Characterization of Landslide Processes From Radar Remote Sensing and Hydromechanical Modeling

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CHARACTERIZATION OF LANDSLIDE PROCESSES FROM RADAR REMOTE SENSING AND HYDROMECHANICAL MODELING

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CHARACTERIZATION OF LANDSLIDE PROCESSES FROM RADAR REMOTE SENSING
AND HYDROMECHANICAL MODELING

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in
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Landslides are a natural geomorphic process yet a dangerous hazard which annually causes thousands of casualties and billions of property loss in a global scale. Understanding landslide motion kinematics from early initiation to final deposition is critical for monitoring, assessing, and forecasting landslide movement in order to mitigate their hazards. Landslides occur under diverse environmental settings and appear in variable types; however, all types of landslides can be mechanically attributed to shearing failure at the basal surface due to stress regime shift contributed by internal and/or external forcing. Typical internal factors include soil/rock weathering, whereas typical external triggering forces encompass precipitation, groundwater, tectonic activity, landslide toe cutting, and landslide head loading. Physically, kinematics of most natural hillslope failures from instigation to cessation can be approached as a hydromechanical problem.

Variable types of landslides were examined and characterized in this thesis from integrating satellite/airborne remote sensing and hydromechanical modeling, with the intention to generate insights for reducing landslide hazards globally. In particular, high-resolution satellite optical and radar images and airborne lidar Digital Elevation Models (DEMs) were extensively utilized through advanced quantitative techniques such as sub-pixel offset tracking and radar interferometry in order to capture landslide motion dynamics. Modeling efforts were incorporated to mechanically interpret the observed landslide kinematics and to further generate insights for
evaluating and forecasting other similar landslides. The five case studies detailed in this thesis involve multiple distinct landslide behaviors and hydromechanical settings which are typical for many worldwide. Particularly, these investigations entail a consistently slow seasonal landslide, an alternately slow and rapid coastal landslide, a retrogressive and potentially catastrophic headscarp landslide, multiple irrigation-triggered slow and catastrophic landslides, and hundreds of other slow landslides near the U.S. west coast. Knowledge from hydrogeology, soil mechanics, grain-flow mechanics, and fluid mechanics was integrated to decipher and model the impacts on landslide dynamics from bedrock lithology, land uplift, precipitation-contributed pore pressure, groundwater, soil shearing dilation and contraction, and basal topography. From these five landslide case studies near the U.S. west coast, we were able to obtain enhanced understanding of the landslide processes and numerically characterize the key elements from failure instigation to movement evolution, interaction with waterbodies on the runout path, and final deposition.

Our investigations particularly demonstrated the potential of integrating satellite observations and hydromechanical modeling to enhance our understanding of landslides and to reduce their hazards. Insights generated from our case studies are applicable to many similar landslides worldwide for their movement characterization and hazard assessment. Hence, this thesis was also aimed to motivate similar efforts globally for landslide hazard mitigation, especially in response to the projected increasingly frequent landslide events in the near future due to global climate change and expanding anthropogenic activities.
TABLE OF CONTENTS

LIST OF FIGURES .................................................................................................................. xii
LIST OF TABLES ..................................................................................................................... xv
ACKNOWLEDGEMENTS ......................................................................................................... xvi

CHAPTER 1: INTRODUCTION ................................................................................................. 1
  1.1 Radar Remote Sensing .................................................................................................... 2
    1.1.1 SAR imaging .......................................................................................................... 2
    1.1.2 InSAR .................................................................................................................... 5
  1.2 Landslide Processes ....................................................................................................... 8
  1.3 Chapter Summaries and Contributions ......................................................................... 10

References ............................................................................................................................. 16

CHAPTER 2: CHARACTERIZING SEASONAL MOTION OF THE SLOW-MOVING LAWSON CREEK LANDSLIDE, OREGON ............................................................. 20
  2.1 Introduction .................................................................................................................... 20
  2.2 Landslide Location and Geological Settings ................................................................ 22
  2.3 Materials and Methods ................................................................................................ 22
    2.3.1 SAR Interferometry for Landslide Time-series Mapping ........................................ 22
    2.3.2 Thickness Inversion .............................................................................................. 26
    2.3.3 Time Lags ............................................................................................................. 28
    2.3.4 Failure Depth using Limit Equilibrium Analysis .................................................... 29
  2.4 Results .......................................................................................................................... 32
2.4.1 Time-series Displacements and Annual Deformation Rates ........................................ 32
2.4.2 Time Retardation to Seasonal Precipitation.......................................................... 34
2.4.2 Basal Depths and Volume Inferred from InSAR Observations ................................ 39
2.4.3 Failure Depths from Limit Equilibrium Analysis..................................................... 40
2.4.4 Potential for Estimating Hydraulic Parameters....................................................... 42
2.5 Discussion .................................................................................................................. 43
2.6 Conclusions ............................................................................................................... 45
Acknowledgments .......................................................................................................... 47
References ...................................................................................................................... 49
CHAPTER 3: DYNAMICS AND PHYSICS-BASED RAINFALL THRESHOLDS FOR THE DEEP-SEATED HOOSKANADEN LANDSLIDE, OREGON ........................................... 54
3.1 Introduction ................................................................................................................ 54
3.2 Geological Setting and Historical Activities ............................................................ 57
  3.2.1 Geographical and Geological Settings ................................................................. 57
  3.2.2 Historical Moderate and Major Slide Movements ................................................. 60
3.3 Data and Methodology .............................................................................................. 60
  3.3.1 Data ....................................................................................................................... 60
  3.3.2 InSAR ..................................................................................................................... 62
  3.3.3 Pixel Offset Tracking .............................................................................................. 63
    3.3.3.1 Preprocessing of Sentinel-1/2 images .............................................................. 64
    3.3.3.2 Preprocessing of LiDAR DEMs ..................................................................... 65
  3.3.4 Reconstruction of Three-dimensional Displacement Field .................................. 66
3.4 Results.............................................................................................................................................. 67
  3.4.1 Three-dimensional Displacement Field of the February 2019 Event ......................... 67
  3.4.2 Movement Rate from Airborne LiDAR DEMs ................................................................. 69
  3.4.3 Motion Dynamics from 2007 to 2019.............................................................................. 71
  3.4.4 Estimation of Hydraulic Conductivity and Diffusivity................................................. 76

3.5 Discussion........................................................................................................................................ 78
  3.5.1 Enhancement of Pixel Offset Tracking ........................................................................... 78
  3.5.2 Proposed Rainfall Threshold for the Moderate/Major Events ...................................... 80
  3.5.3 Mechanism of Landslide Motions Modulated by Precipitation and Coastal Erosion . 83

3.6 Conclusions....................................................................................................................................... 85

Acknowledgments................................................................................................................................. 86

References............................................................................................................................................... 88

CHAPTER 4: MOVEMENT MONITORING AND RUNOUT HAZARD ASSESSMENT OF THE GOLD BASIN LANDSLIDE, WASHINGTON.................................................. 91

4.1 Introduction....................................................................................................................................... 91

4.2 Geological Setting and History................................................................................................. 96
  4.2.1 Regional Setting................................................................................................................... 96
  4.2.2 Historical Landslide Activity .......................................................................................... 96

4.3 Methodology and Data............................................................................................................... 97
  4.3.1 Measuring Landslide Movement Using Remote Sensing ........................................... 97
    4.3.1.1 LiDAR DEM differencing ......................................................................................... 97
    4.3.1.2 InSAR ..................................................................................................................... 98
    4.3.1.3 SAR intensity differencing and pixel offset tracking ........................................... 100
### 4.3.2 Runout Scenario Simulation

- **4.3.2.1 D-claw model** ................................................................. 101
- **4.3.2.2 Log-spiral basal surfaces** ........................................... 104
- **4.3.2.3 Landslide volume estimations** .................................... 106
- **4.3.2.4 D-claw simulations setup** ............................................ 107

### 4.4 Results

- **4.4.1 Remote Sensing of Landslide Activity** ................................ 108
  - **4.4.1.1 LiDAR DEM differencing** ........................................... 108
  - **4.4.1.2 InSAR** .................................................................. 108
  - **4.4.1.3 SAR intensity changes and pixel offset tracking** .......... 109

- **4.4.2 Simulations of Hypothetical Runout Scenarios** .................. 113

- **4.4.3 Simulations of Interactions with the Stillaguamish River** ...... 116

### 4.5 Discussion

- ........................................................................................................... 120

### 4.6 Conclusions

- ........................................................................................................... 121

### Acknowledgments

- ........................................................................................................... 122

### References

- ........................................................................................................... 124

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**CHAPTER 5: GEOLOGIC CONTROLS OF SLOW-MOVING LANDSLIDES HIDDEN NEAR THE U.S. WEST COAST.** ................................................................. 127

- **5.1 Introduction** ........................................................................... 127

- **5.2 Materials and Methods** .......................................................... 129
  - **5.2.1 SAR Interferogram Generation and Unwrapping** ............. 129
  - **5.2.2 Identification of Active Landslides** .................................. 131
  - **5.2.3 Bedrock of the Landslides** ............................................ 131
5.2.4 Landslide Area-volume Scaling and Average Slope Angle ........................................... 135
5.2.5 Land Uplift Rate ........................................................................................................... 135

5.3 Results .......................................................................................................................... 137
5.3.1 Discovery of Hidden Landslide Hazards ..................................................................... 137
5.3.2 Bedrock Control of Slow-moving Landslides ............................................................... 141
5.3.3 Landsliding Contributed by Land Uplift ..................................................................... 145

5.4 Discussion and Conclusions ......................................................................................... 147
5.4.1 Landslide Identification Using Radar Interferometry .................................................. 147
5.4.2 Geologic Impacts on Landslide Character and Kinematics ....................................... 149
5.4.3 Hydrological Impacts on Landslide Motion ................................................................ 149
5.4.4 Implication on Landslide and Geomorphic Studies .................................................... 152

Acknowledgments ............................................................................................................... 152

References .......................................................................................................................... 155

CHAPTER 6: KINEMATICS OF IRRIGATION-INDUCED LANDSLIDES IN A
WASHINGTON DESERT: PRELIMINARY RESULTS .......................................................... 161

6.1 Introduction ..................................................................................................................... 161
6.2 Study Area ....................................................................................................................... 163
6.3 Data and Methods ......................................................................................................... 165
6.3.1 Data ............................................................................................................................. 166
6.3.2 Multitemporal InSAR Processing ............................................................................... 166
6.3.3 Forced Water Circulation on A Wavy Sliding Surface .............................................. 167
6.4 Preliminary Results ........................................................................................................ 171
6.4.1 Mapping Slow and Catastrophic Landslides .................................................. 171

6.4.2 Kinematics of Slow Landslides ........................................................................ 175
   6.4.2.1 The slow life cycle from initiation to deposition ...................................... 175
   6.4.2.2 Slow motion modulated by external force disturbances .......................... 178

6.4.3 Kinematics of Catastrophic Landslides ............................................................. 182

6.4.4 Landslide Motion Regulated by Basal Topography .......................................... 184
   6.4.4.1 Basal topography regulates slow landslides by forced water circulation .... 184
   6.4.4.2 Basal topography bifurcates slow and catastrophic movements ............. 186

6.5 Discussion ............................................................................................................. 190
   6.5.1 Satellite Imagery for Landslide Identification and Monitoring .................... 190
   6.5.2 Human-Induced Landslides and Potential Prevention Measures .................. 191
   6.5.3 Implications of Basal Topography Control on Landslide Behaviors ............ 192

6.6 Conclusions ......................................................................................................... 193

References .................................................................................................................. 195

CHAPTER 7: CONCLUDING REMARKS ...................................................................... 198

7.1 Highlights ............................................................................................................. 199

7.1 Future Work ......................................................................................................... 201
LIST OF FIGURES

Figure 1.1 Typical radar geometry and the resulted image distortion 3
Figure 1.2 Azimuth and range compressions of a raw SAR image 5
Figure 1.3 SAR interferometry imaging geometry in the plane normal to the flight direction 7
Figure 1.4 Stress regime evolution of a landslide over time 10
Figure 2.1 Geographical location of the Lawson Creek landslide and the used SAR data 23
Figure 2.2 Historic landslide deposits 24
Figure 2.3 Geological settings of the landslide 25
Figure 2.4 Spatial and temporal baselines of used InSAR pairs from multiple tracks 26
Figure 2.5 Sketch of a hillslope consisting of soil column cells 30
Figure 2.6 Relationships among landslide displacements, precipitation, and soil moisture 33
Figure 2.7 Average along-slope displacement rates and spatial deformation patterns 35
Figure 2.8 Annual along-slope deformation rates from ALOS2 tracks T69 and T171 36
Figure 2.9 Surface velocity vector and thickness of the Lawson Creek landslide 40
Figure 3.1 Photos of the 2019 February major slide 56
Figure 3.2 Geographical and geological settings of the Hooskanaden landslide 59
Figure 3.3 Historical major landslide movements and timespans for the used data 61
Figure 3.4 Three-dimensional displacement field of the 2019 February movement 68
Figure 3.5 Uncertainties of the inverted three-dimensional displacement field ................. 70
Figure 3.6 Cumulative slow motions of the Hooskanaden slide from LiDAR DEMs ........... 71
Figure 3.7 Long-term motion dynamics of the Hooskanaden slide from 2007 to 2019 ............ 73
Figure 3.8. Average coherences of the used ALOS and Sentinel-1 interferograms .......... 74
Figure 3.9 A close-up of the landslide motion dynamics between 2016 and 2019 ............. 75
Figure 3.10 Rainfall thresholds for forecasting moderate/major landslide events .......... 79
Figure 3.11 Daily and hourly precipitation near special dates ...................................... 81
Figure 3.12 Unsaturated hydraulic conductivity and coastal erosions .......................... 84
Figure 4.1 Comparison between the Gold Basin landslide and the Oso slide ................. 93
Figure 4.2 Geographical and geological setting of the Gold Basin landslide complex ......... 95
Figure 4.3 Historical images of the Gold Basin landslide ............................................. 99
Figure 4.4 Illustration of logarithmic spiral failure surface ......................................... 105
Figure 4.5 Estimated maximum landslide volume ..................................................... 107
Figure 4.6 Slope deformation captured by LiDAR DEMs ............................................. 110
Figure 4.7 Detected active landslides nearby Gold Basin from an ALOS-2 interferogram .... 111
Figure 4.8 Intensity changes and tracked displacements of TerraSAR-X images ............. 112
Figure 4.9 Simulated maximum campground damages with $m_0 - m_{crit} = 0.02 $ .......... 114
Figure 4.10 Simulated maximum campground damages with $m_0 - m_{crit} = -0.02 $ ......... 115
Figure 4.11 Simulated interactions between the debris flow and the Stillaguamish River .... 118
Figure 4.12 Impacts of the river on landslide runout at different geographical locations .... 119
Figure 5.1 Coverage of satellite radar images and the identified landslides .................... 138
Figure 5.2 Active landslides detected by radar satellites ............................................. 139
Figure 5.3 Surface geometry of the identified landslides ............................................. 140
Figure 5.4 Examples of hidden active landslides discovered by SAR interferograms .......... 142
Figure 5.5 Landslide spatial density by bedrock ......................................................... 143
Figure 5.6 Landslide size by bedrock ................................................................. 143
Figure 5.7 Vertical land motions near the U.S. west coast ........................................ 148
Figure 5.8 Comparison of landslide distribution and precipitation in the U.S west coast .......... 151
Figure 6.1 Geographical location of the study area ......................................................... 164
Figure 6.2 Sketch of a landslide block sliding on a wavy surface ................................. 169
Figure 6.3 Irrigation-triggered landslides in a desert near Hanford, Washington ................ 172
Figure 6.4 Landslides observed from space ................................................................. 174
Figure 6.5 Landscape of the Locke landslide complex ................................................. 176
Figure 6.6 Landscape evolution at the southern Wiehl Ranch landslide complex ............... 177
Figure 6.7 Time-series displacements of seven slow-moving landslides ......................... 180
Figure 6.8 Relationship of landslide motion with rainfall and groundwater level ............... 181
Figure 6.9 Post-failure photos of catastrophic landslides at Basin Hill ......................... 183
Figure 6.10 Landscape of the Johnson landslide complex ............................................ 187
Figure 6.11 Groundwater level changes near the Johnson landslide complex .................... 188
Figure 6.12 Comparison between basal topography of slow and catastrophic landslides ....... 189
LIST OF TABLES

Table 2.1 Spaceborne SAR datasets and usages ......................................................... 25
Table 2.2 Saturated hydraulic conductivity for soils with low bulk density .................... 38
Table 5.1 Descriptions of major bedrock formations ................................................... 132
Table 5.2 Source literature of the uplift data for the U.S. west coast ............................. 136
Table 5.3 Uplift rates by excluding flat regions ......................................................... 147
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CHAPTER 1

INTRODUCTION

Landslides are the downslope movement of soil and/or rock under the influence of gravity (Cruden, 1991). They are a natural geomorphic process that gradually modifies landscape and a significant hazard that endangers human and infrastructure safety in the vicinity. Globally, landslide hazards cause billions of dollars in damages (Spiker and Gori, 2003) and thousands of casualties (Kirschbaum et al., 2010; Petley, 2012) on an annual basis. Landslides are often triggered by one or multiple factors: elevated basal pore pressure by rainfall or snowmelt (e.g., Iverson, 2000), ground shaking by earthquake or volcanic eruption (e.g., Malamud et al., 2004), coastal and stream erosion (e.g., Leshchinsky et al., 2017), atmospheric tides (e.g., Schulz et al., 2009), and anthropogenic activities such as deforestation and constructions (e.g., Highland and Bobrowsky, 2008). The hazard and landscape change caused by landslides are largely affected by the timing of their occurrence, their size, speed, the duration, and the total amount of movement (Schulz et al., 2018). Consequently, understanding and characterizing the landslide process from early initiation to final deposition is critical for reducing their hazards.

Field instrumentation such as in situ extensometers, inclinometers, piezometers has long been traditionally relied upon for monitoring landslide dynamics (e.g., Angeli et al. 2000; Terzis et al.
Emerging in the past two decades, the newly available remote sensing techniques further improved the capability for capturing landslide kinematics with extended spatial scales. The widely used remote sensing techniques include LiDAR (Light Detection and Ranging) DEMs (Digital Elevation Model), high-resolution optical images, and SAR (Synthetic Aperture Radar) imagery (Xu et al., 2020a). Particularly, the SAR imagery which provides routinely acquired global datasets independent of daylight, cloud coverage, and weather conditions, has greatly enhanced the efficiency for large-scale landslide identification and the availability for near-real-time landslide monitoring (e.g., Fruneau et al. 1996; Squarzoni et al. 2003; Colesanti and Wasowski 2006; Xu et al. 2019; Xu et al., 2020b). By coupling landslide measurements (from both remote sensing and field instrumentation) and hydromechanical modelling, new understandings of landslide processes can be achieved (e.g., Xu et al., 2019; Xu et al., 2020b; Iverson et al., 2015; Xu et al., 2020a) and be used for evaluating landslide risks and protecting local residents from potential life and property losses.

