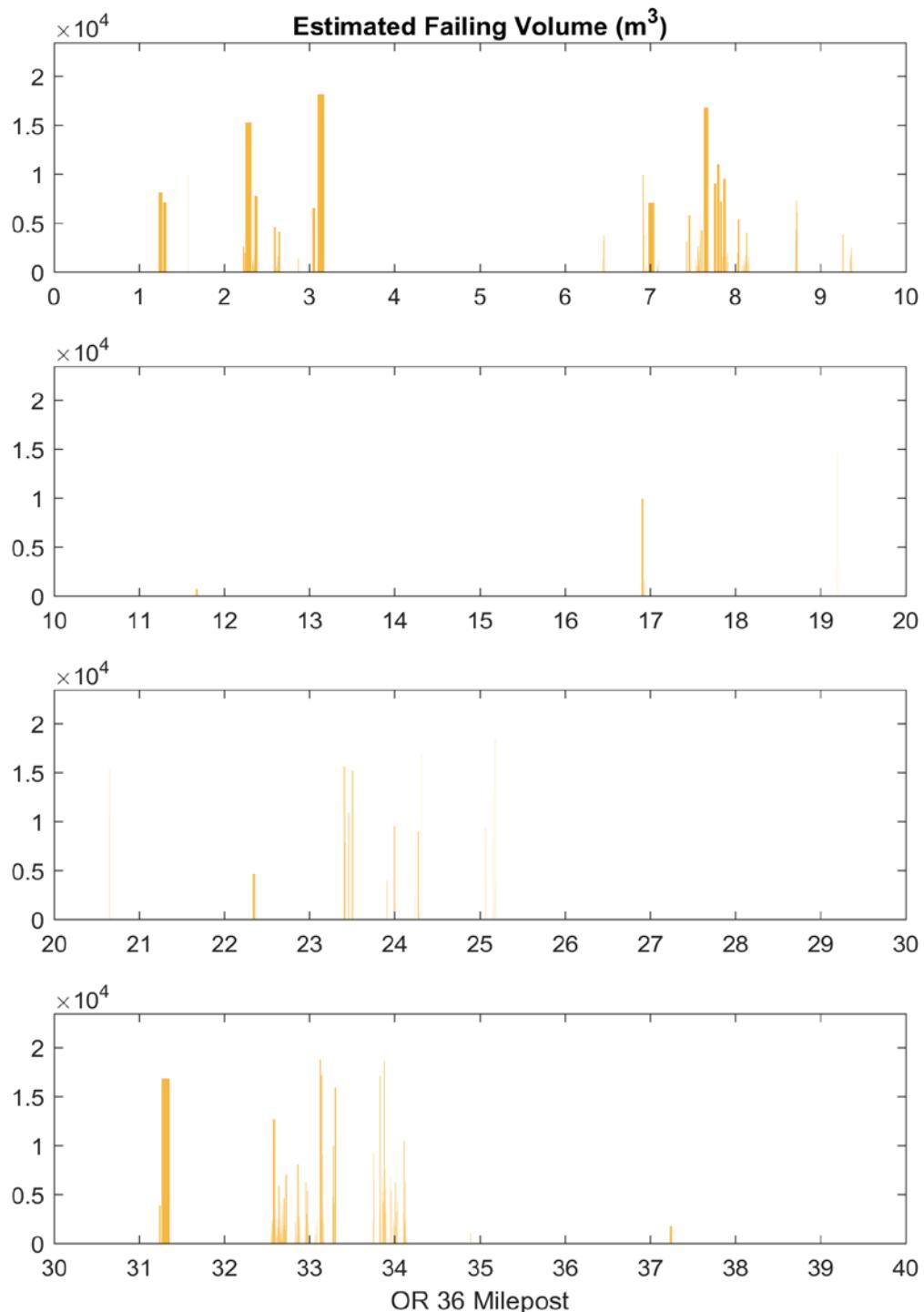


Figure 5.5: Estimated volume unstable soil underlying Oregon Route 36 by milepost.

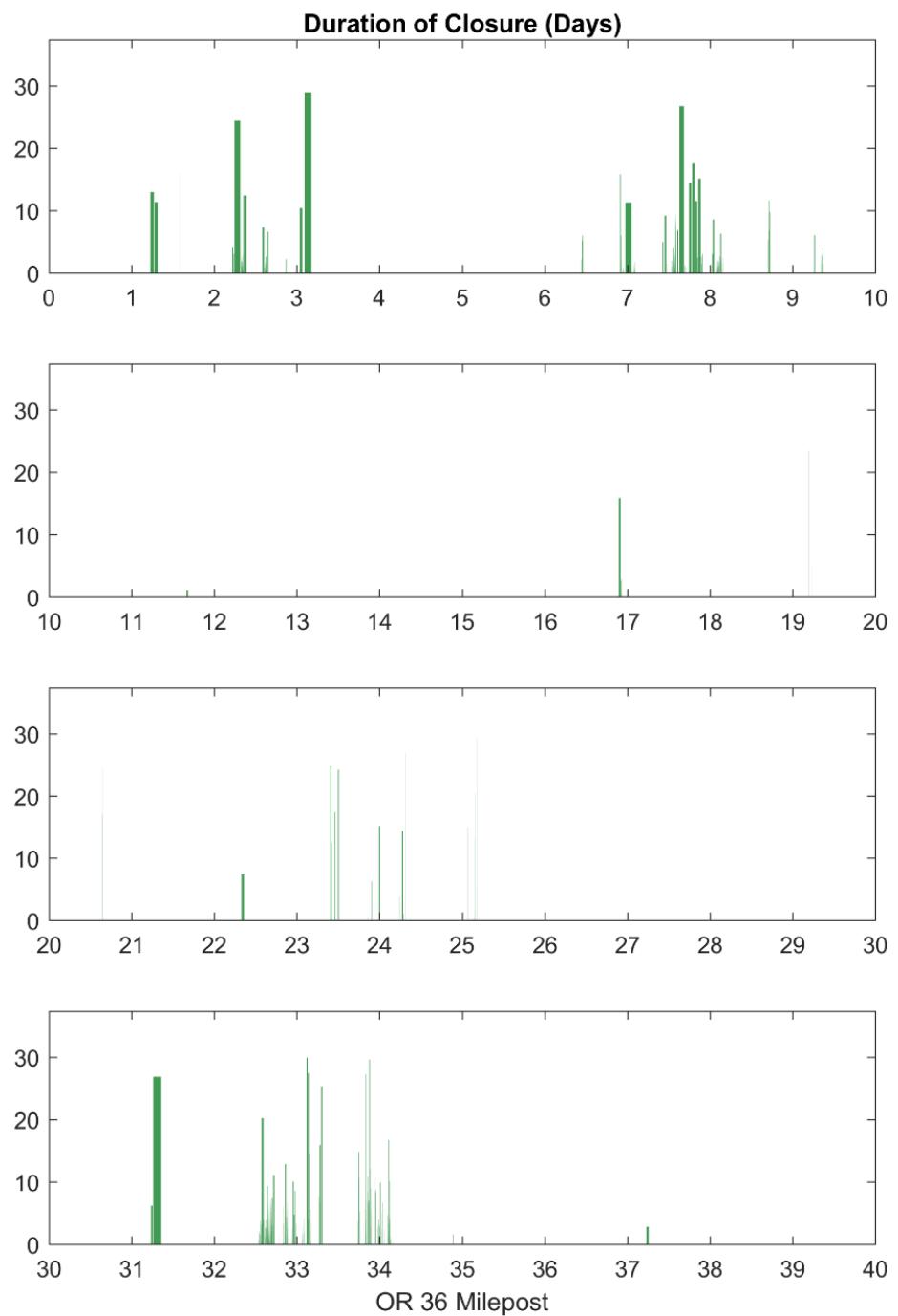


Figure 5.6: Estimated duration of closures along Oregon Route 36.

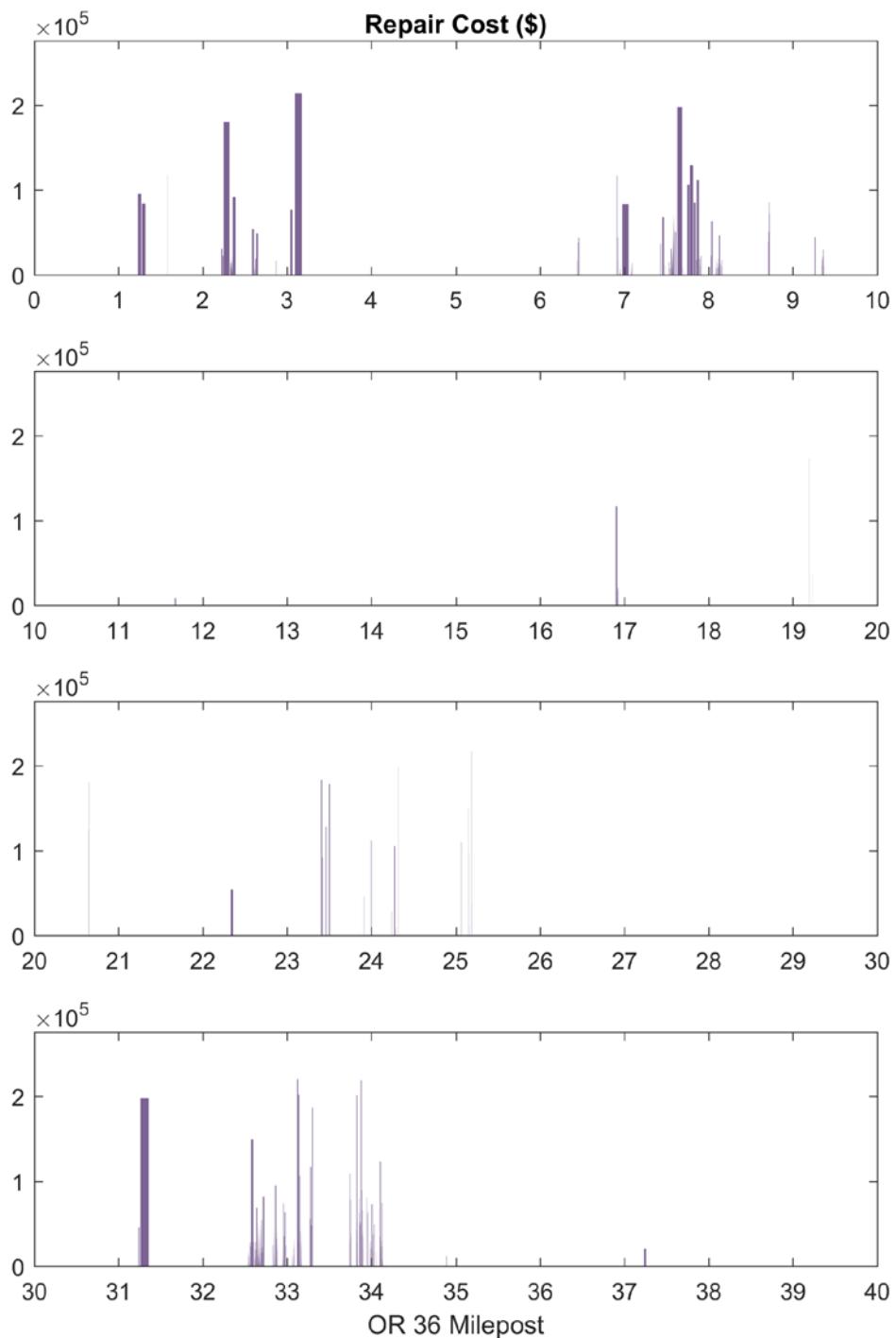


Figure 5.7: Estimated repair cost associated with reopening of Oregon Route 36 following landslides the reactivation of mapped landslides.

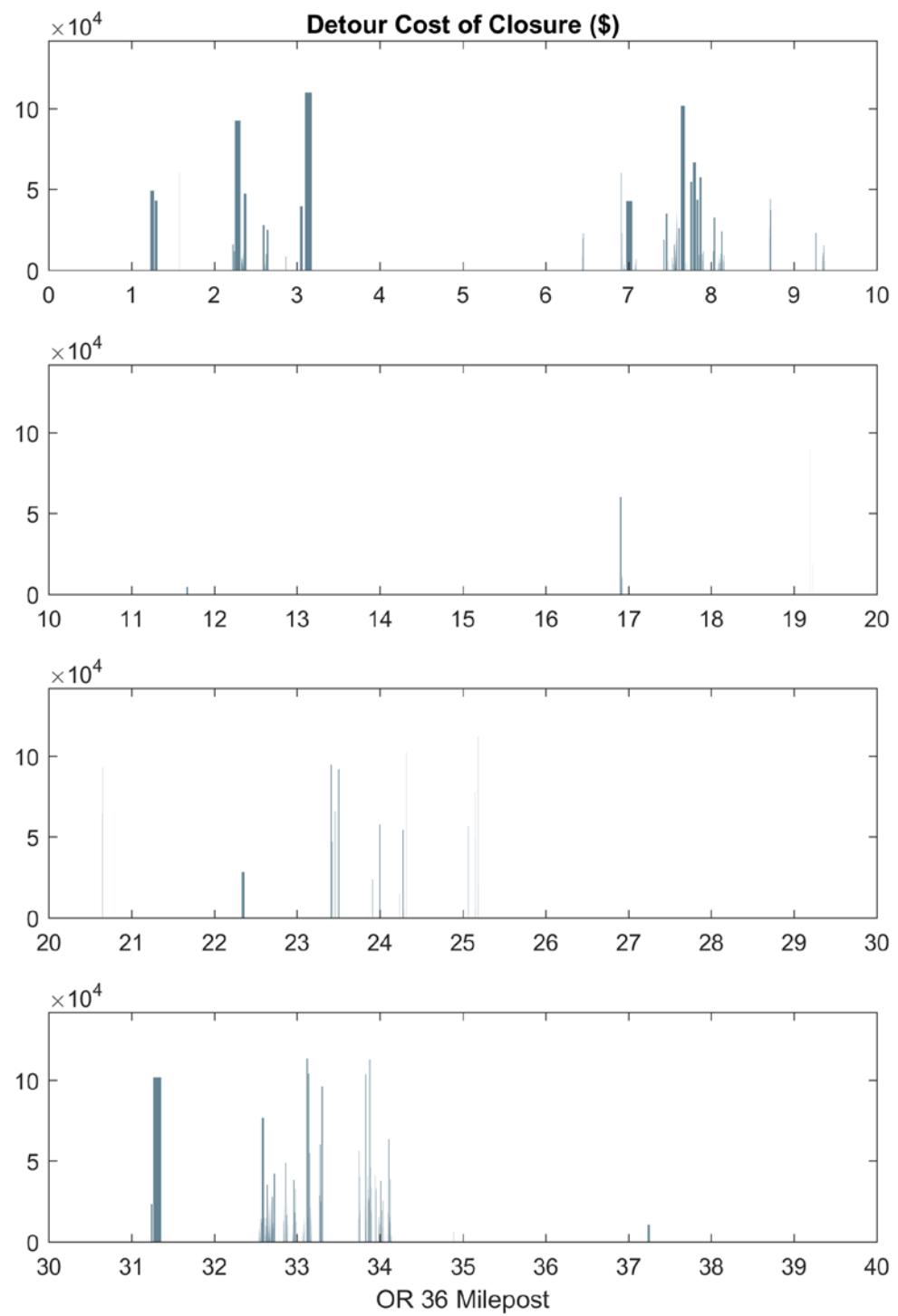


Figure 5.8: Approximate economic costs incurred by closures on Oregon Route 36.

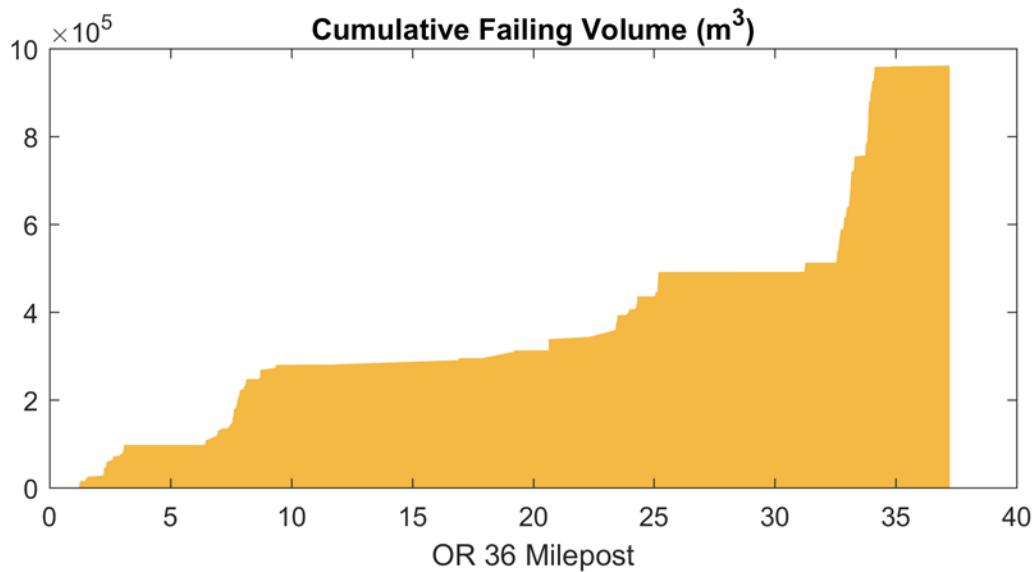


Figure 5.9: Cumulative volume of unstable soil estimated to underlie Oregon Route 36.

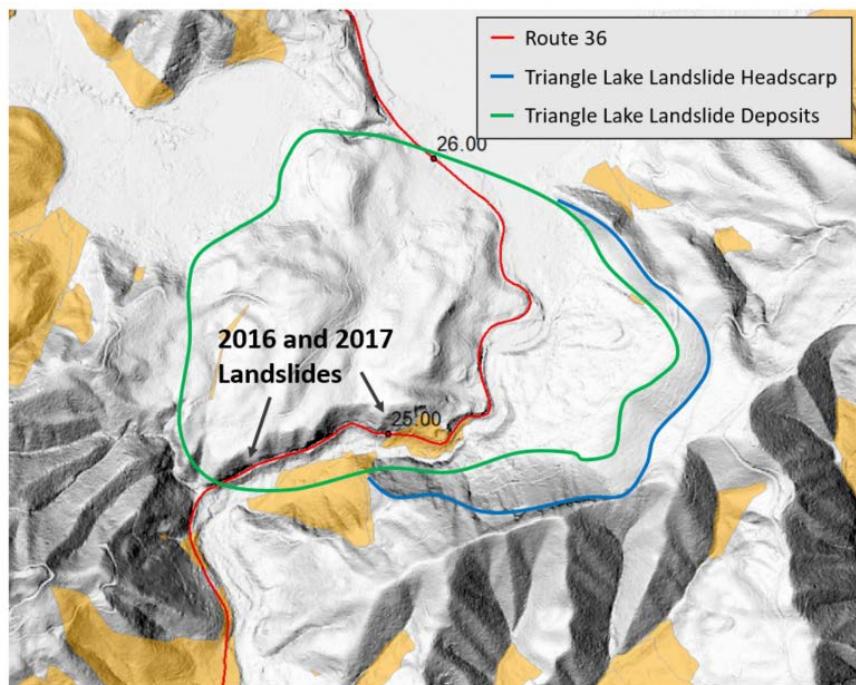


Figure 5.10: Approximate extents of the ancient Triangle Lake landslide near Route 36.

More than 42,000 years (Baldwin, 1958) of sediment deposition makes much of the landslide too flat for deposit mapping to occur, but the headscarp is well enough defined that scarp identification should be expected to work. The reason why scarp identification failed is that the landslide was too large for its headscarp to be mapped using a 20 foot resolution DEM. This observation shows that while SICCM is flexible enough to capture many shapes and sizes of landslides, it still cannot capture all landslides.

The risk analysis for Route 126 is presented in Figures 5.11 to 5.15 below.

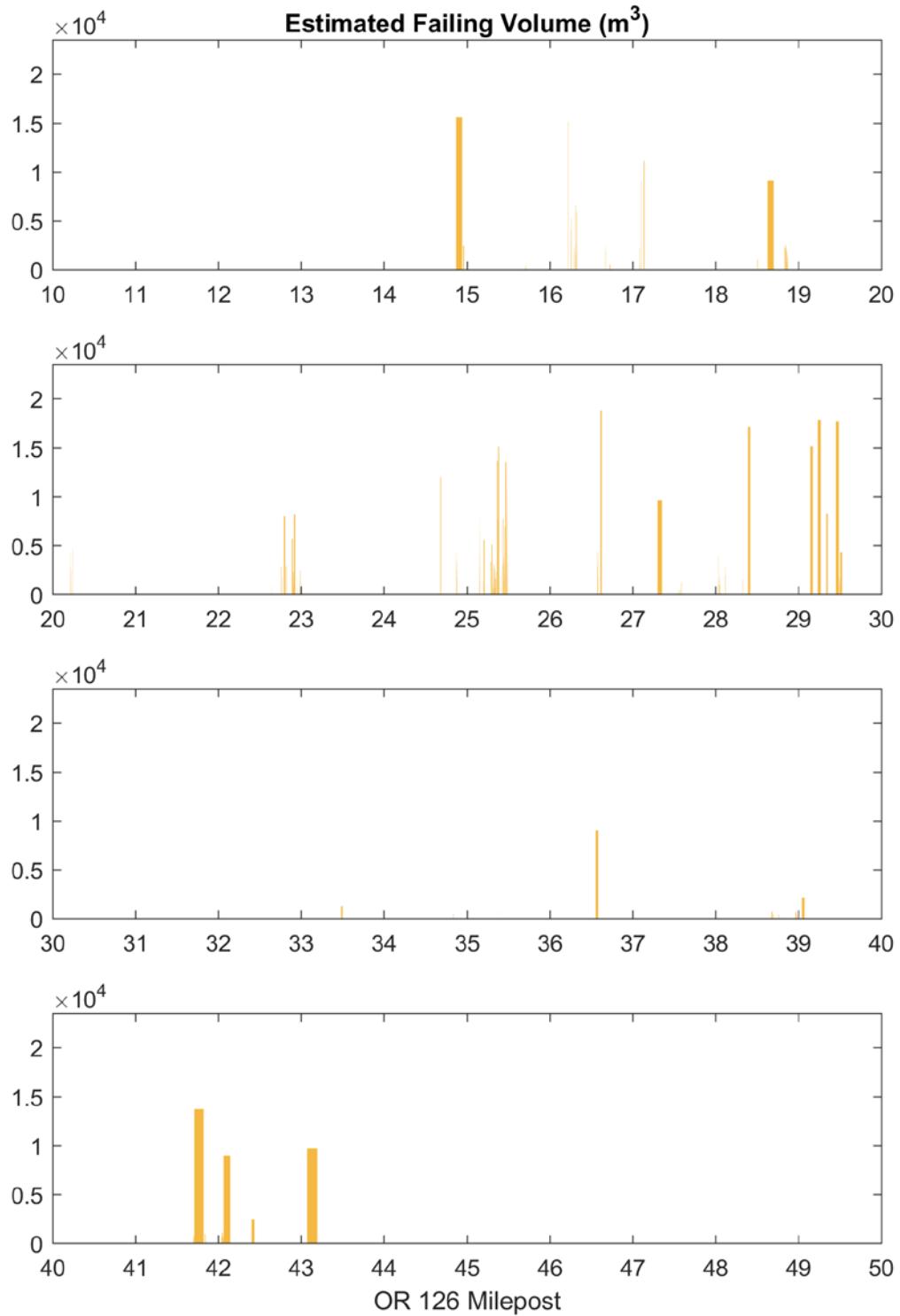


Figure 5.11: Estimated volume unstable soil underlying Oregon Route 126 by milepost.

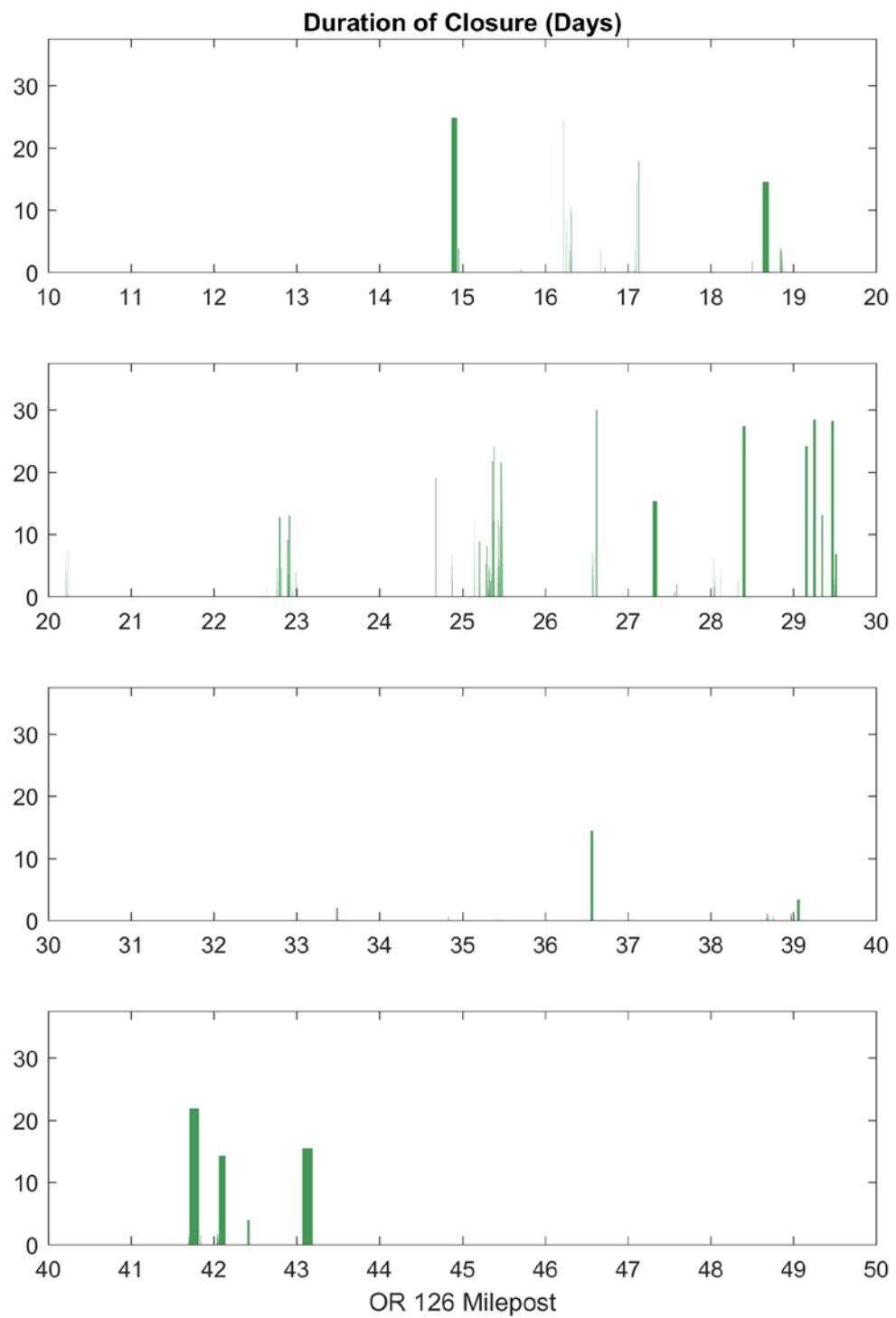


Figure 5.12: Estimated duration of closures along Oregon Route 126.

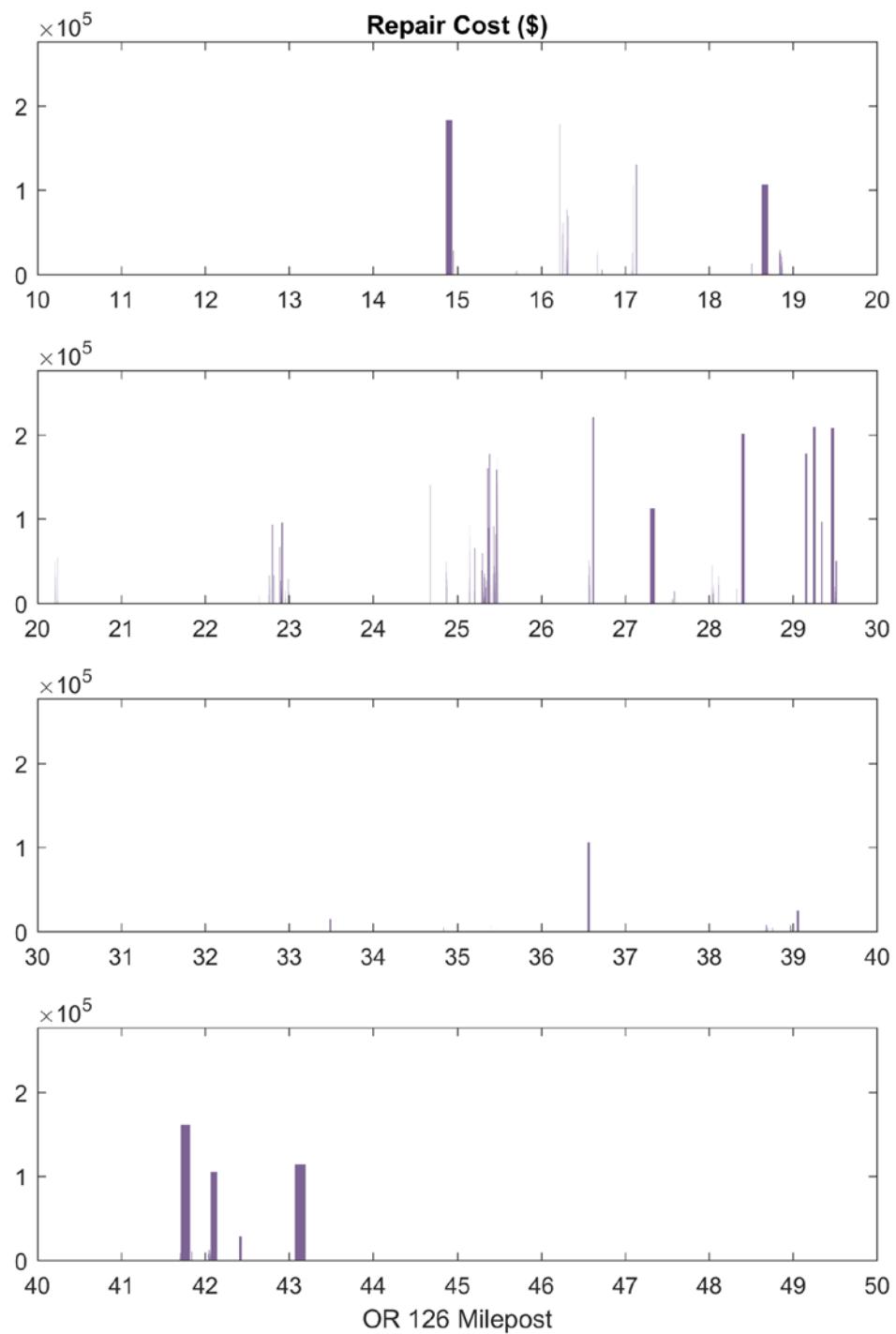


Figure 5.13: Estimated repair cost associated with reopening of Oregon Route 126 following landslides the reactivation of mapped landslides.

