When the Highway goes for a ride

Monitoring infrastructure traversing coastal landslides

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CE 560 Advanced GIS

Final Project

Introduction

Background

Landslides present a significant risk to the safety, reliability, and robustness of human infrastructure and operations that occupy their geographic space. Landslides occur when the gravitation forces acting downslope exceed the strength, or frictional forces of the soils/materials that compose the slope. Common triggers of landslides include: heavy precipitation, changes in ground water, erosion at the base of the landslide, earthquakes, and human disturbances.

Many infrastructures such as road networks traverse landslides. Highway 101 traverses nearly 20 miles landslides in Oregon alone (ODOT, 2014). Repairing existing high priority landslides would cost an estimated $592 million determined in a recent ODOT public report (ODOT, 2012). This cost only accounts for repairs of sites that have 1) been identified and 2) been assigned a high priority. It is also worth noting that repairs on large bodied landslide are rarely a permanent fix, rather techniques often used, such as drainage installation, retaining walls, and buttressing often begin to fail over time often 15 to 20 years after they were installed.

Given that many of the landslides on the Oregon Coast are "coastal landslides" (the toe of the landslide occurs in the coastal zone), climate change may be an additional factor effecting the rate, movement and impact of these landslides. A recent study by Leshchinsky et al, 2019 showed a correlation between the erosion rate and displacement rate of simulated coastal landslides as shown in Figure 1. The exact increase in horizontal movement varied depending on the geometry and assumed frictional strength of each landslide but in some cases a 10% increase in erosion rate lead to a 30% increase in landslide displacement (Leshchinsky et al, 2019).

Due to the factors outlined above, including: the high cost of remediation efforts, failing repairs, and potential increase in landslide displacement due to climate change identifying, it is imperative that transportation agencies such as ODOT (Oregon Department Of Transportation) create frameworks to actively monitor these active landslides in order to prioritize remediation efforts.