1.1 Radar Remote Sensing

1.1.1 SAR imaging

A Synthetic Aperture Radar is an imaging radar mounted on a moving vehicle or airborne and spaceborne platform. The radar system transmits electromagnetic waves sequentially to the Earth surface and receives backscattered echoes from ground objects by the radar antenna. Only a portion of the transmitted radar pulse is backscattered to the receiving antenna after interaction with objects on the Earth surface; hence the physical (i.e., geometry, roughness) and electrical properties (i.e., permittivity) of the imaged objects affect the amplitude and phase of the backscattered signal (Moreira et al., 2013). Figure 1.1a illustrates the typical SAR geometry, where the platform moves in the azimuth direction and the slant-range direction is perpendicular to the radar’s flight path,
and the radar swath gives the ground-range of the radar scene. Because of the side-looking design, the radar images are geometrically distorted from ground coordinate (Figure 1.1b) and a geocoding processing is required to reproject the radar image into the ground coordinate.

![Typical radar geometry and the resulted image distortion](image)

Figure 1.1 Typical radar geometry and the resulted image distortion (after Rosen, 2000; Simons, 2005).

Imaging radar collects and forms a two-dimensional image composed of multiple lines and columns of pixels. The slant-range resolution $\delta_r$ (pixel size along the range direction) of a radar image is inversely proportional to the system bandwidth $B_r$ as

$$\delta_r = \frac{c_0}{2B_r}$$

where $c_0$ is the speed of light. The azimuth resolution $\sigma_a$ depends on the length of radar antenna $d_a$:

$$\sigma_a = \frac{d_a}{2}$$
The above equation suggests that a short antenna corresponds to a fine azimuth resolution, which is because a radar with a shorter antenna “sees” any ground objects for a longer time (Moreira et al., 2013). The illumination time can be approximated as

\[ T_{\text{illum}} \approx \frac{\lambda r_0}{v d_a} \]  

(1.3)

where \( \lambda \) is the wavelength of radar sensor, \( r_0 \) is the distance between radar sensor and ground objects, \( v \) is the moving speed of the platform along the azimuth direction.

The received echo signal is recorded as a two-dimensional data matrix in complex numbers with a real in-phase component and an imaginary quadrature component, which can be converted to amplitude and phase measures of the received echo. Unlike optical images, raw SAR images do not give any useful visible information before data compression processing. As shown in Figure 1.2, the basic SAR compression steps comprise of two separate matching filter processing along the range and the azimuth directions.

The first step is to compress the transmitted chirp signal along the range direction into a short pulse. Practically, range compression is implemented in the frequency domain through Fast Fourier Transformation (FFT) in order to reduce computation load. Each range line is multiplied by the complex conjugate of the spectrum of the transmitted chirp in the frequency domain. The generated range-compressed image only reveals information about the relative distance between the radar sensor and any ground objects (Hassen, 2001). Azimuth compression follows the similar principle as the range compression by multiplication with the complex conjugate of the expected response signal from a point target on the ground. However, the azimuth reference function depends on the geometry and varies with radar-to-target distance, whereas the range reference function relies on the transmitted chirp waveform (Moreira et al., 2013). After completion of the range and azimuth compressions, image calibration and geocoding are implemented to form an
intensity image in which the pixel values denote the reflectivity of the corresponding point on the ground.

Figure 1.2 Azimuth and range compressions of a raw SAR image (after Moreira et al., 2013). The symbol “*” denotes convolution operation.

1.1.2 InSAR

Interferometric Synthetic Aperture Radar (InSAR) utilizes the phase information of two SAR acquisitions to measure the position change of the ground objects between the two acquisitions. The differential phase $\phi(i,j)$ at pixel location $(i,j)$ on the InSAR interferogram can be expressed as

$$
\phi(i,j) = -\frac{4\pi}{\lambda} [r_1(i,j) - r_2(i,j)]
$$

(1.4)
where \( r_1 \) and \( r_2 \) are the slant ranges between the same ground object to the radar sensor in the first and the second acquisition, respectively. The differential phase \( \phi \) comprises multiple contributions:

\[
\phi = W\{\phi_{\text{defo}} + \phi_{\text{topo}} + \phi_{\text{atm}} + \phi_{\text{orb}} + \phi_{\text{noise}}\}
\]

where \( \phi_{\text{defo}} \), \( \phi_{\text{topo}} \), \( \phi_{\text{atm}} \), \( \phi_{\text{orb}} \), and \( \phi_{\text{noise}} \) denote phases contributed by ground deformation, topographic elevation change, atmospheric variation, orbital difference, signal noise between the first and the second acquisition, and \( W\{\cdot\} \) is the wrapping operator that drops whole phase cycles \((2\pi)\), as only a fractional part of a cycle can be measured with SAR interferometry. In order to measure ground deformation \( \phi_{\text{defo}} \) from a SAR interferogram, other contributing terms must be removed or suppressed.

The phase difference \( \Delta\phi \) of two neighboring pixels on the SAR interferogram can be decomposed into the slant range difference \( s \) and the height difference \( h \) in the plane normal to the flight direction (Figure 1.3).

\[
\Delta\phi = -\frac{4\pi}{\lambda}\left(\frac{B_\perp s}{R\tan\theta} + \frac{B_\perp h}{R\tan\theta}\right)
\]

where \( B_\perp \) is the perpendicular baseline of the radar sensors’ positions at the two different acquisition time, \( R \) is the slant range between the radar sensor to the ground objects (here \( R = r_1 \) in Figure 1.3), and \( \theta \) is the side-looking angle of the radar sensor. The phase contribution from slant-range difference \( \Delta\phi_s \) can be removed using SAR system parameters \((s, R, \theta, \text{and} \ B_\perp)\):

\[
\Delta\phi_s = -\frac{4\pi}{\lambda}\frac{B_\perp s}{R\tan\theta}
\]

After removing the contribution from slant-range difference from equation 1.6, the remaining part is the phase contributed by topography \( \Delta\phi_{\text{topo}} \):
\[ \Delta \phi_{\text{topo}} = \Delta \phi - \Delta \phi_s = -\frac{4\pi}{\lambda} \frac{B_1 h}{R \tan \theta} \] (1.8)

Therefore, if no deformation occurred between the two acquisitions, equation 1.8 can be used to estimated topographic elevation on the earth surface. On the other hand, the topographic phase contributions can be removed with given DEMs.

The orbit-related artifacts \( \phi_{\text{orb}} \) can be simulated with the quadratic fitting (Fattahi and Amelung, 2014). The stratified atmospheric artifacts related to regional topography can be reduced by using a linear fitting, and other large-spatial-scale phase artifacts can be suppressed based on polynomial fitting or weather models that estimate precipitable water content in the troposphere.
InSAR coherence is an indicator of the similarities of the backscattered signals in the two acquisitions and reflects noise level of the InSAR phase. A moving-window cross-correlation analysis is usually used to estimate the coherence $\gamma$ of two complex SAR images $u_1$ and $u_2$ (Lu and Dzurisin, 2014; Lopes et al., 1992; Bamler and Just, 1993; Tough et al., 1994):

$$\gamma = \frac{E[u_1u_2^*]}{\sqrt{E[|u_1|^2]E[|u_2|^2]}}$$

(1.9)

Where $E[\cdot]$ denotes the expectation value that in practice will be approximated with a sampled average (Lopes et al., 1992; Just and Bamler, 1994; Anxi et al., 2014).

The above-described contents introduce the steps to generate one single interferogram from two SAR acquisitions. With multiple InSAR pairs available, the multi-temporal processing such as Permanent scatterer InSAR (PS-InSAR; Ferretti et al., 2001; Hooper, 2004) and small baseline subset (SBAS) InSAR (Berardino et al., 2002) can be implemented to retrieve deformation time series of ground objects.

1.2 Landslide Processes

In a full life cycle from early initiation to final deposition, landslides undergo one or multiple rounds of acceleration-deceleration movements. Catastrophic landslides usually experience abrupt failure followed by rapid downslope motion and start to slow down upon hitting flat or uphill grounds to reach final deposition (Highland and Bobrowsky, 2008). The entire process may only include one acceleration-deceleration cycle. In contrast, many reactivated clayey landslides undergo multiple acceleration-deceleration cycles characterized by slow motions which are often associated with seasonal precipitation (e.g., Keefer and Johnson, 1983). Nonetheless, both types
of post-failure movements follow Newton’s Law of Motion and the landslide initiation follows the Mohr-Coulomb shearing failure criteria:

$$\tau_{lim} = c + \sigma_e \tan \varphi$$  \hspace{1cm} (1.10)

where $\tau_{lim}$ is the limit shear strength, $c$ the effective cohesion, $\varphi$ the internal friction angle. The effective stress $\sigma_e$ is defined as (Lu et al., 2010)

$$\sigma_e = \sigma - u_a - [\theta_e (u_a - u_w)]$$  \hspace{1cm} (1.11)

where $\sigma$ is the normal stress component of gravity, $u_a$ the atmospheric pressure, $u_w$ the water pressure, and $\theta_e$ the effective saturation. Landslide instigates when the basal shear stress exceeds the material’s shear strength.

Once slope failures instigate, their subsequent post-failure behaviors may vary depending on basal topography, soil contraction/dilation, and external stress inputs. Contractive landslide materials on a steep slope tend to evolve into rapid debris flows by constantly gaining movement momentum, whereas dilative materials on a gentle slope may quickly slow down if without extra pushing stress such as rainfall. Fundamentally, landslide motions obey the principles of classical mechanics such as conservation of mass and conservation of momentum.

Hillslope failures are the final result of multiple contributing factors that function in variable time scales (Figure 1.4). Physical and chemical weathering is one of the primary factors that consistently weaken the landslide material over a geological time scale and progressively render hillslopes susceptible to failure. Earthquake shaking and rainfall are the two common factors that trigger slope failure in a short timescale by increasing effective shear stress. Other factors such as
stream erosion of the landslide toe and extra loading at the landslide head could also alter the stress regime and shift a stable hillslope into failure.

Capturing landslide kinematics using remote sensing helps to understand landslide behaviors under variable internal and external forcing (e.g., Hu et al., 2020) and to generate insights for forecasting potential future hazards of unstable hillslopes (e.g., Intrieri et al., 2018).

Figure 1.4 Stress regime evolution of a landslide over time. Landslide failure occurs when the shear stress exceeds the shear strength. \( t_1, t_2, t_3 \) denote the time.

1.3 Chapter Summarizes and Contributions

Chapters 2, 3, 4, 5, and 6 are written for peer-reviewed publication. Chapters 2 – 4 includes my research published in three journals: Remote Sensing (Xu et al., 2019), Landslides (Xu et al., 2020a), and Journal of Geophysical Research: Earth Surface (Xu et al., 2020b). Chapter 5 is submitted to a peer-reviewed journal Landslides (Xu et al., 2021a). Chapter 6 is part of a manuscript which is in preparation for submission to a peer-reviewed journal (Xu et al., 2021b). Chapter 7 highlights the findings of the dissertation and discusses topics of future work.
**Chapter 2:** This chapter presents a case study of the constantly slow-moving Lawson Creek landslide in southwestern Oregon, where InSAR, space-sensed soil moisture, and thickness inversion and hydromechanical models were used to characterize the landslide motion dynamics (Xu et al., 2019). Typical of most slow-moving landslides, precipitation infiltrates into basal shearing zones and triggers seasonal landslide motion by increasing pore-pressure and reducing shear resistance. This process is jointly controlled by basal depth, rainfall intensity, soil moisture, and hydraulic conductivity/diffusivity. Using interferometric synthetic aperture radar (InSAR), we detected and mapped a typical slow-moving landslide in the southwestern Oregon – the Lawson Creek landslide. Its basal depths are estimated using InSAR derived pseudo-3D surface velocity fields based on the mass conservation approach by assuming a power-law rheology. The estimated maximum thickness over the central region of the landslide is 6.9 ± 2.6 m, and this result is further confirmed by an independent limit equilibrium analysis that solely relies on soil mechanical properties. By incorporating satellites-captured time lags of 27 – 49 days between the onset of wet seasons and the initiation of landslide motions, we estimated the averaged characteristic hydraulic conductivity and diffusivity of the landslide material as $1.2 \times 10^{-5}$ m/s and $1.9 \times 10^{-4}$ m$^2$/s, respectively. This investigation laid out a framework for using InSAR and satellite-sensed soil moisture to infer landslide basal geometry and estimate corresponding hydraulic parameters.

**Chapter 3:** This chapter provides a case study of the alternatingly slow and rapidly moving Hooskanaden landslide in the southern Oregon coast, where multi-sensor remote sensing (LiDAR, InSAR, and optical images) and one-dimensional rainfall infiltration and pore pressure diffusion models were integrated to obtain 3D landslide surface motions, and to derive physics-based rainfall thresholds for the observed contrasting landslide motion behaviors (Xu et al., 2020b). The Hooskanaden landslide is a large (~600 m wide × 1,300 m long), deep (~30 – 45 m) slide located
in southwestern Oregon. Since 1958, it has had five moderate/major movements that
catastrophically damaged the intersecting U.S. Highway 101, along with persistent slow wet-
season movements and a long-term accelerating trend due to coastal erosion. Multiple remote
sensing approaches, borehole measurements, and hydrological observations have been integrated
to interpret the motion behaviors of the slide. Pixel offset tracking of both Sentinel-1 and Sentinel-
2 images was carried out to reconstruct the 3D displacement field of the 2019 major event, and the
results agree well with field measurements. A 12-year displacement history of the landslide from
2007 to 2019 has been retrieved by incorporating offsets from LiDAR DEM gradients and InSAR
processing of ALOS and Sentinel-1 images. Comparisons with daily/hourly ground precipitation
reveal that the motion dynamics are predominantly controlled by intensity and temporal pattern of
rainfall. A new empirical threefold rainfall threshold was therefore proposed to forecast the dates
for the moderate/major movements. This threshold relies upon antecedent water-year and previous
3-day and daily precipitation, and was able to represent observed movement periods well.
Adaptation of our threshold methodology could prove useful for other large, deep landslides for
which temporal forecasting has long been generally intractable. The averaged characteristic
hydraulic conductivity and diffusivity were estimated as $6.6 \times 10^{-6}$ m/s and $6.6 \times 10^{-4}$ m$^2$/s,
respectively, based on the time lags between rainfall pulses and slide accelerations. The ability of
the new rainfall threshold was explained by hydrologic modeling.

Chapter 4: This chapter shows a case study of a potentially catastrophic landslide – the Gold
Basin landslide complex in northern Washington, where multisource remote sensing approaches
(LiDAR DEM differencing, sub-pixel offset tracking, and InSAR) and the D-claw runout model
(Iverson and George, 2014; George and Iverson, 2014) were employed to monitor recent landslide
activities and estimate potential inundation zones upon a hypothetical catastrophic failure (Xu et
The landslide complex at Gold Basin, Washington, has been drawing considerable attention after a catastrophic runout of the nearby landslide at Oso, Washington, in 2014. To evaluate potential threats of the Gold Basin landslide to the campground down the slope, remote sensing and numerical modeling were integrated to monitor recent landslide activity and simulate hypothetical runout scenarios. Bare-earth LiDAR DEM differencing, InSAR, and offset tracking of SAR images reveal that localized collapses at the headscarp have been the primary type of landslide activity at Gold Basin from 2005 to 2019, and currently no signs indicative of movement of a large, centralized block or a deep-seated main body were detected. The maximum horizontal deformation rate is 5 m/year occurring primarily from headscarp recession of the middle lobe, and the annual landsliding volume of the whole landslide complex averages $1.03 \times 10^5$ m$^3$. From three-dimensional limit equilibrium analysis of generalized terrace structures, the maximum landslide volume is estimated as $2.0 \times 10^6$ m$^3$. Simulations of hypothetical runout scenarios were carried out using the depth-averaged two-phase model D-claw with above-obtained landslide geometry constraints. The simulation results demonstrate that debris flows with volume less than $10^5$ m$^3$ only pose limited threats to the campground, while volumes over $10^6$ m$^3$ could cause severe damages. Consequently, the estimated maximum landslide volume of $2.0 \times 10^6$ m$^3$ suggests a potential risk to the campground nearby. In addition, our simulations of a river at the landslide toe demonstrate that interactions between debris flow and waterbodies could impact the flow kinematics considerably depending on flow speed, waterbody volume, and topographical settings. This study provided a useful methodology for evaluating other similar landslides globally for hazards prevention and mitigation.

**Chapter 5:** This chapter is focused on discovering slow-moving landslides near the United States west coast and investigating their geologic controls from bedrock lithology and land uplift (Xu et
Slow-moving landslides, often with nearly imperceptible creeping motion, are an important landscape shaper and a dangerous natural hazard across the globe, yet their spatial distribution and geologic controls are still poorly known owing to a paucity of detailed, large-scale observations. Here we use interferometry of L-band satellite radar images to reveal 630 spatially large ($4 \times 10^4 - 13 \times 10^6 \text{ m}^2$) and presently active (2007–2019) slow-moving landslides hidden near the populous United States west coast (only 4.6% of these slides were previously known) and provide evidence for their fundamental controls by bedrock lithology and vertical land motion. We found that slow-moving landslides are generally larger and more spatially frequent in homogeneous bedrock with low rock strength, and they are preferentially located on hillslopes with geologically recent uplift. Notably, landslide size and spatial density in the relatively weak metamorphic rocks and mélange (due to pervasive tectonically sheared discontinuities, foliation, and abundant clay minerals) were two times larger than those in sedimentary and igneous rocks, and the hillslopes with landslides were found to be uplifting approximately three times faster than the average for the whole region. These analysis suggests that occurrence and character of slow-moving landslides may be anticipated from vertical land motion rates and bedrock lithology. Hence, this study provides understanding critical for reducing landslide hazards and quantifying landslide impacts on landscape change.

**Chapter 6:** This chapter presents a case study of irrigation-triggered landslides in a Washington dessert and their motion kinematics regulated by basal topography (Xu and Lu, 2021). Landslides are usually a natural geomorphic process, while anthropogenic activities such as agricultural irrigation in semiarid regions could produce widespread landslides which damage infrastructures, endanger safety of local residents, and cause considerable ecological prices. Here we utilized both satellite optical and radar images acquired between 1996 and 2020 to identify 13 slow landslide
complexes and 12 catastrophic landslides which were triggered by excessive irrigation water in a Washington desert near Hanford. InSAR time-series displacements of seven slow landslides reveal that riverside landslides were strongly modulated by water level of the Columbia River where the landslide toes reside, yet their seasonal instigation and cessation were not controlled by a single fixed groundwater level threshold. Our numerical modeling shows that such phenomenon could be explained by the forced water circulation on an irregular slip surface where accelerated landslide velocity increases the upslope resistance and consequently contributes to slowing down the landslide body. By integrating satellite observations of two highly similar slow landslides, we characterized the life cycle of slow landslides in the region as a rapid acceleration to the peak rate within 3 years followed by a slow deceleration in exponentially decreasing rates for about 40 years. In addition, comparison of longitudinal topographical profiles of five typical slow landslides and five catastrophic landslides demonstrates that steep basal surface and runout path are more likely to produce catastrophic landslides with a long runout due to rapid kinetic energy gain during the movement. Basal topography of slow landslides at particularly the toe section exerts critical impacts on their motion evolution. Our investigation provides understandings critical for characterizing motion dynamics of both slow and catastrophic landslides with irregular basal surfaces, and therefore is widely applicable to many landslides globally for hazard reduction.