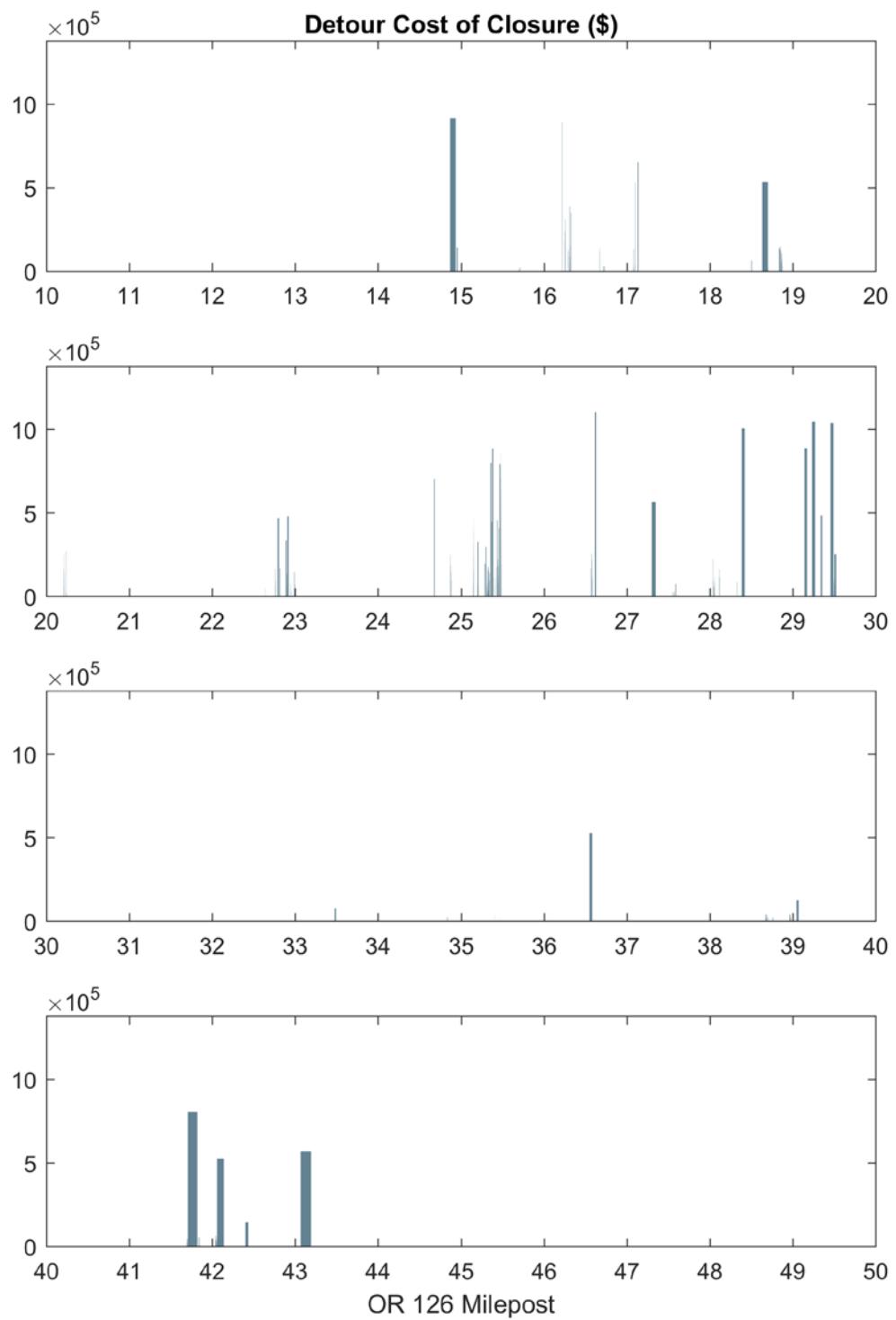


Figure 5.14: Approximate economic costs incurred by closures on Oregon Route 126.

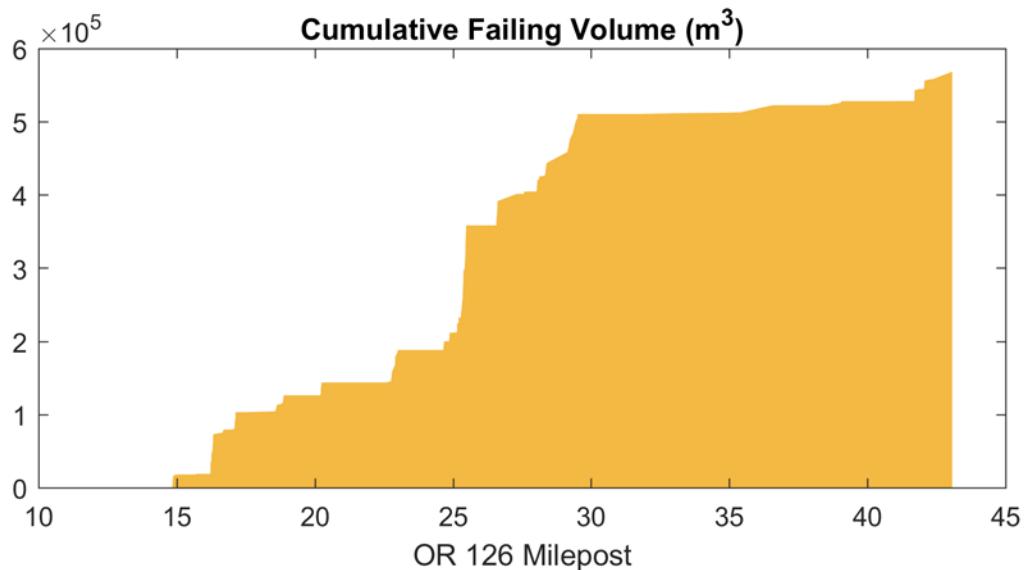


Figure 5.15: Cumulative volume of unstable soil estimated to underlie Oregon Route 126.

The risk plots for Route 126 in Figure 5.11 to 5.15 are similar to those for Route 36, with most landslide risk being estimated in areas where the highway is pinched between a river and a hillslope.

5.3 OREGON ROUTE 42

5.3.1 Route 42 Overview

Oregon Route 42 connects Roseburg and Interstate 5 to the Oregon Coast communities of Coos Bay, North Bend, and Bandon, as well as servicing numerous small towns and the cities of Myrtle Point and Coquille along the way. AADT is greatest between Coquille and Coos Bay, at greater than 8,000, and is lowest east of the junction with Oregon Route 542 (Powers Highway), at less than 3,000. Detailed geologic information is generally unavailable for the road, but most sources suggest similar geology to the Tyee Formation (Baldwin & Hess, 1971; Niem & Neim, 1990; Wells et al., 2000). A major landslide, resulting in a one-month highway closure, occurred during the 2015-16 winter in an area of exposed bedding, which indicates that bedrock may be weaker than expected of the Tyee Formation. Much of the highway east of Myrtle Point is in a narrow canyon with limited stable ground, and is considerably more vulnerable to landslides and rock fall than other routes traversing the Oregon Coast Range.

5.3.2 Route 42 Inventory Map

The SICCM methodology was used to map 480 square miles surrounding nearly 50 miles of Route 42. The full-resolution landslide inventory map has been included with this report, but a reduced size version can be found in Figure 5.16. A quantitative summary of the corridor is presented in Table 5.2.

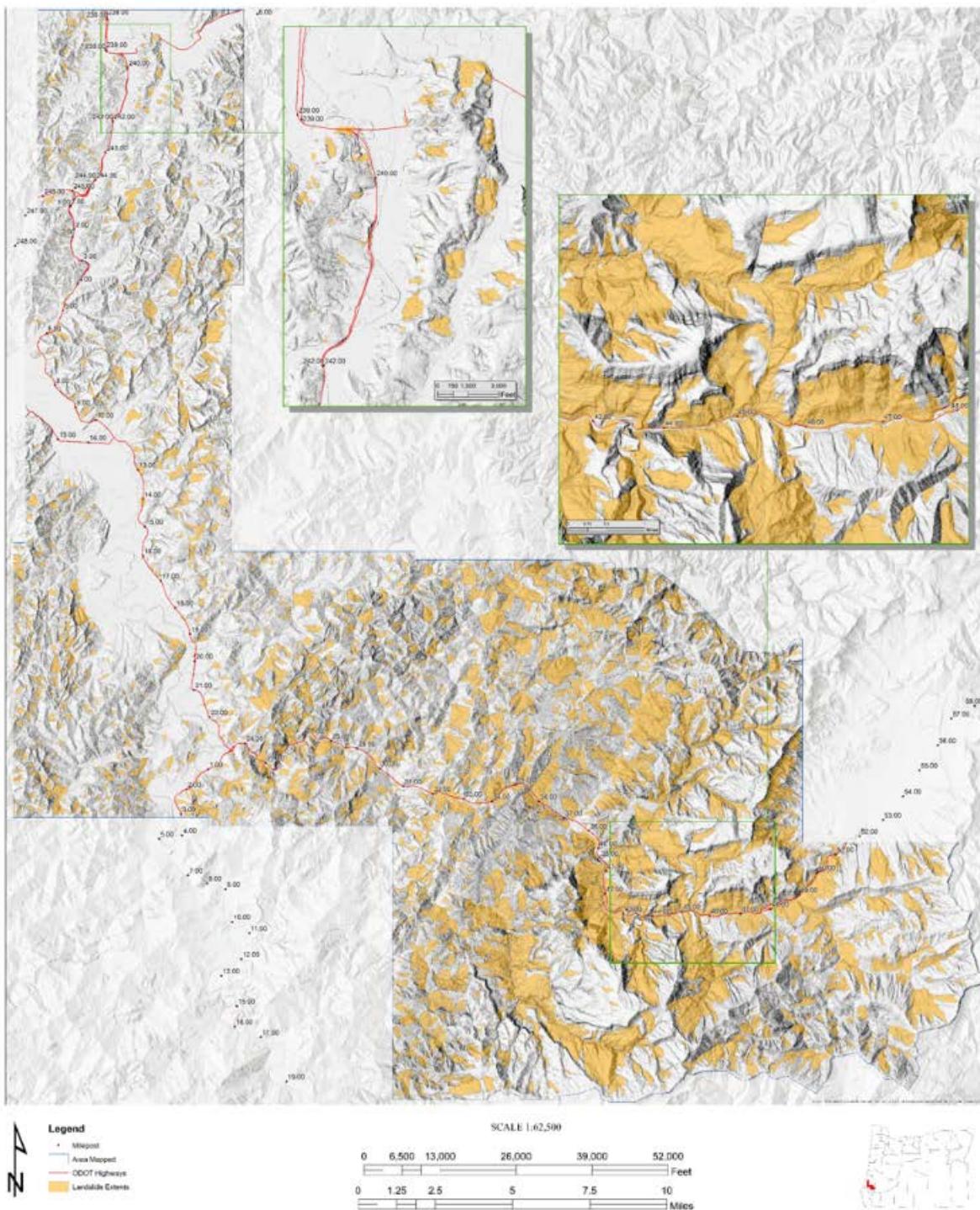


Figure 5.16: Landslide deposit inventory map for the Oregon Route 42 corridor of the Oregon Coast Range. Inset maps have been provided to add detail in locations where the highway passes through predicted areas of high landslide activity.

Table 5.2: Quantitative Summary of the Oregon Route 42 Landslide Inventory.

Quantity	Route 42
Area Mapped	480 sq. mi.
Number of Mapped Landslide Features	13,606
Number of Landslide Features that Intersect Highway	313
Length of Highway	49.4 mi.
Length of Highway Crossing Landslide Deposits	18.6 mi.
Percent of Highway Length that Crosses Landslide Deposits	38 %

The inventory map for Route 42 exhibits two major landsliding patterns. First, a narrow canyon on the eastern side (MP 40 – 50) leaves little stable ground for the highway, and results in a major portion of Route 42 crossing landslide deposits. Second, small slumps between Coos Bay and Myrtle Point (MP 0 – 22) present regular hazards to the highway, and endanger infrastructure in the communities of Coos Bay, Coquille (MP 11), and Myrtle Point (MP 21).

As was done with Routes 36 and 126, a distribution of landslides within 1,000 feet of the highway was prepared (Figure 5.17). Even more so than for Route 36, Figure 5.17 shows a concentration of landslides in close proximity to the highway. This observation is likely related to the geographic constraint posed by the narrow canyon mentioned previously.

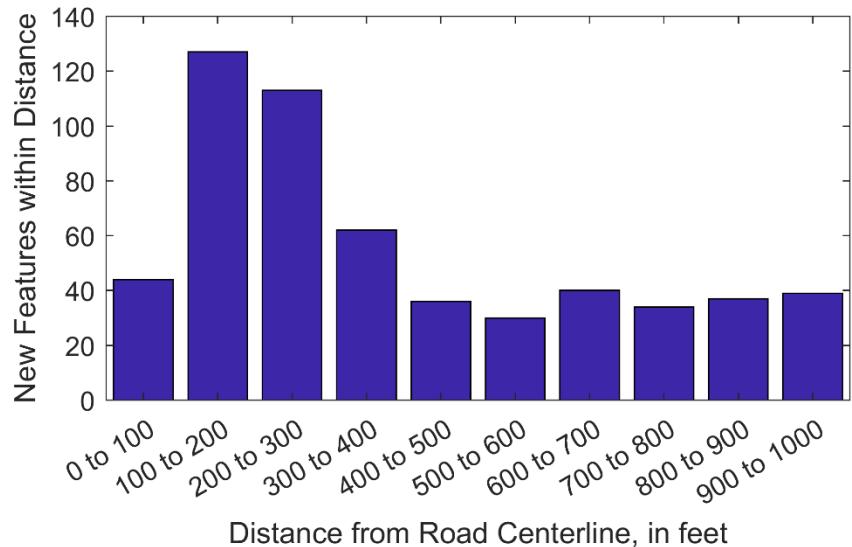


Figure 5.17: Distribution of landslide features within 1,000 feet of Oregon Route 42. The figure does not include landslides that intersect highway.

The inventory-conveyed hazard observed in the narrow canyon (MP 40 – 50) is challenged by the bedding planes evident in the canyon walls. A typical assumption is that the interbedded sediments would be weakest along their bedding plane, and not orthogonal to it, as is visible in Figure 5.18. Furthermore, this expected behavior is visible on the south canyon walls, where shallow landslides appear to follow bedding. Initially, this observation might mean that the inventory is incorrect, but closer examination shows that the bedding dips toward the east, and

that the assumption is being satisfied. The reason for confusion is that the river has eroded the formation in a way that gives the appearance of a strong northward dip.

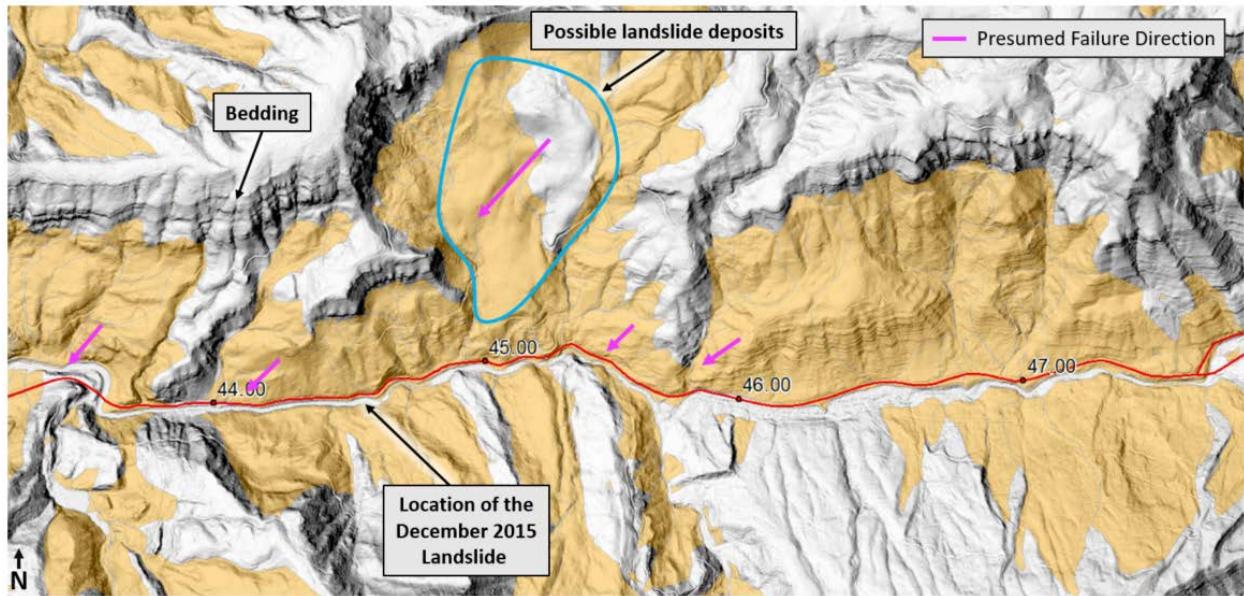


Figure 5.18: Illustration of assumed landslide behavior in a narrow canyon alongside Route 42.

5.3.3 Route 42 Risk Analysis

The risk analysis for Route 42 follows in Figures 5.19 to 5.23. Refer to Chapter 3.2 of this report for details on how the plots were generated.

The risk plots correspond with the trend described previously, where gradual, consistent hazards on the west transition into severe hazards within the narrow canyon on the east. Of the severe hazards, those near milepost 35 and from milepost 40 to 50 appear to be the worst. The problem is similar in both locations, where both sides of the canyon are unstable, and highway has been built on an embankment above the river. In these cases, knowing costs associated with the repair of the December 2015 landslide (Figure 5.21, MP 44.5) may be useful for predicting the magnitude of future instabilities.

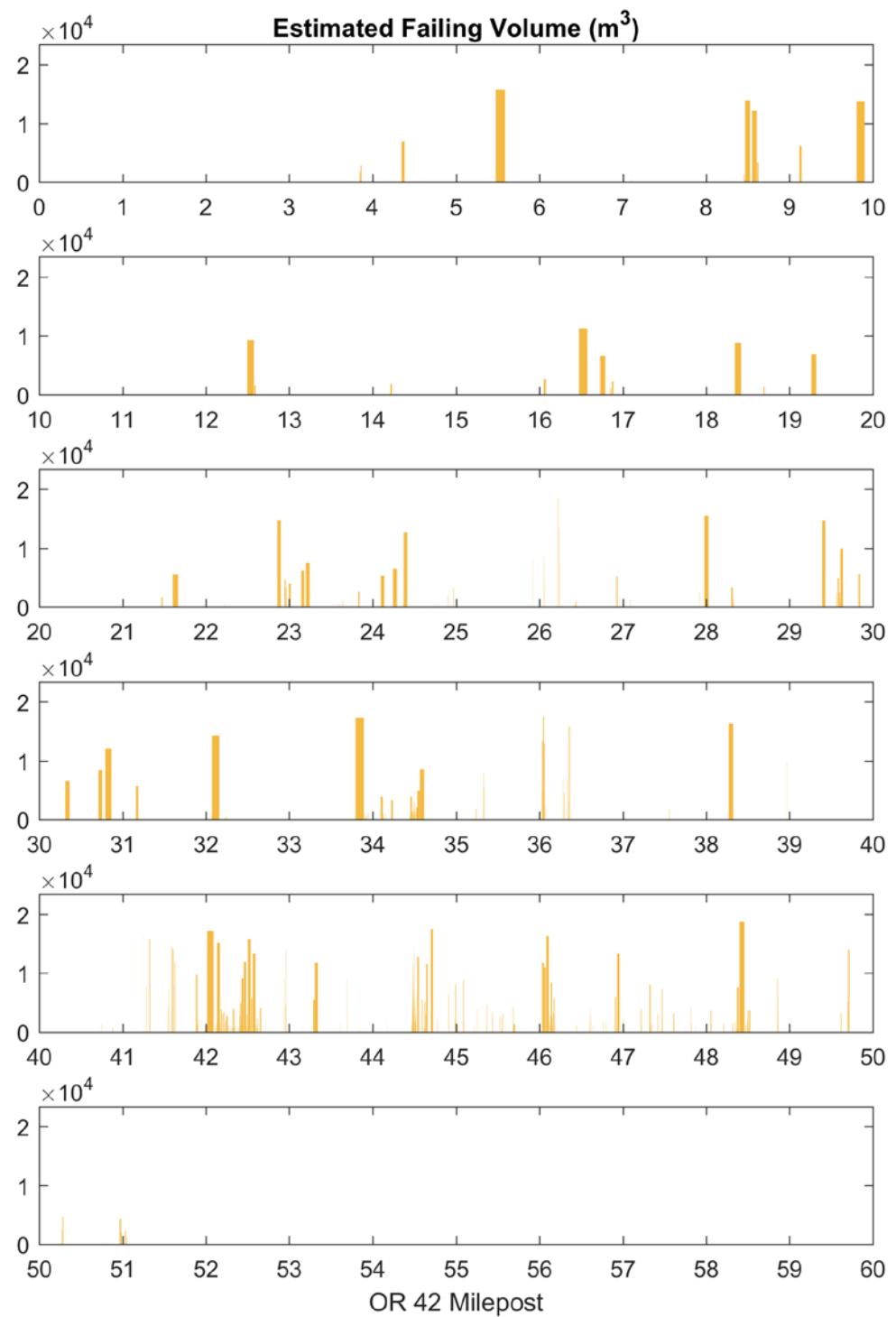


Figure 5.19: Estimated volume of unstable soil underlying Oregon Route 42 by milepost.

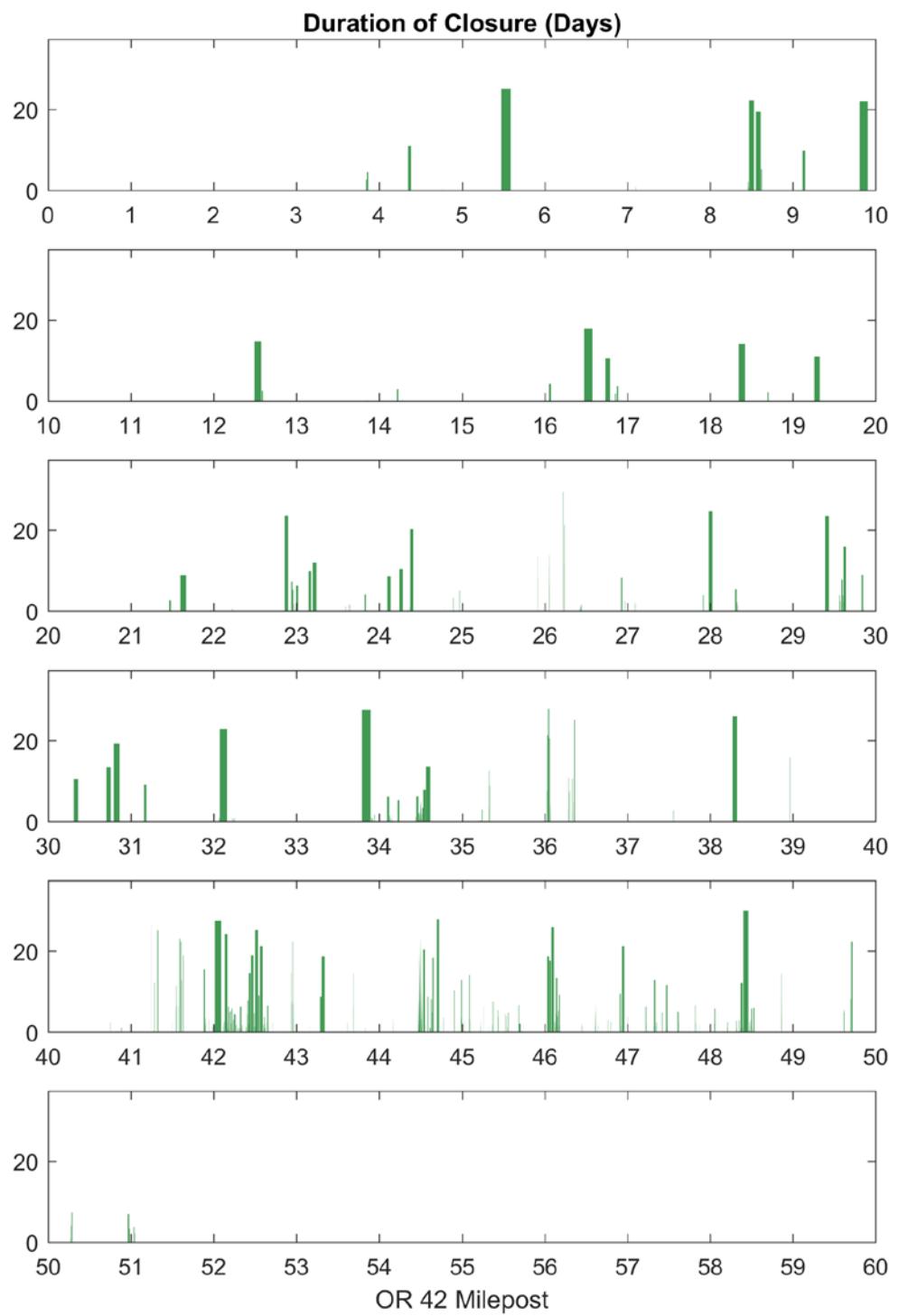


Figure 5.20: Estimated duration of closures along Oregon Route 42.

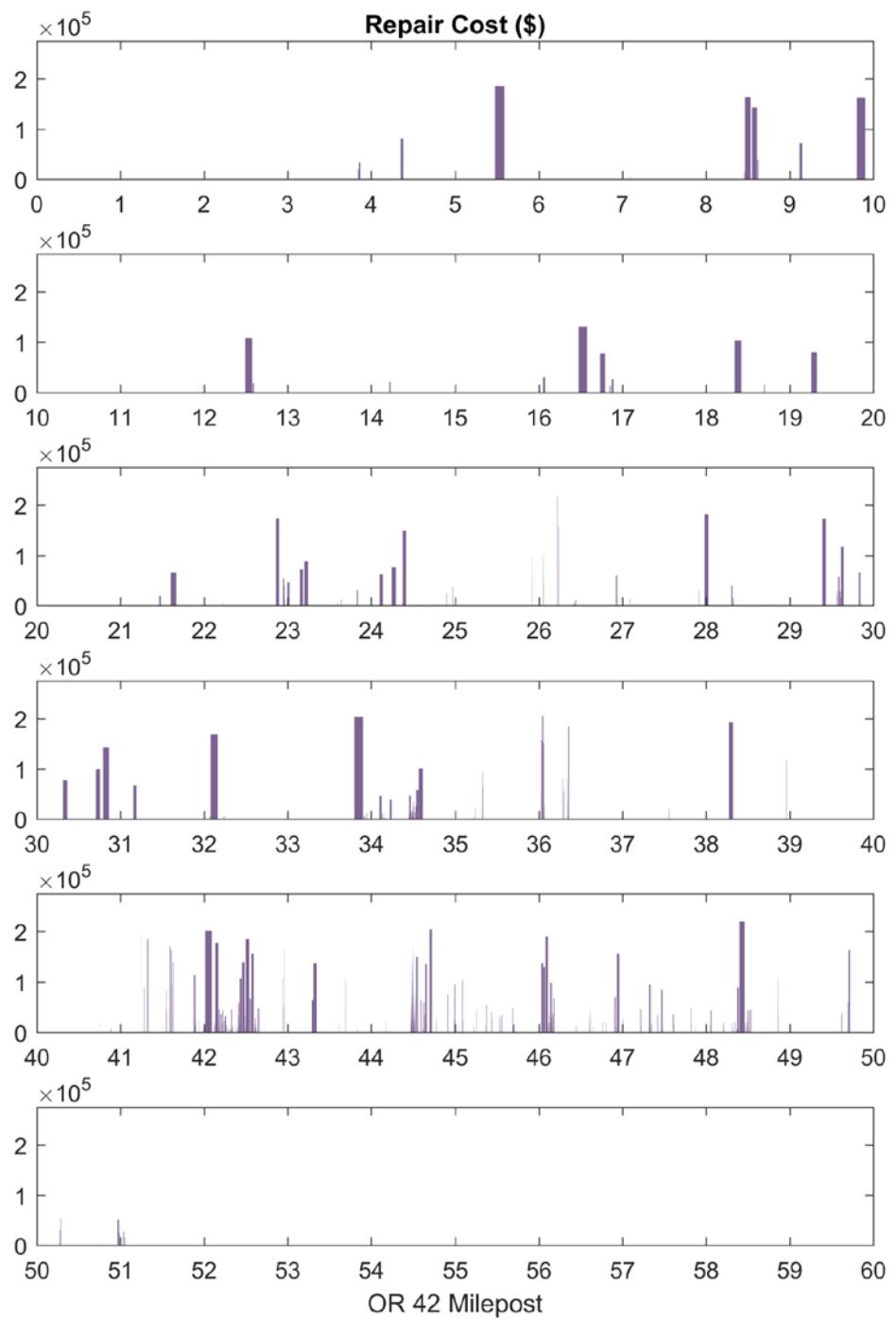


Figure 5.21: Estimated repair cost associated with reopening of Oregon Route 42 following landslides the reactivation of mapped landslides.

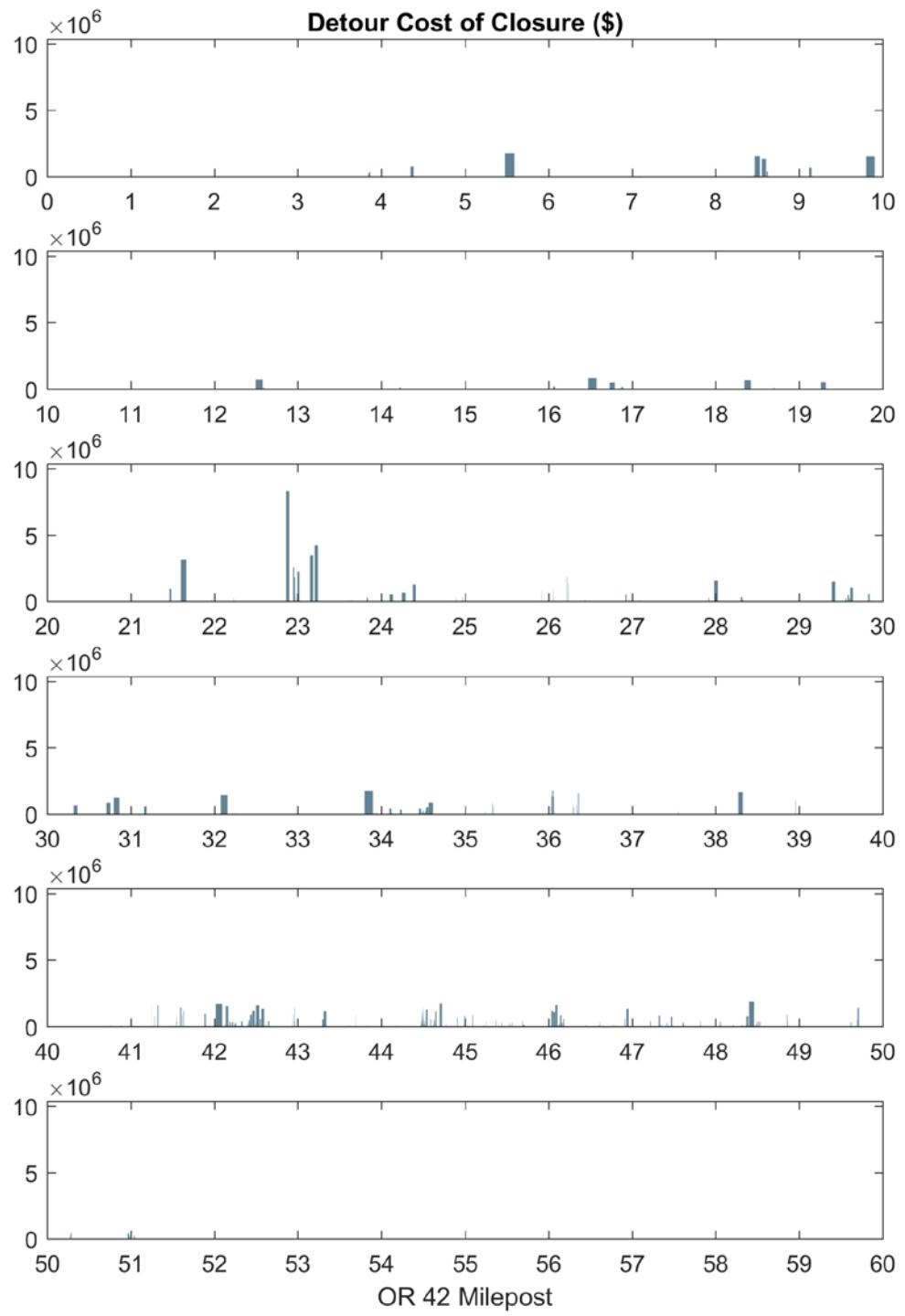


Figure 5.22: Approximate economic costs incurred by closures on Oregon Route 42.

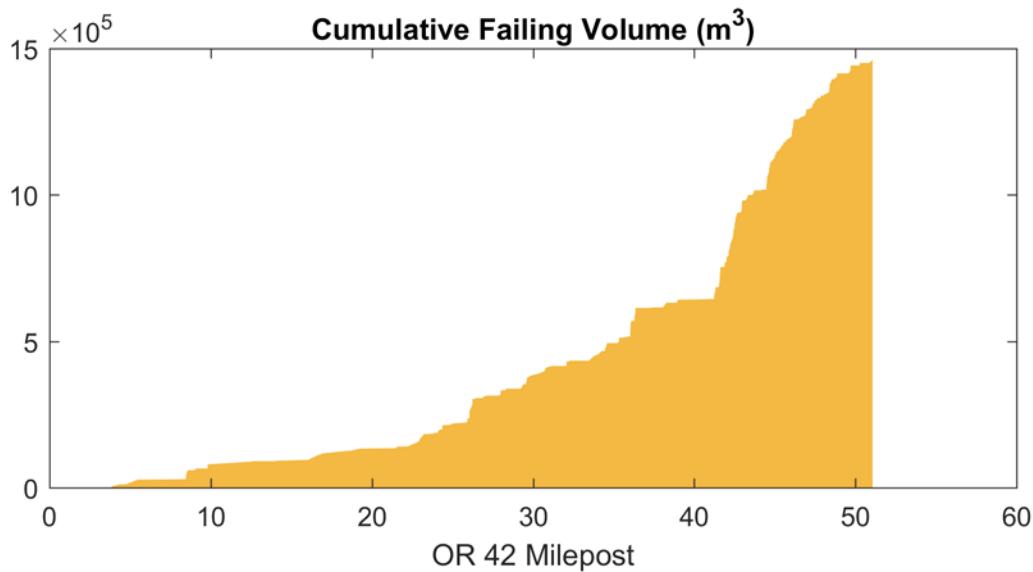


Figure 5.23: Cumulative volume of unstable soil estimated to underlie Oregon Route 42.