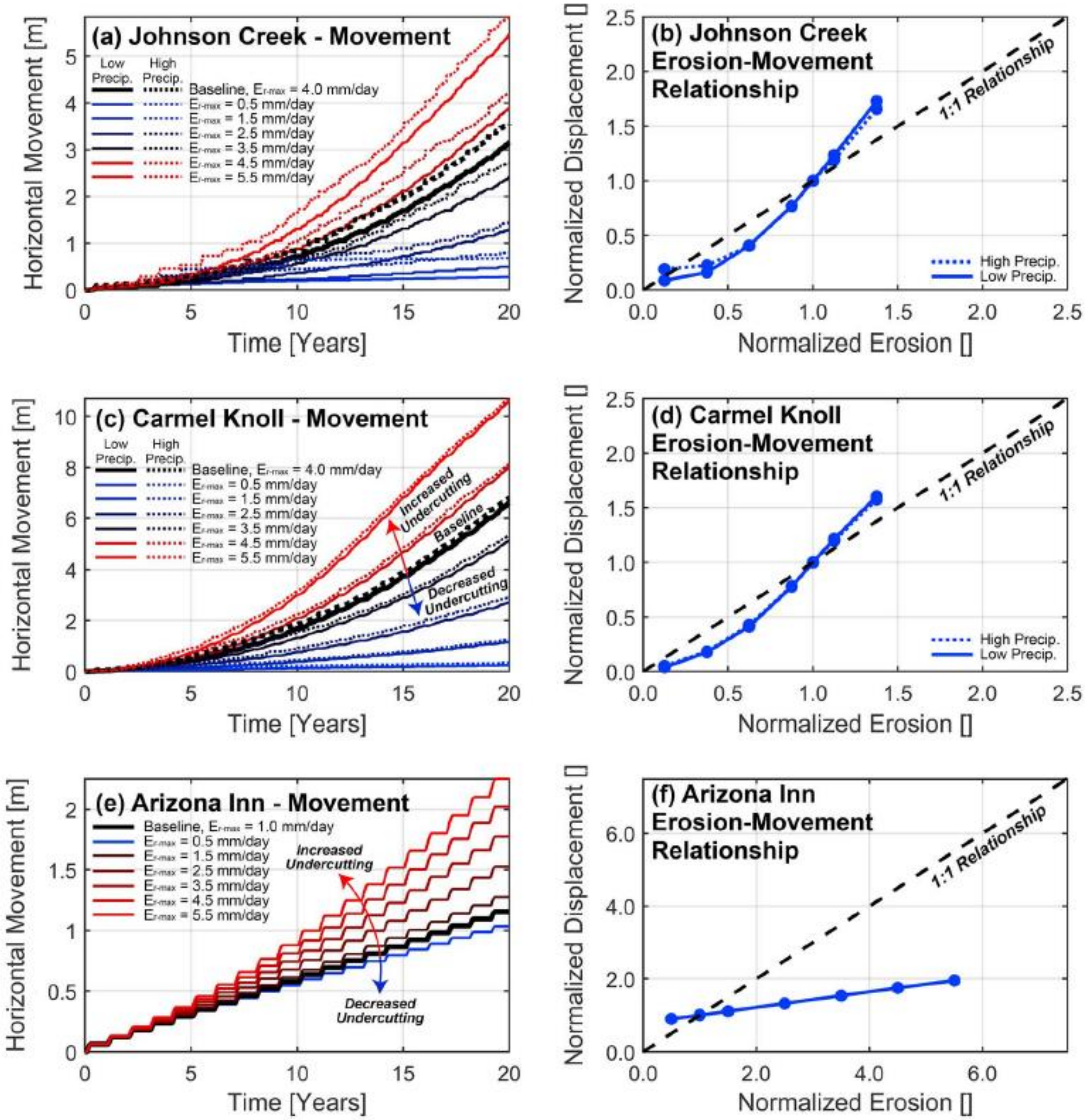

Figure 1: Modeled landslide movements for 3 different landslide over the next 20 years for varying baseline erosion scenarios. Taken from Leshchinsky et al, 2019.

Objectives

The objectives of this research is to create a monitoring framework that can be implemented along an important corridor such as HWY 101 to identify and monitor risk and hazard. A successful monitoring framework will consider the following factors:

1. Consistent
    a. In order to successfully compare the risk factors associated at various sites along the coast, the created monitoring frameworks needs to evaluate these sites on consistent basis so that a fair and even comparison can be conducted.
2. Quantitative
    a. Due to the scale and number of sites, the created monitoring framework must be based on quantitative comparisons to ensure consistency and allow for the best engineering decisions to be made.
3. Implementable
    a. The created monitoring framework must be implementable across multiple sites. To achieve this, the monitoring framework must be affordable both in terms of cost and in terms of time.

This class report will consist of an evaluation of a potential semi-automated technique for extracting landslide displacements known as PIV (Particle Image Velocimetry).

Particle image Velocimetry

PIV (particle image velocimetry) is a method of flow visualization commonly used to derive velocity measurements of particles within a moving body of air or fluid in lab experimentation (such as a wind tunnel). By taking repeated images from the same location particles can be tracked as they move across the camera using image correlation techniques to identify common patterns and features across images thereby allowing particles to be tracked through time. Given that digital images are a form of raster these techniques can be applied to other raster products assuming: 1) The images occupy the same space, that is they are geo-referenced. 2) The raster cell size represents the same area in both raster datasets. Given this, accurately geo-referenced terrestrial lidar derived DEMs make a potentially suitable candidate for this technique which will be explored in this final project.

PIV uses a 2D image cross-correlation technique, a simplified demonstration of this technique is illustrated in Figure 2. A pixel (or cell) and its neighboring pixels are selected from one of the raster datasets often as a 3x3 or 5x5 window. This “window” of pixels is then iteratively compared to every possible “window” of pixels from the compared raster dataset. To compare these windows, the 2D cross-correlation of these windows is calculated using pixel values (elevation, RGB, intensity etc) using matrix math with the following formula:

eq 1 - $$\frac{1}{n}\sum_{x,y}\frac{1}{\sigma_f\sigma_t}f(x,y)t(x,y)$$

Where:

n = number of pixels

x = x coordinate

y = y coordinate

f = matrix or window 1

t = matrix or window 2

The cross correlation comparison between the two windows that yields the highest correlation value is determined to be the same pixel in each image and thus the horizontal displacement between the two locations can be calculated.