**Chapter 7:** This chapter provides conclusions and discusses future work.
REFERENCES


CHAPTER 2

CHARACTERIZING SEASONAL MOTION OF THE SLOW-MOVING LAWSON CREEK LANDSLIDE, OREGON


2.1 Introduction

Mountainous topography and intense precipitation during winter seasons frequently give rise to slope failures in the northwestern US, even devastating ones such as the 2014 Oso landslide in Washington State (Wartman et al., 2016; Iverson et al., 2015). Understanding the process of rainfall infiltration triggering landslides is the key to mitigating potential hazards. For landslide studies, Interferometric Synthetic Aperture Radar (InSAR), a remote sensing technique with wide spatial coverage and centimeter/millimeter-level accuracy, is one of the most powerful and widely used tools and has been successfully applied to numerous landslides all over the world (e.g., Hilley et al., 2004; Tong and Schmidt, 2016; Liu et al., 2013; Jebur et al., 2014; Schlögel et al., 2015). More importantly, InSAR-derived surface velocity vectors are able to infer basal geometry and sliding volume of landslides for further modeling by simplifying landslide movement to classical physical models: i) a dislocation model (Nikolaeva et al., 2014) which idealizes the slide as motion
on a rectangular planar basal surface assuming elastic sliding materials; ii) a cross-section method (Aryal et al., 2015) which regards a landslide as a set of independent cross-sections and ignores the connection between adjacent blocks; iii) a mass conservation approach which assumes that sliding materials have homogeneous rheological properties and are incompressible (Booth et al., 2013). These simplified models vary in accuracy depending on both the particular landslide behavior and the InSAR derived displacement vectors.

Elevated basal pore-fluid pressure through rainwater infiltration is considered the primary trigger for seasonal landslides by weakening the soil’s resistive strength (Iverson et al., 1987; Reid, 1994; Baum and Reid, 1995; Bogaard and Greco, 2016). Pore pressure transmission in saturated soils approximates a diffusive process depending on hydraulic diffusivity (Berti and Simoni, 2010; Iverson, 2000), yet basal pore-water’s pressure response to precipitation in post-summer unsaturated soils is strongly affected by water infiltration rates (advective flow) that rely on hydraulic conductivity. Therefore, landslide geometry, soil properties and the initial soil moisture jointly control the response time of slope failure to seasonal precipitation. Nevertheless, the characteristic hydraulic parameters can be quantified if the failure depth and the water infiltration time are known.

Using SAR imagery from three spaceborne radar systems including Advanced Land Observing Satellite (ALOS) Phased Array type L-band synthetic aperture radar (PALSAR), ALOS-2 PALSAR-2 and Sentinel-1A/B, we detected a slow-moving landslide in southern Oregon and mapped its time-series deformation from 2007 to 2011 and 2016 to 2018. The basal depth and volume of the landslide are estimated using InSAR-derived surface velocity fields and the mass conservation approach (Rutt et al., 2009; Booth et al., 2013). The limit equilibrium analysis is implemented to validate the estimated failure depth. By incorporating the failure depth and derived
time lags between the arrival of wet seasons and the initiation of seasonally landslide motions using InSAR and satellite soil moisture from SMAP (Soil Moisture Active and Passive), we estimated the lower and upper bounds of characteristic hydraulic conductivity and diffusivity of the landslide material.

2.2 Landslide Location and Geological Settings

The Lawson Creek landslide is a slow-moving translational landslide located in southwestern Oregon with a ~1.5 km long and ~500 m wide sliding body (Figure 2.1). The slope faces northwest with an aspect of ~294° clockwise from north, and the average slope is ~10°. There are no obvious scarps near the landslide’s head as it has been seated on deposits of a previous landslide, and the currently active slide is only a small part of the ancient landslide deposits mapped in the Statewide Landslide Information Database for Oregon (SLIDO (Burns, 2014); Figure 2.2). The bedrock of the slide is composed of marine sedimentary rocks with sandstone/mudstone lithologies at the upper section, metamorphic rocks with majorly serpentine at the middle section, and metamorphic rocks with phyllite/schist lithologies at the lower section (Figure 2.3). The toe of the landslide enters Lawson Creek at an elevation of 358 m, and its crown stands at 610 m. The primary precipitation in this region falls between mid-October and mid-April, while little rainfall comes in other months. Moderately dense vegetation covers the landslide site.

2.3 Materials and Methods

2.3.1 SAR Interferometry for Landslide Time-series Mapping

SAR imagery from the ALOS ascending track T224, ALOS-2 ascending tracks T68 and T69 and descending track T171, and the Sentinel-1A/B ascending track T35 were used to map displacements of the Lawson Creek landslide (Figure 2.1; Table 2.1). The 1-arcsec Shuttle Radar
Topography Mission (SRTM) Digital Elevation Model (DEM) obtained from U.S. Geological Survey (USGS) was used in the InSAR processing. Baseline error and stratified atmospheric artifacts were removed before phase unwrapping. The GAMMA software (Werner et al., 2002) was used for interferogram generation, phase unwrapping, and removal of stratified atmospheric artifacts. Unwrapping errors in a few interferograms caused by high-gradient sliding movements were corrected by separating the original wrapped phase into an estimated high-gradient displacement component and a residual-phase component (within $2\pi$ variation). We unwrapped only the residual-phase component and added it back to the estimated high-gradient component to obtain the final unwrapped phase. The high-gradient displacement component was estimated based on interferograms with short temporal baselines and very good coherences. Manual check is required to confirm the corrections. The corrected interferograms have been listed in the supplementary table in Xu et al. 2019.

Figure 2.1 Geographical location of the Lawson Creek landslide and SAR data used in this study. The landslide (marked with a red star) is located in Curry county, southwestern Oregon, about 27
km inland from the Pacific Ocean. The location of Oregon is outlined in blue in both scaled-down (top-left corner) and scaled-up (bottom-left corner) maps. The red box at the bottom-left-corner figure represents geographical location of the whole Figure 1, and the magenta point represents a ground reference site for soil-moisture measurements (Miller Woods station). The red diamond near the landslide site represents a precipitation collection site (Agness station). SAR imagery covering the landslide is denoted with colored rectangular boxes annotated by track names in corresponding colors. The background shaded relief map was accessed from U.S. Geological Survey.

Figure 2.2 Historic landslide deposits. (a) The red pattern-filled polygon denotes an ancient (>150 years) deep-seated (> 4.5 m) landslide deposit. The yellow polygon outlines the actively deforming region captured by InSAR from 2007 to 2018. (b) Landslides view from optical remote sensing. The background RGB image was obtained in June 2019.

SAR acquisitions from the ALOS T224 and the Sentinel-1A/B T35 were used to generate time-series displacement maps of the landslide, as they provide temporally dense and coherent observations that allow construction of a fully connected network for time-series inversions (Figure 2.4). To verify the C-band sentinel-1A/B time series measurements, we also produced results using the L-band ALOS-2 T68 images spanning the same time period (Figure 2.6d). The full set of interferograms that contain moderate or better coherence (over 0.2 for C-band data and over 0.4 for L-band data) were used for time-series maps: 36 interferograms from the ALOS T224,
5 from the ALOS-2 T68, and 73 from the Sentinel-1A/B T35 (Figure 2.4) were selected and processed based on the coherence-weighted small baseline subset (SBAS) method (Tong and Schmidt, 2016; Berardino et al., 2002).

Figure 2.3 Geological settings of the landslide. The landslide is outlined with the black polygon. Oregon geological maps are accessed from: https://www.oregongeology.org/geologicmap/

<table>
<thead>
<tr>
<th>Radar satellites</th>
<th>Tracks</th>
<th>Flying directions</th>
<th>Time span</th>
<th>Usages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sentinel-1A/B</td>
<td>T35</td>
<td>Ascending</td>
<td>2016 - 2018</td>
<td>Time-series mapping / surface velocity inversion</td>
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<tr>
<td>ALOS</td>
<td>T224</td>
<td>Ascending</td>
<td>2007 - 2011</td>
<td>Time-series mapping</td>
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<td></td>
<td>T68</td>
<td>Ascending</td>
<td>2015 - 2018</td>
<td>Time-series mapping / surface velocity inversion</td>
</tr>
<tr>
<td>ALOS-2</td>
<td>T69</td>
<td>Ascending</td>
<td>2014 - 2018</td>
<td>Surface velocity inversion</td>
</tr>
<tr>
<td></td>
<td>T171</td>
<td>Descending</td>
<td>2015 - 2018</td>
<td>Surface velocity inversion</td>
</tr>
</tbody>
</table>
Annual deformation rates in LOS (Line of Sight) directions from the three ALOS-2 tracks and the Sentinel-1A/B track T35 were generated with the stacking method for deriving 3D surface velocity fields of the landslide (Table 2.2), as these data overlap almost the same time period and provide varied LOS observations.

![Spatial and temporal baselines of used InSAR pairs from multiple tracks.](image)

Figure 2.4 Spatial and temporal baselines of used InSAR pairs from multiple tracks. (a) ALOS track T224, (b) Sentinel-1A/B track T35, (c) ALOS-2 track T68, (d) ALOS-2 track T69, and (e) ALOS-2 track T171.

2.3.2. Thickness Inversion

Constraining the basal depth of a landslide is critical for characterizing movement and estimating the sliding volume. The landslide thickness inversion is achieved by using the surface velocity field obtained from InSAR measurements and applying the principle of mass conservation.
with assumptions about the variation of the landslide velocity field below the surface [Delbridge et al., 2016]:

\[ w = \nabla \cdot (f \mathbf{u}_{surf} h) + \mathbf{u}_{surf} \cdot \nabla h \] (2.1)

where \( w \) is the vertical component (outwardly perpendicular to the basal plane as positive) of surface velocity vectors, \( \mathbf{u}_{surf} \) the surface horizontal components, and \( h \) the landslide thickness. 

\( f = (3 - Y/P)/3 \) is a constant between 0 and 1 depending on landslide rheology, where \( Y \) and \( P \) is thickness of the yield zone and the overlaying plug region respectively (Hu et al., 2018). \( f = 1/2 \) is consistent with a linear vertical velocity profile, \( f = 2/3 \) with Newtonian viscous flow, \( 2/3 < f < 1 \) with plug flow, and \( f = 1 \) with a rigid sliding block (Booth et al., 2013). Equation (2.1) can be converted to matrix form with finite difference approximations:

\[ w_{i,j} = u_{i,j} \frac{f h_{i+1,j} - f h_{i-1,j}}{\Delta x} + v_{i,j} \frac{f h_{i,j+1} - f h_{i,j-1}}{\Delta y} + f h_{i,j} \left( \frac{u_{i+1,j} - u_{i-1,j}}{2\Delta x} + \frac{v_{i,j+1} - v_{i,j-1}}{2\Delta y} \right) \] (2.2)

where \( \Delta t \) is the time increment, \( u \) and \( v \) are surface velocity vectors (Figure 2.5), \( \Delta x \) and \( \Delta y \) are grid sizes in \( u \) and \( v \) direction, respectively, and subscripted \( i \) and \( j \) are indices in \( u \) and \( v \).

The surface velocity field can be derived from LOS observations of InSAR, yet reconstructing 3D surface velocity vectors requires at least three independent measurements. In this study, assuming that the sliding body only moves along the downslope direction on the slip plane (i.e., \( u = 0 \)) (Hu et al., 2018; Cascini et al., 2010), we construct a pseudo three-dimensional velocity field using the LOS velocities from the ALOS-2 ascending tracks T68 and T69, ALOS-2 descending track T171, and Sentinel-1A/B ascending track T35. Defining \( \theta \) as the radar look angle, \( \phi \) the satellite heading angle, \( \alpha \) the slope angle, \( \beta \) the slope aspect, and \( \mathbf{w} \) a vector perpendicular to the slope surface defined by vectors \( u \) and \( v \), the surface velocity field \( \mathbf{V} = [u, v, w]^T \) of each point is related to LOS measurements as:
\[
\begin{bmatrix}
\mathbf{l} \\
c_v
\end{bmatrix}\cdot s \cdot \mathbf{v} = \begin{bmatrix}
\mathbf{LOS} \\
0
\end{bmatrix}
\] (2.3)

where \(\mathbf{l} = [l_1, l_2, l_3, \cdots, l_k]^T\) is the radar look vector of \(k\) independent LOS observations, and \(l_1 = l_2 = \cdots = l_k = [-\sin \theta \sin \phi \quad \sin \theta \cos \phi \quad -\cos \phi]^T, c_v = [-\sin \beta \quad \cos \beta \quad 0]\) is the constrain condition, \(\mathbf{LOS}\) is the \(k\) independent InSAR measurements, and \(s\) is a coordinate transformation matrix:

\[
s = \begin{bmatrix}
\cos \beta \cos \alpha & \sin \beta \cos \alpha & -\sin \alpha \\
-\sin \beta & \cos \beta & 0 \\
\cos \beta \sin \alpha & \sin \beta \sin \alpha & \cos \alpha
\end{bmatrix}
\] (2.4)

We solve Equation (2.3) to obtain the pseudo 3D surface velocity vectors with the least squares approach, and solve Equation (2.2) for \(h\) by using a nonnegative least squares method (Booth et al., 2013; Grant et al., 2008) and setting boundary conditions that the landslide’s thicknesses range from 0 to 200 m and non-landslide regions have a thickness of zero.

### 2.3.3 Time Lags

The initiation of seasonally active landslides typically begins days to several weeks after the wet season has arrived (Iverson, 2000). This time lag characterizes how fast the basal pore-air pressure responds to an intense rainfall event, and is jointly controlled by several factors, including the hydraulic conductivity/diffusivity of the landslide material, the landslide thickness, and the rainfall intensity (Hilley et al., 2004; Priest et al., 2011). Assuming the top soil layers have been unsaturated due to considerable water loss during dry summers, water infiltration (advective flow) in the top layers is controlled by unsaturated hydraulic conductivity \(K\), which is related to the corresponding saturated hydraulic conductivity \(K_{sat}\) as (Van Genuchten, 1980):
where $L = 0.5$ is an empirical parameter (Mualem, 1976), $n = 2$ is a measure of pore-size distribution (Lehmann and Or, 2012), and the effective saturation $S_e$ is calculated as

$$S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r}$$  \hspace{1cm} (2.6)$$

with the measured volumetric soil moisture $\theta$, the residual water content $\theta_r$, and the saturated water content $\theta_s$. Assuming that the landslide consists of multiple homogenous soil layers, the time lag $T_K$ for surface water vertically infiltrating to depth $H_s$ is given as:

$$T_K = \Sigma^m_i \left( \frac{R_i}{K_i} \right)$$  \hspace{1cm} (2.7)$$

where $R_i$ and $K_i$ are the thickness and the hydraulic conductivity of the $i$-th layer, respectively, and the sliding body comprises $m$ soil layers. In saturated soils, an approximately diffusive process would dominate pore pressure responses. The time scale $T_D$ for pore pressure to diffuse vertically downward for depth $H$ is given by

$$T_D = \frac{H^2}{D_0}$$  \hspace{1cm} (2.8)$$

where $D_0$ is the hydraulic diffusivity. Advective water flow is slower than hydraulic diffusion, and they together control the response time of basal pore pressure to rainfall events if the groundwater level is between the basal plane and the ground surface.

2.3.4 Failure Depth using Limit Equilibrium Analysis
Slope stability evaluation is implemented based on the Mohr-Coulomb shearing failure criterion. Assuming that the hillslope consists of soil columns with cross-section area $A$ and height $H_s$, and cohesion $c$ exists among column cells (Lehmann and Or, 2012; Figure 2.5). Due to the self-gravity, a vertical force $F_g$ is posed on the base of each soil column:

$$F_g = Mg = AH_s[\theta \rho_w + (1 - \phi) \rho_s]g$$  
(2.9)

where $M$ is the mass of each soil column, $g$ the gravity of earth, $\theta$ the volumetric water content, $\rho_w$ the density of water, $\rho_s$ the bulk density of soil, and $\phi$ the porosity of soil.

![Figure 2.5 Sketch of a hillslope consisting of soil column cells.](image)

Relating $F_g$ to the cross-section area of soil columns along the slope $A / \cos \beta$, $F_g$ can be decomposed into normal stress $\sigma_N$ and downslope driving component $\sigma_d$:
\[ \sigma_N = \frac{F_N}{A/\cos \alpha} = \frac{F_G \cos \alpha}{A/\cos \alpha} = H_s[\theta \rho_w + (1 - n)\rho_s]g \cos^2 \alpha \]  \hspace{1cm} (2.10)

\[ \sigma_d = \frac{F_d}{A/\cos \alpha} = \frac{F_G \sin \alpha}{A/\cos \alpha} = H_s[\theta \rho_w + (1 - \phi)\rho_s]g \sin \alpha \cos \alpha \]  \hspace{1cm} (2.11)

where \( F_N \) is the counteracting normal force, \( F_d \) the downslope driving force, and \( \alpha \) the slope angle.

When perched water table reaches height \( H_w \), the resisting forces \( \tau_f \) are reduced as the pore pressure \( u_w \) weakens the effective stress \( \sigma_e \) by \( u_a = H_w \rho_w g \cos^2 \alpha \) under saturated conditions

\[ \tau_f = c + \sigma_e \tan \gamma = c + (\sigma_N - u_w) \tan \gamma \]
\[ = c + \{H_s[\theta \rho_w + (1 - \phi)\rho_s]g \cos^2 \alpha - H_w \rho_w g \cos^2 \alpha\} \tan \gamma \]  \hspace{1cm} (2.12)

Slope failures occur when driving force \( \sigma_d \) exceeds shearing resistance \( \tau_f \). We can obtain \( H_w \) as a function of \( H_s \) using the critical condition \( \sigma_d = \tau_f \)

\[ H_w = -\frac{\theta \rho_w + (1 - \phi)\rho_s \cos \alpha (\sin \alpha - \cos \alpha \tan \gamma)}{\rho_w g \cos^2 \alpha \tan \gamma} H_s + \frac{c}{\rho_w g \cos^2 \alpha \tan \gamma} \]  \hspace{1cm} (2.13)

\( H_w \) is a monotonically increasing function with respect to \( H_s \) if \( \alpha < \gamma \), as \( \frac{dH_w}{dH_s} > 0 \). Moreover, \( H_w \) must be less than or equal to \( H_s \) as overland flow would form when \( H_w > H_s \). Letting \( H_w = H_s \) yields the maximum height that a saturated soil column can maintain stable without shearing failure.

Under unsaturated soil conditions, soil strength is enhanced by \( \tau_h \) due to capillary pressure. The shearing resistance \( \tau_f \) can be expressed as

\[ \tau_f = c + \{H_s[\theta \rho_w + (1 - \phi)\rho_s]g \cos^2 \alpha - \tau_h\} \tan \gamma \]  \hspace{1cm} (2.14)

\[ \tau_h = \rho_w g |h_e S_e| = \rho_w g \left| h_b S_e^{1-\lambda} \right| \]  \hspace{1cm} (2.15)
with capillary pressure head $h_c$, air-entry value $h_p$, pore size distribution parameter $\lambda$ (Brooks and Corey, 1964), and effective saturation $S_e$.