5.4 US ROUTE 101

5.4.1 Route 101 Overview

US Route 101 traces the Oregon coastline from Washington to California, passing through many landslide-prone areas along the way. One particularly active area is where the highway passes through Curry County in southern Oregon. Geology ranges from broken down, yet still identifiable, strata, all the way to completely deformed mélange, leading to widespread instabilities. Frequent creeping slides lead to road closures or travel delays, and the risk of a major landslide movement threatens several communities along the route. Route 101 is the primary, and in several places, the only link between Curry County's communities, including the county seat of Gold Beach and the largest city of Brookings. AADT ranges from 3,000 in between cities to over 10,000 near Brookings.

Unique for this report, most of the US Route 101 corridor has been the subject of recent geologic mapping (MP 274-341; McClaughry et al., 2013; Wiley et al., 2014) and manual landslide inventory mapping (Burns, 2014). The high detail and accuracy of the manual landslide inventory provided an excellent means for evaluating the performance of the scarp identification and CCM methodology (shown previously in Table 4.3).

5.4.2 Route 101 Inventory Map

The SICCM methodology was used to map 380 square miles surrounding more than 80 miles of Route 101. The full-resolution landslide inventory map has been included with this report, but a reduced size version can be found in Figure 5.24. A quantitative summary of the corridor is presented in Table 5.3.



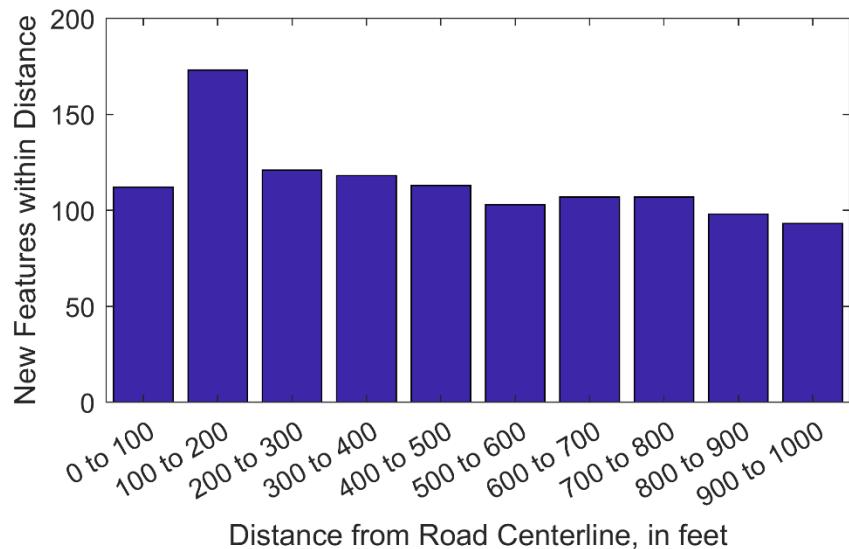
Figure 5.24: Landslide deposit inventory map for the US Route 101 corridor in Curry County, Oregon.

Table 5.3: Quantitative Summary of the US Route 101 Landslide Inventory.

Quantity	Route 101
Area Mapped	383 sq. mi.
Number of Mapped Landslide Features	20,269
Number of Landslide Features that Intersect Highway	625
Length of Highway	80.6 mi.
Length of Highway Crossing Landslide Deposits	29.2 mi.
Percent of Highway Length that Crosses Landslide Deposits	36 %

The inventory map for Route 101 shows that the highway consistently traverses landslide deposits from Port Orford to the California Border (MP 301 – 363). Between Port Orford and Gold Beach (MP 330), several landslide hot spots are evident on the map (MP 305, MP 310 – 313, and MP 320 – 322), but there are still many stable areas. South of Gold Beach, there is a pronounced increase in the frequency and size of landslides. Much of this change in frequency may be attributed to a reduction in the amount of flat ground.

The landslide distribution within 1,000 feet of Route 101 is very consistent (Figure 5.25), when compared to that of the previous corridors. This consistency can likely be attributed to the highway's exposure to similar shapes and sizes of landslides along its entire length.

**Figure 5.25: Distribution of landslide features within 1,000 feet of US Route 101. The figure does not include landslides that intersect highway.**

5.4.3 Route 101 Risk Analysis

The risk analysis for Route 101 follows in Figures 5.26 to 5.35. Refer to Chapter 3.2 of this report for details on how the plots were generated.

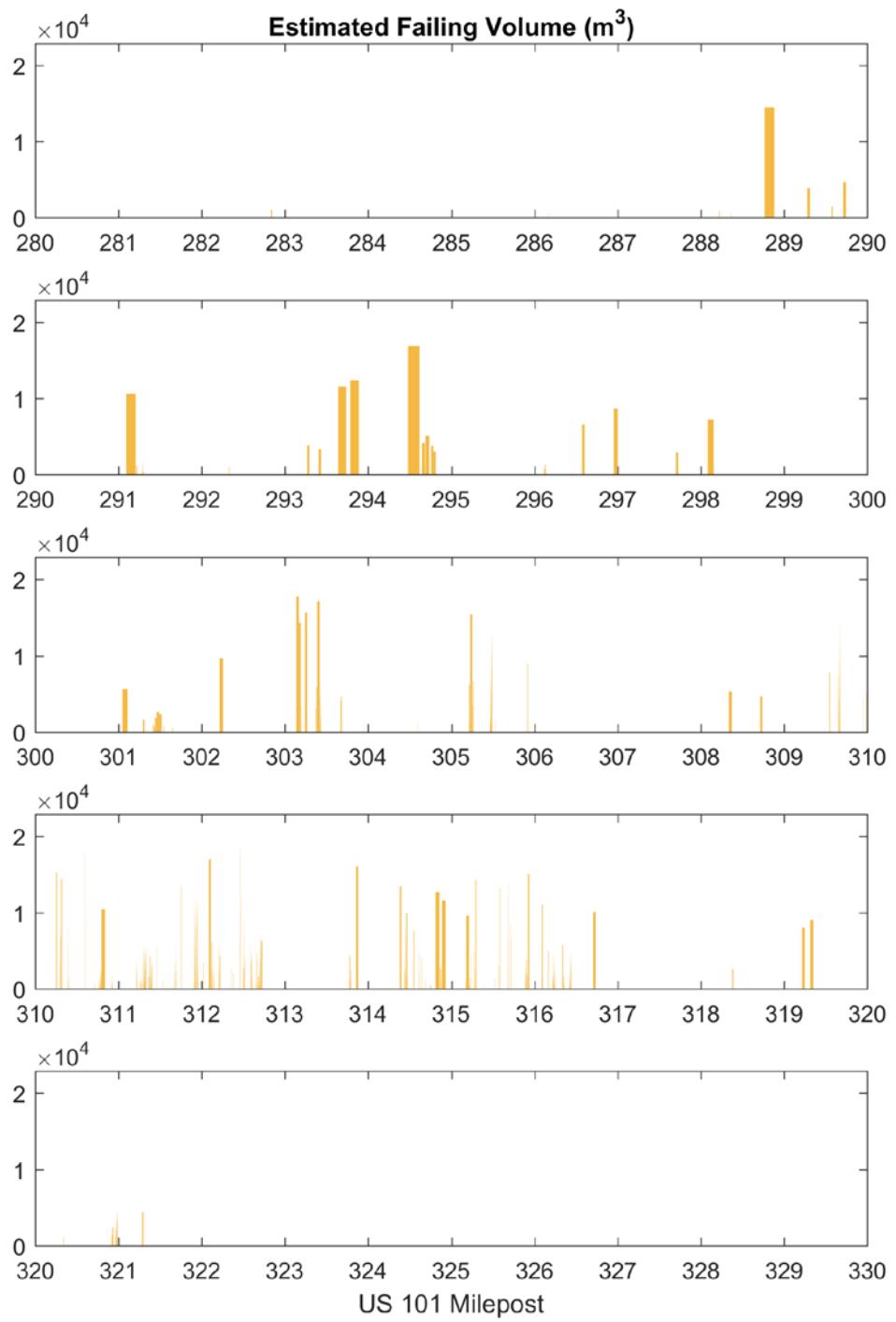


Figure 5.26: Estimated volume unstable soil underlying US Route 101 from milepost 290 to 322.

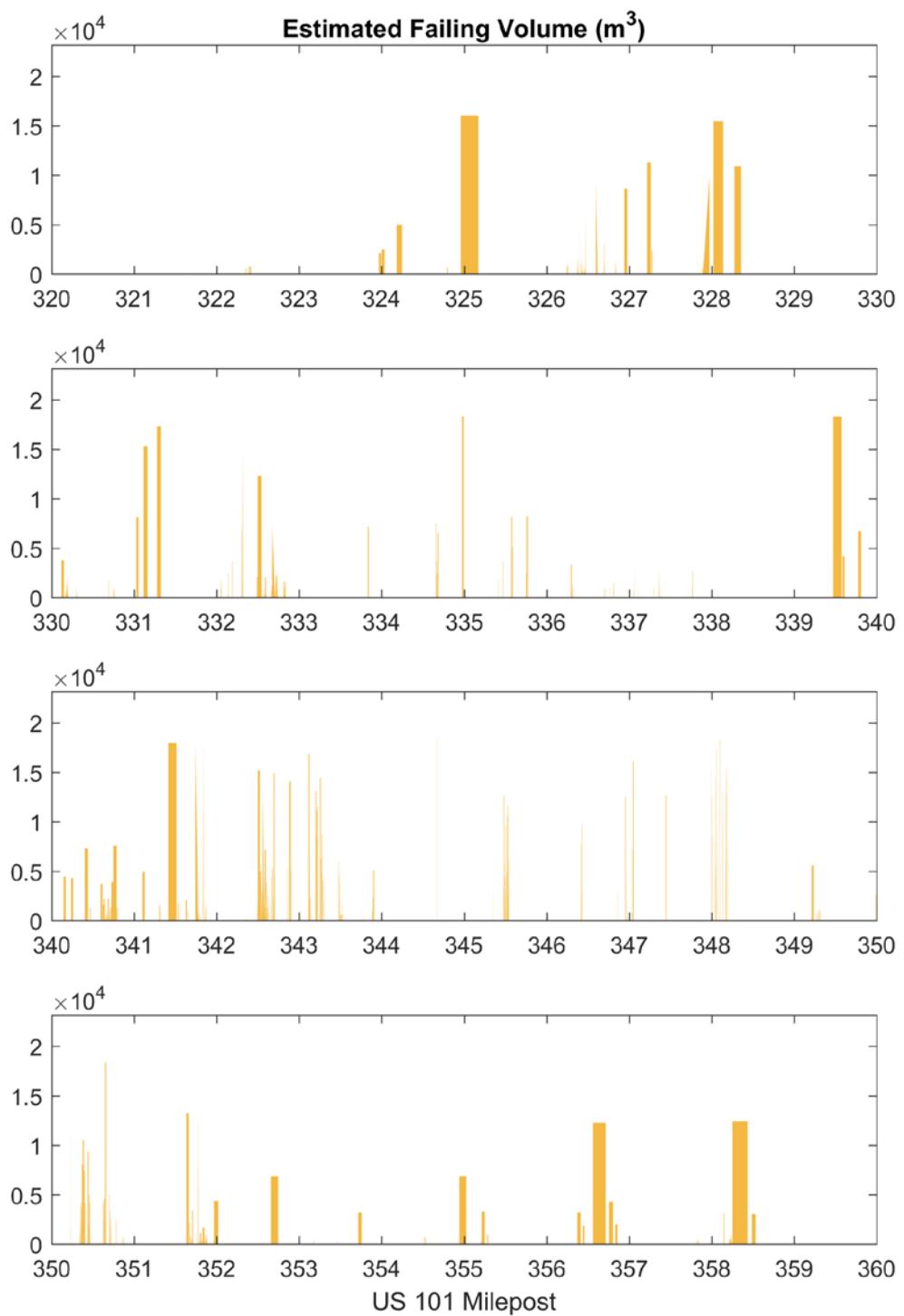


Figure 5.27: Estimated volume unstable soil underlying US Route 101 from milepost 322 to 358.

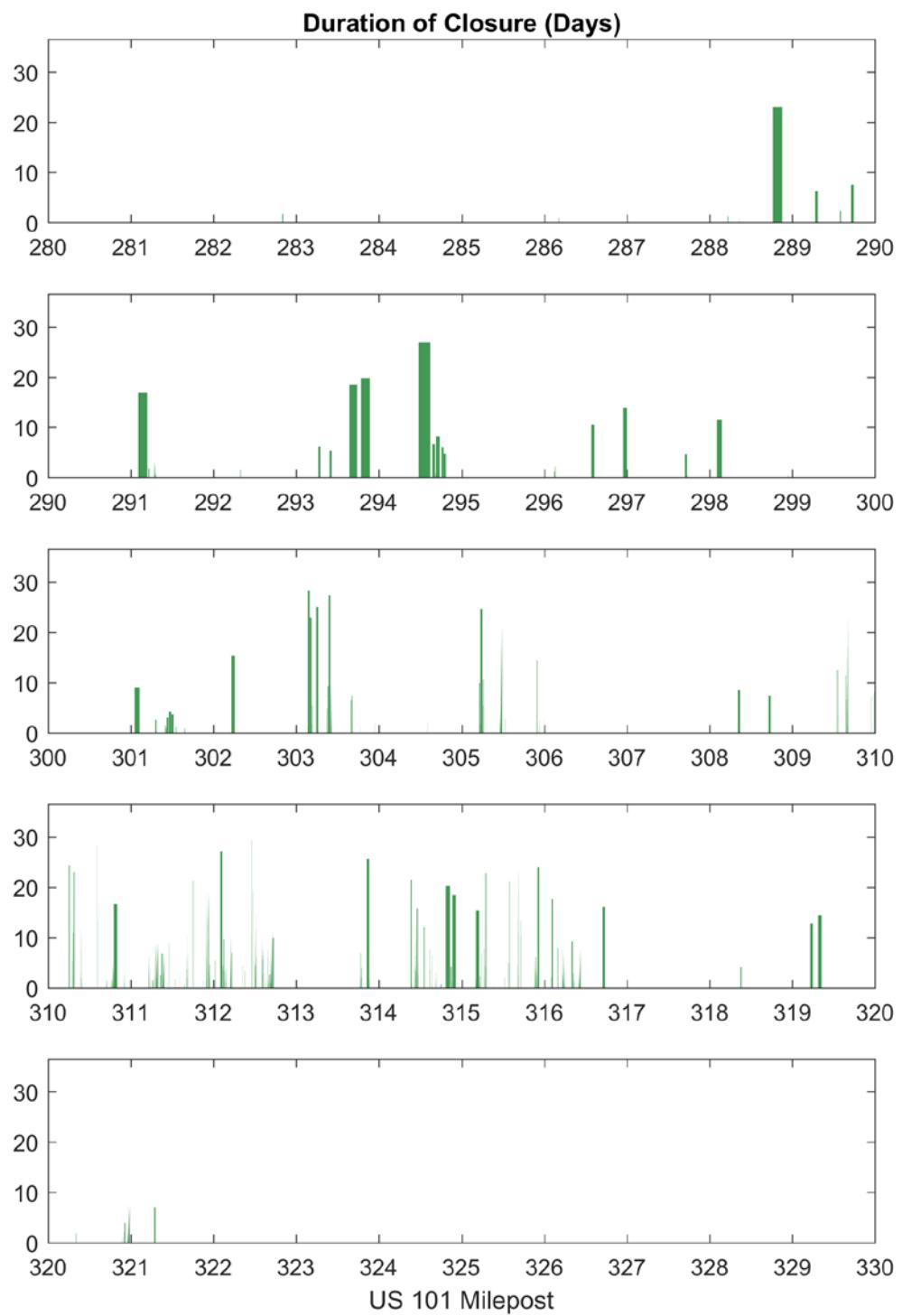


Figure 5.28: Estimated duration of closures along US Route 101 from milepost 290 to 322.

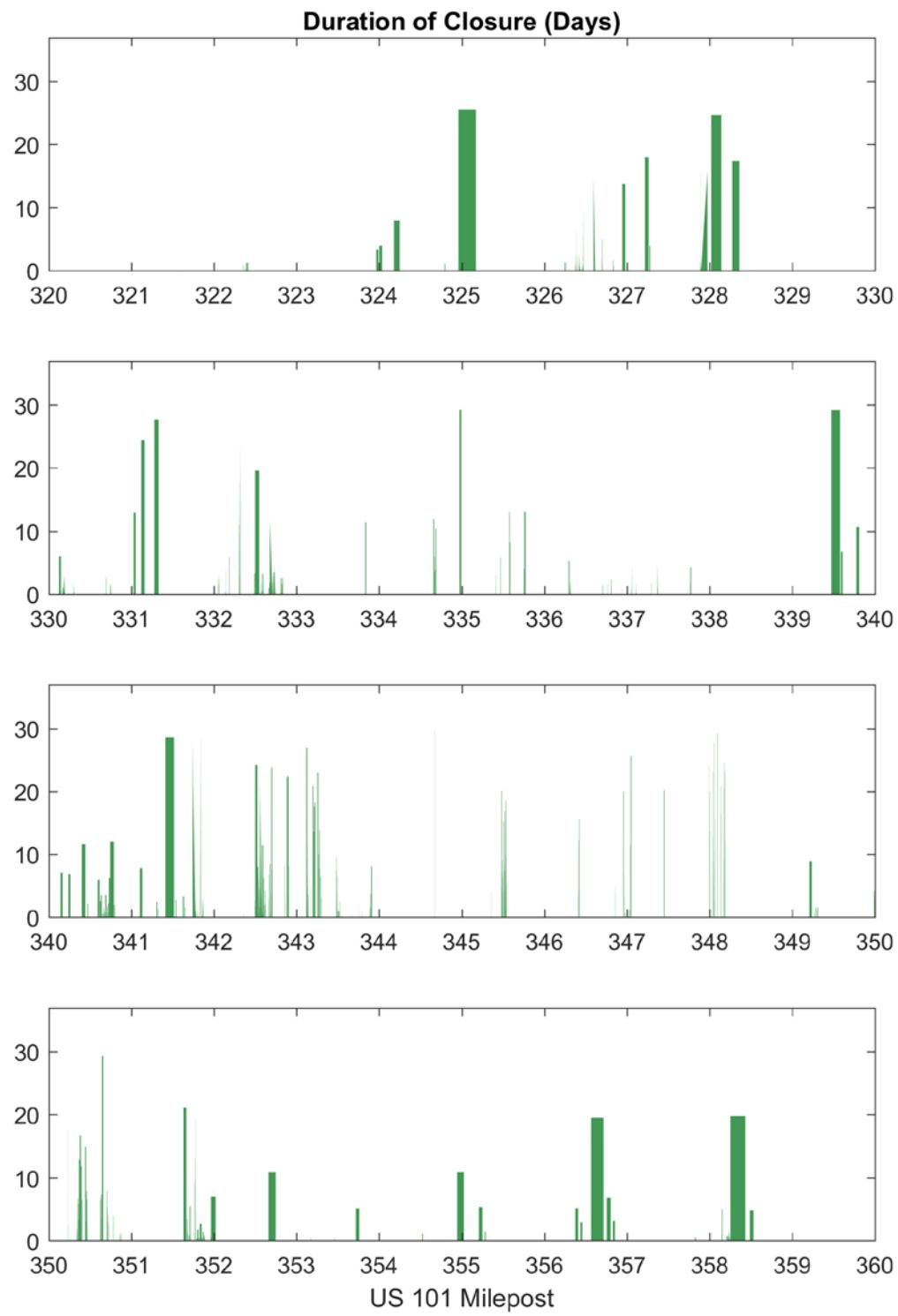


Figure 5.29: Estimated duration of closures along US Route 101 from milepost 322 to 358.

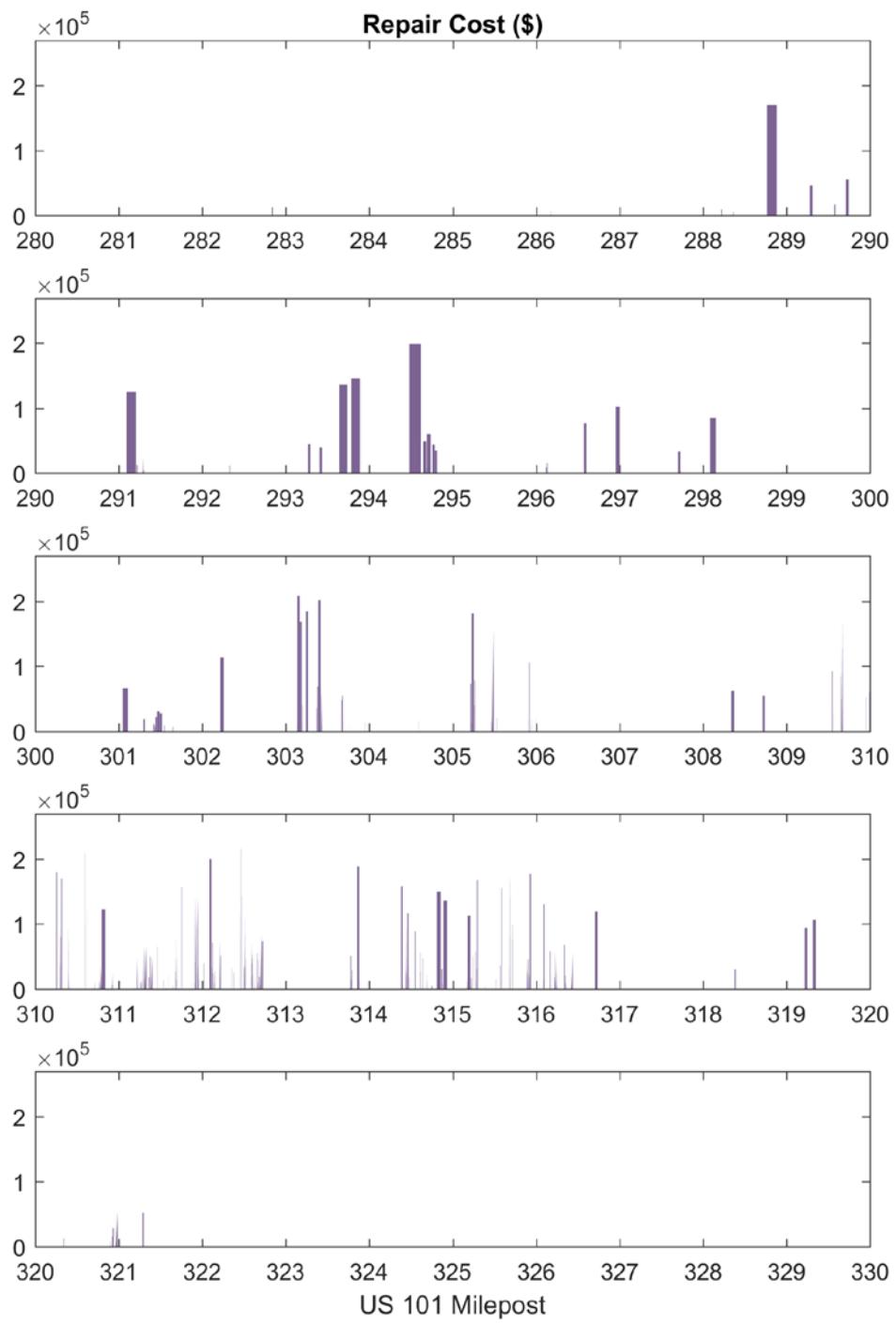


Figure 5.30: Estimated repair cost associated with reopening of US Route 101 following landslides the reactivation of mapped landslides from milepost 290 to 322.

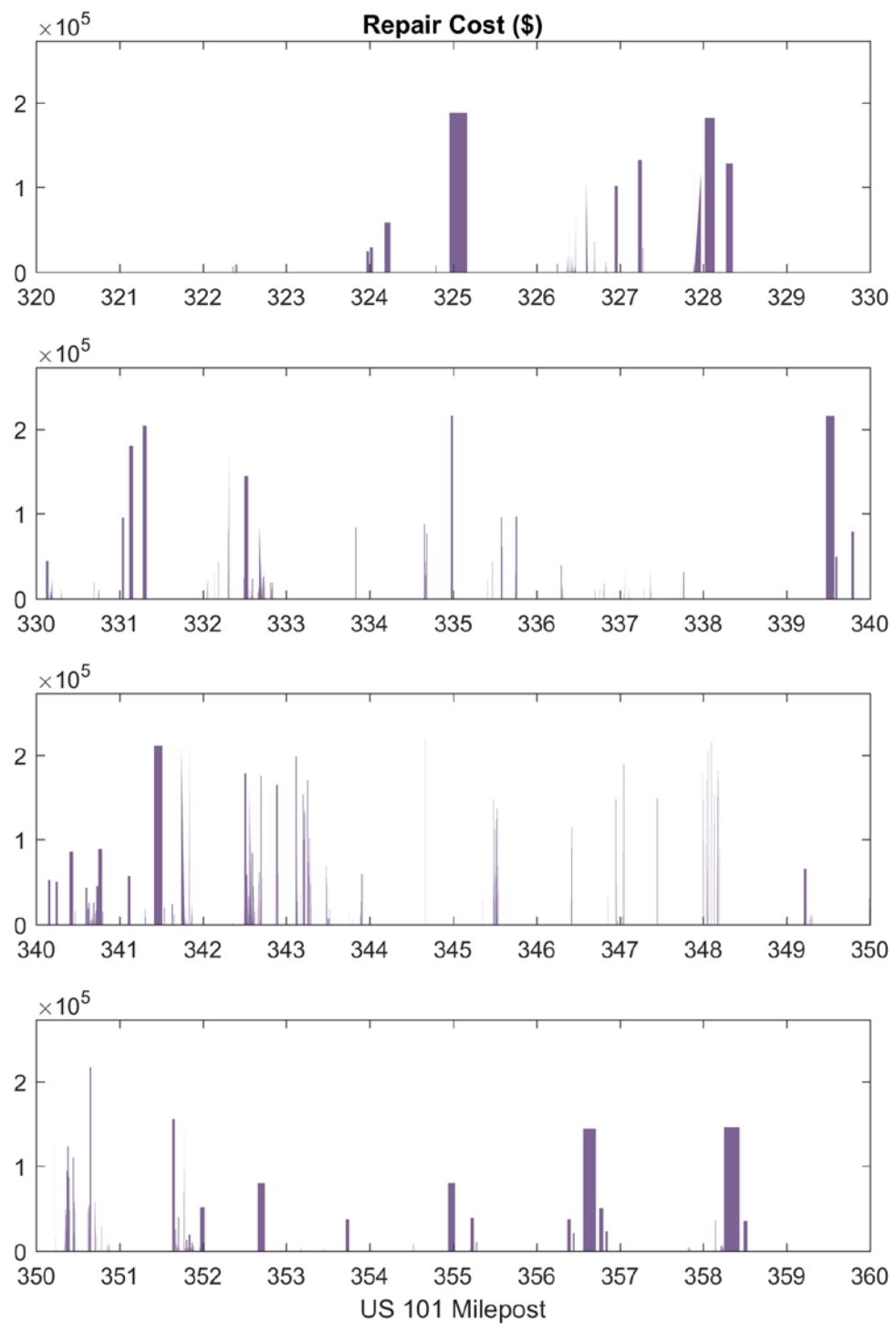


Figure 5.31: Estimated repair cost associated with reopening of US Route 101 following landslides the reactivation of mapped landslides from milepost 322 to 358.

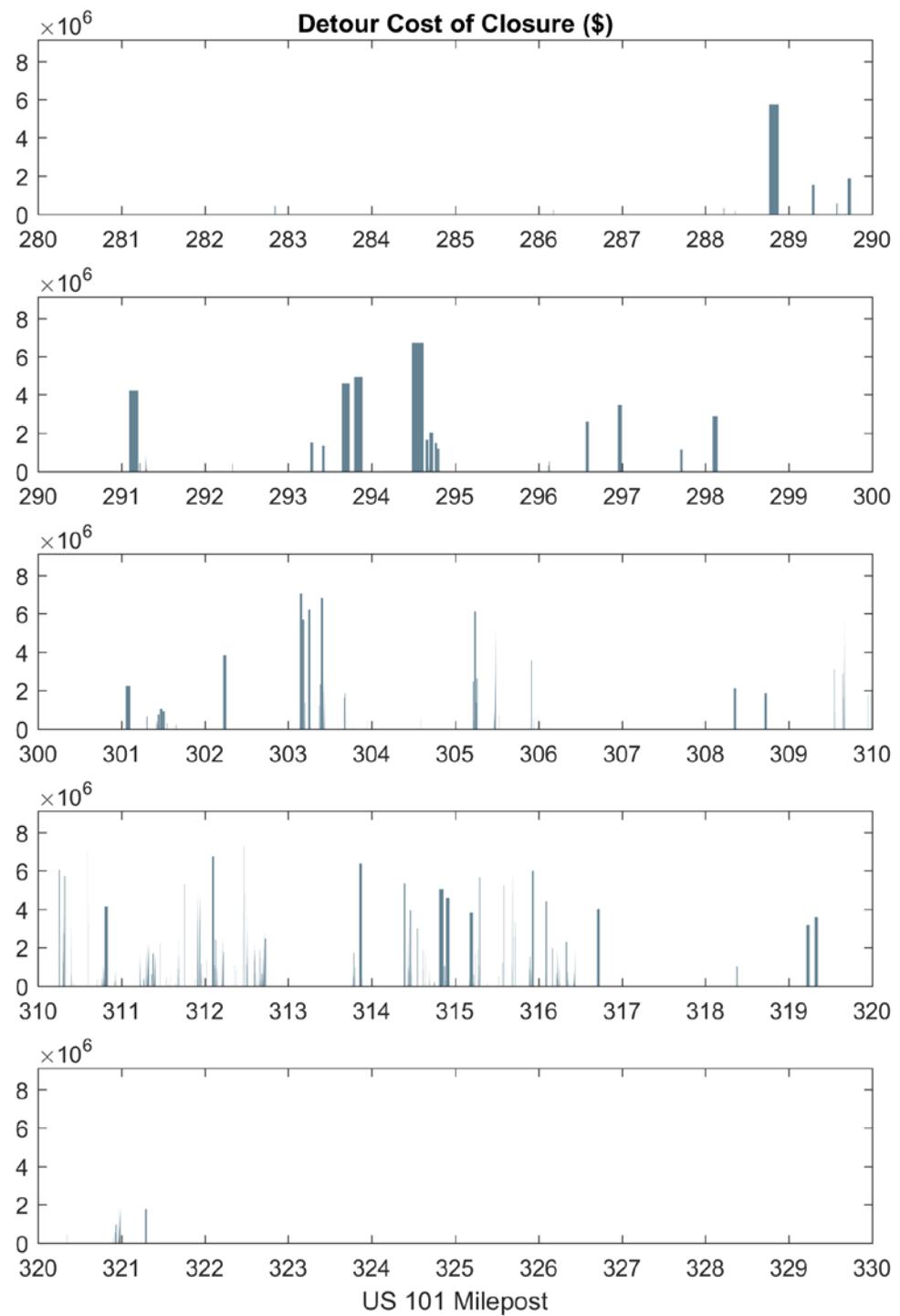


Figure 5.32: Approximate economic costs incurred by closures on US Route 101 from milepost 290 to 322.