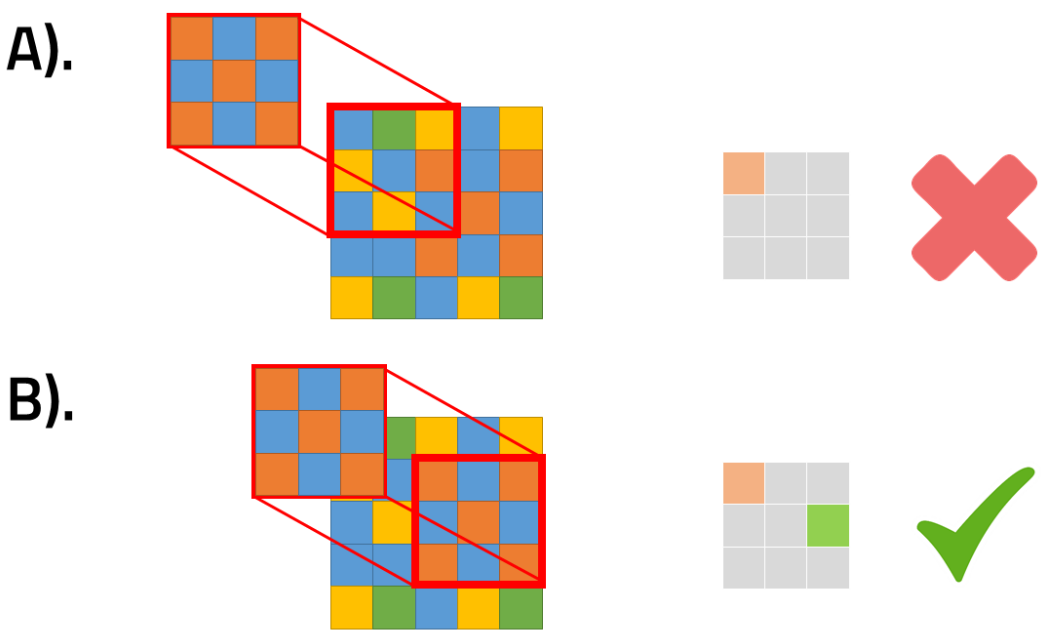

Figure 2: Visual illustration of the 2D image cross correlation process. Each color represents a unique pixel value. In example A the window does not match the window of raster two so it calculates a low correlation value. In Example B the window does match the window of raster two, so it calculates a high correlation value, this would be perceived as a match.

Study Site

To test this analysis out, a landslide in southern Oregon was chosen for analysis. During March of 2019, this site experienced 130ft of displacement over the period of 1 week, during this time, repeat terrestrial lidar surveys (TLS) where carried out capturing the displacement of the road while the landslide was actively moving. This data was chosen for use for the following reasons:

1. The TLS setups occurred in the same locations giving a consistent field of view.
2. The displacement of the road was rigid, that is there was little deformation that may obscure results.
3. The displacement was consistent across the small area, so accurate statistics of comparison could be computed.
4. Good point spacing was collected across this section with little in the way of data occlusions.

Figure 3 shows imagery map of the site section that was chosen to be used and ***Figure 4*** shows the RGB colored point cloud of that section collected using the TLS.

Figure 3: Imagery map of the test site, the black polygon highlights the area used during the experiment.

B)

Figure 4: Point cloud of the test site, the black polygon highlights the area used during the experiment.

Methodology

The first step in this analysis was to take the georeferenced terrestrial lidar derived point clouds and create a validation dataset. To do this, the raw georeferenced point cloud was loaded into a point cloud viewing software and displacements of similar objects were manually measured as shown in Figure 5. Figure 6 shows all of the manually measured displacements measured at the test site, 20 measurements were made in total.