2.4 Results

2.4.1 Time-series Displacements and Annual Deformation Rates

From 2007 to 2011, sliding movement of the Lawson Creek landslide is captured by SAR data from the ALOS ascending track T224. Figure 2.6a illustrates the time-series displacements of a typical fast-moving point P (Figure 2.7c) between 2007 and 2011. As the measurement of one single pixel can be easily contaminated by noises, we averaged the time-series deformation of the $3 \times 3$ array of adjacent points, which corresponds to a 60 m $\times$ 60 m area on the landslide surface. Similarly, we mapped time-series displacements of the same point from 2016 to 2018 using imagery from the Sentinel-1A/B ascending track T35, and from the ALOS-2 ascending track T68 for cross-validation. The results show that both the L-band ALOS-2 and the C-band Sentinel-1A/B datasets produce highly similar results (Figure 2.6d). The cumulative downslope displacement of the slide is about 1.5 m from 2007 to 2011 and around 0.8 m from 2016 to 2018, and movement patterns resemble an annual cycle throughout the years: the sliding motion starts to accelerate after wet seasons arrive and decelerates substantially when summer comes; while a considerable amount of deformation occurs from mid-November to mid-May, few displacements appear during the dry seasons from mid-May to mid-November (Figures 2.7d, 2.7e). Nevertheless, the landslide movement does not totally stop even during dry summers; similar behaviors have been observed at other landslides over the pacific northwest (Liu et al., 2013; Hu et al., 2018).
Figure 2.6 Relationships among landslide displacements, precipitation, and soil moisture. (a) Red points show the along-slope time-series displacement of a selected fast-deforming point P within the landslide area measured by ALOS track T224, and (b) gray points depict sliding acceleration (generated by differencing the time-series deformation) of the point P. The black line at the bottom, scaled by the right axis labeling, represents daily precipitation, which is collected at the Agness meteorological station, about 10 km northern from the landslide site. Time lag in each year is marked with green double-headed arrows. (c) In-situ soil moistures measured at the Miller Woods station at multiple depths. (d) Red circles and blue diamond represent time-series displacements measured from Sentinel-1 track T35 and ALOS-2 track T68, respectively. (e) The black line at the bottom, scaled by the right axis labeling, represents daily precipitation collected at the Agness
meteorological station. (f) In-situ soil moistures measured at the Miller Woods station at multiple depths, and SMAP soil moisture acquisitions (5 cm in depth) at the landslide site and the Miller Woods station.

The map of annual deformation rates show that the Lawson creek landslide had been moving downslope at almost the same rates (maximum 40 cm/yr) with spatially similar patterns during the two separate observation periods (Figures 2.7a, 2.7b, 2.8). It has been continuously creeping for the past decade. Specifically, the middle section presents much faster movements than both the landslide head and toe sections. It’s worth noting that, despite the spatial differences in movement rates, all the points on the landslide surface demonstrate a highly similar trend on the temporal axis. As shown in Figures 2.7d, 2.7e, the points in varied locations present apparent seasonal accelerations on the same dates near mid-November.

2.4.2 Time Retardation to Seasonal Precipitation

To further characterize the dynamic behavior of the landslide responding to season changes, we used the point P as a representative and employed the finite-difference formula to obtain the acceleration of its motions:

\[
a_j = \frac{2(v^+ - v^-)}{t_{j+1} - t_{j-1}} \quad (2.16a)
\]

\[
v^+ = \frac{d_{j+1} - d_j}{t_{j+1} - t_j} \quad (2.16b)
\]

\[
v^- = \frac{d_j - d_{j-1}}{t_j - t_{j-1}} \quad (2.16c)
\]

where \(d_j \) and \(a_j \) represent, respectively, the cumulative displacement and the acceleration of the point P at time \(t_j\). \(v^- \) and \(v^+ \) represent the deformation rate. Seasonal landslide movements start
when $a_j > 0$. For the temporally dense Sentinel-1A/B measurements, recognizing onset dates of the seasonal movements is easy and straightforward through visual interpretation (Figure 2.6d), while for the temporally sparse ALOS T224 results, the finite-difference method is applied to determine the dates when seasonal sliding commence every year. Note that though there are several visible motion accelerations from the Sentinel-1A/B displacement time series, here we only focus on the most noticeable seasonal acceleration, namely, the first wet-season acceleration in around mid-November after a continuous summer deceleration.

Figure 2.7 Average along-slope displacement rates and spatial deformation patterns. Annual along-slope movement rates (a) during the period 2007 - 2011 measured from ALOS T224, (b) during 2015 - 2018 from ALOS-2 T68, and (c) during 2016 - 2018 from Sentinel-1 T35. The point P was selected for obtaining displacement time series, and the landslide moves downward towards the Lawson Creek. (d) Downslope cumulative displacements at varied locations M1 - M7 as shown in
(a), mapped with ALOS T224 imagery. (e) Downslope cumulative displacements at varied locations S1 - S7 as shown in (c), mapped with Sentinel-1A/B T35 images.

Figure 2.8 Annual along-slope deformation rates of the landslide obtained from ALOS2 tracks T69 during 2014 - 2018 and T171 during 2015 - 2018.

As shown in Figures 2.6b, 2.6e, although the wet-season arrives in mid-October regularly every year, the landslide does not begin to accelerate until several weeks later, generally in November. However, the exact time lags vary by years. The maximum values stand at 41 days, 41 days, 31 days, 26 days, 43 days, and 37 days for 2007, 2008, 2009, 2010, 2016 and 2017 respectively (Figures 2.6a, 2.6d) as the displacements might happen before the date when satellites capture the deformation. The 46-day revisit cycle of the ALOS acquisitions cannot provide an effective lower bound to the time lags for years 2007 - 2011, but the Sentinel-1A/B datasets with a minimum revisit period of six days successfully set the lower boundaries to 25 days for both years 2016 and 2017. As the landslide always accelerate after the arrival of wet-seasons (i.e., the
theoretical lower boundary is 0 day), the time lag ranges are 0 - 41 days, 0 - 41 days, 0 - 31 days, 0 - 26 days, 25 - 43 days, and 25 - 37 days for 2007, 2008, 2009, 2010, 2016 and 2017, respectively.

Every year, the soil moisture gradually falls to a year low in the summer and rises back to a high level as the wet-season approaches, and it maintains at this high level until the next summer comes (Figures 2.6c, 2.6f). Here we define the arrival date of wet seasons as when the 40-inch-depth (~ 1m) soil moisture at the Miller Woods station rises back to the same level of previous wet seasons, based on the assumption that a few slight early-autumn rainfall events can hardly mark the coming of wet seasons. In other words, the top 40-inch soils have been saturated.

There is a threefold justification for using soil moisture records from the Miller Woods station to represent for the landslide site. First, both sites undergo almost the same rainfall events as revealed by the SMAP soil moisture acquisitions at these two sites. As illustrated in Figure 2.6f, each rise of the fluctuated SMAP soil moisture can be interpreted as a distinguishable rainfall event, and SMAP data at both sites constantly exhibit such rise responses at the same dates. It’s worth noting that SMAP soil moisture data used here are captured by satellites independently. The values are the mean soil moisture of the top 5-centimeter soil layers, thus even slight rainfall events can lead to a rising fluctuation on the SMAP data. Second, both sites have similar soil layer compositions. Soils at the Miller woods station constitute layers of silt loam (0 - 16 cm depth), silty clay loam (16 - 33 cm), silty clay (33 - 63 cm), and gravely clay loam (63 - 152 cm). These soil layers have similar saturated hydraulic conductivity as that at the landslide site, which comprise of channery loam (0 - 30 cm), silt loam (30 - 56 cm), silty clay loam (56 - 74 cm), sandy loam (74 - 158 cm), and silty clay loam (158 - 183 cm) (from NCSS soil pedons (USDA, 2019) and local surveys (USDA, 1994)). Calculating infiltration time of the top 40-inch soils at both sites using Equation (2.7) and the mean hydraulic conductivities in Table 2.2 shows that the landslide
site would respond earlier than the Miller Woods by only 3.7 days. Third, soil moisture measured at the Miller Woods ground station matches well with the SMAP acquisitions in terms of rainfall responses though the absolute value varies; however, here only use the post-summer soil moisture rise rather than the absolute value to determine the dates.

Be aware that the SMAP data which represent average volumetric water contents of the top 5 cm soils are sensitive to any sight rainfall events, thus it is helpful to refer to the ground soil moisture at the 40-inch level to determine the dates according to our definition of the arrival of wet-seasons. An alternate empirical approach to is thresholding SMAP soil moisture by a 25% post-summer rise in that year, that is:

\[
\frac{\theta_{\text{thresh}} - \theta_{\text{min}}}{\theta_{\text{max}} - \theta_{\text{min}}} = 25\%
\]  

(2.17)

where \(\theta_{\text{max}}\) is the mean SMAP soil moisture during the wet season, \(\theta_{\text{min}}\) is the minimum SMAP soil moisture in the summer, and the arrival date of the wet season can be determined when the SMAP soil moisture rises back to \(\theta_{\text{thresh}}\) after a dry summer. For years 2016 and 2017, this method can produce the same results with an uncertainty of 2 days as using the ground-truth data.

Table 2.2 Saturated hydraulic conductivity for soils with low bulk density (data modified from Pachepsky and Park, 2015)

<table>
<thead>
<tr>
<th>Soil types</th>
<th>Data samples</th>
<th>Saturated hydraulic conductivity (m/s)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>25% quartiles</td>
<td>75% quartiles</td>
</tr>
<tr>
<td>Silt loam</td>
<td>58</td>
<td>3.6×10⁻⁶</td>
<td>2.8×10⁻⁵</td>
</tr>
<tr>
<td>Silty clay loam</td>
<td>18</td>
<td>1.2×10⁻⁶</td>
<td>1.6×10⁻⁵</td>
</tr>
<tr>
<td>Clay loam</td>
<td>17</td>
<td>4.2×10⁻⁶</td>
<td>1.6×10⁻⁵</td>
</tr>
<tr>
<td>Sandy loam</td>
<td>127</td>
<td>6.6×10⁻⁶</td>
<td>4.1×10⁻⁵</td>
</tr>
<tr>
<td>Silty clay*</td>
<td>-</td>
<td>4.2×10⁻⁷ - 1.4×10⁻⁶</td>
<td></td>
</tr>
</tbody>
</table>

* from National Soil Survey Handbook
Soil moisture records at the 40-inch depth of the Miller Woods station are unavailable from 2007 to 2011, therefore, the corresponding time lags are calculated by using soil moisture data at the 20-inch depth and adding on extra 5 days. The extra days are the observed time interval between successive soil moisture surges at the 20-inch and 40-inch depths right after the 2016 and 2017 summers, which represent the water infiltration time from the 20-inch to the 40-inch depths (Figure 2.6f).

2.4.2 Basal Depths and Volume Inferred from InSAR Observations

Annual displacement rates from two ALOS-2 ascending tracks T68 and T69, one descending track T171, and one Sentinel-1A/B ascending track T35 were employed to derive the 3D surface velocity fields of the landslide (Table 2.1; Figures 2.7, 2.8). As the observations from the three ascending tracks are not highly independent due to the similar LOS directions, we constrain the landslide motions to be along-slope to achieve stable inversions. The 3D surface velocity vectors are shown in Figures 2.9a, 2.9b.

Thickness inversion of surface points corresponding to every SAR-interferogram pixel (20 m × 20 m) were implemented by using the mass conservation approach and assuming a power-law rheology as Equation (2.1). Here the yield slope-perpendicular depth of each pixel has been converted to vertical thickness (Figures 2.9c, 2.9d). The thickness map shows that the sliding plane at the middle and upper sections are seated deepest, with a maximum mean basal depth of the central region as 5.8 m to 7.8 m (Figure 2.9c, 2.9d), assuming the landslide is characterized by a plug flow (2/3 < f < 1) as suggested by borehole measurements of multiple slow-moving landslides (Delbridge et al., 2016; Wasowski, 1998; Gould, 1960; Mainsant et al., 2012; Iverson, 1985; Van Asch et al., 2009; Malet and Maquaire, 2003). The basal plane has an upwardly concave shape that exhibits greater thickness in the central and gradually shallows to the margin area.
Figure 2.9 Surface velocity vector and thickness of the Lawson Creek landslide. (a) Surface velocity fields derived from InSAR LOS measurements and (b) a close-up of a typical fast-moving area. Thickness inversion results by setting (c) $f = 1$ and (d) $f = 2/3$ are shown with the same view angle as (a), and the non-landslide regions are manually masked out. The dashed blue square in (d) outlines the central region for calculating average depth.

The uncertainty caused by the $u = 0$ assumption can be largely quantified by defining $u = kv$, where $k$ is a constant mediating movement direction of the landslide. The constraint in Equation (2.3) is modified to $c_v = [k \cos \beta + \sin \beta \quad k \sin \beta - \cos \beta \quad 0]$, accordingly. Letting $k = \pm 0.2$ is equivalent to varying the landslide movement direction by $\pm 11^\circ$, which yields mean basal depths of the central region as 4.3 m to 6.9 m for $f = 1$, and 6.0 m to 9.5 m for $f = 2/3$. Taking into account the uncertainties, the estimated basal depth is expanded to $6.9 \pm 2.6$ m. Then, the estimated volume of the sliding body ranges from $2.9 \times 10^6$ to $5.9 \times 10^6$ m$^3$. 

40
2.4.3 Failure Depths from Limit Equilibrium Analysis

Basal geometry inversions illustrate that the landslide body is thick in the central section yet shallow in the head and toe sections. However, it remains unclear whether the initial rainfall-triggered motions start from the shallow sections or commence from the thickest central section. The limit equilibrium analysis was implemented to obtain the theoretical initial failure depth.

Slope failures may occur under both saturated and unsaturated soil conditions (Iverson, 2000; Lu et al., 2010). Mohr-Coulomb failure criterion is applicable to both cases for slope stability evaluation:

\[
\tau_f = c + \sigma_e \tan \gamma
\]

where \( \tau_f \) is the limit shear strength, \( c \) the effective cohesion, \( \gamma \) the internal friction angle, and \( \sigma_e \) the effective stress. Slopes failures occur when the driving force along the downslope direction \( \sigma_d \) exceeds the limit shear strength \( \tau_f \).

Limit equilibrium analysis of the landslide in an unsaturated condition (Equations (2.14), (2.15)) with parameters from (Rawls et al., 1982) demonstrates that shearing failures cannot occur unless the soil moisture is over 0.39, yet soil moisture records (SMAP satellite acquisitions and ground records) at both the Miller Woods station and the landslide site suggest that soil moisture at the landslide site is less than 0.35 during summers. Therefore, the seasonal movement of the landslide is initiated by shear failures of saturated soils.

Geotechnical logs of a nearby 69-feet deep water well (CURR 1286) suggests that the shearing zones of the Lawson Creek landslide is primarily composed of brown clay. As detailed soil mechanical parameters are unavailable, the uncertainties are accounted by expanding the parameter range to include soils ranging from silty clay to clay based on global laboratory and field tests: internal friction angle \( \gamma = 29 \pm 7^\circ \) and cohesion \( c = 12 \pm 3 \) kpa (USDA, 2019; Hall...
et al., 1994; Alto, 1981; MnDOT, 2019; Ouyang and Mayne, 2017; Jeong et al., 2017; Thunder 2016; Msilimba, 2007). The slope angles of the landslide on the basal surface is less than 15°. Using the measured volumetric water content $\theta = 0.41$ during wet-seasons and soil porosity $\phi = 0.47$ (Rawls, 1982), we can obtain the critical basal depth $H_c = 7.6 \pm 1.6$ m where shearing failures would commence using Equation (2.13), based on the Mohr-Coulomb failure criterion. This result agrees well with the InSAR-inferred basal depth of $6.9 \pm 2.6$ m, which confirms the correctness of the inverted thickness based on mass conservation and surface velocities. Meanwhile, it indicates that the deep-seated central region is close to stress equilibrium when the soils are fully saturated, and a slight pore pressure rise would trigger the motion acceleration. Note that the landslide had motions even during the dry summer, while intermittent post-summer rainfall did not cause simultaneous motion acceleration (Figure 2.6), implying that the seasonal acceleration is caused by pore pressure rise rather than loading from rainwater.

2.4.4 Potential for Estimating Hydraulic Parameters

Taking into account the uncertainties caused by SMAP data ($\pm 2$ days) and soil compositions (-3.7 days), the time lags of 25 - 43 days observed from satellite remote sensing is expanded to 26.7 - 48.7 days. With the known time lags and InSAR-inferred basal depth of $6.9 \pm 2.6$ m, the rainwater infiltration rate can be quantified. Here the time lags stand for water infiltration from the 40-inch depth to the initial failure depth.

As groundwater level decreases during the dry summers, initial wet-season precipitation must saturate the top soil layers via advective flow first before the hydraulic diffusion process takes control of the basal pore-pressure response. The averaged hydraulic conductivity of soil layers above the groundwater table and the averaged hydraulic diffusivity below the table can both be effectively quantified with given groundwater levels. However, such data is not available for this
case study and therefore only the upper and lower bound of the hydraulic parameters can be estimated.

Assuming the groundwater table is below the basal plane leads to an estimate of characteristic hydraulic conductivity $K_s$ (upper bound) as $2.4 \times 10^{-5}$ m/s using Equations (2.5), (2.7), whereas assuming fully saturated soils yields an estimated characteristic hydraulic diffusivity $D_0$ (lower bound) as $2.6 \times 10^{-6}$ m$^2$/s using Equation (2.8). Note that here characteristic hydraulic conductivity/diffusivity means to treat a soil column that constitutes multiple heterogeneous layers as one single soil sample.

Employing empirical relationship between $K_s$ and $D_0$ of the same soils can provide the other bounds for the estimations. The vertical soil profile of the Lawson Creek landslide comprises boulders and clay brown, clay brown, and clay blue layers from the nearby water well log (CURR 1286), we interpret the characteristic hydraulic conductivity as similar to that of silty clay and obtain an empirical approximation as $D_0 = 10^2 \cdot K_s$ (Lambe and Whitman, 2008; Berti and Simoni, 2010). It can yield a lower bound for the $K_s$ as $2.6 \times 10^{-8}$ m/s and an upper bound for $D_0$ as $3.7 \times 10^{-4}$ m$^2$/s. Accordingly, combining both approaches can bound the characteristic hydraulic conductivity to $(2.6 \times 10^{-8}, 2.4 \times 10^{-5})$ m/s and the characteristic hydraulic diffusivity to $(2.6 \times 10^{-6}, 3.7 \times 10^{-4})$ m$^2$/s. The average is given as $K_s=1.2 \times 10^{-5}$ m/s and $D_0=1.9 \times 10^{-4}$ m$^2$/s. Given the fact that even field-measured hydraulic conductivity has an uncertainty by three orders (Berti and Simoni, 2010; Berti and Simoni, 2012), the above-described estimations is of important practical value.

2.5 Discussion

In this investigation, basal depth inversion of the landslide is achieved based on mass conservation and InSAR-captured surface velocity. A $u = 0$ (Figure 2.5) assumption is employed
to reconstruct the 3D surface velocity field as currently spaceborne SAR images can only provide two independent LOS observations. This assumption largely agrees with the landslide behavior monitored by continuous GPS (Global Positioning System) at several sites (Hu et al., 2018; Madson et al., 2019) and can provide a reasonable estimation of the thickness distribution over the whole landslide area, as confirmed by the uncertainty analysis and by the independent limit equilibrium analysis by feeding a wide range of soil mechanical parameters. Besides, it is worth noting that the selected wide range of rheological parameter ($2/3 < f < 1$) has also partly compensated the uncertainty derived from 3D surface velocity reconstruction.

Determining the starting date of the wet season is a key difficulty in estimating time lags. Thresholding cumulative precipitation is one of the options. However, analyzing cumulative rainfall from summer to the date of the first motion acceleration reveals that there are significant variations by years. For instance, the cumulative precipitation stands at 290 mm, 256 mm, 232 mm, 341 mm, 381 mm, and 336 mm for year 2007, 2008, 2009, 2010, 2016 and 2017, respectively (Figure 2.6b, 2.6e), which can hardly lead to a reliable and accurate threshold value. In-situ precipitation data show that the first several post-summer rainfall events are generally intermittent, while a single rainfall event cannot represent the arrival of wet-seasons. Cumulative rainfall infiltrates into the basal plane to trigger seasonal landslide motions, yet a single rainfall with a short duration and a small intensity is unlikely to saturate the entire sliding material and raise pore pressure on the basal plane. In contrast, the soil moisture that reflects the degree of saturation of soils can thus be a good indicator to define the starting date of wet seasons.