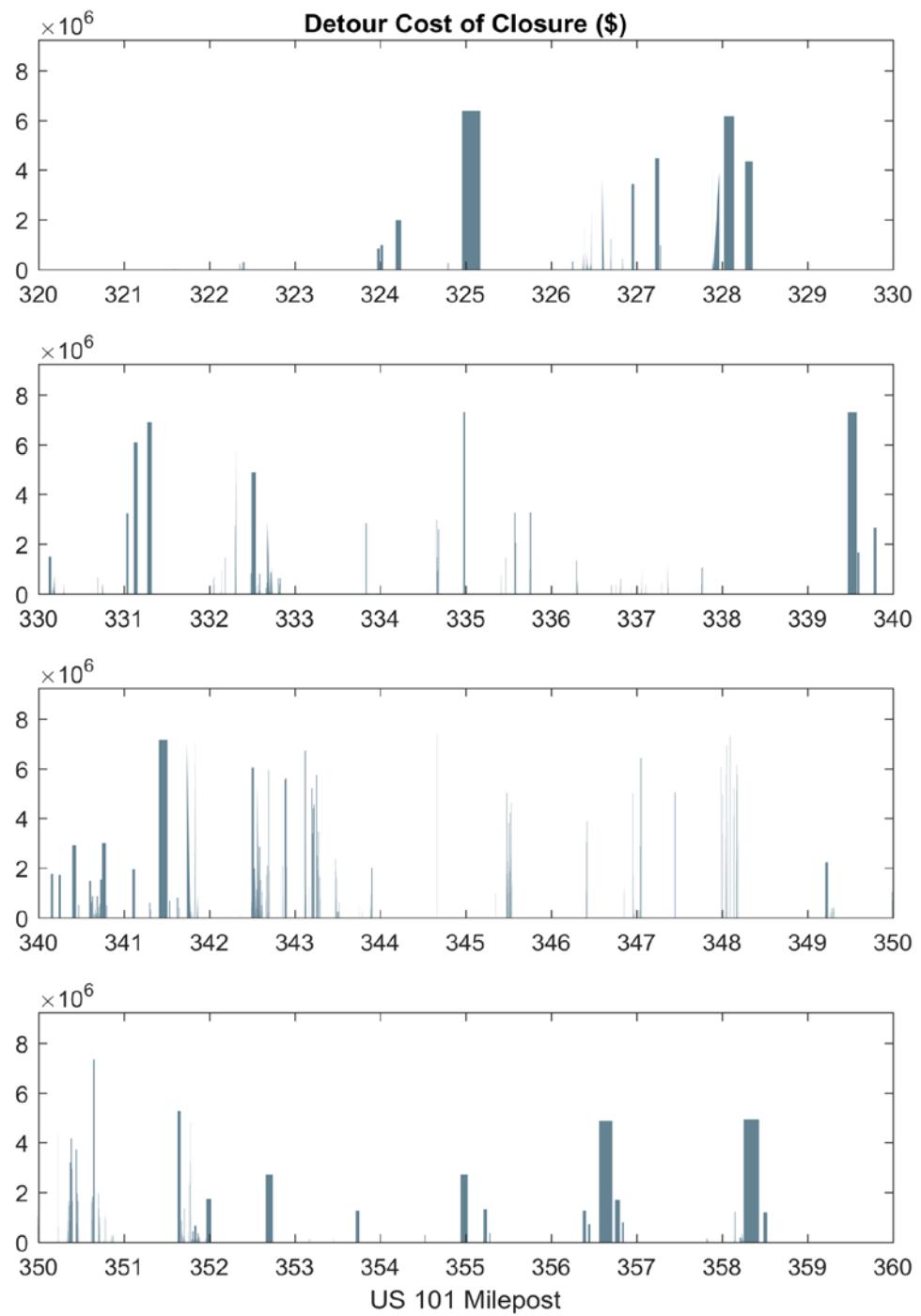


Figure 5.33: Approximate economic costs incurred by closures on US Route 101 from milepost 322 to 358.

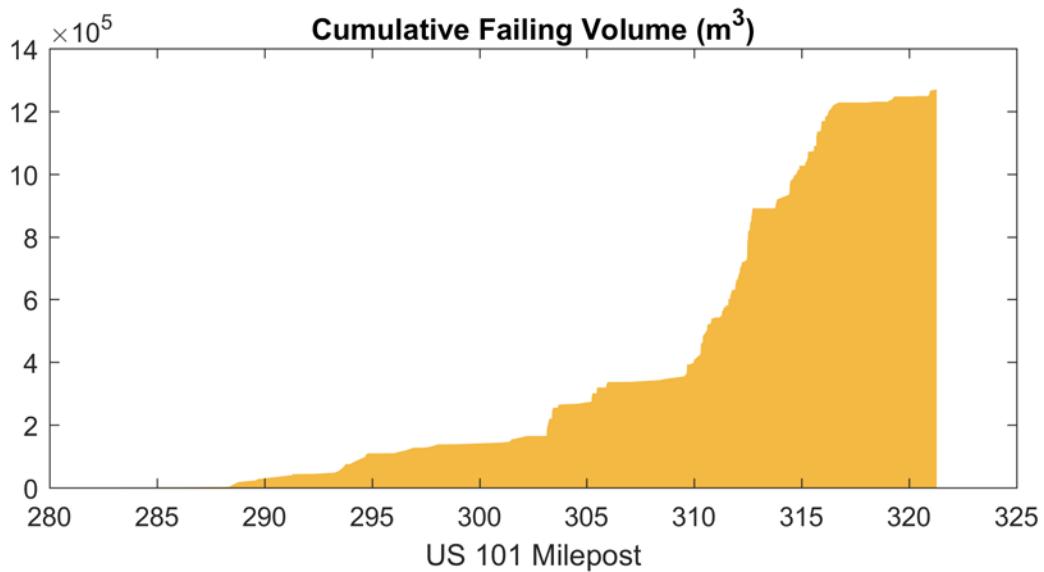


Figure 5.34: Cumulative volume of unstable soil estimated to underlie US Route 101 from milepost 290 to 322.

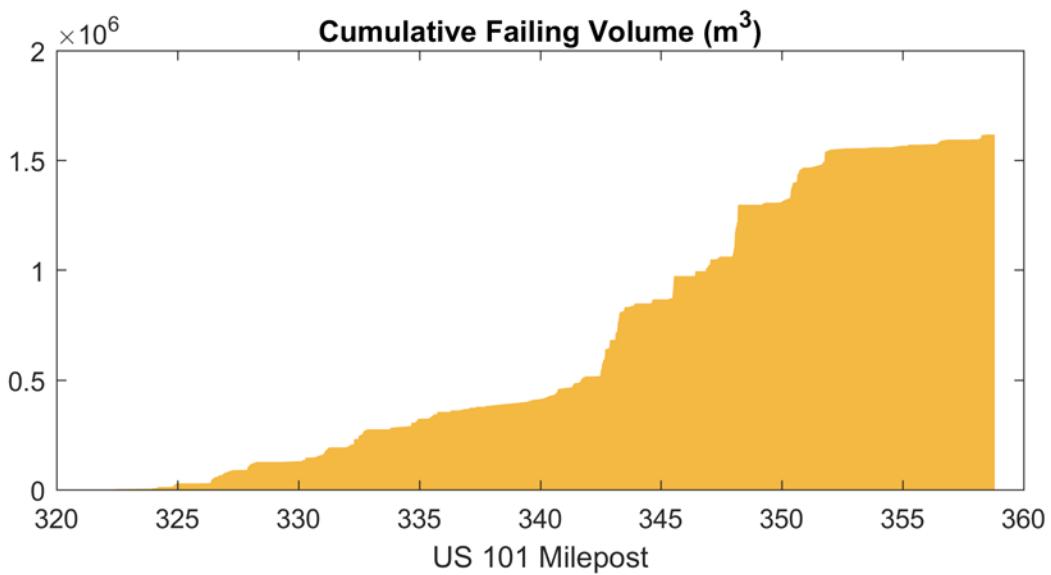


Figure 5.35: Cumulative volume of unstable soil estimated to underlie US Route 101 from milepost 322 to 358.

The risk plots in Figures 5.26 to 5.35 agree with the inventory map appraisal, showing that Route 101 south of Port Orford is consistently at risk to landslides. North of Gold Beach (MP 330), the

plots indicate several landslide hot spots that all seem to correspond with hazards visible on the inventory map and when driving down Route 101.

The Curry County Natural Hazards Mitigation Plan (University of Oregon, 2016) includes a list of previous landslides in the area, along with some repair costs (Table 5.4). A comparison shows that the landslides described in the table all spatially correspond to high-risk areas on the plots, but the values for repair costs are much higher for the table than they are for the plots. This difference is likely attributed to the fact that repair cost calculations only account for excavation, and do not factor in any construction or labor costs.

Table 5.4: List of landslide closures of Route 101 (from the Curry County Natural Hazards Mitigation Plan).

Year	Milepost	Name	Repair Cost
2001	311	Slide Creek	\$1,100,000
2001	307	Bear Trap Creek	\$175,000
2000	311-312	Reinhart Creek	\$1,300,000
2000	333	80 Acres Road	\$500,000
1999	310	Brush Creek	\$550,000
1998	349-350	Whaleshead Cove	\$550,000
1994-1995	344	Hooskanaden Slide	Not Provided
1993	312	Arizona Inn Slide	Not Provided

6.0 CONCLUSIONS AND RECOMMENDATIONS

6.1 CONCLUSIONS

6.1.1 Summary

This report has presented and implemented a methodology to semi-automatically detect landslides and evaluate the risks they pose to highway infrastructure. Key details from Chapters 1 through 5 are as follows:

- Landslides are frequent hazards that result in major economic, environmental and social impacts for operation, maintenance and construction of Oregon highways. Current databases of landslides in Oregon are limited and sometimes inconsistent due to the subjective mapping process. Generating new maps is a time consuming process.
- A new algorithm, called the Contour Connection Method (CCM, Leshchinsky et al., 2015), utilizes any digital elevation model (DEM), including bare earth lidar, to consistently detect landslide deposits on a landscape scale in an automated manner.
- The CCM algorithm has been modified to reduce landslide over-prediction and to improve computational efficiency, resulting in the SICCM methodology.
- SICCM is a two-part process that first identifies landslide scarps, and then uses them as initiation for the CCM algorithm to map landslide deposits.
- Operation of SICCM is semi-automatic, meaning that the person performing the mapping is given opportunities to intervene at strategic locations within the procedure to improve results.
- A newly-developed risk analysis methodology uses landslide deposits, which may be produced by SICCM or any other digital inventorying method, to calculate several measures of risk from landslide reactivation and unstable deposits within the inventory. The measures can then be applied to a corresponding highway to produce simple plots showing which lengths of road face the greatest risk.
- The accuracy of SICCM was evaluated using existing landslide inventories produced by DOGAMI. Results showed high pixel-to-pixel accuracy for most areas. Furthermore, SICCM showed accuracy levels on par with other automated inventorying methods while adhering to a simple-to-use process based on physics to enable efficient and rapid mapping of areas of interest.
- Inventory maps and risk analyses were performed on four ODOT-managed highways, Oregon Route 36, and Oregon Route 42 in the Oregon Coast Range, and US Route 101 in Curry County. All four highways are known for landslide activity, but these results show that Route 42 and Route 101 face the greatest landslide risk.

6.1.2 Conclusions

Based on the accuracy assessment results, and observations from the highway corridor landslide inventories and risk analyses, possible conclusions include:

- SICCM performs well in producing inventories of landslide deposits. Measures of accuracy are comparable, or better, than other similar methodologies (Appendix B), and deposits mapped in each highway corridor correspond with known landslide problem areas.
- Despite strong performance, most accuracy measures demonstrate that no automated approach is a substitute for expertise. While SICCM is effective for quickly producing useful landslide inventories, it does not substitute for the trained eye and judgment of an expert geologist performing manual mapping. However, the intervention opportunities built into application of SICCM provide opportunities to combine automation with professional judgment. SICCM may be used for planning purposes, and it is recommended that more detailed analyses be performed in cases of life-safety or legislative action.
- The presented methodology for assessing highway risk using a landslide inventory is an effective tool for identifying dangerous lengths of highway, and for determining the relative magnitude of risk from one area to another.
- The highway risk methodology does not solely require SICCM landslide deposits in order to operate. Manually produced inventories, such as those produced by DOGAMI to Special Paper 42 specifications, are a good alternative in places where results of the risk analysis need higher confidence.

6.2 IMPLEMENTATION

This report and its supporting files represent both immediate and long-term assets for ODOT:

- Inventory maps and milepost risk plots provided in Chapter 5 may be compared to existing ODOT knowledge of high-risk areas. This activity may identify potentially unstable areas that warrant more detailed investigations.
- Milepost risk plots of soil volume may be used to approximate amounts of fill that ODOT can store near high-risk areas in order to improve response to possible landslide events.
- Unstable blocks, included as shapefiles to this report, may be used to predict volumes of soil that may fall onto the roadway during seasonal landslide activity.
- Extents of landslide deposits from the inventory map may be used to plan alternative highway routes, should an important section of roadway be damaged or destroyed.
- The inclusion of both methodologies, inventory and risk mapping, with instructions and computer programs for implementing them means that ODOT may quickly investigate more

highway corridors, or remap one of the corridors of this report when future lidar data is acquired.

Another key research product produced through this research project is a forthcoming DOGAMI Special Paper (Bunn, 2018), which describes how SICCM can be used to generate landslide inventory maps in conjunction with DOGAMI Special Paper 42 for enhanced efficiency. Based on the assessment performed by DOGAMI, the SICCM methodology will save substantial time in future mapping efforts across the state. As a result, DOGAMI will be directly implementing this process into their current workflows.

6.3 RECOMMENDATIONS FOR FUTURE WORK

This report provides inventories for several corridors. Future work could assess event-based susceptibility, hazard and risk. Some of these components of this are anticipated to be completed in SPR-808.

This report only creates inventories of landslides that tend to be deep-seated or translational, typically exhibiting well-defined headscarp morphology, many of which directly affect ODOT right-of-way. Future work could better characterize other “landslide” hazards, such as rockfalls (SPR-809), topples, flows, or creeping landslides (SPR-807).

This work is not meant to replace expertise in landslide mapping, which is inherently a subjective effort due to the relative complexity associated with every landslide – each of which shows different features. Future work could refine the process to provide a level of confidence and mapping that is directly complementary to these ongoing efforts, particularly if outputs will serve at a regulatory level.

This work was performed primarily using lidar DEMs. Future work could assess the utility of alternative or multiple datasets for enhancing inventorying in locales where lidar are not yet available. (Note that initiatives such as the USGS 3DEP program have the goal of seamless coverage of lidar topographic data across the conterminous United States). The integration of various satellite-derived datasets, such as InSAR, imagery, multispectral response, and others, may enhance inventorying efforts and provide information on the level of activity associated with inventoried landslides.

With increased collection of lidar, mapping efforts and refinements of inventorying procedures will continue. In the future, mapping and remapping efforts will provide a more comprehensive inventory of mountainous terrain in the state of Oregon. .

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APPENDIX A – LIST OF FILES INCLUDED WITH THIS REPORT

List of files included with this report

1. Transportation Planning and Analysis Unit Memorandum GIS Files:
 - a. **ValueTon_Summary.shp** – shapefile showing daily value of commodities traveling at each study point.
 - b. **Data_Dictionary.xlsx** – glossary of abbreviated field names in ValueTon_Summary.shp
2. Tools and Scripts for Running SICCM:
 - a. **SICCMToolbox.tbx** – ArcGIS™ toolbox containing the tools associated with the SICCM methodology:
 - i. 01 Create Inventory Mapping Project (create_project.py)
 - ii. 02 Prepare Visualization Layers (prepare_visualization_layers.py)
 - iii. 03 Find Cell Size for Mapping (select_DEM_resolution.py)
 - iv. 04 Create Mixture Raster (prepare_mixture_raster.py)
 - v. 05 Create Candidates (create_candidates.py)
 - vi. 06 Digitize Stream Channels (digitize_streams.py)
 - vii. 07 Create Rock Score (create_rock_score.py)
 - viii. 08 Identify Rocks from Rock Score (id_rock_from_score.py)
 - ix. 09 Classify by Removing Non Scarps (eliminate_non_scars.py)
 - x. 10 Create Scarp Lines (thin_to_lines.py)
 - xi. 11 Run CCM (run_ccm.py)
 - b. **RiskToolbox.tbx**
 - i. Create Risk Maps (create_risk_maps.py)
 - ii. Compute Risk Metrics (compute_risk_metrics.py)
3. Standalone Deposit Mapping Application Installers:
 - a. **CCMFlow-gui-x64 Setup 1.6.2.exe** – 64-bit Graphical User Interface (GUI) version (Does not require administrative privileges to install)
 - b. **CCMFlow-gui-x86 Setup 1.6.2.exe** – 32-bit Graphical User Interface (GUI) version (Does not require administrative privileges to install)
 - c. **ccmflow-x64-cli-setup-2017091901.exe** – 64-bit command line version
 - d. **ccmflow-x86-cli-setup-2017091901.exe** – 32-bit command line version
4. SICCM Landslide Inventory Maps:
 - a. **HWY126_36_Corridor.pdf** – 36 x 36” map of the Route 36 and 126 corridor. Scale 1:62,500 (15-Minute).
 - b. **HWY42_Corridor.pdf** – 34 x 43” map of the Route 42 corridor. Scale 1:62,500 (15-Minute).
 - c. **HWY101_Corridor.pdf** – 34 x 43” map of the Route 101 corridor. Scale 1:62,500 (15-Minute).
 - d. **HWY126_CCMFlow.shp** – a shapefile of the Route 126 landslide inventory (polygons).
 - e. **HWY42_CCMFlow.shp** – a shapefile of the Route 42 landslide inventory (polygons).
 - f. **HWY101N_CCMFlow.shp** – a shapefile of the Route 101 landslide inventory north of MP 322 (polygons).
 - g. **HWY101S_CCMFlow.shp** – a shapefile of the Route 101 landslide inventory south of MP 322 (polygons).

**APPENDIX B – INITIAL ACCURACY ASSESSMENTS AND SENSITIVITY
ANALYSIS OF CCM PARAMETERS**

Initial accuracy assessments and sensitivity analysis of CCM parameters

B.1 OVERVIEW OF ACCURACY ASSESSMENTS IN THE LITERATURE

Table B.1 presents a list of accuracy measures and their values, as reported by automated landslide inventory mapping literature. The table contains many blank cells due to the fact that most papers tend to report different measures. In the situation that the literature provided enough information to compute a measure, but did not present it, the computations were performed for this paper, and are shown as non-bold numbers.

The main takeaways from Table B.1 are:

1. Literature has been focused on landslides throughout the world, and while some methods perform well in a specific place, they typically have not been proven to perform elsewhere.
2. The *Landslide Percent of Map* measure is important to consider. Values near 50 percent may result in equal numbers of landslide and non-landslide examples, which makes machine learning classifications, such as those from support vector machines (SVM) or random forest (RF), easier to perform.
3. The only methodology applied to a similar breadth of terrain as SICCM is that of Booth et al. (2009).

Table B.1: Summary of Accuracy Assessments from the Literature. Bold Values are those Reported by Literature.

Location	Reference	Model Name	TP	TN	FP	FN	Accuracy	Landslide Percent of Map	Recall	Precision	>50% of Inventory
Outer West Carpathians, Poland	Pawluszek and Borkowski (2016)	SVM	46.91	34.7	8.87	13.92	0.78	0.58	0.77	0.84	-
Outer West Carpathians, Poland	Pawluszek and Borkowski (2016)	PCA+SVM	43.62	30.94	9.11	14.75	0.76	0.59	0.75	0.83	-
Pittsburg (actually Gales Creek)*	Leshchinsky et al. (2015)	CCM	0.91	0.59	0.41	0.09	0.75	0.50	0.91	0.69	-
Dixie Mountain*	Leshchinsky et al. (2015)	CCM	0.3	0.89	0.11	0.7	0.60	0.50	0.30	0.73	-
MTC - Lower Puget Sound, Washington	Booth et al. (2009)	DFT	3.9	152.8	2.9	16.9	0.89	0.12	0.19	0.57	-
MTC - Lower Puget Sound, Washington	Booth et al. (2009)	CWT	4.2	147.7	2.5	22	0.86	0.15	0.16	0.63	-
SEA - Lower Puget Sound, Washington	Booth et al. (2009)	DFT	21.8	163.2	9.9	17.6	0.87	0.19	0.55	0.69	-
SEA - Lower Puget Sound, Washington	Booth et al. (2009)	CWT	22.6	163.2	8.7	17.1	0.88	0.19	0.57	0.72	-
CBP - Lower Puget Sound, Washington	Booth et al. (2009)	DFT	0.7	2.1	0.2	0.5	0.80	0.34	0.58	0.78	-
CBP - Lower Puget Sound, Washington	Booth et al. (2009)	CWT	0.8	2	0.1	0.5	0.82	0.38	0.62	0.89	-
DMQ - Dixie Mountain, Oregon	Booth et al. (2009)	DFT	32.2	11.9	1.9	18.5	0.68	0.79	0.64	0.94	-
DMQ - Dixie Mountain, Oregon	Booth et al. (2009)	CWT	32.3	11.4	1.8	19	0.68	0.80	0.63	0.95	-
NWD - Dixie Mountain, Oregon	Booth et al. (2009)	DFT	5.2	0.7	0.2	0.7	0.87	0.87	0.88	0.96	-
NWD - Dixie Mountain, Oregon	Booth et al. (2009)	CWT	5.3	0.6	0.1	0.8	0.87	0.90	0.87	0.98	-
Data Set A - Dujiangyan, China	Cao, Tong, Liu, and Wang (2016)		-	-	-	-	89.58	-	-	-	-
Data Set B - Ya'an City, China	Cao et al. (2016)		-	-	-	-	84	-	-	-	-
Data Set C - Neijiang-Liupanshui Railway, China	Cao et al. (2016)		-	-	-	-	88.33	-	-	-	-
Shazhenxi, Zigui County, China	Li et al. (2015)	Feature-reduced RF	-	-	-	-	77.36	-	-	-	-
Shazhenxi, Zigui County, China	Li et al. (2015)	Full-Feature RF	-	-	-	-	76.5	-	-	-	-
Shazhenxi, Zigui County, China	Li et al. (2015)	Feature-reduced SVM	-	-	-	-	76.87	-	-	-	-
Shazhenxi, Zigui County, China	Li et al. (2015)	Full-Feature SVM	-	-	-	-	74.53	-	-	-	-
Flemish Ardennes	Van Den Eeckhaut et al. (2012)	OOA	-	-	-	-	-	-	-	-	0.71

B.2 SENSITIVITY OF SICCM DEPOSIT MAPPING PARAMETERS

The best SICCM deposit mapping parameters will likely vary based on the type of terrain and the scale at which mapping is being performed. Despite this variation, there is still a range of values for each parameter that will always perform better than parameter values selected outside of the range. The purpose of a deposit mapping sensitivity analysis was determine the significance of proper parameter selection, and to develop a strategy for finding the best parameters for each terrain or scale.

The sensitivity analysis began by performing 81 trials with three values of each parameter (all possible combinations). Each value was selected based on experience from previous SICCM trials, with the goal of one value being the lowest reasonable number, one value being the highest reasonable number, and one value being in the middle. Selected values are presented in Table B.2. Trials were performed on a portion of the Big Elk Creek SLIDO inventory (Burns, 2012a), due to its location within the Tyee Formation, which underlies all of the Route 36 and 126 inventory and much of the Route 42 inventory.

Table B.2: Parameters used in Deposit Mapping Parameter Sensitivity Analysis.

Parameter	Selected Values
Contour interval (feet)	10, 20, 30
Nodal spacing (feet)	10, 20, 30
Active slope (rise/run)	0.02, 0.06, 0.10
Branch parameter	2, 4, 6

The first experiment was meant to investigate the accuracy achieved from a collection of samples using randomly sampled parameters. For example, if five of the 81 trials were selected at random, what would be the accuracy of the best trial and the worst trial, and what would be the mean value of all five accuracies. Figure B.1 illustrates these results, where n represents the number of randomly selected trials (5 in example), and m represents the number of times that n trials were randomly sampled. In the figure, the value of m is 50, meaning that the blue line represents the mean best accuracy of 50 selections of n trials, the red line represents the mean worst accuracy of 50 selections of n trials, and the black line represents the mean value of all 50 mean accuracies. Changing the value of m has little effect on the shape of each dataset.

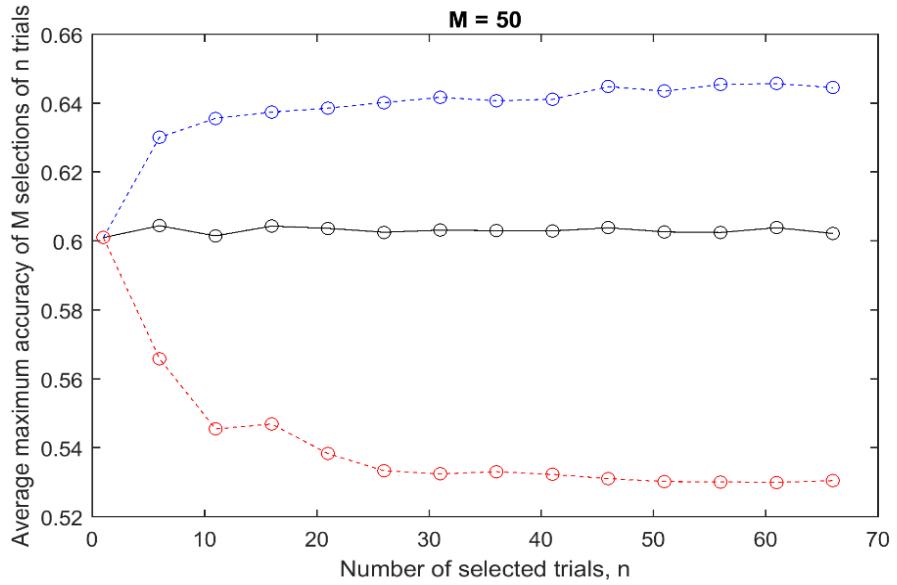


Figure B.1: Results of random sampling parameters from the 81 trials.

Figure B.1 shows that randomly sampling somewhere between 10 and 20 trials will typically yield results with similar best, worst, and average values to those obtained from all 81 trials. While 10 to 20 trials are not an insignificant amount of work, they do help to simplify the process. Because of this simplification, the results of this experiment helped to design the parametric analysis displayed in Table 4.1.

A question that remained after the first experiment was how to know which of the n selected trials was the best, if there was no validation inventory available. The answer lies in a consensus-based approach, where the extents of all 81 trials were converted into a raster (valued 1 for landslide, 0 for non-landslide) and summed to create a new consensus raster (Figure B.2). By summing all raster cells within the extents of each SICCM trial, a simulated accuracy can be derived, with the highest summation reflecting the highest accuracy. The approach generally works for identifying a good trial, but it does not necessarily identify the highest accuracy trial.

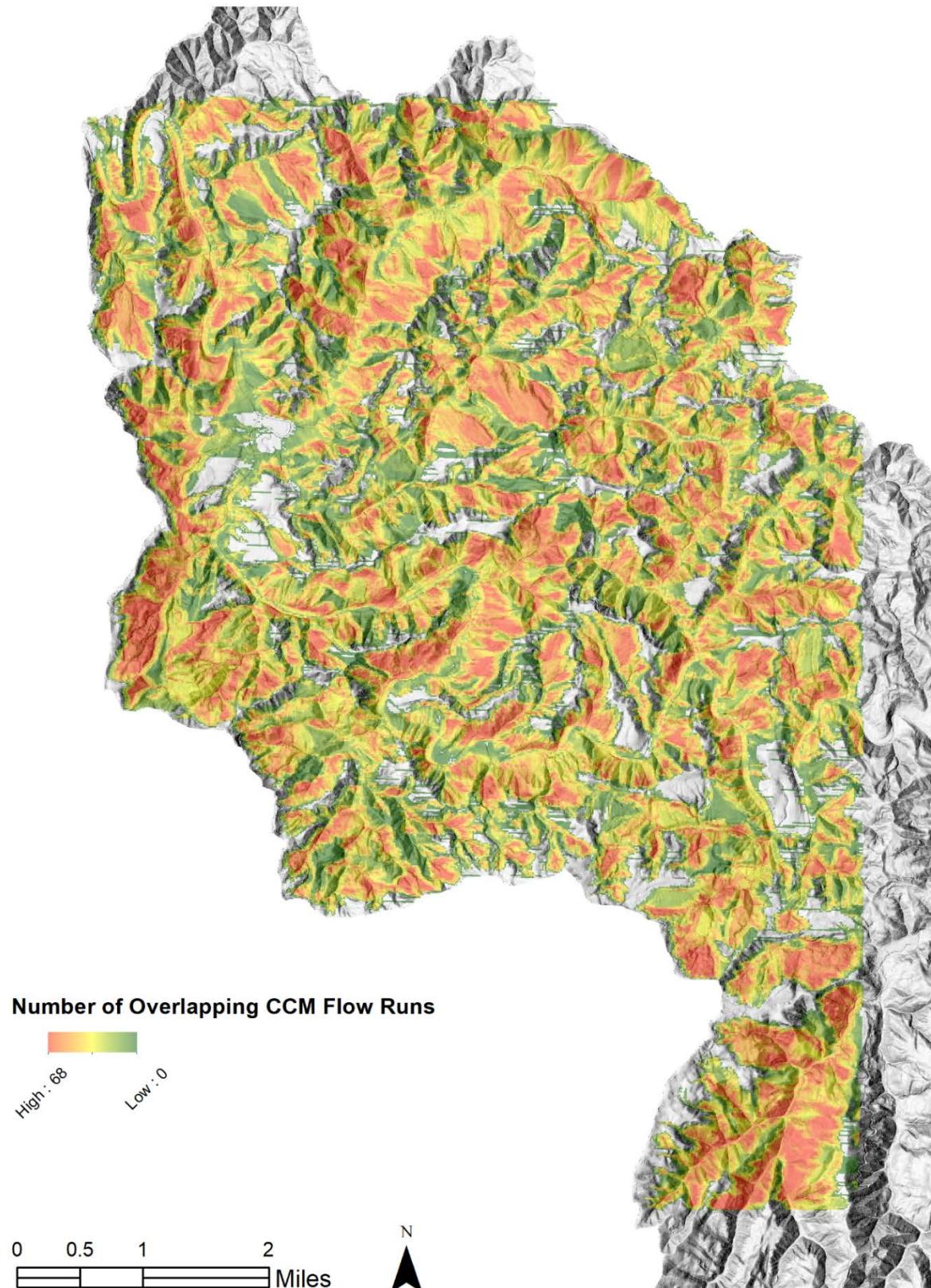


Figure B.2: Consensus raster for the 81 SICCM trials.

The final experiment was an evaluation of whether or not the consensus raster would be suitable as a proxy for confidence in landslide identification. Thresholds were chosen from 1 to 81, and pixels exceeding each threshold were then evaluated for accuracy by the manual inventory. For example, if the threshold was 21, only pixels in Figure B.2 with a value greater than 21 were called landslides. The thresholded raster was then compared to the manual inventory to compute accuracy and a confusion matrix (Figure B.3).

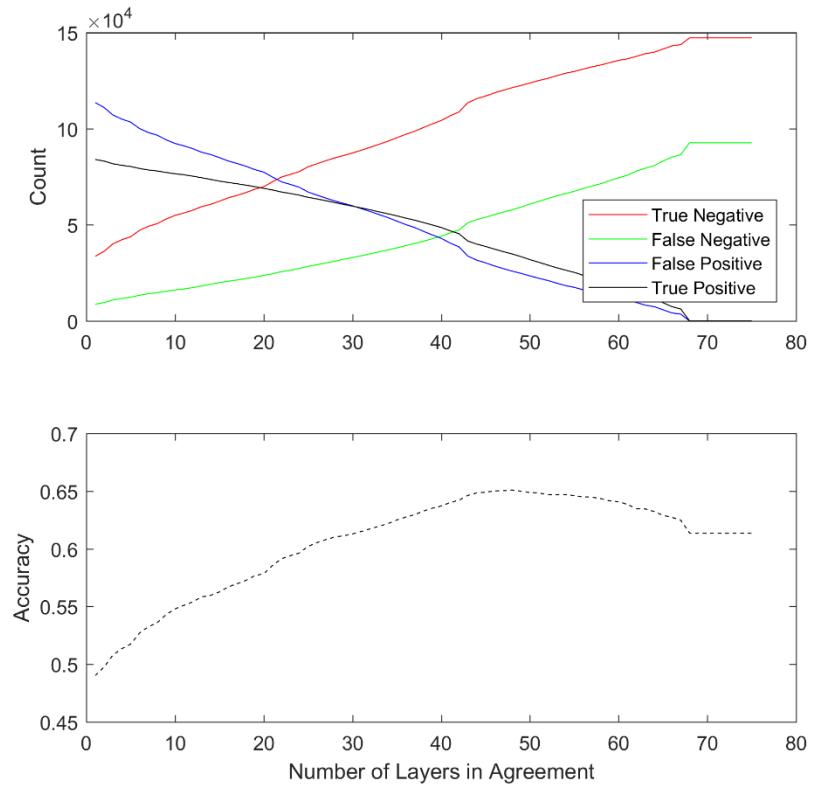


Figure B.3: Accuracy assessment of the thresholded consensus raster.

Figure B.3 shows that as the threshold value increases, accuracy generally increases and false positives decreases, meaning that the consensus raster may be a valid estimate of confidence in landslide identification. More trials will need to be performed with consensus rasters computed from a more feasible, fewer number of trials, to determine if the approach is still applicable.