The next step was to remove the non-ground (vegetation and noise) points from the point cloud. To do this, large pieces of noise and vegetation were first removed using manual cropping, and then the point cloud was ran through a vegetation filter algorithm outlined in Olsen et al, 2015 to achieve a bare earth model of the point cloud. Next, a DEM (digital elevation model) was created from the point cloud using the bin n grid software created by Michael Olsen. A cell size of 0.1m was chosen as this allowed a for high resolution analysis while limiting the number of holes present in the DEM surface. Similar rasters where also created using the lidar intensity (strength of return) as the raster pixel value.

Next, the DEM was taken into ArcGIS pro and a hillshade model was created using the DEM's created in the step above. A high pass Gaussian filter was then applied to both the DEM and intensity raster using the code shown in Appendix A. This was applied in order to exaggerate the changes in elevation/intensity.

PIV analysis was conducted on each raster type comparing the each of raster types one by one. To do this the open source software PIVLAB was used. A mask was set around the boundary of the DEM to limit erroneous edge effects and the following settings as highlighted below were used. These settings were chosen for numerous reasons including: the pixel size of the raster, the observed displacement, and empirical experimentation.

These settings were maintained for each raster type experiment in order to keep each comparison consistent. Once the PIV analysis was conducted, the resulting displacements for each window size were exported as an asci text file and converted displacement in pixels (u & v) to total displacement magnitude and orientation using the python script shown in Appendix B. Basic statistics were calculated to compare the results of each raster type with the results from manual extraction.

Table 1: PIV LAB settings used during this experiment.

Pass #	Interrogation area	Sub pixel estimator	Algorithm type
1	64	Gauss 2x3-point	FIT window deformation
2	32	Gauss 2x3-point	FIT window deformation
3	16	Gauss 2x3-point	FIT window deformation