The lack of in-situ measurements such as groundwater level from this faraway landslide site has posed challenges to the hydraulic parameter estimation. Hence, only lower and upper bounds for characteristic hydraulic conductivity and diffusivity are estimated. To account for all related
uncertainties, the average basal depth of the central landslide region is used, rather than a single point. The derived time lags also have included the uncertainties that stem from satellite revisit cycle and varied soil moisture methods and locations. Due to the limited field data, here we only aim to layout a framework for estimating landslide thickness and corresponding hydraulic parameters, and better results can be obtained if more field data are available.

Regarding SAR datasets for landslide studies, L-band data overall exhibit better coherence on vegetated terrain than C-band data, while the C-band sentinel-1 imagery has unique advantages on time-series mapping due to the dense temporal acquisitions. The free ALOS and Sentinel-1 images have greatly contributed the data availability between 2007 and 2011 and after 2015, and the gap between 2011 and 2015 can be filled with commercial SAR datasets. Currently, spaceborne SAR datasets can only provide two independent observations, yet incorporating data from airborne missions such as Uninhabited Aerial Vehicle SAR (UAVSAR (Rosen et al., 2006)) is a potential solution to obtain real three-dimensional surface velocity fields of a landslide.

The Lawson Creek landslide is a typical slow-moving slide that is seated on the deposit of an ancient landslide (> 150 years (Burns, 2014)). The slow-moving behavior is very likely attributed to the soil porosity (Iverson et al. 2000) yet the seasonal dynamics are primarily associated with precipitation. InSAR observations reveal that the central region has greater displacement rate than the toe and head sections, which potentially implies that the central area is the active part, while movements of the landslide head and toe might be passive. During the past decade, the moving rate has been slow and stable, and currently no signs of runout have been captured.

2.6 Conclusions

This investigation employs multiple SAR datasets including ALOS, ALOS-2, and Sentinel images spanning 2007-2011 and 2016-2018 to map time-series displacement of a translational
landslide in the southern Oregon, which reveals that the landslide has been continuously creeping for the whole past decade with a maximum rate of 40 cm/yr in the upper middle section. The landslide motion exhibits apparent seasonal patterns with considerable displacements during wet seasons from mid-November to mid-May while little deformation during dry summers. The basal depth of the landslide is inverted based on mass conservation theory and InSAR-inferred surface velocity fields by assuming a power-law rheology. The results show that the Lawson Creek landslide is seated deepest in the central region and gradually shallow to the margin area. The mean thickness of the central region stands at $6.9 \pm 2.6$ meters. This estimation is also validated and confirmed by an independent limit equilibrium analysis which demonstrates that initial shearing failure of saturated soil columns would occur at $7.6 \pm 1.6$ m depth.

The time lags between the arrival of wet seasons and the onset of seasonal landslide motions are determined based on the observed periodic post-summer rise of soil moisture (SMAP and ground records) and InSAR time-series measurements. During the observation period, the time lags range from 26.7 to 48.7 days including uncertainties. InSAR observations reveals that the landslide kept moving even during dry summers and intermittent post-summer rainfall did not cause simultaneous acceleration of landslide motion, implying that seasonal accelerations are caused by basal pore-pressure rise rather than loading of rainwater. Accordingly, we take the water infiltration as purely advective flow and purely water diffusion respectively to estimate the lower and upper bounds of the characteristic hydraulic conductivity $K_s$ and diffusivity $D_0$ of the landslide material, as groundwater level data are unavailable. The yield average values are $K_s=1.2\times10^{-5}$ m/s and $D_0=1.9\times10^{-4}$ m$^2$/s.

As with most landslides all over the globe, for the Lawson Creek landslide, in-situ measurements of basal depth and hydraulic parameters are unavailable despite their importance.
for characterizing landslide behaviors. However, here we have explored the possibility of using primarily remote sensing datasets to infer the landslide thickness and estimate the hydraulic conductivity and diffusivity. More importantly, this established framework is able to yield better estimates when extra inputs are available. For instance, thickness inversion can be improved with more than there independent LOS observations, and hydraulic estimations can be enhanced with known groundwater levels.
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CHAPTER 3

DYNAMICS AND PHYSICS-BASED RAINFALL THRESHOLDS FOR THE
DEEP-SEATED HOOSKANADEN LANDSLIDE, OREGON


3.1 Introduction

Landslides annually cause billions of dollars of property loss and thousands of casualties on a global scale (Spiker and Gori, 2003; Froude and Petley, 2018), and act as a primary instrument for geomorphic changes in many regions (Mackey and Roering, 2011; Simoni et al., 2013). Mitigating landslide hazards and understanding landslide-induced landscape evolution require knowledge of landslide kinematics and timing. However, the timing of deep-seated landslides is particularly problematic to forecast even with subsurface pore-water pressure observations (Angeli et al., 1996; Massey et al., 2013; Gasparitto et al., 1996; Schulz et al., 2009, 2018; Pyles et al., 1987). Here we sought to use multiple remote sensing approaches and ground precipitation records to characterize motion behaviors of a typical deep-seated coastal landslide, and to develop a rainfall thresholding strategy for forecasting the timing of its movements.
The Hooskanaden landslide, located in southwestern Oregon and crossed by U.S. Highway 101, has been constantly damaging the highway and has resulted in significant repair costs to the Oregon Department of Transportation (ODOT). The slide is large (~600 m wide × 1,300 m long), deep (~30-45m), and has been active since at least 1958 (Parker, 1979) with typically slow motions in most years and occasional destructive moderate to major movements. Road maintenance during the slow-moving years annually cost ODOT about $75,000, while repair costs of a single major event usually amount to $5-7 million (ODOT, 2019). The most recent major event occurred on February 25, 2019, which displaced the road surface about 40 meters to the west and 17 meters downward (Figure 3.1; Britton, 2019) and closed the highway for 13 days until a temporary gravel lane was opened (ODOT, 2019). Two paved lanes were later reconstructed and opened on May 6, and a total of $1.12 million had been spent by that time (ODOT, 2019). The Hooskanaden slide is a distinct example demonstrating that deep-seated landslides with long-term creeping behaviors may also move violently at certain times and cause significant damages.

To understand the motion behaviors of the Hooskanaden landslide, multiple remote sensing datasets and tools, borehole measurements, and hydrological observations were used for this investigation to retrieve its long-term surface and subsurface displacement history and reveal the role that precipitation plays. Specifically, InSAR (Interferometric Synthetic Aperture Radar) and pixel offset tracking of SAR images, optical images, and LiDAR (Light Detection and Ranging) DEMs (Digital Elevation Model) were implemented to quantify the time-series motion of the landslide from 2007 to 2019. The 2019 February event with significant block-like movements provided a special opportunity to reconstruct the three-dimensional surface deformation field by using pixel offset tracking of both the Sentinel-1 SAR images and the Sentinel-2 optical images. In addition, borehole inclinometer measurements were employed to reveal the landslide’s
subsurface motion dynamics and basal depths (Castro et al. 2019). Space-captured soil moisture from SMAP (Soil Moisture Active and Passive; Entekhabi et al., 2014) and ground precipitation measurements were used to quantify the hydraulic characteristics of the landslide and help investigate how rainfall impacts its motion dynamics.

Figure 3.1 Photos of the 2019 February major slide. (a) Destructed roadway, and (b) a close-up and (c) a side view of the damages from Tidewater Contractors, Inc. Note vehicles in each panel for scale. The white dashed line in (a) outlines boundaries of the 2019 February event based on field-surveyed fresh post-event cracks (Castro et al., 2019).

This investigation demonstrates the ability of using multiple remote sensing approaches (InSAR, pixel offset tracking) and datasets (SAR, optical images, LiDAR DEMs) to reveal a landslide’s movement time series and basal geometry (e.g., relative speeds and rotational failure mode) without application of any calibrated rheological models. These three-dimensional characterizations are of great importance for forecasting future landslide motions. Moreover, we
successfully developed a threefold hydrological threshold to forecast the timing of the deep-seated landslide’s seasonal onsets and moderate/major movements, by integrating shallow soil moisture from SMAP and daily/hourly ground precipitation. In contrast to the demanding and sometimes unreliable pore-pressure thresholds (Angeli et al., 1996; Massey et al., 2013; Gasparitto et al., 1996), our hydrological thresholds do not require any expensive, potentially dangerous or impossible subsurface exploration and monitoring of pore-water pressures, and therefore can be easily adapted for other similar landslides.

3.2 Geological Setting and Historical Activities

3.2.1 Geographical and Geological Settings

The Hooskanaden landslide is located in Curry County, Oregon (Figure 3.2). It is crossed near its center by U.S. Highway 101, and its toe reaches the Pacific Ocean (Figure 3.2b). The landslide crown is located at about 200 m in elevation, and the currently active body is about 1,300 m long and 600 m wide, with an average slope of 17°. Moderate surface vegetation consisting of grasses and deciduous and coniferous trees covers the lower half of the slide below the road, while sparse vegetation grows on the upper half (Figure 3.1a). The regional topography from the hillshade map (Figure 3.2b) indicates that the landslide at Hooskanaden may have experienced a large ancient event, along with subsequent fluvial erosions and mass wasting that have significantly modified the original landforms.

Materials of the slide are derived from the Otter Point Formation of late Jurassic geologic age (Walker and Macleod, 1991), which consists of a matrix of sheared sandstone, mudstone, conglomerate, and interbedded sandstone and shale, with scattered BIMs (blocks-in-matrix, composed of more resistant sandstone, greenstones, chert and blueschist). These materials, geologically referred to as mélange (Castro et al., 2019), were accumulated as an accretionary
wedge along the Cascadia subduction zone during tectonic displacement and formed the accreted western margin of the Klamath Mountains region (Orr and Orr, 2012). Stratigraphically, the slide consists of harder upper layers with predominantly sandstone and softer lower layers of mixed shale and siltstone, as indicated by samples collected from four boreholes drilled between September 1978 and January 1979 (Boreholes 1-4 in Figure 3.2a; Parker, 1979) and one borehole drilled in December 2017 (BH-5 in Figure 3.2a, ODOT drilling logs [Hole No. SPR808-H1]). Rocks in the borehole are either moderately weathered or highly fractured with numerous joints and slickensides. Depths of the main mass vary from 30 to 45 meters (Parker, 1979).

Surface deformation patterns including localized slumps, compression ridges, transverse/semi-transverse internal cracks and closed depressions (Figure 3.2b) indicate that the whole landslide comprises several compartmentalized zones of movement rather than a single mass moving as a coherent block. Individual compartment masses partly move along discrete basal shear zones but together contribute to the overall movement of the slide mass by alternatively providing and removing passive resistance and/or driving force to the compartments above and below. Lateral slide boundaries are potentially constrained by large BIMs present along the flanks of the landslide (Castro et al. 2019).
Figure 3.2 Geographical and geological settings of the Hooskanaden landslide. (a) A vertical cross section of the slide along A-A’ shown in (b) and the stratigraphy inferred from five boreholes (BH-1 – BH-5). Boreholes 1-4 were drilled during 1978-1979, while BH-5 was drilled in 2017. (b) Geographical location of the landslide (red star mapped at the top-left corner) and a shaded relief map generated from a 2008 LiDAR DEM. Boundaries of the February 2019 event are inferred from field-surveyed fresh post-event cracks (Castro et al., 2019).
3.2.2 Historical Moderate and Major Slide Movements

The highway section near the Hooskanaden slide was opened in the early 1960s (Parker, 1979), and since 1958 there have been three major events and two moderate ones noted by ODOT that had reportedly displaced the highway by a significant amount (Figure 3.3; ODOT, 2019). The earliest major slide event was recorded on December 14, 1977, and the road surface dropped 2.5-3 m and slid 9 m to the west in the first 24 hours. The road was subsequently closed for five days. Seventeen years later on January 11, 1995, another major slide occurred, which shifted the roadway 4.3 m down and 12.2 m west in the first 24 hours and had closed the highway for 8 days. After that, two moderate events were noted on January 10, 2006 and December 14, 2016, both dropping the road surface by 1.8 to 3 m. Most recently on February 25, 2019, another major movement was triggered and most of the movement occurred in the first few days. It dropped the highway by 15-18 m in elevation and shifted the road 40 m to the west (Britton, 2019), and the road was consequently closed for about two weeks (ODOT, 2019). All the recorded moderate and major events were triggered in the wet winter rainy seasons from October to April.

3.3 Data and Methodology

3.3.1 Data

Multiple remote sensing and ground-measured datasets were used in this study. Remote sensing data including spaceborne SAR images from ALOS PALSAR (Advanced Land Observing Satellite; Phased Array type L-band Synthetic Aperture Radar), ALOS-2 PALSAR-2, and Sentinel-1A/B; airborne LiDAR DEMs, and Sentinel-2 optical images were employed for quantitative measurements of the slide motions (Figure 3.3). Specifically, 21 ALOS images from ascending track T224 between 2007 and 2011, three LiDAR DEMs acquired in 2008, 2014 and
2016 (OLC, 2020), and 84 Sentinel-1A/B images from ascending track T35 between 2016 and 2019 were used altogether to retrieve the long-term displacement history of the Hooskanaden slide from February 2007 to November 2019. Two Sentinel-2 images acquired on January 2019 and March 2019, and 10 Sentinel-1A/B images between January 2019 and March 2019 were used to reconstruct the three-dimensional displacement field of the February 2019 major movement. The 68-meter-deep borehole inclinometer observations with 0.5 m vertical intervals between December 2017 and January 2018 were used to reveal the subsurface motion dynamics of the slide before the inclinometer was destroyed by slide movement (Castro et al., 2019). In addition, space-captured SMAP level-4 soil moisture with 9×9 km grid size from 2015 to 2019 (Entekhabi et al. 2014) and daily precipitation from a ground station located 12 km southwest of the slide from December 1994 to March 2020 (WRCC, 2020) were used to provide hydrological observations.

Figure 3.3 Historical moderate (smaller star) and major movements (bigger star), and time spans of remote sensing and ground-based data as shown by the timeline and corresponding data processing methods.
3.3.2 InSAR

The InSAR method incorporates the phase information of SAR imagery to allow millimeter-scale displacement measurements along the LOS (line-of-sight) direction, and we used this technique to quantify the long-term time-series of slide displacement. The LiDAR DEM acquired in 2008 was used during interferogram generation using the GAMMA software (Werner et al., 2000), and the stratified tropospheric artifacts associated with surface topography were removed before phase unwrapping. Potential artifacts sourcing from regional soil moisture change and turbulent troposphere in each interferogram were removed by subtracting the InSAR phase of a common reference region (16×16 pixels after multi-looking). This reference region is stable, very close to the landslide (within one kilometer), and has constantly high coherence (greater than 0.7). The InSAR method was applied to the ALOS and Sentinel-1A/B SAR datasets, and the multilooking factors were set as 3×7 (range by azimuth) and 5×2, respectively. Accuracy of InSAR measurement can be quantified based on the coherence (Rodriguez and Martin, 1992; Lu and Dzurisin, 2014):

\[ \sigma = \frac{\lambda}{4\pi} \sqrt{\frac{1}{2NM} \left(1 - \gamma^2\right)} \]  

(3.1)

where \( \sigma \) is the uncertainty of InSAR measurements, \( \lambda \) the radar wavelength, \( N \) and \( M \) the window sizes for the coherence estimation, and \( \gamma \) the coherence. Time-series measurements were achieved by using a coherence-weighted small baseline subset (SBAS) method (Tarantola, 2005; Tong and Schmidt, 2013). In matrix form, the time-series inversion problem can be expressed as \( Gm = M \), where \( G \) is a matrix in the size of \( [n \times s + 1] \) entailing InSAR observations and physical constraints, \( m \) a matrix containing incremental displacements, and \( M \) the displacement...
observations of every interferogram. \( n \) is the number of interferograms and \( s \) the number of temporal increments. The equation can be expanded as:

\[
\begin{bmatrix}
1 & 1 & 0 & \ldots & \chi B_1 \\
0 & 1 & 1 & \ldots & \chi B_2 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
\lambda / \Delta t_1 & -\lambda / \Delta t_1 & 0 & \ldots & 0 \\
0 & \lambda / \Delta t_2 & -\lambda / \Delta t_2 & \ldots & 0
\end{bmatrix}
\begin{bmatrix}
m_1 \\
m_2 \\
\vdots \\
m_s \\
\Delta h
\end{bmatrix}
= 
\begin{bmatrix}
M_1 \\
M_2 \\
\vdots \\
0 \\
0
\end{bmatrix}
\tag{3.2}
\]

where \( B_i \) and \( \Delta t_i \) is the perpendicular baseline and time interval of the \( i \)th interferogram, respectively. \( \chi \) is a scaling factor determined by radar wavelength and the relative location between the satellite and ground targets. By introducing a weight matrix \( P = \text{diag}\{y_1, y_2, y_3, \ldots, y_n\} \), the incremental displacements can be solved as:

\[
m = (G^T P G)^{-1} G^T P M
\]

where \( G^T \) denotes the transpose of \( G \). The covariance matrix of \( m \) can be estimated as:

\[
Q = (G^T P G)^{-1} \sigma^2
\]

where \( \sigma^2 \) is the variance of the InSAR measurements. The small-baseline interferograms used for time-series inversion were selected by setting a minimum coherence threshold of 0.4 for the L-band ALOS-1/2 SAR images and 0.2 for the C-band Sentinel-1A/B images before any filtering. A 32×32 moving window was used for coherence estimation, which corresponds to a minimum measurement uncertainty of \( \sim 1.4 \) mm for ALOS/ALOS-2 and \( \sim 0.7 \) mm for Sentinel-1A/B interferograms.

3.3.3 Pixel Offset Tracking

Pixel offset tracking that uses the normalized cross correlation (Bernstein and Colby, 1983; Scambos et al., 1992) to identify matched features and track the offsets between the features is another method to quantitatively measure landslide movements from remote sensing data. The
achievable accuracy $\sigma_{cr}$ of offset estimation via cross correlation is given as equation (3.5) based on the Cramer-Rao bound (Bamler and Eineder, 2005):

$$\sigma_{cr} = \sqrt{\frac{3}{2NM} \frac{\sqrt{1 - \rho^2}}{\pi \rho}} \cdot \sigma_{pix}$$  \hspace{1cm} (3.5)

where $N$ and $M$ are window sizes for cross correlation. $\rho$ is the cross-correlation coefficient, and $\sigma_{pix}$ the pixel resolution. A $32 \times 32$ window was used for cross correlation of all data (note that the window size must be two times greater than the to-be-measured displacement), and thresholds of cross-correlation coefficient were set to 0.2 for Sentinel-1 images, and 0.4 for Sentinel-2 and LiDAR data. Hence, the measurement accuracy ranges from 0.01 m for the 0.35-meter-resolution LiDAR DEMs, 0.28 m for the 10-meter-resolution Sentinel-2 images, to 0.8 m for the 14-meter-resolution Sentinel-1 images in azimuth direction.

Offset tracking was applied to LiDAR DEMs, Sentinel-1A/B SAR images, and Sentinel-2 optical images in this investigation. In contrast to the high-accuracy InSAR that uses phase information, pixel offset tracking of SAR data uses backscattered intensities and provides a rather lower accuracy. However, SAR offset tracking works better for measuring high-gradient displacement that could potentially cause decorrelation and phase unwrapping errors for InSAR. To enhance the performance of pixel offset tracking, varied preprocessing was implemented on Sentinel-1A/B SAR data, Sentinel-2 optical images, and LiDAR DEMs.