**APPENDIX C – MAPS PRODUCED FOR BIG ELK CREEK, GALES
CREEK, AND DIXIE MOUNTAIN**

Maps produced for Big Elk, Gales Creek, and Dixie Mountain

The inventory maps included in this appendix were produced as part of the accuracy assessment of Chapter 4. Each map was produced using SICCM with the deposit mapping parameters provided in Table 4.2. Accuracy measures of these inventories can be found in Table 4.3

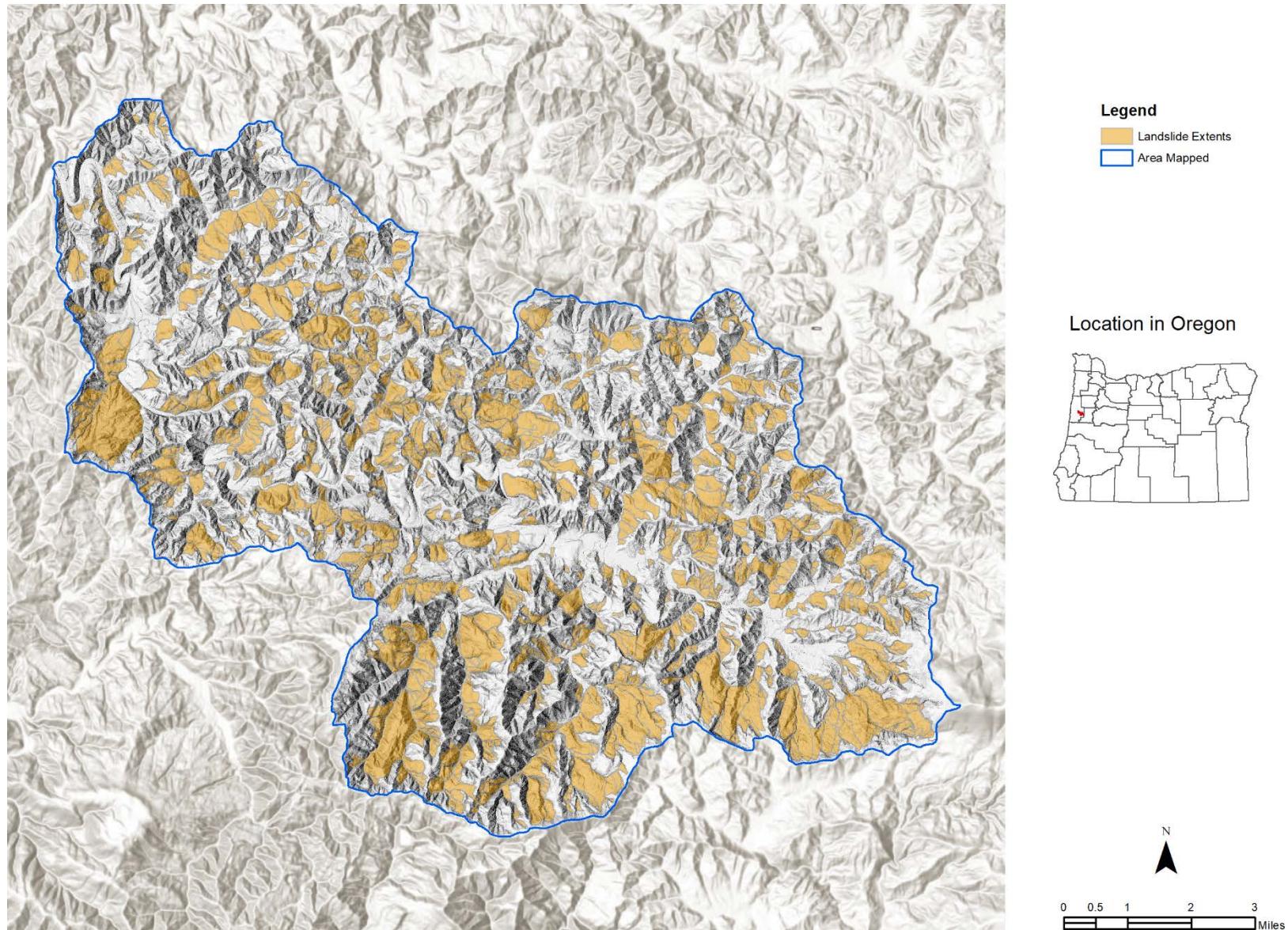


Figure C-1: SICCM produced landslide inventory map produced for the Big Elk Creek watershed, Oregon.

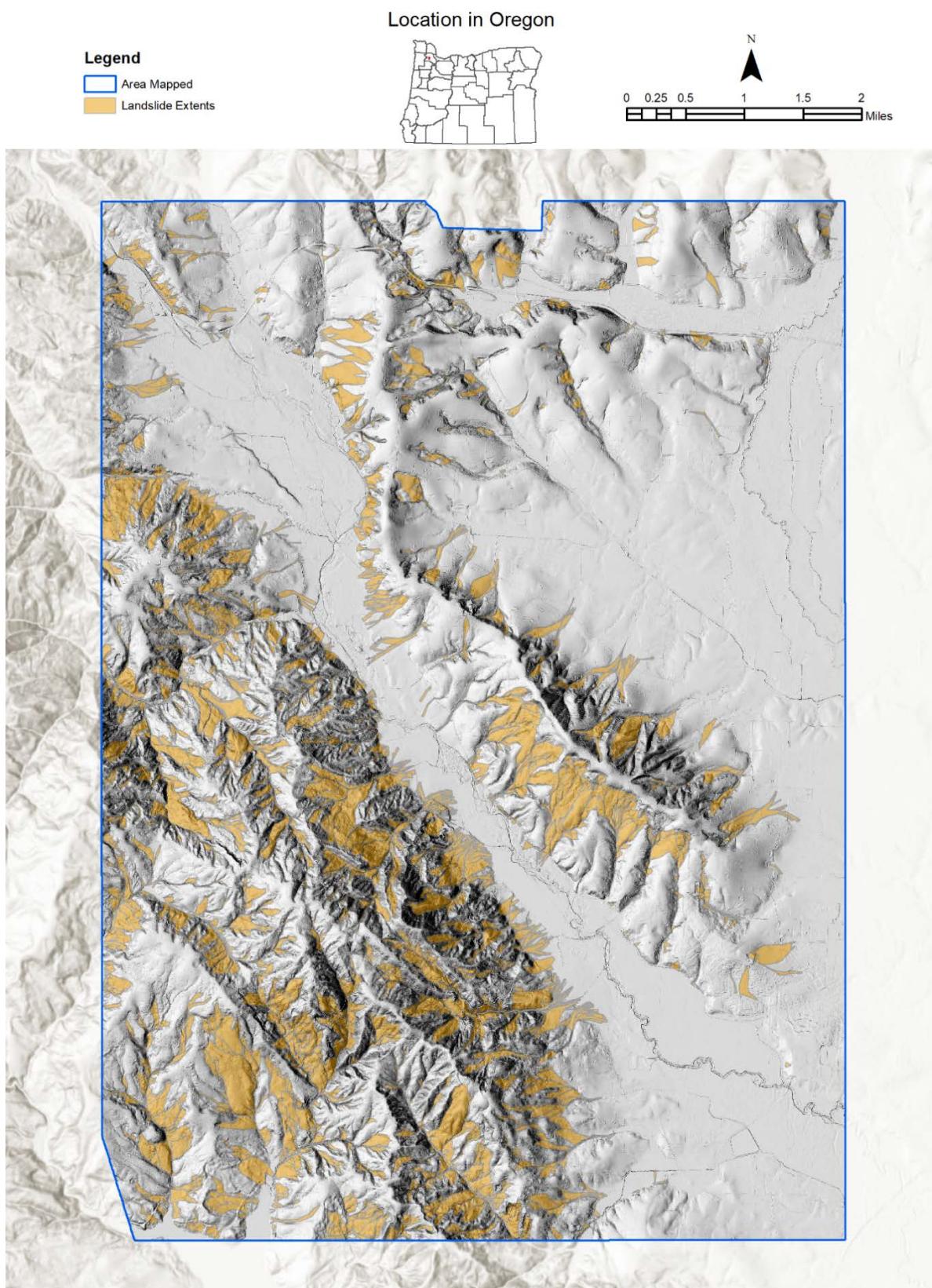


Figure C-2: SICCM produced landslide inventory map of the Gales Creek USGS quadrangle, Oregon.

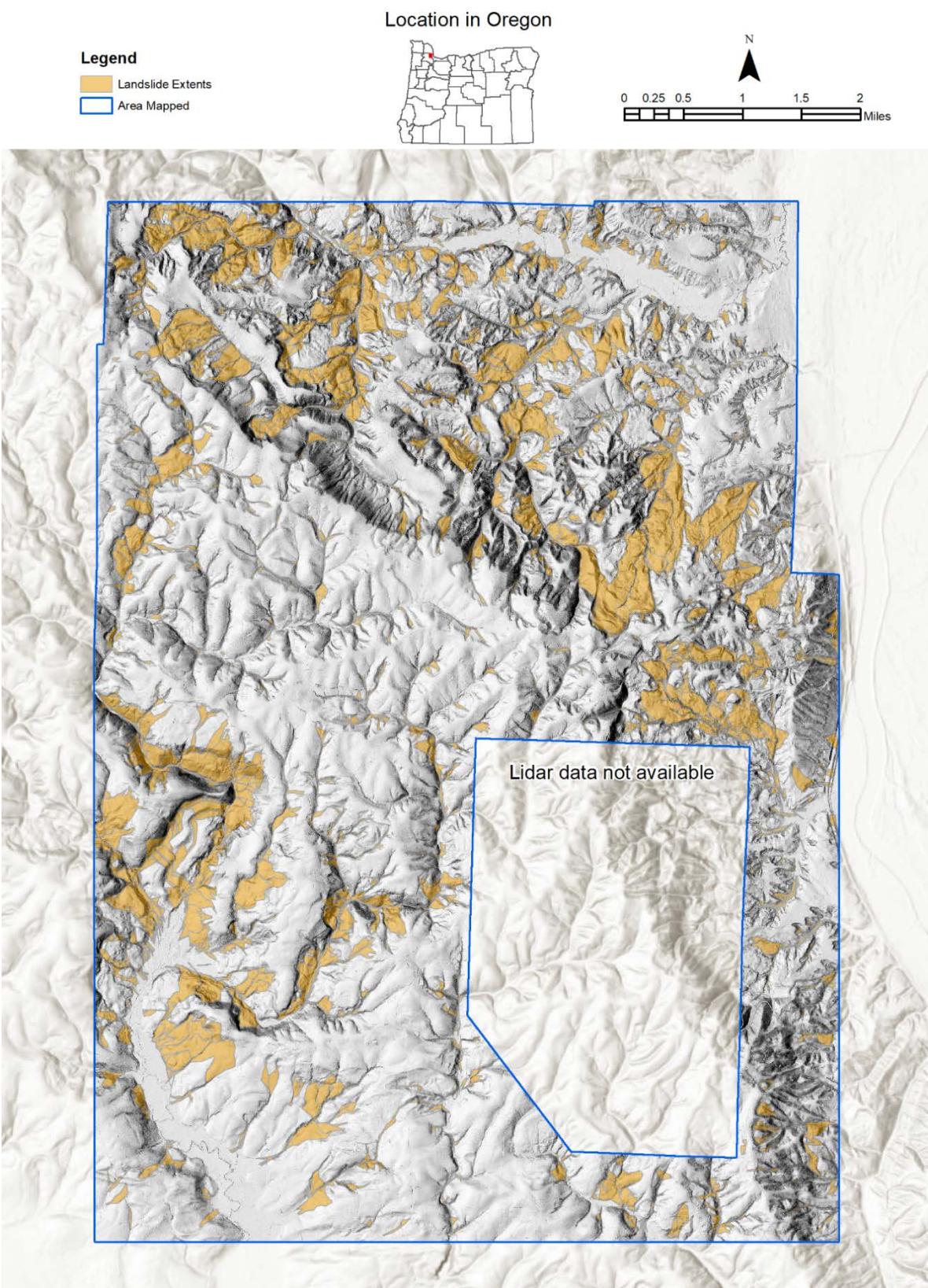


Figure C-3: SICCM produced landslide inventory map of the Dixie Mountain USGS quadrangle, Oregon.

**APPENDIX D – MEMORANDUMS FROM THE TRANSPORTATION
PLANNING AND ANALYSIS UNIT (TPAU)**

***Memorandums from the Transportation Planning and Analysis Unit
(TPAU)***

STATE OF OREGON

TECHNICAL REQUEST MEMO

**Department of Transportation
Transportation Development Division**
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(503) 986-4112 FAX (503) 986-4174

Date: February 26th, 2018

TO: Kira Glover-Cutter, Research Coordinator
ODOT TDD Research Section

CC: Curran Mohney, Engineering Geology Program Lead, ODOT
Michael Bunn, PhD Candidate, Civil & Construction Engineering, OSU
Ben Leshchinsky, Assistant Prof., Forest Engineering, Resources & Management,
OSU
Michael Olsen, Associate Prof., Civil & Construction Engineering, OSU

FROM: Dejan Dudich, Transportation Analyst/Modeler;
Becky Knudson, Senior Transportation Economist;
Transportation Planning Analysis Unit, ODOT

SUBJECT: Estimated economic impacts of road closure due to major landslide for select
locations identified for SPR 786.

Attachments: DetourReportingTable.xlsx, SPR786_Selections.7z

In November 2016 Kira Glover-Cutter and a team of OSU researchers provided an overview of a project related to potential landslide locations: "SPR 786 Enhancing Landslide Inventory, Hazard Assessment and Asset Management Using LIDAR." The research team wanted to explore the availability of economic data for use in the study. Becky Knudson described analytical capability using the Oregon Statewide Integrated Model (SWIM). Together, the project team identified information to be prepared using SWIM in support of the SPR 786 project.

The initial request completed April 2017 was expanded to include additional locations in January 2018. This secondary request provides information on commodity flows along designated landslide risk corridors submitted by the project team. It was determined that SWIM could be used in a similar fashion as the previous request to generate the information that the research team was interested in.

Description of Request

The OSU research team requested commodity flow information for three corridors:

Highway	Start Mile Point	End Mile Point	Description
OR 42	10	53	Junction with OR 42S to Camas Valley
OR 126	1	45	Florence to Veneta
US 101	280	363	Bandon to CA border

The OSU team identified 3 highways corridors and their corresponding SWIM links using a GIS file provided by TPAU. The OSU team identified a total of 333 SWIM links that corresponded to their needs; TPAU reduced that number to 65 specific links that could be utilized to represent commodity flow along the corridors. TPAU provided the commodity flow data in shape files as requested by the OSU team. The methodology used to generate this data is described in the Methodology section of this memo.

In addition, the OSU team requested detour analysis related to closure on these three corridors, 6 locations were chosen based on provided geocoded points: 1 on US 101, 4 on OR 42, and 1 on OR 36. TPAU used a network select link process to identify the highway users forced to reroute when the highways are closed. This information was used to estimate the user costs associated with the closures with respect to travel time and route distance. The methodology used to prepare this information is provided in the Methodology section of this memo.

SWIM Model Description

The Oregon Statewide Integrated Model (SWIM) is a data driven forecast model designed to represent the Oregon economy with respect to land-use and transportation by simulating the activity and market exchanges made by people and businesses. Household and business location decisions are simulated, as well as the travel generated by activities - such as commuting to work, purchasing commodities for industrial production and transporting final goods to markets within Oregon and outside of the state. It is designed for statewide and regional long range transportation planning and policy analysis. Information from SWIM is designed to inform other modeling tools, such as metropolitan planning organization travel models, freight models, and regional studies.

The statewide model is described as an “integrated” model because the sub-models are interconnected. Information is shared back and forth between sub-models, mimicking the reactive and interactive behaviors observed in the real world. The model is designed to represent how people and businesses share information and exchange goods and services based on prices and location. The integrated modular design better represents real-world conditions and activity, but requires an immense amount of data, significant development time, powerful computing capabilities and trained staff. For these



reasons, very few states have a statewide economic, land use and transportation model like Oregon's.

Detailed technical documentation on the design of SWIM is available online:

<https://www.oregon.gov/ODOT/TD/TP/docs/statewide/swim2.pdf> . SWIM consists of specialized sub-models that interconnect with each other, which is illustrated in **Figure 1**. There are seven key sub-models:

- **Economic Model (NED):** provides the model-wide production activity levels, employment, imports and exports based upon long range forecasts consistent with the Department of Administrative Services' Oregon Economic & Revenue Forecast and the associated baseline macroeconomic forecast from IHS Markit;
- **Population Synthesizer (SPG):** simulates a population with observed Oregon characteristics such as age, household size, household location, income, worker status, and occupation;
- **Activity Allocation Model (AA):** simulates where businesses locate, the commodities they purchase to use as production inputs, the amount and type of labor (workers) hired, the amount of floorspace residence and businesses purchase/lease, and production of and sales of goods and services based on market prices;
- **Aggregate Land Development Model (ALD):** identifies land availability based on Oregon local jurisdiction zoning and develops residential and commercial buildings (square footage) based on floorspace prices and vacancy rates for firms and households to rent or purchase;
- **Person Travel (PT):** simulates person travel activity for a typical weekday for the population of Oregon simulated by the Population Synthesizer and located by the Activity Allocation Model. Activity involving travel is assigned a travel mode such as auto, transit, rail, bike, or walk;
- **Commercial Transport (CT):** simulates how commodities are moved as freight by different modes of transport, such as marine, rail, and truck for a typical weekday. For trucks specifically, shipments are simulated to appropriately transport daily commodity shipments modeled by the Activity Allocation Model;
- **Transport Model (VISUM):** assigns trips to a computer representation of the statewide transportation network, trips generated in the Person Travel Model and Commercial Transport Model, generating routes with distance and travel time information.

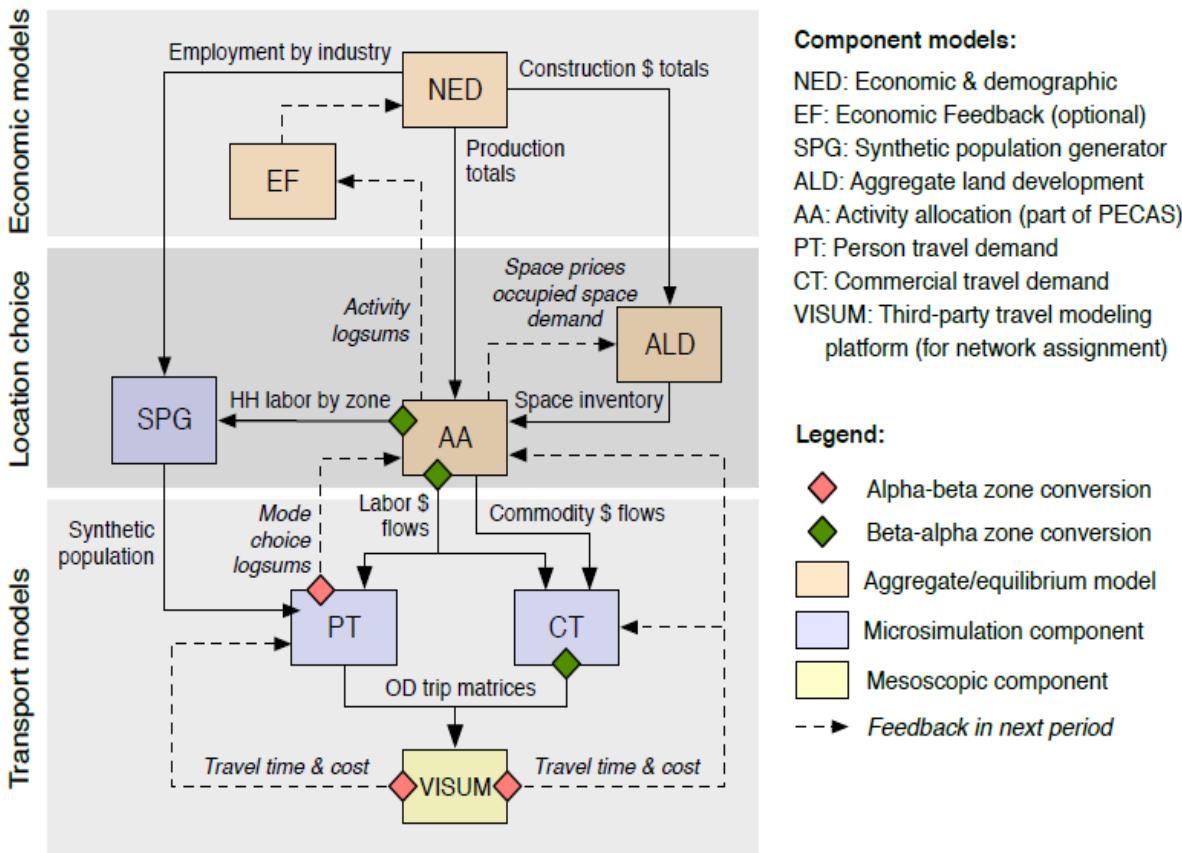


Figure 8.1. SWIM Design Schematic

Select Link Methodology: Commodity Flows

The SWIM Commercial Travel (CT) module generates discrete truck trips. These truck trips are created from two sources, the federal Freight Analysis Framework¹(FAF), which provides Oregon commodity flow data and the Activity Allocation (AA) module which generates the buying and selling allocations of commodities within SWIM. CT uses the FAF commodity flows and disaggregates them into the SWIM zones (~3000) using AA spatial allocation, enabling commodity flows to be represented along Oregon's roadways using network assignment software.

To pull the required commodity flow data from SWIM the requested highway corridors were matched up to the existing SWIM roadway network, which is managed using the commercial network assignment software VISUM². Once SWIM roadway links are identified, a custom process in SWIM, referred to as “select link”, is run twice, once for each direction, for the identified corridors. The Select Link (SL) process tags all trips utilizing the identified link and

¹ https://ops.fhwa.dot.gov/freight/freight_analysis/faf/

² <https://data.ptvamerica.com/docs/VISUM%20Slideshow.pdf>

creates origin/destination matrices for those trips. A detailed explanation of the SL process is available on the SWIM Wiki online at: <https://github.com/tlumip/tlumip/wiki/SL>.

The SL process creates a series of csv files containing the trips using the corridor selected links, as well as the associated commodity flows by value and weight. Using the R programming language, truck trips are tabulated to produce total tons and values for the requested corridors for over 40 commodity categories. These categories are aggregated into 7 commodity groups used for reporting, illustrated in **Table 1** on the next page. Further detailed technical documentation of this process is available online: <https://github.com/tlumip/tlumip/wiki/Analyzing-Disaggregate-FAF-Flows>. The model base year is 2010, so the value and tonnage is scaled to represent the year requested using FAF growth rates to adjust to the year requested. Model data and summary tables developed for this memo are provided in the attached file “ValueTon_Summary.zip”.

Select Link Methodology: Highway Closure Traffic Response

Simulated closures due to landslide blockage were requested along three corridors. Six locations were evaluated as illustrated in **Figures 2, 3, and 4**. VISUM software was used to run the select link process for each location in each direction. The assignment results are saved as four individual VISUM version files (*.ver).

SL process was run, identifying users of the directional roadway links and tagging them in order to observe the detour routes after the roadway links are closed. Next the SL process is run with the roadway links “closed” within VISUM by restricting all vehicle access to the links. After a VISUM network link is coded for closure, traffic is reassigned using VISUM to follow the detour routes chosen for trips previously tagged as using the landslide link(s).

VISUM link tables are copied into Excel for the closure and non-closure assignment results for the two locations. Using link speed, link length, and link traffic volume (autos and trucks), vehicle-miles-traveled (VMT) and vehicle-hours-traveled (VHT) for both autos and trucks detoured by the closure and all other background traffic are calculated. Once the VMT and VHT are calculated for both the closure and non-closure scenarios, the difference in travel time and distance for the detoured segment users are calculated and monetized in order to represent user economic impacts associated with a closure due to a landslide.

Results

Estimated commodity flows along the corridors were prepared as a shape file and are provided as an attachment in “SPR786_Selections.7z.” Understanding commodities shipped on highway corridors reveals potential impacts on Oregon businesses relying on these corridors to access goods used for their production activity. Flows for seven aggregate commodity groups are reported by value and tons from SWIM. The commodity groups are described in **Table 1**.

Table 1**Commodity Group Descriptions**

Clay, Minerals & Stone: monument or building stone; natural sands; gravel and crushed stone; nonmetallic minerals; metallic ores and concentrates; and nonmetallic mineral products;

Food & Kindred Products: live animals and fish; cereal grains; animal feed; meat, seafood; milled grain products; alcoholic beverages; and tobacco products;

Forest & Wood Products: logs and other wood in the rough and wood products;

Machinery, Instruments, & Transportation Equipment: base metal in primary or semi-finished form; articles of base metal; machinery; electronic and other electrical equipment; motorized and other vehicles (including parts); transportation equipment; precision instruments and apparatus;

Other Miscellaneous: textiles, leather, furniture, mattresses, and miscellaneous manufactured products;

Petroleum, Coal & Chemicals: crude petroleum, gasoline and aviation fuel; fuel oils, pharmaceutical products, fertilizers, plastics and rubber;

Pulp & Paper Products: newsprint, paperboard, paper or paperboard products, and printed products.

- For more detailed descriptions of commodities, refer to the Standard Classification of Transported Goods booklet published by the U.S. Census Bureau: https://www.census.gov/econ/cfs/2017/CFS-1200_17.pdf
- Commodity flows provided by the Oregon Statewide Integrated Model based on the federal Freight Analysis Framework 4 data for Oregon.

Estimated user costs associated with an unexpected closure on US 101 and OR 36 at one location each and OR 42 at 4 locations were prepared to represent the direct economic impacts of the road closure for each location. User costs were estimated for two distinct categories – costs associated with additional travel time and variable vehicle operating costs associated with additional travel distance. Using the SWIM select link process described earlier in this memo, the additional travel time and distance was measured for users of the highway at the closure locations. The US 101 location is provided in **Figure 2**, OR 42 locations are illustrated in **Figure 3**, and the OR 36 location is shown in **Figure 4**.

Figure 2: US 101

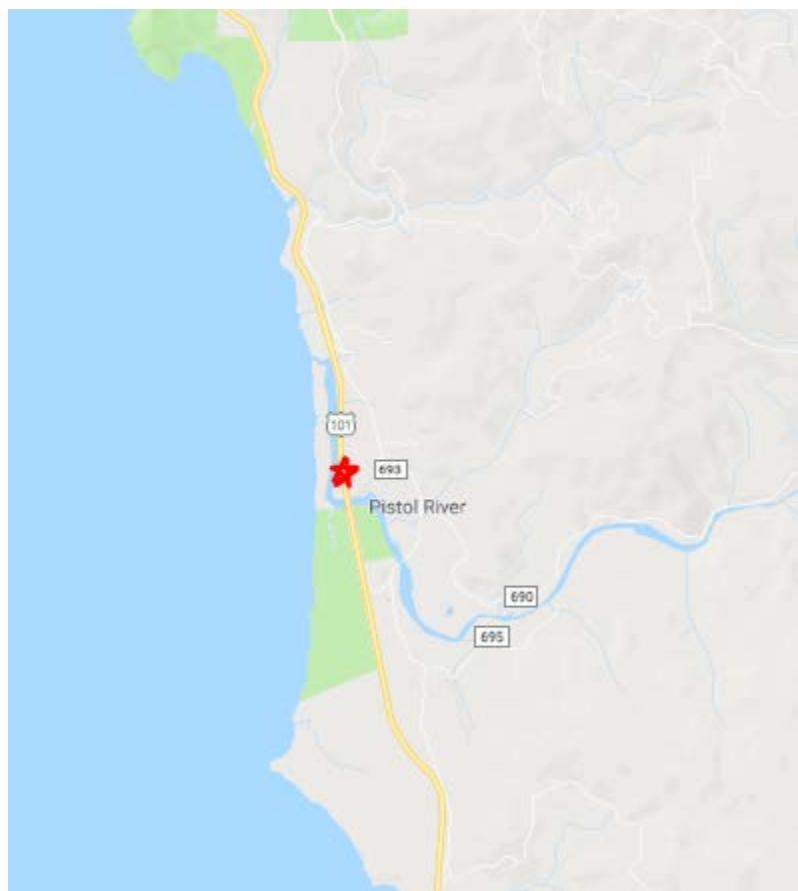


Figure 3: OR 42 Locations

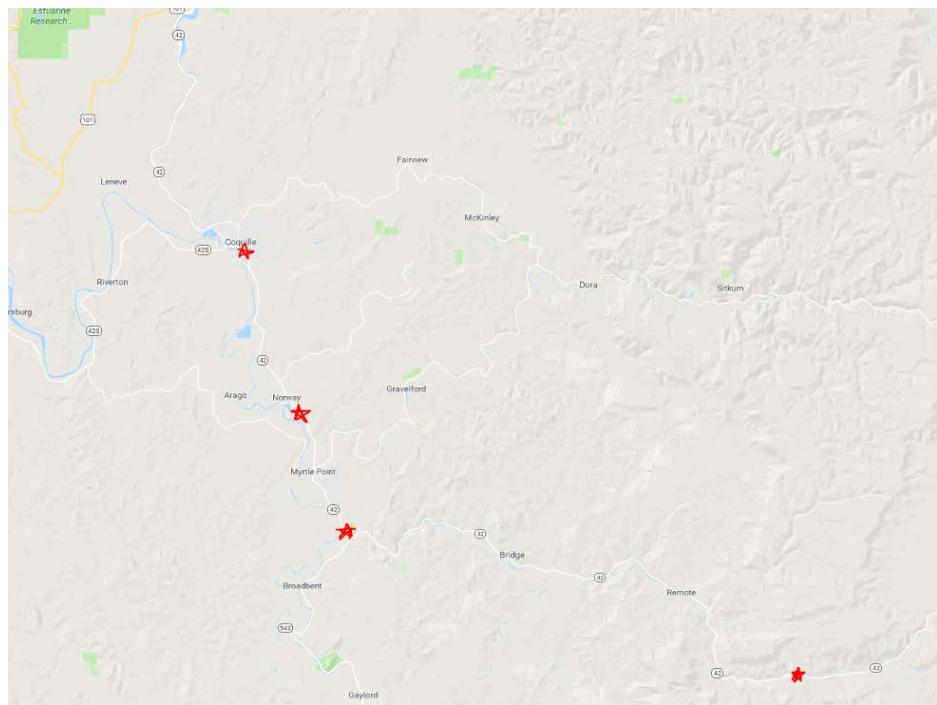
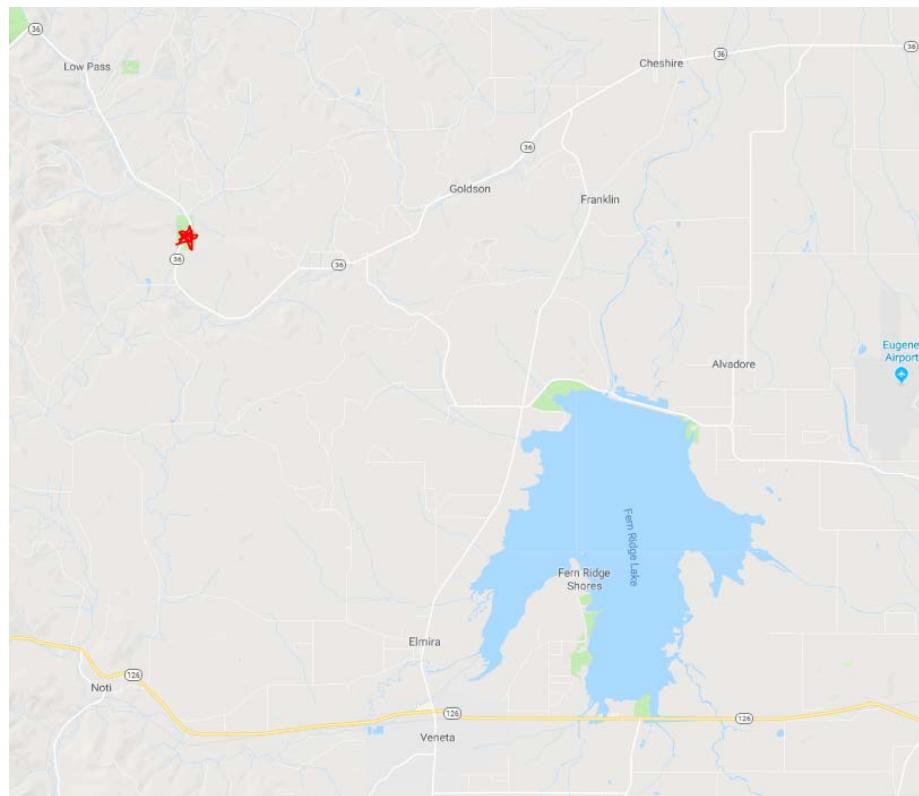


Figure 4: OR 36



The time and distance costs caused by a detour route are monetized using an estimated value of travel time for autos and trucks and an average variable vehicle operating cost estimate for a medium sedan and heavy truck. These estimates are provided in **Table 2**, including links to the source documents.

Table 2. Value of Travel Time and Vehicle Operating Costs

	Auto	Truck
Value of Time: per Hour*	\$25.78	\$31.32
Operating Cost per Mile**	\$ 0.15	\$ 0.20

*https://www.oregon.gov/ODOT/TD/TP/Reports/Value_of_TravelTime.pdf
**<https://exchange.aaa.com/wp-content/uploads/2017/05/2016-YDC-Brochure.pdf> for auto,
<https://www.rtsfinancial.com/guides/trucking-calculations-formulas> for truck.