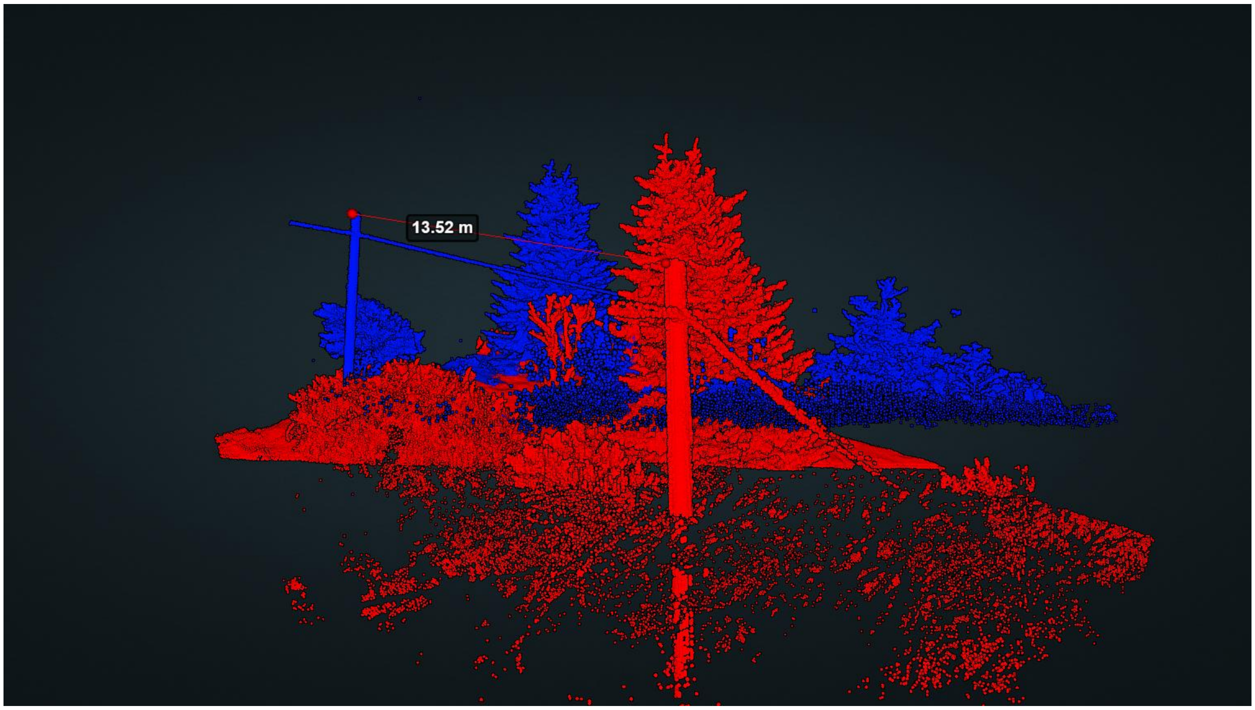

Figure 5: Example of manual measurement of a displaced object between two point clouds derived from different lidar survey epochs (before and after landslide failure).

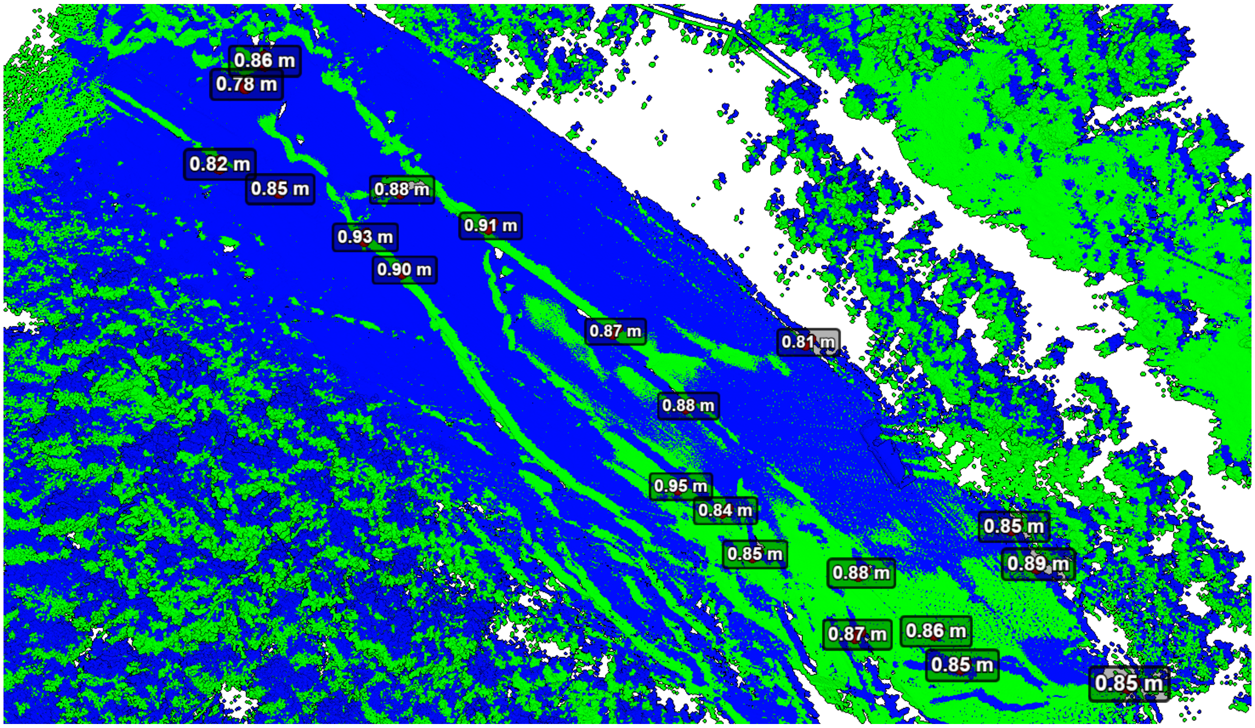

Figure 6: Distances found using manual extraction methods across the test site. Distances labeled are 3D distances and were transformed into 2D distances for use in this experiment.