3.3.3.1 Preprocessing of Sentinel-1/2 images

We averaged multiple Sentinel-1A/B SAR images to reduce the speckle noises and applied oversampling on the azimuth direction. The 10-m-resolution Sentinel-2 images were oversampled.
on both northing and easting directions, and both red and near-infrared bands of the multi-band Sentinel-2 images were combined to enhance ground features by calculating $SR$ (simple ratio):

$$SR = \frac{NIR}{R}$$

where $NIR$ and $R$ denote the near-infrared and red band respectively. The simple ratio takes advantage of the relationship between high absorption by chlorophyll of red radiant energy and high reflectance of near-infrared energy for healthy leaves and plant canopies (Ollinger, 2011), and can therefore particularly highlight ground features composed of healthy vegetation and augment the performance of offset tracking.

Specifically, five Sentinel-1A/B SAR images acquired before the event between January 1, 2019 and February 18, 2019 were averaged to form one SAR intensity image named 20190218.ave (Figure 3.4a), while another five acquired after the event between March 14, 2019 and May 1, 2019 were averaged to form an image named 20190314.ave (Figure 3.4b). Original 2.3 m × 14 m (range by azimuth) pixel-sized Sentinel-1A/B images were oversampled in the range direction to 2.3 m × 2.8 m pixel size before offset tracking. Pixel offset tracking was implemented on the simple ratio (equation 3.6) of Sentinel-2 images acquired on January 31, 2019 and March 2, 2019. An oversampling factor of four was applied to both northing and easting directions (Figures 3.4d, e).

3.3.3.2 Preprocessing of LiDAR DEMs

We applied pixel offset tracking of LiDAR DEMs on the elevation gradients instead of the elevations, as elevation gradient can better preserve topographical features than the elevation itself when vertical deformation exists. No oversampling was applied to the LiDAR DEM gradients before offset tracking. The elevation gradient $G$ was calculated as:
\[ G = \sqrt{\left(\frac{\partial H}{\partial x}\right)^2 + \left(\frac{\partial H}{\partial y}\right)^2} \]  

(3.7)

where \( H \) denotes the elevation, and \( x \) and \( y \) represent the easting and northing directions, respectively. The pixelwise finite difference approximations of elevation gradient for pixel \( H(i,j) \) are expressed as:

\[ G(i,j) = \sqrt{\left(\frac{H_{i+1,j} - H_{i-1,j}}{2\Delta x}\right)^2 + \left(\frac{H_{i,j+1} - H_{i,j-1}}{2\Delta y}\right)^2} \]  

(3.8)

where \( \Delta x \) and \( \Delta y \) are pixel size in \( x \) and \( y \) directions, respectively. The gradient along the edges of the matrix is calculated with single-sided differences.

3.3.4 Reconstruction of Three-dimensional Displacement Field

Three-dimensional displacement field of major slides can be reconstructed by combining pixel offset tracking results from both Sentinel-1A/B SAR data and Sentinel-2 optical images. Defining \( \theta \) as the radar incidence angle, \( \phi \) the satellite heading angle and \( \mathbf{d} = [E,N,Z]^T \) as the pixelwise displacement vector consisting of northing, easting, and upward components, respectively, \( \mathbf{d} \) is related to the measured offsets as:

\[ \mathbf{l} \cdot \mathbf{d} = \mathbf{L} \]  

(3.9)

where \( \mathbf{l} \) is the unit vector of pixel offsets in the \( ENZ \) coordinate, and \( \mathbf{L} \) is the measured pixel offsets from both Sentinel-1A/B and Sentinel-2 images. Equation (3.9) can be expanded as:

\[
\begin{bmatrix}
-\sin \theta \cos \phi & \sin \theta \sin \phi & \cos \theta \\
\sin \phi & \cos \phi & 0 \\
0 & 1 & 0 \\
1 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
E \\
N \\
Z
\end{bmatrix}
= 
\begin{bmatrix}
L_{S1R} \\
L_{S1AZ} \\
L_{S2N} \\
L_{S2E}
\end{bmatrix}
\]

(3.10)
where \( L_{s1,R}, L_{s1,AZ}, L_{s2,N}, \) and \( L_{s2,E} \) denote offset measurements from Sentinel-1A/B images in azimuth and range directions, and that from Sentinel-2 images on northing and easting directions, respectively. A weighted least squares solution was employed to solve equation (3.10). Similar to equations (3.3) and (3.4), the 3D vector components can be obtained as \( d = (l^T W l)^{-1} l^T W l \) by introducing a diagonal weight matrix \( W \) based on varied accuracy of the offset measurements. The covariance matrix of \( d \) can be estimated as \( C = (l^T W l)^{-1} \delta^2 \), where \( \delta^2 \) is the variance of the offset tracking measurements.

As to LiDAR DEMs, the horizontal displacement vectors can be directly obtained from pixel offset tracking of two LiDAR DEMs while the vertical deformation is attainable from the elevation changes of DEM based on the measured horizontal offsets. A three-dimensional deformation field can therefore be reconstructed.

### 3.4 Results

#### 3.4.1 Three-dimensional Displacement Field of the February 2019 Event

Reconstructing the three-dimensional displacement field of the major movement on February 25, 2019 was achieved by integrating pixel offset tracking of both Sentinel-1A/B SAR images from Descending track T13 and Sentinel-2 images. Specifically, the three-dimensional movement vectors (Figure 3.4c) were calculated by constructing and solving equation (3.10) using the four independent observations from Sentinel-1/2 data. The associated uncertainties of the inverted 3D motion vectors are depicted in Figure 3.5. Note that each arrow in Figure 3.4c represents the average horizontal displacement of a 14×14 array of adjacent pixels, which corresponds to a 32 m \( \times \) 39 m area on the ground surface. The results show that the 2019 February major slide mainly moved along the downslope direction with an aspect of 229° (clockwise from north), though the
head and toe sections have slightly larger west-facing components with aspects of around 240° and 250° respectively. The motion direction predominantly follows the regional bedding dip direction (Parker, 1979). Overall, the middle section of the slide had much larger movements than both the head and toe sections, and a maximum horizontal displacement of 40 m and a vertical movement of 13 m were observed near U.S. Highway 101 from our offset tracking results (Figure 3.4c). Comparison with results generated by ODOT using LiDAR DEMs acquired before and after the event demonstrates a very good mutual agreement. Specifically, two terrestrial LiDAR DEMs acquired on October 16, 2018 and March 3, 2019 revealed a maximum horizontal displacement of 40 meters near the road, and both magnitude and orientation of the movement vectors match well with our results (see Britton, 2019).

Figure 3.4 Three-dimensional displacement field of the 2019 February movement reconstructed from Sentinel-1/2 pixel offset tracking. (a) and (b) are the averaged Sentinel-1 SAR intensity from the descending track T13 (heading angle of 194°) before and after the 2019 February slide respectively. Both figures are shown in the radar coordinate system. The reconstructed 3D
displacement field is illustrated in (c) with arrows showing movement direction and relative magnitude. (d) and (e) are the two Sentinel-2 truecolor images used for pixel offset tracking.

3.4.2 Movement Rate from Airborne LiDAR DEMs

We applied pixel offset tracking to the three publicly accessible LiDAR DEMs from the Oregon Lidar Consortium (OLC, 2020) to reveal the long-term movement rate of the Hooskanaden slide. The three freely downloadable LiDAR DEMs with a vertical RSME (Root-mean-square error) of 4.6 mm were acquired on 20081017 (YYYYMMDD), 20140730, and 20160501. However, the three DEMs can only form two pairs (2008-2014 and 2008-2016) for pixel offset tracking as the 2014 and 2016 LiDAR DEMs barely overlap (Figures 3.6a, b, c).

As shown in Fig 3.6d, the slide section above the road had moved downslope at about 35 cm/yr from 2008 to 2014, and the movement direction resembles that of the 2019 February event. Across the data-missing area below the highway, the displacement rate starts from 30 cm/yr and gradually decreases towards the coastline. A similar movement pattern was also observed from the 2008-2016 LiDAR DEM offsets (Figure 3.6e), and much larger motion rates of 45 cm/yr were captured slightly below the road. The displacement directions remain almost identical during both the 2008-2014 and 2008-2016 periods. In contrast, the 2019 February event has much smaller south-orientating components at the slide toe than the slow motions between 2008 and 2016 (Figures 3.4c, 3.6), which suggest that the 2019 major event and the slow motions might have occurred on different slip surfaces. Various slickensides found in the borehole samples had confirmed the existence of multiple slip surfaces within the slide body (Figure 3.2a). Moreover, it is also indicated by the varied vertical slip angles primarily near the road (Figures 3.6f, g, h). The slip angle is defined as the angle between the displacement vector and the horizontal plane:
\[ \theta = \tan^{-1}\left( \frac{d_z}{\sqrt{d_N^2 + d_E^2}} \right) \]  

(3.11)

where \( \theta \) is the slip angle, and \( d_N, d_E, \) and \( d_z \) are the northing, easting, and vertical displacement components, respectively. The uncertainties of estimated slip angles are within \( \pm 1.2^\circ \) and \( \pm 4^\circ \) for that obtained from LiDAR DEMs and Sentinel-1/2 images, respectively, based on equation (3.10).

Figure 3.5 Uncertainties of the inverted three-dimensional displacement field as shown in Figure 3.4c. The left, middle, and right figures depict the inversion uncertainties in east, north, and vertical directions, respectively.

The inferred slip angles together suggest an overall concave-up-shaped slip surface and a rotational failure mode for the landslide, with a deepest-seated middle section near the highway (Figure 3.6f, g, h). As is commonly seen in many landslides, the very top region of the Hooskanaden slide exhibits near-horizontal passive movements as affected by the motion of the lower section. The slip angle near the highway is \( 30^\circ \pm 4^\circ \), consistent with the angle of \( 31.4^\circ \) inferred from ODOT’s report (ODOT, 2019).
Figure 3.6 Cumulative slow motions of the Hooskanaden slide retrieved from LiDAR DEMs. LiDAR DEMs acquired in (a) 2008, (b) 2014 and (c) 2016 were formed into two overlapped pairs to measure displacement during (d) 2008–2014, and (e) 2008–2016, where the arrows denote direction and relative magnitude. Vertical slip angles (colored circles) of the slow movement during (f) 2008–2014, (g) 2008–2016 and (h) the 2019 February major movement, derived from the 3D surface movement vectors. All figures cover the same spatial scope.

3.4.3 Motion Dynamics from 2007 to 2019

To reveal historical motion behaviors of the slide, 21 ALOS images from ascending track T224 between February 2007 and January 2011, and 84 Sentinel-1A/B images from ascending track T35
between July 2016 and October 2019 were processed with InSAR to retrieve the movement time series from 2007 to 2019. The gap between 2011 and 2016 was bridged with tracked pixel offsets from LiDAR DEMs (Figure 3.7a). InSAR measurements separated by the 2016 and 2019 events were bridged together by using averaged motion rates right before and after the events (Figure 3.7a), as the large event displacements caused jumps of InSAR phase by over $2\pi$, and therefore cannot be directly measured by the InSAR method (Xu et al., 2019; Rosen et al., 2000). The 2008-2016 LiDAR DEM offsets do not cover the upper half of the landslide, a reference area below the road (blue dashed box in Figure 3.7b) was selected to infer the 2008-2016 motion rates above the road based on the averaged displacement rate from ALOS observations (Figure 3.7b). Geographical location of the five selected points A-F and the corresponding averaged InSAR coherence are shown in Figure 3.8.

As seen from Figures 3.7a, 3.9, the long-term slow motion exhibits seasonal variations. Annually, most displacements took place during the wet winter seasons along with faster movement rates, whereas little deformation occurred during the dry summer seasons. The starting dates of the winter acceleration vary by years (e.g., approximately 2016-10-27, 2017-11-27, 2018-12-13 and 2019-10-06) but have good correspondences to the root-zone SMAP soil moisture (average value of the top ~1 m depth) that reveals soil saturation level (Figure 3.7c): wet-season acceleration usually starts 3-5 weeks after the wet season arrives (defined as 25% post-summer soil moisture rise) (Figures 3.7a, c; Figures 3.9a, c; Xu et al., 2019). Essentially, the rapid post-summer rise and a constant winter-season high level of soil moisture implies a nearly continuous input of water infiltration after the onset of wet seasons, which would gradually infiltrate downward to elevate basal pore pressure and trigger/accelerate slide motion by reducing effective normal stress and consequent frictional shear resistance along the landslide base (Terzaghi, 1950).
Figure 3.7 Long-term motion dynamics of the Hooskanaden slide from 2007 to 2019. (a) Cumulative along-slope displacements of points A–F as shown in (b) retrieved from ALOS, LiDAR DEM and Sentinel-1A/B data. Note that along-slope displacements of the 2016 event (~4 m) and the 2019 event (~43 m) are not included for figure clarity. Average coherences of the used interferograms are depicted in Figure 3.8. (b) Average along-slope movement rate from 2007-2011 ALOS InSAR. The dashed rectangle denotes the reference area used for helping interpret offsets from LiDAR DEMs. (c) Daily precipitation (gray bars) and root-zone SMAP soil moisture (green polyline) from a 12-km-distant meteorological station (Red Mound) and a 9 × 9 km SMAP grid respectively as shown in (d). Note that SMAP soil moisture is shown in volumetric water content rather than effective saturation level.

The decadal-scale slow motion of the slide presents an overall accelerating trend, with an average downslope rate of 13 cm/yr from 2007-2011, 21 cm/yr from 2011 to 2016, and 53 cm/yr from 2016 to 2019 (Figure 3.7a). The long-term accelerating trend could be attributed to coastal erosions of the landslide toe (see Discussion). Both the 2006 moderate movement and the 2019 major movement occurred in the wet season while SMAP soil moistures remained at a constant high level of around 49%. However, the 2006 event happened 68 days after the wet season started,
while the 2019 event took place after 92 days into the wet season (Figure 3.9c). These variable lag times illustrate that shallow soil moisture may be indicative of general, overall groundwater conditions, but may not directly reveal the movement behavior of deep landslides. In fact, the exceptionally heavy rainfall in December 2016 and February 2019 suggests that the moderate/major slide events were likely triggered by short-term but high-intensity rainfall spikes (Figures 3.7a, c; Figure 3.9).

Figure 3.8. Average coherences of all the used ALOS interferograms (left) and Sentinel-1 interferograms (right) for deriving time-series displacement of the landslide. The marked points, A-F, are the same as those shown in Figure 3.7b.

Figures 3.7, 3.9 show that post-event movement rates of the points (A, B, C, D, and F) remain almost unchanged from those before the 2016 and 2019 moderate/major events. The water year 2017 (September 1, 2016 – September 1, 2017) experienced the longest wet season and the greatest cumulative rainfall compared to water years 2018 and 2019, as indicated by soil moisture and water-year rainfall records (Figure 3.9c). It is also the water year that the landslide had the greatest
annual displacements and non-stop movements even during summer (Figures 3.7a, 3.9a). In contrast, all six points (A-F) had lower total displacements in both water years 2018 and 2019 and had temporary movement stoppages in both 2018 and 2019 summers. All the above observations indicate a strong correlation between precipitation and the landslide’s slow motions.

Figure 3.9 A close-up of the landslide motion dynamics between 2016 and 2019. (a) Cumulative along-slope displacements of three points (A, D, and E as shown in Figure 3.7b), and time lags between arrival of wet seasons and seasonal accelerations from 2016 to 2019. (b) Movement rates of the three points (in consistent colors) obtained from displacement time series using forward difference approximations. (c) Daily rainfall (gray bars), cumulative water-year rainfall starting
from September 1 (red line), and soil moisture (green line) are scaled by y-axes in corresponding colors. The dashed boxes show drop rates of soil moisture during dry summers.

3.4.4 Estimation of Hydraulic Conductivity and Diffusivity

Borehole inclinometer measurements from a borehole slightly below the highway (BH-5 in Figure 3.2) between December 1, 2017 and the end of January 2018 reveal that the slow block-like motion of the slide during this period dominantly occurred on a 33 m deep basal surface. Very slight displacements had also taken place on two potential slip surfaces at ~15 m and ~21 m level below the ground surface (Castro et al., 2019; Alberti et al., 2020). The groundwater level was found at 3 m beneath the surface during the drilling in December 2017 (Figure 3.2a). Assuming that the post-summer precipitation vertically infiltrates into soils as a convective flow above the groundwater table and transmits elevated pore pressure to the basal surface in an approximately diffusive manner below the groundwater table, and that landslide acceleration temporally correlates with elevation of basal pore pressure, the characteristic hydraulic conductivity and diffusivity at the borehole can be estimated based on the time lags between rainfall and InSAR-captured slide acceleration (Xu et al. 2019).

For the unsaturated soils above the groundwater level during dry summers, the unsaturated hydraulic conductivity \( K \) relates to the saturated hydraulic conductivity \( K_s \) as (Van Genuchten, 1980):

\[
K = K_s S_e^L \left(1 - \left[1 - S_e^{n} \right]^{1-\frac{1}{n}} \right)^2
\]

(3.12)
where the effective saturation 
\[ S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r} \]
is related to measured volumetric water content \( \theta \), residual water content \( \theta_r \) and saturated water content \( \theta_s \) (Brooks and Corey, 1964; Rawls et al., 1982). \( L = 0.5 \) is an empirical parameter and \( n = 2 \) is a measure of pore-size distribution (Mualem, 1976; Schaap et al., 2001). The time lag, \( T_k \), for the advective flow to infiltrate downward by \( h_k \) can be estimated as \( T_k = h_k/K \). In the saturated soils, the pore-pressure response can be approximated as one-dimensional transmission and attenuation of rainfall-induced oscillating flux from the top surface (i.e. the groundwater table for the partially drained summer soils or the ground surface for the fully saturated wet-season soils):

\[
\frac{\partial P}{\partial t} = D_0 \frac{\partial^2 P}{\partial z^2} \quad (3.13)
\]

where \( P \) is pore-water pressure head, \( t \) is time, \( D_0 \) is hydraulic diffusivity, and \( z \) is depth. The time lag, \( T_d \), between the sinusoidally oscillating source signal and the pressure peak response at depth \( h_d \) can be solved as (Carslaw and Jaeger, 1959; Baum and Reid, 1995)

\[
T_d = h_d \sqrt{\frac{t_0}{4\pi D_0}} \quad (3.14)
\]

where \( t_0 \) is the period of the osculating signal, and here it was assumed as one day based on rainfall records. An empirical relationship between the magnitude of saturated hydraulic conductivity \( K_s \) and hydraulic diffusivity \( D_0 \) is that \( D_0/K_s = dP/d\theta = 10^2 \) (in consistent length and time units) (Mualem, 1976; Van Genuchten, 1980). The time lags, \( T = T_k + T_d \), between the arrival of the wet season (defined by a 25% post-summer soil moisture rise) and post-summer slide acceleration were observed ranging from 16 to 37 days in years 2016, 2017, 2018 and 2019 (Figure 3.9a). Taking 49% as the saturated water content and 28% as the measured unsaturated water content of
the surface-one-meter soils (Figure 3.9c), the averaged characteristic hydraulic conductivity \( K_s \) and diffusivity \( D_0 \) were estimated as \( 6.6 \times 10^{-6} \) m/s and \( 6.6 \times 10^{-4} \) m\(^2\)/s, respectively.