Table 3 presents the impact closures have on highway users' travel time and distance traveled. It is important to note these estimates represent behavior assuming the highway users know of the closure in advance. Without advance notice, additional time and miles would be incurred from driving to the closure point and responding with a new route. If these closures were to last for long periods (months or years), travel destinations would likely start to change, which could have larger impacts than accounted for in this short term analysis. It is important to note that any closure in the coastal vicinity has the potential to impose greater impacts to trucks due to the limited presence of alternative routes designed to accommodate trucks' larger sizes and weights.

Table 3. Estimated Impacts to Users of Unexpected Closure Due to Landslide: Travel Time and Distance

Location	Average Per Vehicle Change in Miles of Travel		Average Per Vehicle Change in Hours of Travel	
	Auto	Truck	Auto	Truck
US101	173	182	194	201
OR42 East of Remote	44	37	54	53
OR42 South of Myrtle Point (E of Myrtle Pt)	120	43	136	50
OR42 At Norway (Bt Coquille and Myrtle Pt)	5	63	15	71
OR42 North of Cedar Point (W of Coquille)	8	93	11	100
OR36 at Alderwood State Wayside	0	0	1	0

On any given day of the year there is a range of potential traffic volumes (system users) at these locations, which is reflected in the range of estimated user costs presented in **Table 4**. The data and calculations are provided in the attached file “DetourReportingTable.xlsx.”

Table 4. Estimated Range of User Costs Due to Landslide Closure for One Day

Location	Time Costs	Vehicle Operating Costs	Range of Total Costs
US101	\$96,471 - \$192,865	\$70,013 - \$139,969	\$166,484 - \$332,834
OR42 East of Remote	\$29,028 - \$72,497	\$7,048 - \$17,601	\$36,075 - \$90,098
OR42 South of Myrtle Point	\$188,021 - \$375,892	\$47,393 - \$94,749	\$235,414 - \$470,640
OR42 At Norway	\$26,303 - \$52,596	\$5,391 - \$10,780	\$31,695 - \$63,376
OR42 North of Cedar Point	\$39,277 - \$78,538	\$6,988 - \$13,973	\$46,265 - \$92,511
OR36 at Alderwood State Wayside	\$2,167 - \$5,412	\$6 - \$16	\$2,173 - \$5,428

For further information regarding this analysis or related materials, please contact:

Dejan Dudich
503-986-3515
dejan.dudich@odot.state.or.us
or
Becky Knudson
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STATE OF OREGON**TECHNICAL REQUEST MEMO**

Department of Transportation
Transportation Development Division
Mill Creek Office Park
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Salem, Oregon 97301-4178
(503) 986-4112 FAX (503) 986-4174

Date: June 15, 2017

TO: Kira Glover-Cutter, Research Coordinator
ODOT TDD Research Section

FROM: Becky Knudson, Senior Transportation Economist;
Dejan Dudich, Transportation Analyst/Modeler;
Transportation Planning Analysis Unit

SUBJECT: Estimated economic impacts of road closure due to major landslide for select locations identified for SPR 786.

Attachments: ValueTon_Summary.xlsx, ClosureVolumeMaps.pdf, ValueTon_Summary.zip

In November 2016 Kira Glover-Cutter and a team of OSU researchers provided an overview of a project related to potential landslide locations: “SPR 786 Enhancing Landslide Inventory, Hazard Assessment and Asset Management Using LIDAR.” The research team wanted to explore the availability of economic data for use in the study. Becky Knudson described analytical capability using the Oregon Statewide Integrated Model. Together, the project team identified information to be prepared using SWIM in support of the SPR 786 project.

Description of Request

The OSU research team requested commodity flow information for five corridors:

Highway	Start Mile Point	End Mile Point	Description
Highway 255 (Carpenter Road)	343	362	Entire highway
OR 36	0	45	Mapleton to Willamette Valley
OR 42	10	53	Junction with OR 42S to Camas Valley
OR 126	1	45	Florence to Veneta
US 101	280	363	Bandon to CA border

The OSU team identified 14 locations for reporting commodity flows. 12 of the 14 locations are on the SWIM highway network. TPAU will provide the commodity flow data in shape files as requested by the OSU team. The methodology used to generate this data is described in the Methodology section of this memo.

In addition, the OSU team requested analysis related to closure on OR 126 at two locations: Tiernan and Walton. TPAU used a network select link process to identify the highway users forced to reroute when the highway is closed. This information was used to estimate the economic impacts associated with the closures with respect to travel time and route distance. The methodology used to prepare this information is provided in the Methodology section of this memo.

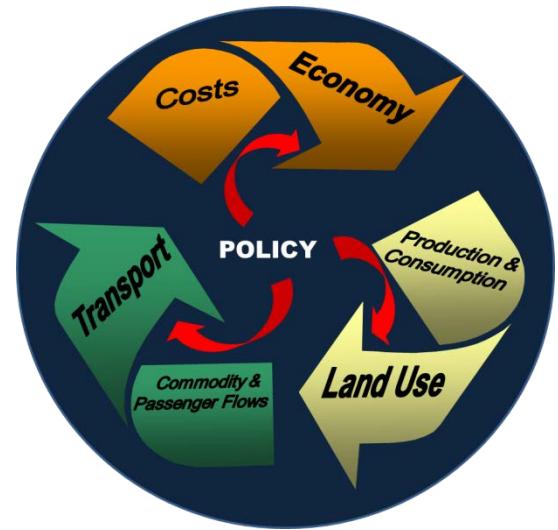
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- **Economic Model (NED):** provides the model-wide production activity levels, employment, imports and exports based upon long range forecasts consistent with the Department of Administrative Services’ Oregon Economic & Revenue Forecast and the associated baseline macroeconomic forecast from IHS Markit;
- **Population Synthesizer (SPG):** simulates a population with observed Oregon characteristics such as age, household size, household location, income, worker status, and occupation;



- **Activity Allocation Model (AA):** simulates where businesses locate, the commodities they purchase to use as production inputs, the amount and type of labor (workers) hired, the amount of floorspace residence and businesses purchase/lease, and production of and sales of goods and services based on market prices;
- **Aggregate Land Development Model (ALD):** identifies land availability based on Oregon local jurisdiction zoning and develops residential and commercial buildings (square footage) based on floorspace prices and vacancy rates for firms and households to rent or purchase;
- **Person Travel (PT):** simulates person travel activity for a typical weekday for the population of Oregon simulated by the Population Synthesizer and located by the Activity Allocation Model. Activity involving travel is assigned a travel mode such as auto, transit, rail, bike, or walk;
- **Commercial Transport (CT):** simulates how commodities are moved as freight by different modes of transport, such as marine, rail, and truck for a typical weekday. For trucks specifically, shipments are simulated to appropriately transport daily commodity shipments modeled by the Activity Allocation Model;
- **Transport Model (VISUM):** assigns trips to a computer representation of the statewide transportation network, trips generated in the Person Travel Model and Commercial Transport Model, generating routes with distance and travel time information.

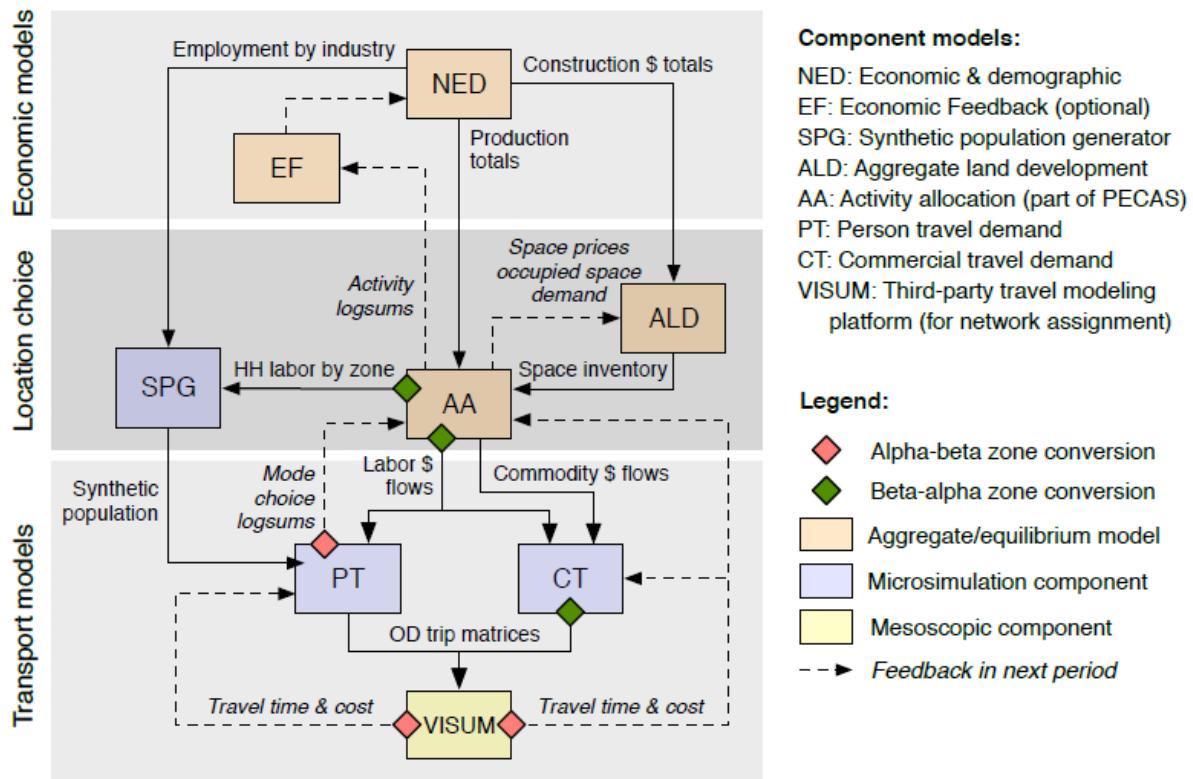


Figure 8.1. SWIM Design Schematic

Select Link Methodology: Commodity Flows

The SWIM Commercial Travel (CT) module generates discrete truck trips. These truck trips are created from two sources, the federal Freight Analysis Framework³(FAF), which provides Oregon commodity flow data and the Activity Allocation (AA) module which generates the buying and selling allocations of commodities within SWIM. CT uses the FAF commodity flows and disaggregates them into the SWIM zones (~3000) using AA spatial allocation, enabling commodity flows to be represented along Oregon’s roadways using network assignment software.

To pull the required commodity flow data from SWIM the requested highway corridors were matched up to the existing SWIM roadway network, which is managed using the commercial network assignment software VISUM⁴. Once SWIM roadway links are identified, a custom process in SWIM, referred to as “select link”, is run twice, once for each direction, for the identified corridors. The Select Link (SL) process tags all trips utilizing the identified link and creates origin/destination matrices for those trips. A detailed explanation of the SL process is available on the SWIM Wiki online at: <https://github.com/tlumip/tlumip/wiki/SL> .

The SL process creates a series of csv files containing the trips using the corridor selected links, as well as the associated commodity flows by value and weight. Using the R programming language, truck trips are tabulated to produce total tons and values for the requested corridors for over 40 commodity categories. These categories are aggregated into 7 commodity groups used for reporting, illustrated in **Table 1** on the next page. Further detailed technical documentation of this process is available online: <https://github.com/tlumip/tlumip/wiki/Analyzing-Disaggregate-FAF-Flows> . The model base year is 2010, so the value and tonnage is scaled to represent the year requested using FAF growth rates to adjust to the year requested. Model data and summary tables developed for this memo are provided in the attached file “ValueTon_Summary.xlsx”.

Select Link Methodology: Highway Closure Traffic Response

Simulated closures due to landslide blockage were requested for two locations on OR 126 at Tiernan and Walton illustrated in **Figures 2 and 3**. VISUM software was used to run the select link process for each location in each direction. The assignment results are saved as four individual VISUM version files (*.ver).

SL was run, identifying users of the directional roadway links and tagging them in order to observe the detour routes after the roadway links are closed. Next the SL process is run with the roadway links “closed” within VISUM by restricting all vehicle access to the links. After a VISUM network link is coded for closure, traffic is reassigned using VISUM to follow the trips previously tagged as using the landslide link(s).

VISUM link tables are copied into Excel for the closure and non-closure assignment results for the two locations. Using link speed, link length, and link traffic volume (autos and trucks), vehicle-miles-traveled (VMT) and vehicle-hours-traveled (VHT) for both autos and trucks detoured by the closure and all other background traffic are calculated. Once the VMT and VHT

³ https://ops.fhwa.dot.gov/freight/freight_analysis/faf/

⁴ <https://data.ptvamerica.com/docs/VISUM%20Slideshow.pdf>

are calculated for both the closure and non-closure scenarios, the difference in travel time and distance for the detoured segment users are calculated and monetized in order to represent user economic impacts associated with a closure due to a landslide.

Results

Estimated commodity flows at the identified locations were prepared as shape files and are provided as an attachment in “ValueTon_Summary.zip.” Understanding commodities shipped on highway corridors reveals potential impacts on Oregon businesses relying on these corridors to access goods used for their production activity. Flows for seven aggregate commodity groups are reported by value and tons from SWIM. The commodity groups are described in **Table 1**.

Table 5

Commodity Group Descriptions

Clay, Minerals & Stone: monument or building stone; natural sands; gravel and crushed stone; nonmetallic minerals; metallic ores and concentrates; and nonmetallic mineral products;

Food & Kindred Products: live animals and fish; cereal grains; animal feed; meat, seafood; milled grain products; alcoholic beverages; and tobacco products;

Forest & Wood Products: logs and other wood in the rough and wood products;

Machinery, Instruments, & Transportation Equipment: base metal in primary or semi-finished form; articles of base metal; machinery; electronic and other electrical equipment; motorized and other vehicles (including parts); transportation equipment; precision instruments and apparatus;

Other Miscellaneous: textiles, leather, furniture, mattresses, and miscellaneous manufactured products;

Petroleum, Coal & Chemicals: crude petroleum, gasoline and aviation fuel; fuel oils, pharmaceutical products, fertilizers, plastics and rubber;

Pulp & Paper Products: newsprint, paperboard, paper or paperboard products, and printed products.

- For more detailed descriptions of commodities, refer to the Standard Classification of Transported Goods booklet published by the U.S. Census Bureau: https://www.census.gov/econ/cfs/2017/CFS-1200_17.pdf
- Commodity flows provided by the Oregon Statewide Integrated Model based on the federal Freight Analysis Framework 4 data for Oregon.

Estimated user costs associated with an unexpected closure on OR 126 for two locations were prepared to represent the direct economic impacts of the road closure for each location. User costs were estimated for two distinct categories – costs associated with additional travel time and vehicle operating costs associated with additional travel distance. Using the SWIM select link process described earlier in this memo, the additional travel time and distance was measured for users of the highway at the two closure locations. Visual representation of the detoured traffic routes is provided in the attached file “ClosureVolumeMaps.pdf.” The two locations on OR 126 are illustrated in **Figure 2** and **Figure 3**.

Figure 2. Tiernan

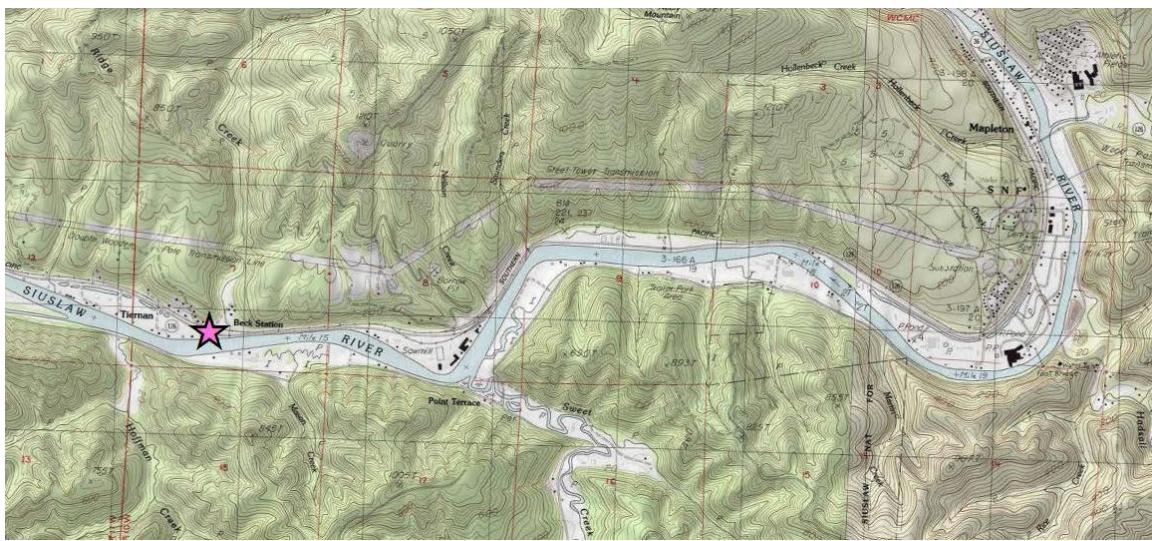
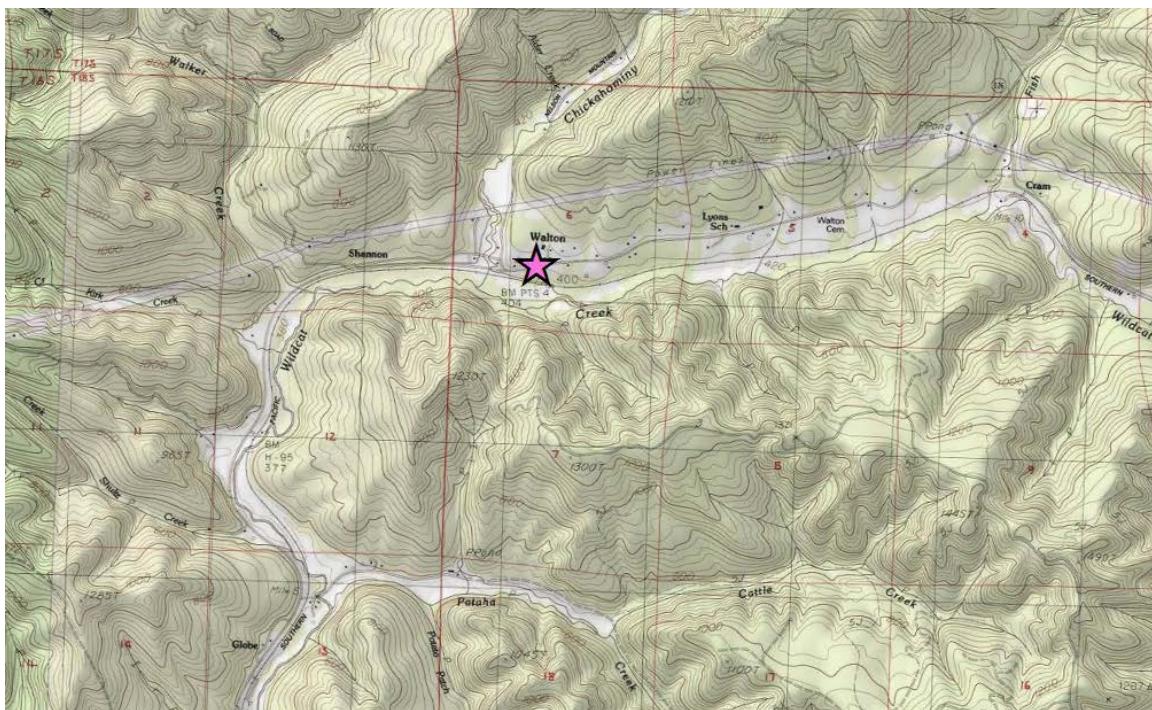


Figure 3. Walton



The time and distance costs caused by a detour route are monetized using an estimated value of travel time for autos and trucks and an average vehicle operating cost estimate for a medium sedan and heavy truck. These estimates are provided in **Table 2**, including links to the source documents.

Table 6. Value of Travel Time and Vehicle Operating Costs

	Auto	Truck
Value of Time: per Hour*	\$25.78	\$31.32
Operating Cost per Mile**	\$ 0.15	\$ 0.20

*https://www.oregon.gov/ODOT/TD/TP/Reports/Value_of_TravelTime.pdf
**<https://exchange.aaa.com/wp-content/uploads/2017/05/2016-YDC-Brochure.pdf> for auto,
<https://www.rtsfinancial.com/guides/trucking-calculations-formulas> for truck.

Table 3 presents the impact closures have on highway users' travel time and distance traveled. It is important to note these estimates represent behavior assuming the highway users know of the closure in advance. Without advance notice, additional time and miles would be incurred from driving to the closure point and responding with a new route. If these closures were to last for long periods (months or years), travel destinations would likely start to change, which could have larger impacts than accounted for in this short term analysis. It is important to note that any closure in the coastal vicinity has the potential to impose greater impacts to trucks due to the limited presence of alternative routes designed to accommodate trucks' larger sizes and weights.

Table 7. Estimated Impacts to Users of Unexpected Closure Due to Landslide: Travel Time and Distance

	Average Additional Miles of Travel		Average Additional Hours of Travel	
	Auto	Truck	Auto	Truck
Tiernan	45	21	50	18
Walton	12	22	10	23

On any given day of the year there is a range of potential traffic volumes (system users) at these two locations, which is reflected in the estimated user costs presented in **Table 4**.

Table 8. Range of Potential Economic Impacts of Landslide on OR 126

Location	Time Costs	Vehicle Operating Costs	Range of Total Costs
Tiernan	\$102,000 – \$143,000	\$38,000 - \$53,000	\$140,000 - \$196,000
Walton	\$ 21,000 - \$33,000	\$ 7,500 - \$12,000	\$ 28,500 - \$45,000

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APPENDIX E – STEP-BY-STEP PROCEDURE FOR USING SICCM

Step-by-step procedure for using SICCM

This appendix shows step-by-step instructions for performing semi-automatic landslide deposit mapping using the Scarp Identification and Contour Connection (SICCM) procedure. Prior to getting started, it is important that the user understand the following items:

1. Updated versions of the SICCM tools may exist. The user should visit the faculty webpage of Dr. Ben Leshchinsky, Oregon State University, to ensure that they are using the newest version. Newer versions will have their own step-by-step documentation, and in the case that a new version exists, the user should disregard this document. Link to webpage: <https://geotech.forestry.oregonstate.edu/>
2. The procedure requires that the user has a basic understanding of ArcMap™, and has Esri® ArcGIS™ 10.3, or greater, installed on their computer. The user will also need to download the appropriate ArcGIS™ toolbox for their software and have the CCM application installed before starting work. In its most basic form, the method inputs a digital elevation model raster (DEM) and outputs polygons representing the extents of landslide deposits. Along the way, there will also be opportunities for the user to introduce other files, such as road and stream features to potentially improve results.
3. The DEM must be in a projected coordinate system, and may not use a latitude/longitude (geographic) system. Tools in the SICCM toolbox are not designed to compensate for discrepancies between horizontal and vertical units, and use of degrees in a geographic coordinate system will cause them to crash. If the user finds that their DEM uses a geographic coordinate system, then they are required to project the raster into a projected coordinate system before attempting to use the toolbox. Numerous projected coordinate systems exist, and if the user is not familiar with which to use for their area of interest, it is recommended that they identify the appropriate Universal Transverse Mercator (UTM) zone and use it.
4. The user should identify a location on their computer with enough available memory to store SICCM outputs. A typical USGS quadrangle (~50 square miles) will require up to 2 gigabytes of space for the Inventory Mapping Project geodatabase, and up to 5 gigabytes of space for each CCM Package. Users who have no prior experience with SICCM are recommended to have at least 15 gigabytes of available space.
5. Each tool in the SICCM toolbox comes with built-in documentation. The documentation may be accessed by clicking the Show Help >> button located at the bottom right corner of a tool's interface.
6. There are a large number of optional inputs associated with operation of the SICCM toolbox, and to help prevent the user from being confused, all optional inputs and default parameters have been summarized in Table E1.
7. Output file names are automatically selected by each SICCM tool based on input parameters in an effort to maintain organization and reproducibility. The naming convention is provided in Table E2.

8. The SICCM toolbox has been tested thoroughly, but there is still the possibility that users may encounter errors. If you encounter any error messages, please contact Dr. Ben Leshchinsky, ben.leshchinsky@oregonstate.edu, with a description of the problem and a copy of the message. Any reported errors will assist in the development of SICCM tools, and are greatly appreciated.

Table E1: Default Tool Inputs.

Tool Name	Optional Parameter	Default Value	How to Input Default
03 Find Cell Size for Mapping	Test Cell Size 1	Three times the cell size of the Input DEM	Leave blank
03 Find Cell Size for Mapping	Test Cell Size 2	Six times the cell size of the Input DEM	Leave blank
03 Find Cell Size for Mapping	Test Cell Size 3	Nine times the cell size of the Input DEM	Leave blank
04 Create Mixture Raster	Selected Cell Size	The default value of Test Cell Size 2: Six times the value of the Input DEM	Leave blank
05 Create Scarp Polygon Candidates	Mixture Raster Value used as Threshold	The class break between the second and third classes of the mixture raster when classified into three groups using Natural Breaks	Leave blank
06 Digitize Stream Channels	First Stream Accumulated Area	1 Acre	Input space is already populated
06 Digitize Stream Channels	Second Stream Accumulated Area	3 Acres	Input space is already populated
06 Digitize Stream Channels	Third Stream Accumulated Area	5 Acres	Input space is already populated
07 Create Rock Score Raster	Cell Size used to Subtract from Input DEM	Twice the cell size of the Input DEM	Leave blank
08 Identify Rocks from Rock Score Raster	Rock Score Threshold	50	Leave blank
09 Eliminate Non Scarp Topography	Input Non Scarps	At a minimum, the 5 acre stream channel layer - the user must select the layer as an input to the tool	The user must select the 5 acre layer from the dropdown menu
11 Run CCM	Number of Nodes used to Cutoff Tails	Tails are not removed	Leave blank
11 Run CCM	Number of Contours to skip during Cutoff	3	Leave blank - only applies when the previous option is filled out
Compute Risk Metrics	Rebuilt Embankment Slope	26 degrees (2H:1V)	Leave blank
Compute Risk Metrics	Maximum Rebuilt Roadway Width	70 feet	Leave blank
Compute Risk Metrics	Repair Rate	250 cubic yards per day	Leave blank
Compute Risk Metrics	Excavation Cost	\$11.00 per cubic yard	Leave blank
Compute Risk Metrics	Fill Cost	\$18.50 per cubic yard	Leave blank

Table E2: Output File Naming Convention

Tool Name	Output	Output Name	Variable Parts	Location Saved
01 Create Inventory Mapping Project	Inventory Mapping Project Folder	Specified by Name of Inventory Mapping Project input		Specified by Location to Save Inventory Mapping Project input
01 Create Inventory Mapping Project	Inventory Mapping Project Geodatabase	Same as Inventory Mapping Project name		Inventory Mapping Project Folder
02 Prepare Visualization Layers	Copy of Input DEM	OriginalDEM		Inventory Mapping Project Geodatabase
02 Prepare Visualization Layers	Hillshade Raster	Hillshade		Inventory Mapping Project Geodatabase
02 Prepare Visualization Layers	Slope Raster	Slope		Inventory Mapping Project Geodatabase
03 Find Cell Size for Mapping	Test Slope 1	TestSlope[1]	[1] Cell size	Inventory Mapping Project Geodatabase
03 Find Cell Size for Mapping	Test Slope 2	TestSlope[2]	[2] Cell size	Inventory Mapping Project Geodatabase
03 Find Cell Size for Mapping	Test Slope 3	TestSlope[3]	[3] Cell size	Inventory Mapping Project Geodatabase
04 Create Mixture Raster	Mixture Raster	Mix_CS[1]	[1] Cell size of the mixture raster	Inventory Mapping Project Geodatabase
04 Create Mixture Raster	Resampled DEM	RS_Elev[2]	[2] Cell size of the resampled DEM	Inventory Mapping Project Geodatabase
05 Create Scarp Polygon Candidates	Candidate Polygons	Cand_CS[1]_MT[2]	[1] Cell size of the mixture raster used to define candidate polygons, and [2] the mixture threshold value (If Natural Breaks were used, [2] becomes "NB")	Inventory Mapping Project Geodatabase
06 Digitize Stream Channels	First Stream Channel Layer	Channels[1]	[1] First stream accumulated area with units	Inventory Mapping Project Geodatabase

06 Digitize Stream Channels	Second Stream Channel Layer	Channels[2]	[2] Second stream accumulated area with units	Inventory Mapping Project Geodatabase
06 Digitize Stream Channels	Third Stream Channel Layer	Channels[3]	[3] Third stream accumulated area with units	Inventory Mapping Project Geodatabase
06 Digitize Stream Channels	Flow Accumulation Raster	FlowAcc		Inventory Mapping Project Geodatabase
07 Create Rock Score Raster	Rock Score Raster	RockScore_[1]	[1] Cell size of the rock score raster	Inventory Mapping Project Geodatabase
08 Identify Rocks from Rock Score Raster	Rock Outcrop Polygons	Rocks_Sc[1]	[1] Rock score threshold used to define outcrops	Inventory Mapping Project Geodatabase
09 Eliminate Non Scarp Topography	None			
10 Create Scarp Lines	Scarp Polylines	Scarps_CS[1]_MT[2]	Same notation as for the candidate polygons used to produce scarp lines	Inventory Mapping Project Geodatabase
10 Create Scarp Lines	CCM Package Folder	CCM_Package_CS[1]_MT[2]	[1] and [2] are the same as the scarps included in the package	Inventory Mapping Project Folder
10 Create Scarp Lines	CCM Package Geodatabase			CCM Package Folder
10 Create Scarp Lines	Geotiff Copy of DEM	CCM_DEM.tif		CCM Package Folder
10 Create Scarp Lines	3D Scarp Polyline Shapefile	CCM_scarps.shp		CCM Package Folder
11 Run CCM	CCM Folder	CI[1]_NS[2]_AS[3]_BP[5]	[1] contour interval, [2] nodal spacing, [3] active slope, and [4] branch parameter used in CCM run	CCM Package Folder
11 Run CCM	Deposit Extents	CI[1]_NS[2]_AS[3]_BP[5]	Same as for the CCM Folder	CCM Package Geodatabase
Create Risk Maps	Risk Zones	Risk_Zones		Specified by User
Compute Risk Metrics	None			

Users should also be aware that this appendix has been color-coded. The key to each color is provided below:

Blue = File Name

Green = Field Name

Orange = ArcGIS Operation

Purple = Tool Variable Name

Red = Process/Tool Name

Understanding the previous items, you are now ready to begin work. Users who have already digitized scarp lines should skip directly to part G.

- **Setup (Tools 01 and 02)**

1. Open ArcGIS
2. Open the ArcToolbox window, and map the location of the SICCM and Risk toolboxes.
3. Run **01 Create Inventory Mapping Project**. Save the project to an appropriate folder with a relevant project name. The project name should not have spaces, and instead should use underscores, for example “My_Project”.
4. **Critical Step:** Open your ArcGIS Map Document Properties and set the **Default Geodatabase** to the geodatabase in your newly created inventory mapping project folder. If you fail to update the **Default Geodatabase**, output files will be sent and stored in the ArcGIS default geodatabase located at within the “ArcGIS” folder of “My Documents” on your computer.
5. Optionally, run **02 Prepare Visualization Layers** with your **Original DEM** as the **Input DEM**. The tool outputs a **hillshade** raster and a formatted **slope** and **elevation (DEM)** combination, which are meant to be used as basemaps for the rest of the analysis. It is recommended that users stick with the default layer, slope, since it is not biased by the choice of sun angle used for hillshade computations (Burns and Madin, 2009). The outputs will be saved to your inventory mapping project geodatabase.

- **Base Data Processing (Tool 03)**

1. Run tool **03 Find Cell Size for Mapping** with the **Original DEM** as the **Input DEM**, or move on to tool 04 and use the default cell size. Operation of **Tool 03** constitutes **Intervention 1**, which is the first opportunity for the user to interject judgement and customize their results.

Intervention 1:

*During the first attempt at **Tool 03**, leave the optional test cell sizes empty. Review the output slope rasters and determine a good cell size. If necessary, run the tool again with different cell sizes (Table E3) and repeat this step.*

Table E3. Recommended Inputs for Tool 03 Find Cell Size for Mapping when Performing Intervention 1.

Tool Attempt	Test Cell Size 1	Test Cell Size 2	Test Cell Size 3
1 (Default Values)	3 x Original Cell Size	6 x Original Cell Size	9 x Original Cell Size
2 (If Necessary)	11 x Original Cell Size	13 x Original Cell Size	x Original Cell Size

- **Determine Scarp Candidate Polygons (Tools 04 and 05)**

1. Run **04 Create Mixture Raster** with the **Original DEM** as the **Input DEM**. Use the cell size that you determined with **Tool 03** as the **Selected Cell Size**, or leave the cell size blank to use the default value. In this case, the default cell size is three times the cell size of the **Input DEM**. The **mixture raster**, and a copy of the **Input DEM** resampled to the **Selected Cell Size (Resampled DEM: RS_Elev)**, will be saved to the project geodatabase. The **mixture raster** will be automatically displayed as three classes defined by natural breaks.
2. If desired, perform **Intervention 2** by inspecting the **mixture raster**.