Results and Discussion

Across the test site, using the manual extraction method there was a mean displacement magnitude of 0.854m (0.039m std dev) with a mean orientation (from north) of 216.5° (8.0° std dev) with a total of 20 measurements made. Table 2 shows the statistical results using the five different raster types. The hillshade raster had the closest results to the manual extraction method with a mean displacement and orientation of 0.868m (Δ +0.014m) and 215° (Δ -1.5°) respectfully. These results are showed graphically in Figure 7. In comparison, the DEM raster types (with and without the high pass gaussian filter) over predicted the displacement with results of 1.006 (Δ +0.152m) and 1.007 (Δ +0. 153m) respectfully. The intensity raster types, with and without the high pass gaussian filter, under predicted the displacement with results of 0.718m (Δ -0.136m) and 0.638m (Δ -0.216m) respectfully.

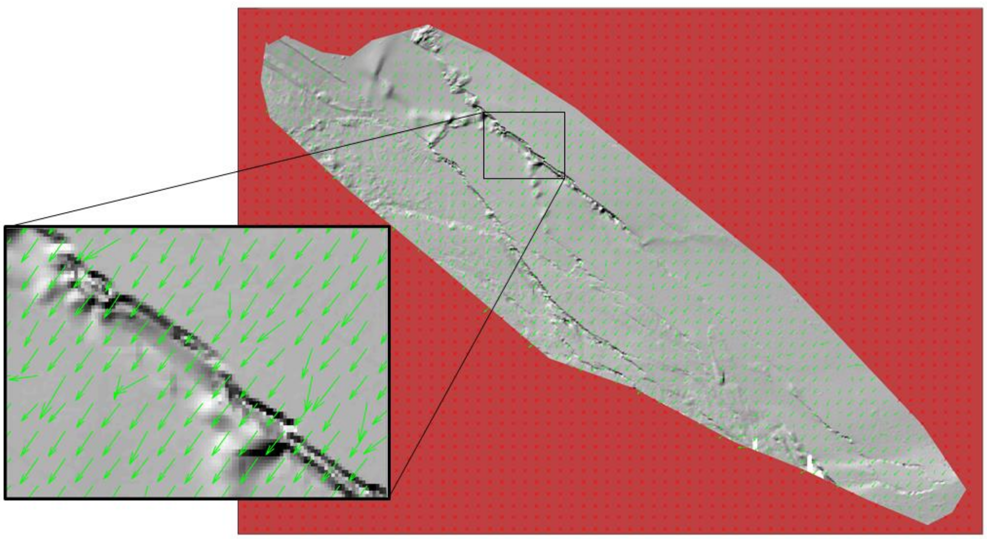

Figure 7: Plot showing the displacement vectors from using the PIV algorithm on two hillshade rasters at the site overlaid on one of the hillshades. Vectors (green arrows) are drawn to scale.

These results show the limitations of this technique when using a DEM raster applied to flat surfaces (surfaces with a low slope value). When a surface is flat the numerical values that make up a DEM for example stay constant over a larger window size. This requires a larger window size to be used for the analysis and thus a greater displacement to take place in order to accurately measure the displacement using a PIV technique. The intensity raster likely failed due to a similar reason (pixel values remaining consistent over a larger window) due to the test area being composed of a single material (asphalt). The success of the hillshade raster type likely stems from the subtle local changes in slope causing changes in the shadow. Due to the cracks in the road at this site, this was likely enough to be picked up by the algorithm, by looking in smoother areas of the test site you can see where even this raster type began to struggle.

Table 2: Statistical results (mean and standard deviation) of the displacement and orientation using the five different raster types in comparison to the manual extraction method.

Method	Mean Displacement (m)	Displacement (Std dev m)	Mean Orientation (from north)	Orientation (from north) (Std dev m)
Manual Extraction	0.854	0.039	216.5	8.0
DEM	1.007	0.503	211.7	94.2
DEM (high pass gaussian filter)	1.058	0.485	208.6	70.67
Hillshade model	0.868	0.142	215.7	13.5
Intensity	0.638	0.667	216.6	71.4
Intensity (high pass gaussian filter)	0.718	0.502	232.4	54.4

Conclusion

In conclusion, the PIV 2D cross correlation technique demonstrated above shows potential use when applied to areas with high/varied slope values. Raster types directly display the local slope value (such as a slope map, or hillshade) show the most promise and performed the best in this analysis. RGB raster types, such as orthomosaic photographs from photogrammetric based UAS (unmanned airborne systems) may provide additional valuable data that can be used in flat textured areas. A potential hybrid approach using a slope based lidar derived raster and an RGB based photogrammetric UAS derived rasters may provide a solution allowing for a data fusion approach by utilizing the strong characteristics of both systems.