### 3.5 Discussion

#### 3.5.1 Enhancement of Pixel Offset Tracking

Pixel offset tracking is one of the key methods used for this investigation to measure slide displacements. Stacking multiple Sentinel-1 SAR images and combining multiple bands of Sentinel-2 acquisitions are of significant importance to highlight the ground feature and enhance offset tracking performance. For Sentinel-2 data, integrating information from multiple bands could potentially improve offset tracking performance. For LiDAR DEMs, elevation gradients are more reliable ground features for block-like landslides than the elevation itself, but neither one would work for debris flows that have entirely altered the original topography. In addition to the elevation gradient (equation 3.7), the second-order gradient \( G_2 \) could be a useful alternative for highlighting ground features from DEMs:

\[
G_2 = \sqrt{\left( \frac{\partial^2 H}{\partial x^2} \right)^2 + \left( \frac{\partial^2 H}{\partial y^2} \right)^2}
\]  

(3.15)

where \( H \) is the elevation, and \( x \) and \( y \) denote the easting and northing directions, respectively. However, our tests on the 2008, 2014 and 2016 LiDAR DEMs show that second-order gradient may also magnify noises and contaminate the results. Therefore, it should be used with caution.
Figure 3.10 Rainfall thresholds for forecasting moderate/major landslide events. (a) Daily precipitation (brown bars), cumulative precipitation starting from every September 1 (gray lines), and moderate and major events (magenta diamonds). (b) Previous-3-day and (c) previous-15-day cumulative precipitation. Our proposed threefold rainfall threshold comprises antecedent water-year cumulative rainfall (red dashed lines in a), daily rainfall (green dashed lines in a), and previous-3-day precipitation (blue dashed line in b). A close-up of previous-3-day rainfall threshold is shown in Figure 11a with a red dashed line. (d) The flag number denotes how many components of the three-component threshold were meet on a specific day between 1994 and 2020.
3.5.2 Proposed Rainfall Threshold for the Moderate/Major Events

It has been shown in Figures 3.7, 3.9 that movements of the Hooskanaden landslide are predominantly associated with precipitation. To further understand the hydrological settings that bifurcate the sliding behavior into slow motions and moderate/major events, 25-year daily precipitation from the Red Mound station (Figure 3.10c) between 1994 and 2020 and hourly precipitation near the historical moderate/major events were collected and processed. As shown in Figure 3.10a, the four moderate/major movements in 1995, 2006, 2016 and 2019 occurred neither on dates with maximum cumulative water-year rainfall (starting from September 1st), nor on the date with the most intense daily rainfall over the 25 years (i.e., Jan 6, 2015). Moreover, thresholding previous-3-day and previous-15-day cumulative rainfall would also fail to predict the dates of the moderate/major events without generating numerous false alarms (Figures 3.10b, c).

Here we propose a threefold threshold composed of three components of different time scales to better predict the moderate/major events of the Hooskanaden landslide: 150 mm daily rainfall, with previous-3-day cumulative rainfall of 40 mm and antecedent water-year precipitation of 1,325 mm after September 1st. Essentially, the water-year-scale antecedent precipitation is used as a proxy for soil saturation level (nearly continuous infiltration of 1,325 mm rainfall would fully saturate the landslide depth after a dry summer), and a daily-scale intense rainfall allows generation of a strong pore-pressure pulse to trigger a moderate/major landslide. The 3-day-scale antecedent rainfall ensures that the top soil layers are moist enough to allow generation of a strong pore-pressure pulse by an intense daily rainfall.
Figure 3.11 Daily and hourly precipitation near special dates. (a) Daily and (b) hourly rainfall near the moderate and major landslide events, where negative x-axis values represent days/hours before the event. (c) Daily and (d) hourly rainfall for two special dates when intense rainfall did not trigger larger landslide movement. Blue lines in (a) and (c) represent previous-3-day cumulative rainfall, while those in (b) and (d) denote previous-48-hour cumulative precipitation. The red dashed line in (a) marks the minimum previous-3-day cumulative precipitation in our proposed threefold rainfall threshold.

The proposed threefold threshold can accurately predict the dates for the four moderate/major events between 1995 and 2020 with only one false alarm on 20061215 [YYYYMMDD] (Figures 3.10a,d, 3.11a). Worth mentioning is that the 3-day-scale rainfall threshold of 40 mm successfully
eliminated two potential false alarms on dates with over 150 mm daily rainfall (i.e., 20100602 and 20150106). A detailed look of the daily and hourly rainfall records reveals that the intense precipitation on 20100602 occurred after seven consecutive dry days, and the extremely intense precipitation on 20150106 (481.58 mm of rainfall fell within one hour) also occurred after 12 continuously dry days (Figures 3.11c, d). The real pore-pressure pulse caused by the storms could have been significantly reduced by what might be expected due to rainwater absorption within the upper, drier part of the landslide and due to overland flows (rainfall rate exceeds $K$), and consequently was not able to trigger a moderate/major movement. Using the averaged drop rate of soil moisture during summers (see black dashed boxes in Figure 3.9c), we estimated that soil moisture would drop from 0.49 to 0.484 after three consecutive dry days, and the corresponding unsaturated hydraulic conductivity $K$ would drop by 30% from $6.6 \times 10^{-6}$ m/s to $4.64 \times 10^{-6}$ m/s (Figure 3.12c) based on equation 3.12. An empirical 40 mm threshold of previous-3-day cumulative rainfall was therefore set to avoid false alarms caused by dried upper soil layers, based on historical pre-3-day rainfall records (Figures 3.11a, c).

The threshold of the antecedent water-year rainfall is tied to the antecedent groundwater level and summer soil moisture. Borehole drilling on December 1, 2017 revealed a groundwater level of 3 m below the surface at the Hooskanaden landslide (Figure 3.2a), and daily logs of a groundwater well (CURR 819) 23.5 km southeast of the landslide show that groundwater levels increased from 16.1 m above sea level (water-year low) on September 1, 2017 to 18.4 m (water-year peak) on April 9, 2018 at the site. It implies a lower bound of groundwater level of -5.3 m at the landslide site in 2017 summer, and consequently a ~1,325 mm cumulative precipitation to fully saturate the landslide materials, as SMAP data shows that average soil moisture of the top-one-meter soils bottoms at 25% during the 2017 summer (Figure 3.9c). The daily rainfall threshold
was set empirically based on daily rainfall records of the first moderate/major event (the 1995 one) shown in Figure 3.10a and can yield accurate forecasting, as validated by the other three later events in 2006, 2016, and 2019. Note that the moderate/major slides may have been triggered by an extremely short-term rainfall spike in a rainy day, which may require rainfall records with finer time scale such as every 5 minutes to be better understood.

Determining the proposed threefold rainfall threshold requires precipitation time-series, landslide thickness and groundwater depth, hydraulic parameters of the landslide material, and past landslide motion records (or soil mechanical parameters). These data and parameters can be obtained through variable means depending on the specific case. Here for the Hooskanaden landslide we employed primarily remote sensing data and ground-based hydrological observations, and our methods can be easily adapted for other similar landslides globally to serve for landslide movement forecasting. Overall, the concept of the “three-component” threshold that accounts for various hydrological processes could be applicable to many deep-seated landslides, but the exact threshold for each component must be site-specific and could be derived from field observations and/or empirical values.

3.5.3 Mechanism of Landslide Motions Modulated by Precipitation and Coastal Erosion

Overall, our analysis has confirmed that both slow motions and moderate/major events of the Hooskanaden landslide are controlled by precipitation, though the exact processes differ. The slow motion usually starts 3-5 weeks after the wet season arrives (defined by a 25% post-summer soil moisture rise), and is controlled by both rainwater infiltration of the top dry layers (unsaturated during summer) and pore pressure transmission in saturated soils (Figures 3.7a, 3.9a; Xu at al., 2019). In contrast, moderate/major slide events respond much faster to rainfall pulses, for example, in approximately 2 days, as the soils are almost saturated in the midst of a wet season and the slide
has already been moving (Figure 3.11). Consequently, both rainfall loading and pulses of increased pore-pressure can quickly accelerate the existing slow motion into a moderate/major slide event. The slowdown of sliding movement can be primarily attributed to pore-pressure drop due to decreased rainfall input and subsurface drainages. In addition, Figures 3.11a, b reveal that time lags between the daily rainfall pulse and the slide accelerations range from 1-2 days, which matches very well with our hydraulic diffusivity estimation of $6.6 \times 10^{-4}$ m$^2$/s and the landslide’s observed depth. To illustrate, pore pressure diffusion for $H = 33$ m roughly takes $T_d = 1.23$ days, as calculated from the estimated hydraulic diffusivity and equation (3.14).

![Figure 3.12 Unsaturated hydraulic conductivity and coastal erosions. (a) Changes of unsaturated Hydraulic conductivity $K_s$ with regard to consecutive drying days and soil moisture. (b) Elevation differences between the 2016 and 2008 LiDAR DEMs at the landslide toe, which is enlarged from the black box in (c).](image)

Our remote sensing observations revealed an accelerating trend of the landslide movements from 2007 to 2019 (Figure 3.7a), which could be attributed to coastal erosion of the landslide toe. Elevation differencing of the 2016 and 2008 LiDAR DEMs demonstrates that the landslide toe has
undergone significant erosions from 2009 to 2016: ~14 m wide of the coast has elevation drops of over 4 m. The annual coastline retreat rate at the landslide toe is ~1.9 m/yr, which might have led to the long-term acceleration of landslide motions by reducing passive resistances.

3.6 Conclusions

Multiple remote sensing datasets and processing methods, borehole measurements, and hydrological observations have been used in this investigation to understand 12-year motion dynamics of the Hooskanaden landslide that exhibited both long-term slow movements and short-term moderate/major slide events. Pixel offset tracking of both Sentinel-1 SAR images and Sentinel-2 optical images was carried out to reconstruct the three-dimensional displacement field of the 2019 February major movement. Offsets of LiDAR DEMs were obtained by using elevation gradients to reveal the 3D motion rates of the landslide between 2008 and 2016. Together with InSAR processing of ALOS and Sentinel-1 SAR images, a 12-year displacement history of the Hooskanaden landslide has been retrieved.

Movement rates of the landslide exhibit substantial seasonal variations on an annual scale with dominating wet-season displacements, and an overall accelerating trend can be seen over the past decade potentially due to coastal erosion. Pixel offset tracking was successfully applied to the Sentinel-1/2 images and LiDAR DEMs to recover the three-dimensional displacement field of the 2019 February major movement, and to reveal that the rapid movement and slow motions may have occurred on slightly different slip surfaces. By using satellite captured SMAP soil moisture and InSAR derived time lags for post-summer rainfall to trigger the first seasonal sliding acceleration, the averaged characteristic hydraulic conductivity $K_s$ and diffusivity $D_o$ of the landslide materials were estimated as $6.6 \times 10^{-6}$ m/s and $6.6 \times 10^{-4}$ m$^2$/s, respectively. These produce timing estimations that agree with the observed 2-day time lag for rainfall pulses to trigger the
1995, 2016 and 2019 moderate/major movements. Comparison between the motion history and ground rainfall records demonstrates that thresholding pre-3-day and pre-15-day cumulative precipitation cannot lead to effective prediction of dates for moderate/major events. In contrast, more accurate prediction can be achieved by using our proposed threefold threshold of 150 mm daily rainfall, with previous-3-day cumulative rainfall of 40 mm and antecedent water-year precipitation of 1,325 mm after September 1st.

Our study demonstrates the utility of integrating multiple remote sensing methods (InSAR and pixel offset tracking) and datasets (ALOS and Sentinel-1 SAR, Sentinel-2 optical images, and LiDAR DEMs) to retrieve long-term displacement time series and achieve 3D characterizations of a landslide, which are of great significance for forecasting the landslide’s future motions (e.g., seasonal accelerations and decelerations, the rotation failure mode, and the long-term acceleration associated with coastal erosion). Furthermore, we propose a new threefold rainfall threshold based on shallow soil moisture from SMAP and 15-year ground precipitation records to forecast both the seasonal onsets of creeping motion as well as moderate/major events of the Hooskanaden landslide. The ability of the proposed threshold has been explained with hydrological modeling and remote sensing observations. Our approaches for developing the threshold predominantly rely on remote sensing data and ground precipitation and does not require expensive and labor-intensive pore-pressure monitoring, and therefore can be easily adapted for other similar landslides worldwide.
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CHAPTER 4

MOVEMENT MONITORING AND RUNOUT HAZARD ASSESSMENT OF
THE GOLD BASIN LANDSLIDE, WASHIGNTON


4.1 Introduction

The Gold Basin landslide in Washington has been drawing considerable attention from officials and local residents after the devastating 2014 landslide at Oso, Washington (Wartman et al., 2016; Iverson et al., 2015) that damaged 49 houses down the slope and caused 43 fatalities. The two landslides are separated by only 23 kilometers (Figure 4.1a) and have measurable similarities in terms of terrain setting, slope angle, and historical failures. Both slides have rivers flowing through the toes that influence landslide processes by eroding the landslide toe, and could potentially increase flow mobility and inundation extent in the event of a failure. An important distinction between these two landslides is their morphological settings. The landslide complex at Gold Basin is comprised by three separate stream valleys with deeply incised channels (Figure 4.1b). The valleys contain deep seated landslide deposits which form moderately sized landslide
blocks with gentle, hummocky terrain immediately upslope from the channel incisions (Figure 4.1b, d). In contrast, the landslide at Oso, Washington expresses a distinct stairstep pattern typical of a recent landslide involving large blocks (Figure 4.1c,e,f). Comparison of the hillshade images of Gold Basin and Oso suggests that the landslide complex at Gold Basin may have experienced a large event similar in size to the 2014 event at Oso (Figures 4.1c, 2a), but the original landforms have been greatly modified by subsequent fluvial erosion and mass wasting (Figure 4.2a).

For the Gold Basin landslide, runout events pose direct threats to the popular campground located on the opposite side of the Stillaguamish River (Figure 4.2a). The campground has been closed since 2014 out of safety concerns, and a detailed hazard assessment is required prior to reopening. In addition to a potential runout event, fine-grained sediments derived from the landslide complex have been persistently transported into the South Fork Stillaguamish River where it negatively impacts migrant salmon spawning grounds that are of critical importance to the Stillaguamish Tribe (Shannon and Wilson, 1954; Staisch, 2018). To better evaluate the Gold Basin landslide complex, we utilized both remote sensing and numerical simulations to assess slope stability and evaluate the potential inundation extent.

Filed surveys are traditionally relied upon for monitoring landslide movement and slope stability. Ground instrumentation, such as GPS, extensometers and tiltmeters, provides reliable and accurate measurements and have been widely used for monitoring dangerous landslides that directly threaten human safety (Angeli et al., 2000; Terzis et al., 2006). In addition, remote sensing techniques that exploit increasingly available data resources such as LiDAR (Light Detection and Ranging) DEMs, space- and airborne optical images, and SAR (Synthetic Aperture Radar), and provide remote access with wide spatial, radiometric, spectral, and temporal coverage, have greatly
improved the efficiency of landslide detection and mapping (e.g. Fruneau et al., 1996; Squarzoni et al., 2003; Colesanti and Wasowski, 2006; Xu et al., 2019).

Figure 4.1 Comparison between the Gold Basin landslide and the Oso slide. (a) Geographic locations of the Gold Basin landslide complex (red square) and the Oso slide (red triangle), with the annotation WA=Washington. Hillshade images of (b) Gold Basin landslide complex (red polygon) and (c) Oso slide. Cyan polylines in (b) represent stream valleys and the yellow square outlines the headscarps shown in (d). True-color images of Oso slide (e) before and (f) after the 2014 runout event. Images were obtained from Google Earth. LiDAR DEMs were accessed from the Washington State Department of Natural Resources.

However, despite multiple available data sources, remote sensing surveillance of slopes in particular terrains and at certain times still presents challenges due to current technical limitations. The effectiveness of utilizing SAR images for landslide studies depends on their spatial resolution, wavelength of the SAR signal, the revisit cycle of SAR satellites, the look angle of SAR sensors, and the motion rate of landslides (e.g. the InSAR method may not be effective for rapidly moving
slides), while that of LiDAR is primarily affected by available repeated acquisitions. For the free or low-cost optical images from satellite platforms such as Landsat and Sentinel-2, coarse spatial resolution and cloud coverage are the two key limiting factors. Consequently, a single remote sensing device might not be adequate to detect and monitor some landslide scenarios (e.g. a small localized collapse of a steep slope at a particular time). Nevertheless, integrating multiple remotely sensed datasets and employing suitable interpretation methods provides a potential solution for certain difficult cases.

In order to evaluate the potential runout and inundation extent, should a slope failure lead to a rapidly flowing landslide and debris flow, we employed numerical modeling using the D-claw package (George and Iverson, 2014) D-claw is a depth-averaged two-phase model that simulates the flow dynamics based on conservation of mass and momentum, and accounting for the important feedbacks between solid grain concentrations and the basal pore-fluid pressure that regulate flow resistance and mobility, based in part on the theory of granular dilatancy for shearing soils (Iverson and George, 2014). Running a D-claw model requires a hypothetical landslide basal slip surface that defines the initial landslide volume and geometry (George and Iverson, 2014; Iverson et al., 2015).

This investigation focuses on using multiple remote sensing datasets to monitor movement of the Gold Basin landslide complex, which also helps constrain initial, hypothetical landslide source geometries as an input for the D-claw simulations of runout scenarios. Due to the steep slopes and large yet localized deformation, multiple SAR processing methods are employed to characterize the landslide motions. D-claw simulations are subsequently performed to evaluate the potential hazard zone. Our methodology of evaluating landslide runout hazards developed for this case study
can be easily adapted for other similar landslides globally to assist on hazard prevention and mitigation.

Figure 4.2 Geographical and geological setting of the Gold Basin landslide complex. (a) The Gold Basin landslide (red polygon) comprises part of a big landslide complex (dashed blue polygon) that is bisected by a stream channel. A campground is located on the opposite side of the South Fork Stillaguamish River. (b) Elevation profile along A-A’ in (c) and a generalized stratigraphy
obtained by McCabe (2016). Soil types were classified following the Unified Soil Classification System (USCS) with GP=poorly graded gravel, MH=silt of high plasticity and elastic silt, CH=clay of high plasticity and fat clay, and SP=poorly graded sand. (c) A true-color image of the slide obtained in July 2018 from Google Earth.

4.2 Geological Setting and History

4.2.1 Regional Setting

The Gold Basin landslide complex, located in Snohomish County, Washington (Figure 4.1a,b), lies above the South Fork of the Stillaguamish River in the Cascade Range (Figure 4.2a). The landslide complex’s elevation ranges from 325 m to 495 m above sea level, and consists of three small, steep tributary valleys that form three separate lobes on the north valley wall and transport landslide debris and sediment downstream to the Stillaguamish River through valley channels (Figure 4.1b). The valleys at Gold Basin were originally filled with recessional glacial deposits to a substantial depth of 175 m. The river has cut through deposits (Benda and Collins, 1992; Staisch, 2018) and form steep-sided valley walls exposing the glacial stratigraphy (Miller and Miller, 1999; Miller, 2019). Stratigraphy is vertically and laterally heterogeneous with discontinuous lenses of silt and clay interspersed in sandy river deposits. Field observations and lab tests indicate that there is a 52.6 m water-perching layer (400.9–453.5 m above sea level) of silt sand clays between strata of poorly sorted gravels and sands in the stratigraphy of the middle lobe (Figure 4.2b; McCabe, 2016).