Intervention 2:

Adjust the mixture threshold, and select a value that best includes most potential scarps.

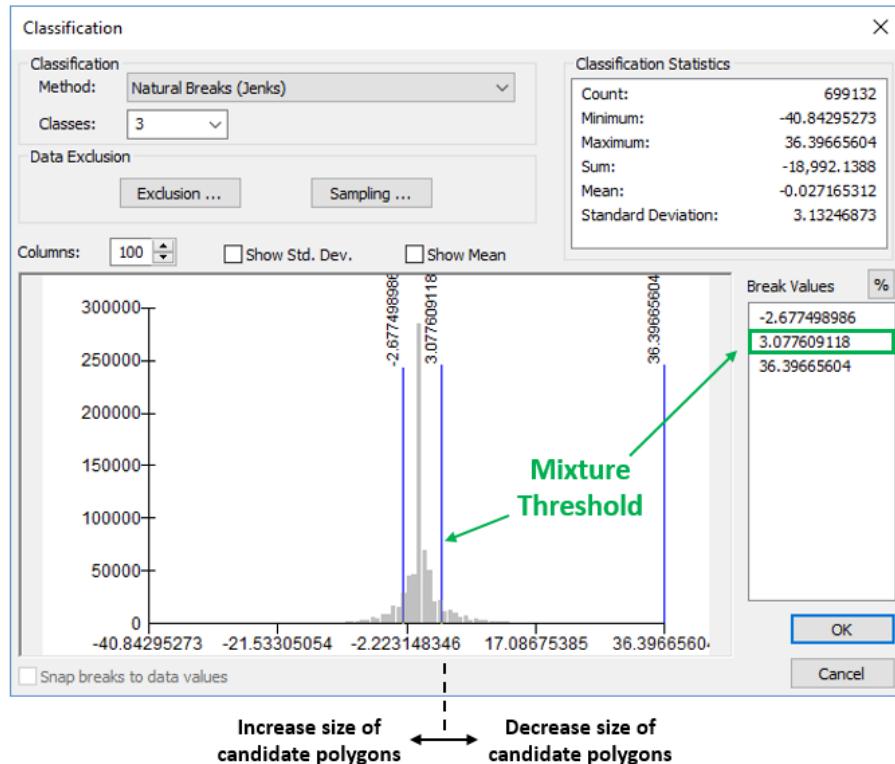


Figure E1. Identification of the mixture threshold within ArcGIS's classification window.

- Run **05 Create Candidates** with the desired **Input Mixture Raster**. If **Intervention 2** was performed, specify the **mixture threshold** for the **Mixture Raster Value used as Threshold**.

- **Identify Non Scarp Features (Optional; Tools 06, 07, and 08)**

- The tools used during the **Identification of Non Scarp Features** process are optional because they present methods to identify stream channels and rock outcroppings, which may be identified by other means. If a user has access to more advanced methods for identifying, or has already identified, either of these features, then they are welcome to use a different approach. While optional, the user should only skip straight to tool 09 if they have a stream channel layer, at a minimum. Use of Tool 09 without at least a stream channel layer will most likely lead to poor results.
- Run **06 Digitize Stream Channels** with the **Resampled DEM** (produced by **Tool 04**) as the **Input DEM** and the DEM's linear unit (found under its **Layer Properties**) as the **DEM Linear Unit**. For the first run, leave the optional cell sizes with default values (1, 3, 5).
- Tool 06 may be performed with or without human interpretation. To not use human interpretation, remove the 1 and 3 acre stream channel layers from the map, and retain the 5 acre layer. Human interpretation is highly recommended, and is performed through **Intervention 3**.

Intervention 3:

*Review the output **stream channels**, using the diagram in the tool's help for guidance, and select the best **stream channel** layer. If the diagram cannot be satisfied by the first three **stream channels**, run **Tool 06** again with different values (Table E4). Different values change the area included in the flow accumulation area; higher numbers include larger drainage areas; smaller values include less*

Table E4. Recommended Inputs for Tool 03 Find Cell Size for Mapping when Performing Intervention 1.

Tool Attempt	Accumulated Area 1	Accumulated Area 2	Accumulated Area 1
1 (Default Values)	1 acres	3 acres	5 acres
2 (If Necessary)	7 acres	10 acres	15 acres

- If the terrain appears to have rock outcrops, run **07 Create Rock Score** with the **Resampled DEM** as the **Input DEM**. Leave the **Cell Size used to Subtract from Input DEM** empty for the first run. If the resulting **rock score raster** does not appear to highlight outcrops (observed on the **basemap** layer), then try another **Cell Size**.
- If **Tool 07** has been performed, run **08 Identify Rock Outcrops from Rock Score** with the desired **Input Rock Score Raster** and save the **Output Rock Outcrop Polygons** to your **working folder**. Leave the **Rock Score Threshold** blank, unless you are comfortable recognizing rock outcrops on the **basemap** layer. If you are comfortable, locate some rocks

and identify their **rock score raster** value using the **Identify** cursor. The minimum observed **rock score raster** value may be used as the **Rock Score Threshold**.

- Once **Tools 06 through 08** have been performed, determine if a **road polyline** layer is available for the map area. If so, inspect the layer against the **basemap** to determine if it is accurate. Inaccurate, or poorly drawn, **road polylines** should not be used.

- **Identify Non Scarp Features (Tool 09)**

- Run **09 Eliminate Non Scarp Topography** with the **candidate polygons** created by **Step 05** as the **Input Candidates**. **Input Non Scars** may be **rock outcrop polygons**, **stream channels**, or **road polylines**, and all available layers may be input together. In the case where poor quality layers must be used as **non scarp** (not recommended), a **Search Distance** may be used to eliminate candidates within a certain distance of the **non scarp**. **Tool 09** does not produce any outputs, but it does edit the “**LS**” field of the **candidate polygons**. Features with an “**LS**” value of 1 following **Tool 09** are now called **scarp polygons**.
- Perform **Intervention 4** to manually eliminate or reconsider classified **candidates**.

Intervention 4:

Consider reclassifying the **candidates** in the attribute table manually. Additionally, the **cut polygon tool** can allow a partial inclusion or exclusion of a candidate into **candidates**.

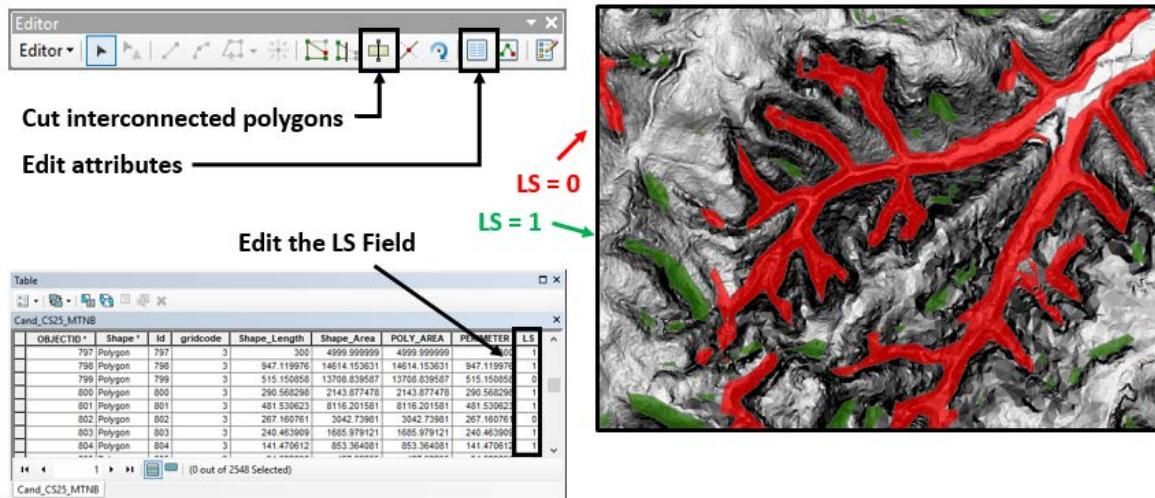


Figure E2. Locations of tools and attributes used to implement Intervention 4.

- **Create Scarp Lines (Tool 10)**

- Run **10 Create Scarp Lines from Scarp Polygons** with the classified **candidates** as **Input Candidates**, and the **Resampled DEM** as the **Input DEM**. The output **scarp lines** will be saved to your project geodatabase, and to a new CCM Package

- **Run CCM to Map Landslide Deposits within ArcMap (Tool 11)**

1. Make sure that you have the CCM Flow CLI (command line interface) application installed on your computer.
2. Perform **12 Run CCM** with the desired **CCM Package** and CCM parameters (contour interval, node spacing, active slope, and branch parameter). If you choose to remove tails, fill in the **Number of Nodes used to Cutoff Tails** and **Number of Contours to skip during Cutoff**. Check the box if for all CCM outputs, or leave the box unchecked if you only want landslide deposit extents.

Table 3.1 from Report: Definitions of Parameters used by the Modified Contour Connection Method. Notation Follows that of Leshchinsky et al. (2015).

Parameter	Name	Definition	Recommended Values
Δ_{active}	Active slope	Minimum gradient for active slide region	0.03, 0.05 (rise/run)
ΔE_z	Contour interval	A fixed vertical distance between X-Y contour layers for a given range Z	10, 20, 30 feet
L_n	Nodal spacing	A fixed length between contour node assignments	10, 20, 30 feet
B_n	Branch parameter	A branching connection parameter.	3, 5

- **Run CCM to Map Landslide Deposits Using Standalone GUI (Only if CCM Flow CLI is not available)**
 1. Save the Map Document, leave ArcMap, and open the CCM Flow GUI application.
 2. Create a **New Model** with the **CCM_DEM.tif** from the CCM Package as the **Input DEM**, the desired **CCM_scarps.shp** from the desired CCM Package as the **Input Scarp**, and the appropriate CCM Package folder as the **Output Folder**. Fill out the remaining required inputs based on Section 4.4. Options on the right side of the **New Model** window may be adjusted to control what is outputted by the model. Click **Add to Queue**.
 3. Check that the model has been added to the queue, then click **Run Queue**. The tool will run for several minutes, depending on the number of scarps and the input parameters.
 4. Once the application has finished, the output prompt will say “Done with...” At this point, go back to ArcMap and open the Map Document. Add the CCM results to the map and inspect results. If necessary create another CCM model.
- **Preparing Risk Maps from SICCM Outputs**
 1. Open the Risk toolbox in ArcMap.
 2. Run the Create Risk Maps tool using your Original DEM as the **Input Elevation Raster** and choose the SICCM Deposit Extents. SICCM Deposit Extents can be found within the CCM Project geodatabase. Input Highway or Road Polyline can be single line features, or networks of roads. A recommended Output Folder is the CCM Package folder.

3. Run Compute Risk Metrics on the outputs from Create Risk Maps. Fill out the various optional parameters to customize the risk map for a variety of circumstances. Values from the following tables may be helpful.

Table 3.3 from Report: Average costs to repair or reconstruct roadway listed by ODOT region (from Unstable Slopes Database)

ODOT Region	General Excavation (Cost per m ³)	Stone Embankment or Fill (Cost per m ³)
1	\$22.44	\$34.61
2	\$10.97	\$20.66
3	\$15.16	\$30.69
4	\$11.85	\$16.65
5	\$9.57	\$17.50
Average	\$14.40 (~\$11.00 per cu. yd.)	\$24.02 (~\$18.50 per cu. yd.)

Table E5: Conversions from H:V slope to degrees.

Horizontal:Vertical (H:V)	Slope (Degrees)
3:1	18.4
2.5:1	21.8
2:1	26.6
1.5:1	33.7
1:1	45

APPENDIX F – GLOSSARY OF SICCM TERMS

Glossary of SICCM Terms

Active Slope – an input to the CCM Algorithm that that dictates the minimum connection slope that may be mapped before the process terminates.

Branch Parameter – an input to the CCM Algorithm that regulates the amount that landslide extents may spread transverse to the downslope direction.

CCM Algorithm – an updated version of the Contour Connection Method of Leshchinsky et al. (2015) that uses inputted landslide scarp lines to draw the extents of landslide deposits.

Classification – the act of assigning labels to scarp candidates. Labels may either be non-landslide scarp or landslide scarp.

Connection – a straight three-dimensional line that connects nodes on adjacent contours.

Contour Interval – the vertical distance between adjacent contours drawn by the CCM algorithm.

Descriptive Variables – single values used to describe a scarp candidate polygon. These variables may be geometric, such as perimeter or area, or topographic, such as statistical measures of elevation derivatives corresponding to the polygon (i.e. mean, standard deviations, etc.).

Elevation Derivative – a raster computed through manipulation of a digital elevation model. Examples include slope, profile curvature, planform curvature, hillshade, and mixture.

Intervention – a break in the procedure that gives the practitioner an opportunity to interpret interim results and to adjust them manually and iteratively.

Mixture Raster – the raster used to emphasize landslide scarps during segmentation. Mathematically, the product of slope and profile curvature rasters.

Mixture Threshold – the value of the mixture raster used to separate scarp candidates from all other terrain.

Nodes – three-dimensional points located at equal spacing on contour lines that are connected by the CCM algorithm.

Node Spacing – the distance along a contour between that dictates the spacing on nodes.

Practitioner – the person performing modeling or mapping.

Scarp Candidate – a shape that represents the extents of features having topography similar to landslide scarps. Computationally, a polygon that encompasses mixture raster values exceeding the mixture threshold.

Segmentation – the act of breaking down a raster into smaller objects that may be classified.

APPENDIX G – SUPPORTING SCRIPTS AND ARCGIS™ MODELS

Supporting Scripts and ArcGIS™ models

Table G1: Summary of tools included in Appendix G

Name	Description
01 Create Inventory Mapping Project	Creates inventory mapping project used to organize tool outputs
02 Prepare Visualization Layers	Computes resampled versions of slope, curvature, and the mixture raster
03 Find Cell Size for Mapping	Aids in the determination of a digital elevation model (DEM) cell size to use for mapping
04 Create Mixture Raster	Resamples the input DEM to the mapping cell size and uses it to compute a mixture raster
05 Create Candidates	Divides mixture raster pixels at a threshold, and converts clusters of pixels into candidate polygons
06 Digitize Stream Channels	Produces example stream channel layers from the resampled DEM
07 Create Rock Score	Produces a roughness raster from the resampled DEM, called the rock score
08 Identify Rocks from Rock Score	Divides the rock score pixels at a threshold, and converts clusters of pixels into rock outcrop polygons
09 Classify by Removing Non Scarp Features	Assigns candidate polygons with scarp or non-scarp classes depending on their interaction with rocks, streams, and any other non-scarp feature
10 Create Scarp Lines	Reduces scarp polygons into lines and assigns elevations to the lines
11 Run CCM	Interface used to operate the CCM application, and perform landslide deposit mapping
Create Risk Maps	Analyzes the topography within SICCM landslide deposits and computes the geometry of unstable soil masses
Compute Risk Metrics	Determines various cost measures for sections of roadway, considering the geometry of each unstable soil mass

SICCM Toolbox

```
#####
# create_project.py
# or "01 Create Inventory Mapping Project" tool in the SICCM toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####

# Import proper modules
import arcpy, os
arcpy.env.overwriteOutput=True

# As user for inputs
proj_loc = arcpy.GetParameterAsText(0)
proj_name = arcpy.GetParameterAsText(1)

directory = proj_loc+"\\"+proj_name

# Create new folder
if not os.path.exists(directory):
    os.makedirs(directory)

# Create file geodatabase
gdbdir = directory+"\\"+proj_name+".gdb"

if not os.path.exists(gdbdir):
    arcpy.CreateFileGDB_management(directory, proj_name, "10.0")
```

```
#####
# prepare_visualization_layers.py
# or "02 Prepare Visualization Layers" tool in the SICCM Toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####

# Import arcpy module
import arcpy, os
from arcpy.sa import *
arcpy.env.overwriteOutput=True

# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")

# Display location
loc = arcpy.env.workspace
commentval = "Outputs will be saved to "+loc
arcpy.AddMessage(commentval)

# Ask user for input DEM
InputDEM = arcpy.GetParameterAsText(0)

# Ask user for output file locations
OrigDEM = "OriginalDEM"
OutputSlopeFR = "Slope"
OutputHills = "Hillshade"

# Compute new rasters
arcpy.CopyRaster_management(InputDEM,OrigDEM)
outSlopeFR = Slope(InputDEM, "DEGREE", " ")
outSlopeFR.save(OutputSlopeFR)
outHS = Hillshade(InputDEM, " ", " ", " ", 1)
outHS.save(OutputHills)

arcpy.CheckInExtension("spatial")
arcpy.CheckInExtension("3D")

## Display mixture raster on map

# Set the map document and data frame
mxd = arcpy.mapping.MapDocument("CURRENT")
df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]

# Find location of layer file
lyrDir = os.path.dirname(__file__)

fileSlp = lyrDir+"\slope.lyr"
fileDEM = lyrDir+"\dem.lyr"
fileHS = lyrDir+"\hillshade.lyr"

lyrHS = arcpy.mapping.Layer(OutputHills)
arcpy.ApplySymbologyFromLayer_management(lyrHS, fileHS)
```

```
 arcpy.mapping.AddLayer(df, lyrHS)

# Create layer file and add to map
lyrSlp = arcpy.mapping.Layer(OutputSlopeFR)
arcpy.ApplySymbologyFromLayer_management(lyrSlp, fileSlp)
arcpy.mapping.AddLayer(df, lyrSlp)

lyrDEM = arcpy.mapping.Layer(OrigDEM)

dir, fname = os.path.split(OrigDEM)

for lyr in arcpy.mapping.ListLayers(mxd, "", df):
    if lyr.name == fname:
        arcpy.mapping.RemoveLayer(df, lyrDEM)

arcpy.ApplySymbologyFromLayer_management(lyrDEM, fileDEM)
arcpy.mapping.AddLayer(df, lyrDEM)

arcpy.CheckInExtension("Spatial")
```

```
#####
# select_DEM_resolution.py
# or "03 Find Cell Size for Mapping" tool in the SICCM Toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####
import arcpy, os
from arcpy.sa import *
arcpy.env.overwriteOutput = True
arcpy.CheckOutExtension('Spatial')

# Display location
loc = arcpy.env.workspace
commentval = "Outputs will be saved to "+loc
arcpy.AddMessage(commentval)

# Ask user for input DEM
input_raster = arcpy.GetParameterAsText(0)

# Determine cellsize of input DEM
description = arcpy.Describe(input_raster)
cellsize = description.children[0].meanCellHeight

# Ask user for test cellsizes - If no value is selected,
# the script will compute values from the current cellszie
resA = arcpy.GetParameterAsText(1)
if resA == '#' or not resA:
    resA = str(int(3*cellsize))

resB = arcpy.GetParameterAsText(2)
if resB == '#' or not resB:
    resB = str(int(6*cellsize))

resC = arcpy.GetParameterAsText(3)
if resC == '#' or not resC:
    resC = str(int(9*cellsize))

# Name of slope files to be outputted (no user involvement)
SlopeA = "TestSlope"+resA
SlopeB = "TestSlope"+resB
SlopeC = "TestSlope"+resC

# Prepare test cellsizes for input into ArcGIS Resample
cellA = resA+" "+resA
cellB = resB+" "+resB
cellC = resC+" "+resC

ResampleA = "RS_TS1"
ResampleB = "RS_TS2"
ResampleC = "RS_TS3"
```

```

# Resample DEM to test cellsize and compute slope raster
arcpy.Resample_management(input_raster, ResampleA, cellA, "NEAREST")
OS1 = Slope(ResampleA, "DEGREE", "1")

arcpy.Resample_management(input_raster, ResampleB, cellB, "NEAREST")
OS2 = Slope(ResampleB, "DEGREE", "1")

arcpy.Resample_management(input_raster, ResampleC, cellC, "NEAREST")
OS3 = Slope(ResampleC, "DEGREE", "1")

# Delete resampled DEMs
arcpy.Delete_management(ResampleA, "")
arcpy.Delete_management(ResampleB, "")
arcpy.Delete_management(ResampleC, "")

# Save slope rasters
OS1.save(SlopeA)
OS2.save(SlopeB)
OS3.save(SlopeC)

## Display slope rasters on map

# Set the map document and data frame
mxd = arcpy.mapping.MapDocument("CURRENT")
df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]

# Find location of layer file
lyrDir = os.path.dirname(__file__)

fileA = lyrDir+"\slope.lyr"
fileB = lyrDir+"\slope.lyr"
fileC = lyrDir+"\slope.lyr"

# Create layer files for each slope raster
lyrA = arcpy.mapping.Layer(SlopeA)
lyrB = arcpy.mapping.Layer(SlopeB)
lyrC = arcpy.mapping.Layer(SlopeC)

# Add layers to map
arcpy.ApplySymbologyFromLayer_management(lyrA, fileA)
arcpy.mapping.AddLayer(df, lyrA)
arcpy.ApplySymbologyFromLayer_management(lyrB, fileB)
arcpy.mapping.AddLayer(df, lyrB)
arcpy.ApplySymbologyFromLayer_management(lyrC, fileC)
arcpy.mapping.AddLayer(df, lyrC)

arcpy.CheckInExtension('Spatial')

```

```
#####
# prepare_mixture_raster.py
# or "04 Create Mixture Raster" tool in the SICCM Toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####

# Import arcpy module
import arcpy, os
from arcpy.sa import *
arcpy.env.overwriteOutput=True

# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")

# Display location
loc = arcpy.env.workspace
commentval = "Outputs will be saved to "+loc
arcpy.AddMessage(commentval)

# Ask user for input DEM
input_raster = arcpy.GetParameterAsText(0)

# Ask user for selected cellsize (determined from tool 01)
res = arcpy.GetParameterAsText(1)
if res == '#' or not res:

    # Determine cellsize of input DEM
    description = arcpy.Describe(input_raster)
    cellsize = description.children[0].meanCellHeight

    # Assign default resolution of 6 x input cellsize
    res = 6*cellsize
strint_res = str(int(res))
Output_Cell_Size = strint_res+" "+strint_res

# Name mixture file that will be output "Mix_CSXX" Cell Size XX
OutputMixture = "Mix_CS"+strint_res

# Name files to be output
OutputRSelev = "RS_Elev"+strint_res

# Name of local files to be deleted
OutputSlope = "SlopeTemp"
OutputProfile = "ProfTemp"
OutputPlan = "PlanTemp"
SmoothInputDEM = "SmDEMTemp"
Curva = "CurvaTemp"
MixUnsmooth = "UnsmMixTemp"

# Perform smoothing on input DEM
arcpy.gp.FocalStatistics_sa(input_raster, SmoothInputDEM, "Rectangle 5 5
CELL", "MEAN", "DATA")
```

```

# Resample smoothed input DEM to selected cellsize
arcpy.Resample_management(SmoothInputDEM, OutputRSelev, Output_Cell_Size,
"BILINEAR")

# Compute slope and profile curvature from resampled DEM
outSlope = Slope(OutputRSelev, "DEGREE", "1")
outSlope.save(OutputSlope)

outCurve = Curvature(OutputRSelev, "1", OutputProfile, OutputPlan)
outCurve.save(Curva)

# Multiply slope and profile curvature together to obtain
# unsmoothed mixture raster
outTimes = Times(OutputSlope, OutputProfile)
outTimes.save(MixUnsmooth)

# Smooth mixture raster
arcpy.gp.FocalStatistics_sa(MixUnsmooth, OutputMixture, "Rectangle 5 5 CELL",
"MEAN", "DATA")

# Delete local files
arcpy.Delete_management(OutputSlope, "")
arcpy.Delete_management(OutputProfile, "")
arcpy.Delete_management(OutputPlan, "")
arcpy.Delete_management(SmoothInputDEM, "")
arcpy.Delete_management(Curva, "")
arcpy.Delete_management(MixUnsmooth, "")

## Display mixture raster on map

# Set the map document and data frame
mxd = arcpy.mapping.MapDocument("CURRENT")
df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]

lyrRS = arcpy.mapping.Layer(OutputRSelev)
lyrRS.transparency = 100
arcpy.mapping.AddLayer(df, lyrRS)

lyrDir = os.path.dirname(__file__)
fileMix = lyrDir+"\mixure.lyr"

lyrMix = arcpy.mapping.Layer(OutputMixture)
arcpy.ApplySymbologyFromLayer_management(lyrMix, fileMix)
arcpy.mapping.AddLayer(df, lyrMix)

arcpy.CheckInExtension("spatial")

```

```
#####
# create_candidates.py
# or "05 Create Candidates" tool in the SICCM Toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####

# Import arcpy module
import arcpy, os
from arcpy.sa import *
arcpy.env.overwriteOutput=True
arcpy.CheckOutExtension("spatial")

# Display location
loc = arcpy.env.workspace
commentval = "Outputs will be saved to "+loc
arcpy.AddMessage(commentval)

# Ask user for input mixture raster
mix_raster = arcpy.GetParameterAsText(0)
iCS = mix_raster.find("CS")
mix_extn = mix_raster[iCS:]
arcpy.AddMessage(mix_extn)

# Display location
loc = arcpy.env.workspace
commentval = "Outputs will be saved to "+loc
arcpy.AddMessage(commentval)

# Determine cellsize of mixture raster
description = arcpy.Describe(mix_raster)
cellsize = description.children[0].meanCellHeight
res = str(int(1*cellsize))

# Assign temporary variables
ExtractTrough = "extTroughTemp"
ExtractPoly = "extPolyTemp"
SliceMix = "SliceMixTemp"

UserThresh = arcpy.GetParameter(1)
if UserThresh == '#' or not UserThresh:
    # Slice the mixture raster into three classes using Jenks
    # natural breaks
    outSlice = Slice(mix_raster, 3, "NATURAL_BREAKS")
    outSlice.save(SliceMix)
    extn = "MTNB"
else:
    Reclassification = RemapRange([[-1000000, UserThresh, 0], [UserThresh, 1000000, 3]])
    OutReclass = Reclassify(mix_raster, "VALUE", Reclassification, "DATA")
    OutReclass.save(SliceMix)
    extn = "MT"+str(int(round(UserThresh)))
```

```

Candidates = "Cand_" + mix_extn + "_" + extn

# Extract all raster cells with a value of 3

OutExtract = ExtractByAttributes(SliceMix, "\"VALUE\" =3")
OutExtract.save(ExtractTrough)

# Convert extracted raster cells into candidate polygons
flip = 0
try:
    arcpy.RasterToPolygon_conversion(ExtractTrough, ExtractPoly, "SIMPLIFY",
    "VALUE")
except:
    flip = 1
    arcpy.AddError("The specified Mixture Threshold lies outside of the range
    of Mixture Values. Please choose a new value or leave the Mixture Threshold
    blank")

arcpy.MakeFeatureLayer_management(ExtractPoly, "polys")
arcpy.SelectLayerByAttribute_management ("polys", "NEW_SELECTION",
    '"GRIDCODE" =3')
arcpy.CopyFeatures_management("polys", Candidates)

# Delete temporary variables
arcpy.Delete_management(ExtractPoly)
arcpy.Delete_management(ExtractTrough)
arcpy.Delete_management(SliceMix)

# Add perimeter and length attributes to the candidate polygons
arcpy.AddGeometryAttributes_management(Candidates, "AREA;PERIMETER_LENGTH",
    "", "", "")

# Create candidates layer
arcpy.MakeFeatureLayer_management(Candidates, "candidates")

# Check if field LS exists in candidates. If not, create it
check = 0
lst = arcpy.ListFields("candidates")
for f in lst:
    if f.name == "LS":
        check = 1
    else:
        continue
if check == 0:
    arcpy.AddField_management("candidates", "LS", "SHORT")
arcpy.Delete_management("candidates")
## Display candidates on map

# Set the map document and data frame
mxd = arcpy.mapping.MapDocument("CURRENT")
df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]
arcpy.Delete_management("polys")

if flip == 0:

```

```
# Create layer file and add to map
lyrDir = os.path.dirname(__file__)

fileCand = lyrDir+"\\candidates.lyr"
lyrCand = arcpy.mapping.Layer(Candidates)

arcpy.ApplySymbologyFromLayer_management(lyrCand, fileCand)
arcpy.mapping.AddLayer(df,lyrCand)

arcpy.CheckInExtension("spatial")
else:
    arcpy.Delete_management(Candidates)
```

```
#####
# digitize_streams.py
# or "06 Digitize Stream Channels" tool in the SICCM Toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####

# Import arcpy module
import arcpy, os
from arcpy.sa import *
arcpy.env.overwriteOutput=True
arcpy.CheckOutExtension("spatial")

# Define conversion function#####
def ArealUnit2Pixel(areal_unit, input_raster, raster_units):
    # Determine the area of an individual DEM cell
    # Units are in raster_units squared
    description = arcpy.Describe(input_raster)
    cell_size = description.children[0].meanCellHeight
    cell_area = cell_size*cell_size

    # Break Areal Unit into two parts; unit and value
    idx = areal_unit.find(" ")
    idx1 = int(idx+1)
    unit = areal_unit[idx1:]
    accval = float(areal_unit[:idx])

    # Create a dictionary with conversion values
    conversions = {"SquareFeet": [1, 0.092903], \
    "Ares": [1076.39, 100], \
    "Acres": [43560, 4046.86], \
    "Hectares": [107639, 10000], \
    "SquareCentimeters": [0.00107639, 0.0001], \
    "SquareDecimeters": [0.107639, 0.01], \
    "SquareInches": [0.00694444, 0.00064516], \
    "SquareKilometers": [10760000, 10000000], \
    "SquareMeters": [10.7639, 0], \
    "SquareMiles": [27880000, 2590000], \
    "SquareMillimeters": [0.0000107639, 0.000001], \
    "SquareYards": [9, 0.836127]}

    # Mutliply the user specified area by a conversion to
    # Square Feet or Square Meters
    if raster_units == "Meters":
        # Accumulated area in square meters
        user_area = accval*conversions[unit][1]
    elif raster_units == "Feet":
        # Accumulated area in square feet
        user_area = accval*conversions[unit][0]

    # Divide user specified area by cell area to get number of pixels
    numpix = user_area/cell_area
    return numpix, user_area
```

```
#####
# Display location
loc = arcpy.env.workspace
commentval = "Outputs will be saved to "+loc
arcpy.AddMessage(commentval)

# Ask user for input DEM and its units
inputDEM = arcpy.GetParameterAsText(0)
DEMunits = arcpy.GetParameterAsText(1)
arcpy.SetProgressorLabel("Processing Inputs and Converting Units...")
# Ask user for minimum number of cells accumulated - If no value is selected,
# the script will use default values
if DEMunits == "Meters":
    extn = "SqM"
else:
    extn = "SqFt"

accA = arcpy.GetParameterAsText(2)
if accA == '#' or not accA:
    # Default 5000 Square Feet
    pixA, areaA = ArealUnit2Pixel("5000 SquareFeet",inputDEM,DEMunits)
    extnA = "SqFt"
else:
    pixA, areaA = ArealUnit2Pixel(accA,inputDEM,DEMunits)
    extnA = extn

accB = arcpy.GetParameterAsText(3)
if accB == '#' or not accB:
    # Default 10000 Square Feet
    pixB, areaB = ArealUnit2Pixel("10000 SquareFeet",inputDEM,DEMunits)
    extnB = "SqFt"
else:
    pixB, areaB = ArealUnit2Pixel(accB,inputDEM,DEMunits)
    extnB = extn

accC = arcpy.GetParameterAsText(4)
if accC == '#' or not accC:
    # Default 15000 Square Feet
    pixC, areaC = ArealUnit2Pixel("15000 SquareFeet",inputDEM,DEMunits)
    extnC = "SqFt"
else:
    pixC, areaC = ArealUnit2Pixel(accC,inputDEM,DEMunits)
    extnC = extn

# Name of outputted stream layers
StreamsA = "Channels"+str(int(areaA))+extnA
StreamsB = "Channels"+str(int(areaB))+extnB
StreamsC = "Channels"+str(int(areaC))+extnC

## Follow typical stream identification workflow in ArcGIS

# Assign temporary variables
FillDEM = "FillDEM"
FlowDir = "FlowDir"
DropRast = "DropRast"
```

```

FlowAcc = "FlowAcc"
ReclassA = "ReclassA"
ReclassB = "ReclassB"
ReclassC = "ReclassC"
arcpy.ResetProgressor()
arcpy.SetProgressor("step", "Developing Flow Accumulation Raster...", 0, 5, 1)

# Fill input DEM
arcpy.gp.Fill_sa(inputDEM, FillDEM, "")

# Compute flow direction from filled DEM
arcpy.gp.FlowDirection_sa(FillDEM, FlowDir, "NORMAL", DropRast)

# Compute flow accumulation raster
arcpy.gp.FlowAccumulation_sa(FlowDir, FlowAcc, "", "FLOAT")

# Reclassify flow accumulation layer using minimum values from above
remapA = RemapRange([[0, pixA, 0], [pixA, 1000000000, 1]])
OutReclassA = Reclassify(FlowAcc, "VALUE", remapA, "DATA")
OutReclassA.save(ReclassA)

remapB = RemapRange([[0, pixB, 0], [pixB, 1000000000, 1]])
OutReclassB = Reclassify(FlowAcc, "VALUE", remapB, "DATA")
OutReclassB.save(ReclassB)

remapC = RemapRange([[0, pixC, 0], [pixC, 1000000000, 1]])
OutReclassC = Reclassify(FlowAcc, "VALUE", remapC, "DATA")
OutReclassC.save(ReclassC)

# Convert stream raster into polyline
arcpy.SetProgressor("step", "Drawing First Set of Stream Channels...", 0, 4, 2)
arcpy.RasterToPolyline_conversion(ReclassA, StreamsA, "ZERO", "0",
    "SIMPLIFY", "VALUE")
arcpy.SetProgressor("step", "First Set Complete, Now Drawing Second...", 0, 5, 3)
arcpy.RasterToPolyline_conversion(ReclassB, StreamsB, "ZERO", "0",
    "SIMPLIFY", "VALUE")
arcpy.SetProgressor("step", "Second Set Complete, Now Drawing Third...", 0, 5, 4)
arcpy.RasterToPolyline_conversion(ReclassC, StreamsC, "ZERO", "0",
    "SIMPLIFY", "VALUE")

# Delete temporary files
arcpy.Delete_management(FillDEM)
arcpy.Delete_management(FlowDir)
arcpy.Delete_management(DropRast)
arcpy.Delete_management(FlowAcc)
arcpy.Delete_management(ReclassA)
arcpy.Delete_management(ReclassB)
arcpy.Delete_management(ReclassC)

## Display streams on map
# Find location of layer file
lyrDir = os.path.dirname(__file__)

fileA = lyrDir+"\streamsA.lyr"
fileB = lyrDir+"\streamsB.lyr"