References

Leshchinsky, B., Olsen, M.J., Mohney, C., O'Banion, M., Bunn, M., Allan, J. and McClung, R., 2019. Quantifying the sensitivity of progressive landslide movements to failure geometry, undercutting processes and hydrological changes. Journal of Geophysical Research: Earth Surface, 124(2), pp.616-638.

ODOT., 2012. ODOT’s Climate Change Adaptation Strategy Report. Oregon Department of Transportation, ODOT

ODOT., 2014. Climate Change Vulnerability Assessment and Adaptation Options Study. Oregon Department of Transportation, ODOT

Olsen, M.J., Wartman, J., McAlister, M., Mahmoudabadi, H., O’Banion, M.S., Dunham, L. and Cunningham, K., 2015. To fill or not to fill: sensitivity analysis of the influence of resolution and hole filling on point cloud surface modeling and individual rockfall event detection. Remote Sensing, 7(9), pp.12103-12134.

Appendix A

```
% read 16-bit rasters
Raster1 =
'F:\CoastalProject\Hooskanaden\Analysis\pivLab\CC_dem\baseline_16bit.tif';
Raster2 =
'F:\CoastalProject\Hooskanaden\Analysis\pivLab\CC_dem\moved_16bit.tif';
Raster13m = imread(Raster1);
Raster23m = imread(Raster2);
% create 8-bit highpass filtered images of the original 16-bit images
h = fspecial('gaussian',5,5);
Raster1_hp = double(Raster13m)-(imfilter(double(Raster13m), h, 'replicate'));
low = prctile(Raster1_hp(:), 1);
high = prctile(Raster1_hp(:), 99);
Raster1_hp = uint8(mat2gray(Raster1_hp, [low high])*255);
imwrite(Raster1_hp,
'F:\CoastalProject\Hooskanaden\Analysis\pivLab\CC_dem\baseline_hp.tif');
Raster2_hp = double(Raster23m)-(imfilter(double(Raster23m), h, 'replicate'));
low = prctile(Raster2_hp(:), 1);
high = prctile(Raster2_hp(:), 99);
ncalm3m_hp = uint8(mat2gray(Raster2_hp, [low high])*255);
imwrite(Raster2_hp,
'F:\CoastalProject\Hooskanaden\Analysis\pivLab\CC_dem\moved_hp.tif');
```

Appendix B

```
import pandas as pd
from matplotlib import pyplot as plt
import numpy as np
import os
file = 'PIVlab_V7_output.txt'
os.chdir('E:\\andrew\\CLASS\\Winter2020\\CE560-
AdvancedGIS\\Final\\pivAnalysis')
df = pd.read_csv(file)
df = df.dropna()
df['pxDistance'] = np.sqrt((df['u']*df['u'])+(df['v']*df['v']))
df['ditanceMeters'] = df['pxDistance']*0.1

meanDistance = df['ditanceMeters'].mean()
minDistance = df['ditanceMeters'].min()
maxDistance = df['ditanceMeters'].max()
stdDistance = df['ditanceMeters'].std()
medianDistance = df['ditanceMeters'].median()
print('mean displacement accross the area is: ', meanDistance)
print('standard deviation of displacements accross the area is: ', std
Distance)

df['orientation'] = np.arctan2(df['u'], df['v']) * 180/np.pi
df['orientation'] = -df['orientation']+180

meanOrientation = df['orientation'].mean()
minOrientation = df['orientation'].min()
maxOrientation = df['orientation'].max()
stdOrientation = df['orientation'].std()
medianOrientation = df['orientation'].median()
print('mean orientation accross the area is: ', meanOrientation)
print('standard deviation of orientations accross the area is: ', stdO
rientation)
```