```

```
fileC = lyrDir+"\streamsC.lyr"

# Set the map document and data frame
mxd = arcpy.mapping.MapDocument("CURRENT")
df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]

# Create layer file and add to map
lyrA = arcpy.mapping.Layer(StreamsA)
arcpy.ApplySymbologyFromLayer_management(lyrA, fileA)
arcpy.mapping.AddLayer(df, lyrA)

lyrB = arcpy.mapping.Layer(StreamsB)
arcpy.ApplySymbologyFromLayer_management(lyrB, fileB)
arcpy.mapping.AddLayer(df, lyrB)

lyrC = arcpy.mapping.Layer(StreamsC)
arcpy.ApplySymbologyFromLayer_management(lyrC, fileC)
arcpy.mapping.AddLayer(df, lyrC)

arcpy.CheckInExtension("spatial")
```

```
#####
# create_rock_score.py
# or "07 Create Rock Score" tool in the SICCM Toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####

# Import arcpy module
import arcpy, os
from arcpy.sa import *
arcpy.env.overwriteOutput=True
arcpy.CheckOutExtension("spatial")
# Ask user for input DEM
inputDEM = arcpy.GetParameterAsText(0)

# Determine cellsize of input DEM
description = arcpy.Describe(inputDEM)
cellsize = description.children[0].meanCellHeight

# Ask user for the resolution to resample to - If no value is selected,
# the script will use a default value of 2*input resolution
RockRes = arcpy.GetParameterAsText(1)
if RockRes == '#' or not RockRes:
    RockRes = str(int(2*cellsize))

# State where to save Rock Score raster
RockScore = "RockScore_"+RockRes

# Assign temporary variables
RockResample = "RockResample"
SmoothResample = "SmoothResample"

# Perform resample
CellRock = RockRes+" "+RockRes
arcpy.Resample_management(inputDEM, RockResample, CellRock, "BILINEAR")

# Smooth resampled DEM
neighborhood = NbrRectangle(5,5, "CELL")
outSmooth = FocalStatistics(RockResample,neighborhood, "MEAN", " ")
outSmooth.save(SmoothResample)

# Subtract smooth resampled DEM from input DEM
outMinus = Minus(inputDEM, SmoothResample)
outMinus.save(RockScore)

# Delete temporary files
arcpy.Delete_management(RockResample)
arcpy.Delete_management(SmoothResample)

## Display Rock Score Raster on map
```

```
lyrDir = os.path.dirname(__file__)

fileRS = lyrDir+"\rockscore.lyr"

# Set the map document and data frame
mxd = arcpy.mapping.MapDocument("CURRENT")
df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]

# Create layer file and add to map
lyrRS = arcpy.mapping.Layer(RockScore)
arcpy.ApplySymbologyFromLayer_management(lyrRS, fileRS)
arcpy.mapping.AddLayer(df, lyrRS)

arcpy.CheckInExtension("spatial")
```

```
#####
# id_rocks_from_score.py
# or "08 Identify Rocks from Rock Score" tool in the SICCM Toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####

# Import arcpy module
import arcpy, os
from arcpy.sa import *
arcpy.env.overwriteOutput=True
arcpy.CheckOutExtension("spatial")
# Ask user for input rock score raster
RockScore = arcpy.GetParameterAsText(0)

# Determine cellsize of input rock score raster
description = arcpy.Describe(RockScore)
cellsize = description.children[0].meanCellHeight

# Ask user for rock score threshold
RockThresh = arcpy.GetParameterAsText(1)
if RockThresh == '#' or not RockThresh:
    RockThresh = str(int(0.25*cellsize*cellsize))

# Ask user where to save output rock outcrop polygons
RockPoly = "Rocks_Sc"+RockThresh

# Assign temporary variables
RockSlice = "RockSlice"
ExtractRock = "ExtractRock"
ExtractPoly = "ExtractPoly"

# Assign output variable
#RockPoly = OutputWorkspace+"\RockOutcrops"+RockThresh+".shp"

# Reclassify the Rock Score raster
Reclassification = RemapRange([-1000000, RockThresh, 0], [RockThresh, 1000000, 1])
OutReclass = Reclassify(RockScore, "VALUE", Reclassification, "DATA")
OutReclass.save(RockSlice)
trigger = 0
try:
    # Extract rock outcrop pixels
    OutExtract = ExtractByAttributes(RockSlice, "\"VALUE\" =1")
    OutExtract.save(ExtractRock)

    # Convert rock score pixels exceeding the threshold to polygons
    arcpy.RasterToPolygon_conversion(ExtractRock, ExtractPoly, "SIMPLIFY",
"VALUE")
    arcpy.MakeFeatureLayer_management(ExtractPoly, "polys")
```

```

    arcpy.SelectLayerByAttribute_management ("polys", "NEW_SELECTION",
    "GRIDCODE" =1)
    arcpy.CopyFeatures_management("polys", RockPoly)
    arcpy.Delete_management(ExtractRock)
    arcpy.Delete_management(ExtractPoly)
    arcpy.Delete_management("polys")

except:
    arcpy.AddError("No Rock Outcrops Identified - Rocks are not a problem, or
the rock score threshold is too large")
    trigger = 1

if trigger == 0:
    arcpy.Delete_management(RockSlice)

## Display Rock Outcrops on map

# Find location of layer file
lyrDir = os.path.dirname(__file__)

fileRock = lyrDir+"\\rockoutcrops.lyr"

# Set the map document and data frame
mxd = arcpy.mapping.MapDocument("CURRENT")
df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]

# Create layer file and add to map
lyrRock = arcpy.mapping.Layer(RockPoly)
arcpy.ApplySymbologyFromLayer_management(lyrRock, fileRock)
arcpy.mapping.AddLayer(df, lyrRock)

arcpy.CheckInExtension("spatial")

```

```
#####
# eliminate_non_scarp.py
# or "09 Classify by Removing Non Scarps" tool in the SICCM Toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####

# Import arcpy module
import arcpy, os
from arcpy.sa import *
arcpy.env.overwriteOutput=True
arcpy.CheckOutExtension("spatial")
# Ask user for candidates shapefile
Candidates = arcpy.GetParameterAsText(0)

# Create candidates layer
arcpy.MakeFeatureLayer_management(Candidates, "candidates2")

# Check if field LS exists in candidates. If not, create it
check = 0
lst = arcpy.ListFields("candidates2")
for f in lst:
    if f.name == "LS":
        check = 1
    else:
        continue
if check == 0:
    arcpy.AddField_management("candidates2", "LS", "SHORT")

# Assign a value of 1 to all candidates
arcpy.CalculateField_management("candidates2", "LS", 1)

# Ask user for digitized non scarp topography shapefiles
NonScarps = arcpy.GetParameterAsText(1)
non_list = NonScarps.split(";")

# Ask user for a search distance
search_distance = arcpy.GetParameter(2)
if search_distance == '#' or not search_distance:
    search_distance = "0 Feet"

# Process each non scarp layer
for NonScarps in non_list:
    arcpy.AddMessage("Processing: {}".format(NonScarps))

    # Create temporary layer for current non scarp
    arcpy.MakeFeatureLayer_management(NonScarps, "NonScarp")

    # Select candidates that are within the search distance of a non scarp
    arcpy.SelectLayerByLocation_management("candidates2",
    "WITHIN_A_DISTANCE", "NonScarp", search_distance, "NEW_SELECTION")
```

```

# Change LS value to 0 for selected candidates
 arcpy.CalculateField_management("candidates2", "LS", 0)

# Clear selected candidates
 arcpy.SelectLayerByAttribute_management("candidates2", "CLEAR_SELECTION")

# Delete temporary non scarp layer
 arcpy.Delete_management("NonScarp")

# # Set the map document and data frame
# mxd = arcpy.mapping.MapDocument("CURRENT")
# df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]
# # Create layer file and add to map
# lyrDir = os.path.dirname(__file__)

# fileCand = lyrDir+"\candidates.lyr"
# lyrCand = arcpy.mapping.Layer(Candidates)
# dir, fname = os.path.split(Candidates)

# for lyr in arcpy.mapping.ListLayers(mxd, "", df):
#     if lyr.name == Candidates:
#         # arcpy.mapping.RemoveLayer(df, lyrCand)
#     elif lyr.name == "candidates2":
#         # arcpy.mapping.RemoveLayer(df, lyrCand)
# arcpy.ApplySymbologyFromLayer_management(lyrCand, fileCand)
# arcpy.mapping.AddLayer(df,lyrCand)

arcpy.Delete_management("candidates2")
arcpy.CheckInExtension("spatial")

```

```
#####
# thin_to_lines.py
# or "10 Create Scarp Lines" tool in the SICCM Toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####

# Import arcpy module
import arcpy, os
from arcpy.sa import *
arcpy.env.overwriteOutput=True
arcpy.CheckOutExtension("spatial")
# Ask user for candidates shapefile
Candidates = arcpy.GetParameterAsText(0)

# Ask user for elevation raster
inputDEM = arcpy.GetParameterAsText(1)

# Find cellsize of input DEM
description = arcpy.Describe(inputDEM)
cellsize = description.children[0].meanCellHeight

# Assign name to scarp line file
idx = Candidates.find("CS")
extn = Candidates[idx:]
Scarps = "Scarps_" + extn

# Assign temporary variables
CandRast = "CandRast"
ThinRast = "ThinRast"
ThinPoly = "ThinPoly"

# Convert candidates into raster
arcpy.PolygonToRaster_conversion(Candidates, "LS", CandRast, "", "", cellsize)

# Thin raster candidates into lines
thinOut = Thin(CandRast)
thinOut.save(ThinRast)

# Convert raster lines to vector polylines
arcpy.RasterToPolyline_conversion(ThinRast, ThinPoly, "", "", "SIMPLIFY", "VALUE")

# Add length field to polylines
arcpy.AddGeometryAttributes_management(ThinPoly, "LENGTH", "", "", "")

# Interpolate DEM to polylines to create polylineZ
try:
    arcpy.CheckOutExtension("3D")
    arcpy.InterpolateShape_3d(inputDEM, ThinPoly, Scarps)
except:
```

```

arcpy.AddMessage("3D Analyst Extension Unavailable")

# Create candidates layer
arcpy.MakeFeatureLayer_management(Scarps, "scarps")

# Check if Id field exists in candidates. If not, create it
check = 0
lst = arcpy.ListFields("scarps")
for f in lst:
    if f.name == "Id":
        check = 1
    else:
        continue
if check == 0:
    arcpy.AddField_management("scarps", "Id", "LONG")

# Assign a value of 1 to all candidates
try:
    arcpy.CalculateField_management("scarps", "Id", "[FID]")
except:
    try:
        arcpy.CalculateField_management("scarps", "Id", "[OBJECTID]")
    except:
        try:
            arcpy.CalculateField_management("scarps", "Id", "[OID]")
        except:
            arcpy.AddError("Scarp file does not have FID or OBJECTID field")

# Delete temporary variables
arcpy.Delete_management(CandRast)
arcpy.Delete_management(ThinRast)
arcpy.Delete_management(ThinPoly)
arcpy.Delete_management("scarps")

## Create CCM Input Package
# Identify project folder
projdir = os.path.dirname(arcpy.env.workspace)
idx = Candidates.find("CS")
foldir = "CCM_Package_"+Candidates[idx:]
newdir = projdir+"\\"+foldir
bool = 0
try:
    os.mkdir(newdir)
except:
    errval = "Folder - "+newdir+" - Already Exists. Delete it and run the tool again"
    arcpy.AddError(errval)
    bool = 1

if bool == 0:
    copyrast = newdir + "\\" + "CCM_DEM.tif"
    copyscarp = newdir + "\\" + "CCM_scarps.shp"
    arcpy.CopyRaster_management(inputDEM,copyrast)
    arcpy.CopyFeatures_management(Scarps,copyscarp)

```

```
## Display scarps on map

lyrDir = os.path.dirname(__file__)
fileScarp = lyrDir+"\scarps.lyr"

# Set the map document and data frame
mxd = arcpy.mapping.MapDocument("CURRENT")
df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]

# Create layer file and add to map
lyrScarp = arcpy.mapping.Layer(Scarps)
arcpy.ApplySymbologyFromLayer_management(lyrScarp, fileScarp)
arcpy.mapping.AddLayer(df,lyrScarp)

arcpy.CheckInExtension("spatial")
```

```
#####
# run_ccm.py
# or "11 Run CCM" tool in the SICCM Toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####

import arcpy, math, os, shutil, subprocess

# Define conversion function#####
def LinearUnit2Pixel(linear_unit, input_raster):
    # Determine the area of an individual DEM cell
    # Units are in raster_units squared
    description = arcpy.Describe(input_raster)
    cell_size = description.children[0].meanCellHeight
    cell_area = cell_size*cell_size

    spat = arcpy.Describe(input_raster).spatialReference
    raster_units = spat.linearUnitName

    # Create a dictionary with conversion values
    conversions = {"Feet": [1, 0.3048], \
    "Centimeters": [0.0328, 0.01], \
    "Decimeters": [0.3281, 0.1], \
    "Inches": [0.0833, 0.0254], \
    "Kilometers": [3280.84, 1000], \
    "Meters": [3.2808, 1], \
    "Miles": [5280, 1609], \
    "Millimeters": [0.0033, 0.001], \
    "NauticalMiles": [6076, 1852], \
    "Yards": [3, 0.9144]}

    # Look up conversion factors
    try:
        if raster_units == "Meter":
            # Input raster in meters
            conv_factor = conversions[linear_unit][1]
        elif raster_units == "Foot":
            # Input raster in feet
            conv_factor = conversions[linear_unit][0]
        elif raster_units == "Foot_US":
            # Input raster in feet
            conv_factor = conversions[linear_unit][0]
    except:
        arcpy.AddError("Selected unit unavailable. Please input another unit.")
        conv_factor = 1

    try:
        return conv_factor
    except:
```

```

    arcpy.AddError("'conv_factor' is empty. Please check that you have
specified Contour Interval and Node Spacing units, and that your DEM has a
spatial reference")
#####
## REQUIRED INPUTS
# Information from a CCM Package
CCM_Package = arcpy.GetParameterAsText(0)
DEM_FP = CCM_Package+"\CCM_DEM.tif"
SCARP_FP = CCM_Package+"\CCM_scarps.shp"
OUTPUT_FP = CCM_Package

# Create CCM Run File Geodatabase
RepDir, PackName = os.path.split(CCM_Package)
newGDBdir = CCM_Package+"\\"+PackName+".gdb"
if not os.path.exists(newGDBdir):
    arcpy.CreateFileGDB_management(CCM_Package, PackName, "10.0")

arcpy.env.workspace = newGDBdir
save_message = "Created new File GDB for CCM Package: "+newGDBdir
arcpy.AddMessage(save_message)

# Other inputs
contour_interval = arcpy.GetParameterAsText(1)
ici = contour_interval.find(" ")
ici1 = int(ici+1)
unit_ci = contour_interval[ici1:]
conv_ci = LinearUnit2Pixel(unit_ci,DEM_FP)

CONTOUR = int(round((int(contour_interval[:ici])*conv_ci)))

node_spacing = arcpy.GetParameterAsText(2)
ins = node_spacing.find(" ")
ins1 = int(ins+1)
unit_ns = node_spacing[ins1:]
conv_ns = LinearUnit2Pixel(unit_ns,DEM_FP)

SPACING = int(round((int(contour_interval[:ins])*conv_ns)))

active_slope = arcpy.GetParameter(3)
SLOPE = round(math.tan(math.radians(active_slope)),3)
BRANCHES = arcpy.GetParameter(4)

## OPTIONAL INPUTS - ACCORDING TO SICCM
if unit_ci == "Meter":
    contour = str(CONTOUR)+"m"
else:
    contour = str(CONTOUR)+"ft"
if unit_ns == "Meter":
    nodal = str(SPACING)+"m"
else:
    nodal = str(SPACING)+"ft"
#####

```

```

run_name =
"CI"+contour+"_"+NS"+nodal+"_"+AS"+str(int(active_slope))+deg"+_BP"+str(BRANCHE
S)
model_name = " --model_name "+run_name
id_field = " --id_field Id"

# Fixed - will never change
metadata = " --no-metadata"
composite_metadata = " --no-composite-metadata"
composite_statistics = " --composite-statistics"
composite_nodes = " --no-composite-nodes"
composite_connections = " --no-composite-connections"
composite_extent = " --composite-extent"

# Optional - user can choose all or none
individual_files = arcpy.GetParameterAsText(7)
if individual_files:
    individual_statistics = " --individual-statistics"
    individual_nodes = " --individual-nodes"
    individual_connections = " --individual-connections"
    individual_extent = " --individual-extent"
else:
    individual_statistics = " --no-individual-statistics"
    individual_nodes = " --no-individual-nodes"
    individual_connections = " --no-individual-connections"
    individual_extent = " --no-individual-extent"

# Optional - user decides whether or not to remove tails
remove_tails = " --remove-tails"
tails_cutoff = arcpy.GetParameter(5)
if tails_cutoff == '#' or not tails_cutoff:
    remove_tails = " --no-remove-tails"
    tails_threshold = ""
    tails_remove_after = ""
else:
    remove_tails = " --remove-tails"
    tails_threshold = " --tails-threshold"
"+str(round((tails_cutoff/float(SPACING)),3))
    tail_remove = arcpy.GetParameterAsText(6)
    if tail_remove =='#' or not tail_remove:
        tails_remove_after = " --tails-remove-after-layer +" + str(3)
    else:
        tails_remove_after = " --tails-remove-after-layer
"+arcpy.GetParameterAsText(6)

```

```

ccm_input = "ccmflow-x64-cli.exe "+model_name+id_field+ \
metadata + composite_metadata + composite_statistics + \
composite_nodes + composite_connections + composite_extent + \
individual_statistics + individual_nodes + \
individual_connections + individual_extent + remove_tails + \
tails_threshold + tails_remove_after + \
" " + DEM_FP + " " + SCARP_FP + " " + OUTPUT_FP + " " + \
str(CONTOUR) + " " + str(SPACING) + " " + str(SLOPE) + " " +

```

```

str(BRANCHES)

ccmdir = OUTPUT_FP+"\\\"+run_name
extent_name = ccmdir+"\\\"+run_name+"_extent_poly.shp"
if os.path.exists(ccmdir):
    shutil.rmtree(ccmdir)

os.chdir('C:\Program Files\CCMFlow-x64-cli')
subprocess.check_call(ccm_input, stdin=None, stdout=None, stderr=None,
shell=False)

#try:
#    arcpy.CopyFeatures_management(extent_name, run_name)
#except:
#    arcpy.AddMessage("Failure during CCM run or extent poly has name with
#decimals")
#    arcpy.RefreshCatalog(CCM_Package)
## Display extents on map

# Set the map document and data frame
mxd = arcpy.mapping.MapDocument("CURRENT")
df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]

# Create layer file and add to map
lyrDir = os.path.dirname(__file__)

fileExt = lyrDir+"\\extents.lyr"
lyrExt = arcpy.mapping.Layer(run_name)
arcpy.ApplySymbologyFromLayer_management(lyrExt, fileExt)
arcpy.mapping.AddLayer(df, lyrExt)

```

Risk Toolbox

```
#####
# create_risk_map.py
# or "Create Risk Maps" tool in the Risk Toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####

# Import modules, initiate arcpy
import arcpy
from arcpy import env
from arcpy.sa import *
arcpy.env.overwriteOutput = True
arcpy.CheckOutExtension("Spatial")

# Get input strings from GUI
#1 - RS_Elev
RS_Elev = arcpy.GetParameterAsText(0)
#2 - Deposits from CCM
Deposits = arcpy.GetParameterAsText(1)
#3 - Highways
Highway = arcpy.GetParameterAsText(2)
#4 - Output Folder
OutFolder = arcpy.GetParameterAsText(3)

# Set 'OutputFolder' as workspace
env.workspace = OutFolder

# Create temporary files
DisDep = "DisDep.shp"
DisRoad = "DisRoad.shp"
UniDep = "UniDep.shp"
RS_Slope = "RS_Slope.tif"
RC_Slope = "RC_Slope.tif"
Ext_Slope = "Ext_Slope.tif"
Ext_Poly = "Ext_Poly.shp"
Blocks = "Blocks.shp"
Zonal_Slope = "Zonal_Slope.tif"
Block_Stats = "Block_Stats"
Risk_Zones = "Risk_Zones_SP.shp"
Risk_Zones_MP = "Risk_Zones_MP.shp"

# Fix Geometry of Deposits
arcpy.RepairGeometry_management(Deposits)

arcpy.AddMessage("Initial Processes Complete (1/5)")

# Create DISS field and dissolve Deposits and Roads - DisDep, DisRoad
check = 0
lst = arcpy.ListFields(Deposits)
for f in lst:
```

```

if f.name == "DIS":
    check = 1
else:
    continue
if check == 0:
    arcpy.AddField_management(Deosits, "DIS", "SHORT")
arcpy.Dissolve_management(Deosits, DisDep, "DIS")

check = 0
lst = arcpy.ListFields(Highway)
for f in lst:
    if f.name == "DIS":
        check = 1
    else:
        continue
if check == 0:
    arcpy.AddField_management(Highway, "DIS", "SHORT")
arcpy.Dissolve_management(Highway, DisRoad, "DIS")

# Perform union on Deposits - UniDep
arcpy.Union_analysis(Deosits, UniDep)

arcpy.AddMessage("Feature Class Manipulation Complete (2/5)")

## PREPARE BLOCK POLYGONS

# Compute Slope - RS_Slope
outSlope = Slope(RS_Elev)
outSlope.save(RS_Slope)

# Reclassify Slope - RC_Slope
outReclass = Reclassify(RS_Slope, "VALUE", "0 5 1;5 30 2;30 90 3", "DATA")
outReclass.save(RC_Slope)

# Extract Slope by attributes - Ext_Slope
attExtract = ExtractByAttributes(RC_Slope, "\"VALUE\" = 1")
attExtract.save(Ext_Slope)

# Convert Extracted Slope to polygons - Ext_Poly
arcpy.RasterToPolygon_conversion(Ext_Slope, Ext_Poly, "SIMPLIFY")

# Clip Slope polygons using dissolved Deposits - Blocks
arcpy.Clip_analysis(Ext_Poly, DisDep, Blocks)

# Compute Area of remaining Slope polygons -
arcpy.AddGeometryAttributes_management(Blocks, "AREA", "", "SQUARE_FEET_US")

arcpy.AddMessage("Unstable Blocks Have Been Identified (3/5)")

## COMPUTE BLOCK SLOPE

# Perform zonal statistics on RS_Slope with UniDep - Zonal_Slope
outZS = ZonalStatistics(UniDep, "FID", RS_Slope, "MEAN")
outZS.save(Zonal_Slope)

```

```

# Perform zonal stats as table on Zonal_Slope with Blocks using FID -
Block_Stats
outZSaT = ZonalStatisticsAsTable(Blocks, "FID", Zonal_Slope, Block_Stats, "", "MEAN")

# Join Block_Stats with Blocks
arcpy.MakeFeatureLayer_management(Blocks, "BlockLyr")
arcpy.AddJoin_management("BlockLyr", "FID", Block_Stats, "FID")

arcpy.AddMessage("Slope Statistics Complete and Assigned to Unstable Blocks
(4/5)")

## INTERSECT

# Intersect Blocks with DisRoad - Risk_Zones
inFeatures = [DisRoad, "BlockLyr"]
arcpy.Intersect_analysis(inFeatures, Risk_Zones_MP)

arcpy.MultipartToSinglepart_management(Risk_Zones_MP, Risk_Zones)

# Compute length of Risk_Zones
arcpy.AddGeometryAttributes_management(Risk_Zones, "LENGTH", "FEET_US", "")

# Delete Temporary Files
arcpy.Delete_management(DisDep)
arcpy.Delete_management(DisRoad)
arcpy.Delete_management(UniDep)
arcpy.Delete_management(RS_Slope)
arcpy.Delete_management(RC_Slope)
arcpy.Delete_management(Ext_Slope)
arcpy.Delete_management(Ext_Poly)
arcpy.Delete_management(Blocks)
arcpy.Delete_management(Zonal_Slope)
arcpy.Delete_management(Block_Stats)
arcpy.Delete_management(Block_Stats)
arcpy.Delete_management(outZSaT)
arcpy.Delete_management(outZS)
arcpy.Delete_management(Risk_Zones_MP)

arcpy.AddMessage("Intersect complete (5/5)")

# Alter field names and delete unnecessary fields
def addField(Features, Fieldname, Type):
    check = 0
    lst = arcpy.ListFields(Features)
    for f in lst:
        if f.name == Fieldname:
            check = 1
        else:
            continue
    if check == 0:
        arcpy.AddField_management(Features, Fieldname, Type)

addField(Risk_Zones, "BLOCK_AREA", "DOUBLE")
arcpy.CalculateField_management(Risk_Zones, "BLOCK_AREA", "!Blocks_POL!", "PYTHON")

```

```
addField(Risk_Zones, "LS_SLOPE", "DOUBLE")
arcpy.CalculateField_management(Risk_Zones, "LS_SLOPE", "!block_st_4!", "PYTHON")

arcpy.DeleteField_management(Risk_Zones, "FID_DisRoa")
arcpy.DeleteField_management(Risk_Zones, "DIS")
arcpy.DeleteField_management(Risk_Zones, "FID_Blocks")
arcpy.DeleteField_management(Risk_Zones, "Blocks_Id")
arcpy.DeleteField_management(Risk_Zones, "Blocks_gri")
arcpy.DeleteField_management(Risk_Zones, "block_stat")
arcpy.DeleteField_management(Risk_Zones, "block_st_1")
arcpy.DeleteField_management(Risk_Zones, "block_st_2")
arcpy.DeleteField_management(Risk_Zones, "block_st_3")
arcpy.DeleteField_management(Risk_Zones, "block_st_4")
arcpy.DeleteField_management(Risk_Zones, "Blocks_POL")
```

```
#####
# compute_risk_metrics.py
# or "Compute Risk Metrics" tool in the Risk Toolbox
#
# By Michael Bunn, Ben Leshchinsky, and Michael Olsen
# Oregon State University
# 05/01/2018
#
# Direct questions to ben.leshchinsky@oregonstate.edu
#####

# Import modules, initiate arcpy
import arcpy
import math
import os
from arcpy import env
from arcpy.sa import *
arcpy.env.overwriteOutput = True
arcpy.CheckOutExtension("Spatial")

# Get parameters from GUI
Risk_Zones = arcpy.GetParameterAsText(0)
#OutFolder = arcpy.GetParameterAsText(1)
Emb_Slope = arcpy.GetParameterAsText(1)
if Emb_Slope == '#' or not Emb_Slope:
    Emb_Slope = str(26)

Max_Width = arcpy.GetParameterAsText(2)
if Max_Width == '#' or not Max_Width:
    Max_Width = str(70.0)

Repair_Rate = arcpy.GetParameterAsText(3)
if Repair_Rate == '#' or not Repair_Rate:
    Repair_Rate = str(250)

Excav = arcpy.GetParameterAsText(4)
if Excav == '#' or not Excav:
    Excav = str(11.00)

Fill = arcpy.GetParameterAsText(5)
if Fill == '#' or not Fill:
    Fill = str(18.50)

# Convert repair rate to cubic feet
RepairR = float(Repair_Rate)*27

# Define new addField function
def addField(Features,Fieldname,Type):
    check = 0
    lst = arcpy.ListFields(Features)
    for f in lst:
        if f.name == Fieldname:
            check = 1
        else:
            continue
```

```

if check == 0:
    arcpy.AddField_management(Features,Fieldname,Type)

#env.workspace = OutFolder

# Add new EMBSLOPE field
addField(Risk_Zones,"EMBSLOPE", "DOUBLE")

# Compute EMBSLOPE field
arcpy.CalculateField_management(Risk_Zones, "EMBSLOPE", Emb_Slope, "VB", "")

# Add new WIDTH field
addField(Risk_Zones,"WIDTH", "DOUBLE")

# Compute WIDTH field
arcpy.CalculateField_management(Risk_Zones, "WIDTH",
    "!BLOCK_AREA!//!LENGTH!", "PYTHON")
arcpy.MakeFeatureLayer_management(Risk_Zones,"RiskLyr")

# Find widths greater than Max_Width and change their value to Max_Width
expr = "\"WIDTH\" >= "+Max_Width
arcpy.SelectLayerByAttribute_management("RiskLyr", "NEW_SELECTION",expr)
arcpy.CalculateField_management("RiskLyr", "WIDTH",Max_Width)
arcpy.SelectLayerByAttribute_management("RiskLyr", "CLEAR_SELECTION")

# Add new XS_AREA field - cross sectional area
addField("RiskLyr","XS_AREA", "DOUBLE")

# Calculate XS_AREA FIELD
codeblock = """def calcArea(emWidth,lsSlope,emSlope):
    A = emWidth
    b = math.radians(180 - emSlope)
    c = math.radians(lsSlope)
    a = math.pi - b - c
    B = (A*math.sin(b))/(math.sin(a))
    C = (A*math.sin(c))/(math.sin(a))
    S = (A+B+C)/2
    if (S*(S-A)*(S-B)*(S-C)) >= 0:
        Aval = math.sqrt(S*(S-A)*(S-B)*(S-C))
    else:
        Aval = 0
    return Aval"""
expression = "calcArea(!WIDTH!,!LS_SLOPE!,!EMBSLOPE!)"
arcpy.CalculateField_management("RiskLyr", "XS_AREA", expression, "PYTHON",
codeblock)

# Add new VOLUME field and compute volume
addField("RiskLyr","VOLUME", "DOUBLE")

arcpy.CalculateField_management("RiskLyr", "VOLUME", "!XS_AREA!*!LENGTH!",
"PYTHON")

# Compute TIME_CLOSE
addField("RiskLyr","TIME_CLOSE", "DOUBLE")
expression = "!VOLUME!/" +str(RepairR)

```

```

arcpy.CalculateField_management("RiskLyr", "TIME_CLOSE", expression,
"PYTHON" )

# Compute Repair Cost
ExcavF = float(Excav)/27
FillF = float(Fill)/27
TotalCost = (ExcavF+FillF)

addField("RiskLyr", "RP_COST", "DOUBLE")
addField("RiskLyr", "RP_COST_FT", "DOUBLE")

expression = "!VOLUME!*"+str(TotalCost)
arcpy.CalculateField_management("RiskLyr", "RP_COST", expression, "PYTHON")
arcpy.CalculateField_management("RiskLyr", "RP_COST_FT",
"!RP_COST!/?LENGTH!", "PYTHON")

# # Set the map document and data frame
# mxd = arcpy.mapping.MapDocument("CURRENT")
# df = arcpy.mapping.ListDataFrames(mxd, "Layers")[0]

# # Find location of layer file
# #lyrDir = os.path.dirname(__file__)

# #fileSlp = lyrDir+"\slope.lyr"

# lyrRisk = arcpy.mapping.Layer(Risk_Zones)
# arcpy.ApplySymbologyFromLayer_management(lyrRisk, fileRisk)

# # Create layer file and add to map
# dir, fname = os.path.split(Risk_Zones)
# for lyr in arcpy.mapping.ListLayers(mxd, "", df):
#     if lyr.name == fname:
#         arcpy.mapping.RemoveLayer(df, lyrRisk)
# arcpy.mapping.AddLayer(df,lyrRisk)

arcpy.Delete_management("RiskLyr")

```