4.2.2 Historical Landslide Activity

Three large historical runout events have been recorded at Gold Basin, though the involved lobes varied over time. Cycles of small, localized collapses and erosion have been occurring intermittently over many decades, followed by subsequent revegetation. The earliest recorded landslide activity can be traced back to 1942 (Benda and Collins, 1992). The landslide source was
confined to the lower portions of the middle lobe and the eastern-most lobe, and the active area was approximately a quarter of the much larger 1964 landslide. The 1964 event occurred in the eastern-most lobe and formed a fan at the mouth of that lobe, as indicated by the exposed bare ground in aerial images (Figure 4.3; Miller and Miller, 1999). Subsequent vegetation regrowth eventually obscured the fan, and by 1983 the river had eroded back the toe of the eastern-most lobe (Miller, 2019). The most recent debris flow occurred in 1996, in the middle and western-most lobes. Debris deposits blocked the river and had shifted the channel to the south where it currently remains. The evolution of the channel course is apparent from comparing the 1995 and 2007 images of the site (Figure 4.3).

4.3 Methodology and Data

4.3.1 Measuring Landslide Movement Using Remote Sensing

4.3.1.1 LiDAR DEM differencing

LiDAR DEMs have proven to be an effective tool for landslide detection because of their high spatial resolution and high measurement accuracy (e.g. Hodgson et al., 2003; Roering et al., 2009). The sub-meter-level spatial resolution and the centimeter-level absolute accuracy provide for reliable and accurate measurements of landslide motions, ranging from localized small displacements to large runout events. Moreover, landslide detection with LiDAR point clouds is largely impervious to the influence of vegetation, slope angle, and ground features. However, at the state level there is presently only limited LiDAR spatial coverage, and typically the datasets are very sparse in terms of repeated temporal sampling. Considering the Gold Basin region for example, LiDAR DEMs are only available for years 2005, 2006, 2013, and 2016 and lack full spatial continuity for the project area, which is essential for differencing. Nevertheless, hillshade
images produced from high resolution DEMs facilitate interpretation of landforms and provide insights into the landslide processes (Figure 4.2a). In this investigation, we applied DEM differencing to all available LiDAR DEMs in the Gold Basin region to quantify the deformation rates and landslide volumes from 2005 to 2016.

4.3.1.2 InSAR

InSAR (Interferometric Synthetic Aperture Radar) methods are focused on the phase information of SAR backscattering and can optimally provide up to millimeter-level measurement accuracy along the LOS (line of sight) direction (e.g. Hanssen, 2001). However, substantial pixel displacements can present coherence degradation and unwrapping problems (e.g. Lu and Dzurisin, 2014). Consequently, applying InSAR to measure landslide movements with high deformation gradients (phase difference between two adjacent pixels exceeds $\pi/2$) requires additional data inputs or assumptions of displacement patterns (e.g. Xu et al., 2019). The long-wavelength L-band data generally maintains better coherence in vegetated terrains and yields better interferometric results than the shorter-wavelength C-band and X-band SAR images (Xu et al., 2019).

As LiDAR DEMs are unavailable after 2016, we processed all available SAR data from the L-band ALOS-2 PALSAR-2, the C-band Sentinel-1A/B, and the X-band TerraSAR-X to detect recent landslide activities between 2017 and 2019 using the InSAR method.
Figure 4.3 Historical images of the Gold Basin landslide. The 1964-2003 figures were adapted from Miller and Miller, 1999; Miller, 2019. Bright features represent areas with bare vegetation. The 2007-2018 figures were obtained from Google Earth.
4.3.1.3 SAR intensity differencing and pixel offset tracking

SAR intensity refers to the strength of the reflected signal from ground objects. Landslide activity that causes measurable changes of the backscattering signal can be detected by differencing SAR intensity images (e.g. Plank et al., 2016). However, solely differencing SAR intensity changes cannot confirm a landslide activity, as other factors, such as changes in soil moisture and variations in forest-cover density (associated with wildfire, disease, or silvicultural activities such as timber harvest thinning or fuel management), also cause fluctuation of backscattering signals. An alternate approach is to track pixel offsets between two SAR intensity images using cross correlation (e.g. Strozzi et al., 2002; Singleton et al., 2014). The offset tracking accuracy can reach 1/20 to 1/10 pixels (Hanssen, 2001). We applied both SAR intensity differencing and pixel offset tracking to detect recent landslide activity at Gold Basin.

First, we implemented intensity change detection methods on the high-spatial-resolution TerraSAR-X data from Jan 2017 to March 2019 to detect the existence of highly localized deformations. As a single-look SAR image generally contains significant speckle noises (e.g. Hassen, 2001), we multi-looked every image with a \(3 \times 3\) multilook factor and averaged five images acquired in the same season to form one image for detecting intensity changes. Three SAR intensity images of years 2017, 2018 and 2019 were generated by averaging SAR images acquired between January and March in corresponding years (~ 5 images for each year), and then utilized to calculate intensity changes.

Second, we applied the pixel offset tracking method to the same Tandem-X datasets from 2017 to 2019. Unlike the intensity change detection, pixel offset tracking can provide quantitative measurements of landslide movement. Similarly, we averaged five SAR intensity images between January and March of each year, before conducting offset tracking. Here we did not employ multi-
looking, because multi-looking would increase pixel size and consequently reduce offset-tracking accuracy. Pixel offset tracking was carried out twice iteratively with downscaling window sizes. A window size of 64×64 pixels was set for the first round of offset tracking, and the output was used as the input for the second-round of offset tracking after eliminating offset anomalies. The second round started with a smaller window size of 32×32 pixels, and the final results were smoothed using a moving window of 2×2 pixels.

4.3.2 Runout Scenario Simulation

4.3.2.1 D-claw model

D-claw is a depth-averaged two-phase model that combines concepts of critical-state soil mechanics, grain-flow mechanics, and fluid dynamics (Iverson and George, 2014; George and Iverson, 2014). The model’s five balance equations describe coupled evolution of the solid volume fraction, basal pore-fluid pressure, flow thickness, and two components of flow velocity are given as:

\[
\frac{\partial h}{\partial t} + \frac{\partial (hu)}{\partial x} + \frac{\partial (hv)}{\partial y} = \frac{\rho - \rho_f}{\rho} D
\]

(4.1a)

\[
\frac{\partial (hu)}{\partial t} + \frac{\partial (hu^2)}{\partial x} + \kappa \frac{\partial}{\partial x} \left( \frac{1}{2} g_z h^2 \right) + \frac{\partial (huv)}{\partial y} + \frac{h(1 - \kappa)}{\rho} \frac{\partial P_b}{\partial x}
\]

\[
= h g_x + u D \frac{\rho - \rho_f}{\rho} - \frac{\tau_{s,x} + \tau_{f,x}}{\rho}
\]

(4.1b)

\[
\frac{\partial (hu)}{\partial t} + \frac{\partial (hv^2)}{\partial x} + \frac{\partial (hv)}{\partial y} + \kappa \frac{\partial}{\partial y} \left( \frac{1}{2} g_z h^2 \right) + \frac{h(1 - \kappa)}{\rho} \frac{\partial P_b}{\partial y}
\]

\[
= h g_y + v D \frac{\rho - \rho_f}{\rho} - \frac{\tau_{s,y} + \tau_{f,y}}{\rho}
\]

(4.1c)
\[
\frac{\partial (hm)}{\partial t} + \frac{\partial (hum)}{\partial x} + \frac{\partial (hvm)}{\partial y} = -Dm \frac{\rho_f}{\rho} \tag{4.1d}
\]

\[
\frac{\partial P_b}{\partial t} - \rho g_z \frac{\partial h}{\partial x} + \rho g_z \frac{\partial (hu)}{\partial x} + u \frac{\partial P_b}{\partial x} - \rho g_z \frac{\partial h}{\partial y} + \rho g_z \frac{\partial (hv)}{\partial y} + v \frac{\partial P_b}{\partial y}
= \zeta D - \frac{3}{\alpha_c h} \|(u, v)\|^2 \tan \varphi_d \tag{4.1e}
\]

where \( h \) is the height normal to the bed of a virtual free surface, \( u \) and \( v \) are the depth-averaged flow velocities in the \( x \) and \( y \) directions, respectively, \( m \) is the depth-averaged solid volume fraction and \( P_b \) denotes the pore-fluid pressure at the basal boundary, \( g_z \) is the gravitational acceleration in the bed-normal direction (i.e. \( \mathbf{g} = (g_x, g_y, g_z)^T \)), \( \kappa \) is the lateral pressure coefficient, \( \alpha_c \) is the elastic compressibility, \( \varphi_d \) is the granular dilatancy angle, the terms \( \mathbf{\tau}_s = (\tau_{sx}, \tau_{sy})^T \) and \( \mathbf{\tau}_f = (\tau_{fx}, \tau_{fy})^T \) are the basal shear traction exerted by the solid phase and fluid phase, respectively, and \( \rho \) is the depth-averaged bulk density, which is a function of the solid volume fraction

\[
\rho = \rho_s m + (1 - m) \rho_f \tag{4.2}
\]

where \( \rho_s \) and \( \rho_f \) are the intrinsic material densities of the solid and fluid constituencies, respectively, which are assumed to be constant. The variable coefficient \( \chi \) is given by

\[
\chi = \frac{\rho_f + 3\rho}{4\rho} \tag{4.3}
\]

The variable \( \zeta \) is introduced in equation 4.1e for notational convenience and is given by

\[
\zeta = \frac{3}{2\alpha_c h} + \frac{g_z \rho_f (\rho - \rho_f)}{4\rho} \tag{4.4}
\]
$D$ is the depth-averaged granular dilation rate, equal to the depth integral of the divergence of the solid-phase velocity field and is proportional to the difference between basal pore-fluid pressure and hydrostatic pressure

$$D = \frac{2k}{\mu h} (p_b - p_f g_z h)$$

(4.5)

where $k$ is the hydraulic permeability and $\mu$ is the pore-fluid viscosity.

The dilatancy angle $\varphi_d$ depending on $m$ is defined as

$$\tan \varphi = m - m_{eq}$$

(4.6)

where

$$m_{eq} = \frac{m_{crit}}{1 + \sqrt{N}}$$

(4.7)

Here $m_{crit}$ is the critical-state solid volume fraction commonly employed in soil mechanics (i.e. the quasi-static equilibrium solid volume fraction such that there is no change in $m$ during shearing, with $\sigma_e$ constant). The quantity $N$ is a dimensionless state parameter defined as

$$N = \frac{\mu \dot{\gamma}}{\rho_s \dot{\gamma}^2 \delta^2 + \sigma_e '}$$

(4.8)

where $\dot{\gamma} = 2\|u, v\|T$ is an estimate of the depth-averaged shear rate, $\sigma_e$ is the effective stress, and $\delta$ is a length scale associated with grain collisions (Iverson and George, 2014). In the USGS plume experiments, $m_{crit}$ ranges from 0.56 to 0.64, and $\delta$ was set as 1mm.

The D-claw model incorporates the theory of soil dilatancy in order to mediate the feedback effects of soil-shearing and fluid-pressure-dependent mobility and resistance. Adjustable parameters in the model are based on well-established and measurable material quantities (e.g. initial porosity, hydraulic permeability, solid-matrix elastic compressibility, etc.) In lieu of site-
specific studies of these parameters, they are constrained to reasonable bounds by sediment tests of materials in analogous studies or geologically similar regions (see e.g. Iverson et al., 2010, 2015).

The predicted debris-flow behavior is influenced by several non-dimensional quantities identified by Iverson and George (2014) and depends on landslide initial conditions and evolving material properties. These quantities include the difference between the initial sediment porosity and an evolving equilibrium porosity, \( m_0 - m_{eqm} \). The evolving equilibrium volume fraction \( m_{eqm} \), depends on the state of flow variables and an initial, or critical equilibrium \( m_{crit} \), which represents the quasi-static equilibrium volume fraction prior to motion. The sign of \( m_0 - m_{eqm} \) determines whether soils are in a contractive state in which initial shearing leads to increased mobility, or a dilative state in which shearing decreases mobility. The two alternative states of the material lead to either positive feedbacks and flow acceleration or negative feedbacks and flow stabilization and deposition. For characterizing hazards that may result from high-mobility landslides, the former, generally contractive initial state of debris is assumed.

4.3.2.2 Log-spiral basal surfaces

To simulate hypothetical runout scenarios using the D-claw package, landslide basal slip surfaces are required. In lieu of additional site-specific data, basal surfaces are typically assumed to have longitudinal transects that conform to a logarithmic-spiral shape, a commonly assumed feature of idealized landslide scarps. For a homogeneous slope and assuming a visco-elastic rheology of shearing soils, the Mohr-Coulomb yield criterion leads to a logarithmic-spiral failure surface (Baker and Garber, 1978; Chen, 2013). In the polar coordinate, the log-spiral is described as

\[
r = r_0 e^{\theta \tan \varphi}
\]  

(4.9)
where \( r \) is the spiral radius, \( \theta \) is the rotation angle with clockwise from the horizontal being positive, \( r_0 \) is the radius value for \( \theta=0^\circ \), and \( \phi \) is the internal friction angle of landslide material. The coordinates \((x_c, y_c)\) are the pole of the log spiral in a Cartesian system with its origin at the toe of the slope (Figure 4.4). \((x_s, y_s)\) and \((x_e, y_e)\) are the coordinates at which the failure surface intersects the slope surface, associated with angles \( \theta_s \) and \( \theta_e \) in the polar coordinates. \( \beta \) is the slope angle, and \( H \) is the height of the slope.

In the longitudinal direction, a vertical profile of the basal surface can be uniquely determined if two intersection points with the ground topography and the two corresponding intersection angles are given. A continuous three-dimensional basal surface can be constructed by interpolating or fitting multiple longitudinal log-spiral profiles. For smoother surfaces, fitting multiple curves in the transverse direction can be employed. We used the 2016 bare-earth LiDAR DEM for constructing hypothetical log-spiral basal surfaces and for runout topography.

Figure 4.4 Illustration of logarithmical spiral failure surface. The resultant vector of normal and frictional forces passes through the pole of the spiral (Klar et al., 2011). \((x_s, y_s)\) and \((x_e, y_e)\) are
the coordinates at which the failure surface intersects the slope surface, associated with angles $\theta_s$ and $\theta_e$ in the polar coordinates. $\beta$ is the slope angle, and $H$ is the height of the slope.

4.3.2.3 Landslide volume estimations

We obtained the annual average landsiding volume of the Gold Basin landslide complex as $1.03 \times 10^5 \text{ m}^3/\text{yr}$ by differencing the 2005 and 2016 LiDAR DEMs.

The maximum landslide volume was estimated from the soil stratigraphy of the Gold Basin landslide complex (Figure 4.2b) based on Perkins et al.’s (2017) simplified model. Three-dimensional limit equilibrium analysis of typical glacial stratigraphy consisting of a weak unit (advance glaciolacustrine deposits) between two strong units (advance outwash sands) in northern Washington demonstrates that the thickness and position of the weak unit exerts a considerable influence on potential landslide volumes (Perkins et al., 2017). In fact, typical landslide volumes can be readily estimated based on geographical information regarding the geometry of the weak layer and the location of the landslide. Such estimates have been performed and validated by field surveys of multiple landslides at the Skagit River and North Fork Stillaguamish River regions (Perkins et al., 2017). For instance, the estimated maximum volume for the Oso landslide is $9.8 \times 10^6 \text{ m}^3$ (Figure 4.5), close to the volume of $7.3 \times 10^6$ to $9.2 \times 10^6 \text{ m}^3$ measured from LiDAR DEMs (Iverson et al., 2015). For the Gold Basin landslide, terrace height above the Stillaguamish River is 170 m; thickness of the weak layer composed of clays and silts is 52.6 m; and elevation difference between the layer top and Stillaguamish River is 128.5 m (Figure 4.2b). Applying Perkins et al.’s (2017) simplified model (Figure 4.5) in this case, implies an estimate of $2.0 \times 10^6 \text{ m}^3$ for the maximum landslide volume.
Figure 4.5 Estimated maximum landslide volume within 10% of minimum FoS (Factor of Safety). The figure was adapted from Perkins et al., 2017. Black square and triangle denote Gold Basin landslide ($2.0 \times 10^6$ m$^3$) and Oso slide ($9.8 \times 10^6$ m$^3$) respectively. $Z_w$ and $t_w$ stands for bed-top height and thickness of the weak layer respectively, and $H$ denotes thickness of the whole terrace.

4.3.2.4 D-claw simulations setup

To evaluate potential inundation extents of the Gold Basin landslide complex, we simulated 12 scenarios. These scenarios can be categorized into two groups, with each group employing a single value of $m_0 - m_{crit}$. Six different initial volumes ranging from $5.7 \times 10^4$ to $4.5 \times 10^6$ m$^3$ were simulated for each group. We set $m_{crit} = 0.62$ in all of the scenarios, which is commensurate with material that has a relatively high mud content of the formed debris (McCabe, 2016, Iverson et al., 2010). Values satisfying $m_0 < m_{crit}$ corresponds to relatively mobile debris flows that are contractive, which is believed to be representative of the 2014 debris flow that occurred at Oso, Washington (Iverson et al., 2015), while $m_0 > m_{crit}$ corresponds to less mobile runout behaviors as soils dilate during failure (Iverson et al., 2000). In addition, we simulated the runout scenarios...
with a flowing river presented at the landslide toe for the case of landslide volume \( V = 2.1 \times 10^6 \) m\(^3\). The water depth was set as two meters for the entire river segment near the landslide.

### 4.4 Results

4.4.1 Remote Sensing of Landslide Activity

#### 4.4.1.1 LiDAR DEM differencing

Differencing of 2005 and 2016 DEMs reveals that substantial localized deformation of the western-most and middle lobes occurred, with a maximum displacement of \(~ 30\) meters, while only slight deformation was observed at the eastern-most lobe (Figure 4.6a). From 2013 to 2016, some localized yet substantial collapses (about 20 m in displacement) appeared at the head scarp of the middle lobe (Figure 4.6b). Similar substantial deformation was also captured by terrestrial LiDAR from July 2015 to January 2016 (McCabe, 2016). As the overlap region of the 2013 and 2016 DEMs only covers the head section of the slope, it is not clear whether localized movements also occurred at the lower sections from 2013 to 2016. Nearly no deformation occurred between June 2005 and March 2006.

#### 4.4.1.2 InSAR

We processed all available SAR acquisitions from ALOS-2 PALSAR-2, Sentinel-1A/B, and TerraSAR-X. However, only the L-band ALOS-2 imagery produced useful interferograms for identifying ground deformation due to severe coherence loss of the shorter-wavelength C-band Sentinel-1A/B and X-band TerraSAR-X images. Five active landslides nearby Gold Basin were detected by an ALOS-2 interferogram spanning from 2016 to 2017 (Figure 4.7), yet deformation signals at the Gold Basin landslide complex were not distinguishable due to poor coherence there. The most likely reason is that the relatively coarse spatial resolution (\(~10\) m) and look angle (\(~35^\circ\)
of ALOS-2 PALSAR-2 limited its ability to capture highly localized deformation on a steep slope. Indeed, the top 50 m of the middle lobe of the landslide complex is nearly vertical (McCabe, 2016; Drury, 2001), which would cause shadow or layover effects for the right-side-looking SAR acquisitions (e.g. Hanssen, 2001).

4.4.1.3 SAR intensity changes and pixel offset tracking

As shown in Figure 4.8, significant intensity changes of TerraSAR-X SAR images from 2017 to 2019 were detected at the head scarp and western side of the middle valley. The intensity changes varied from -2 dB to 2 dB depending on the location. Small intensity changes were observed at the riverbank at the mouth of the middle valley. However, the detected intensity changes do not irrefutably confirm landslide activity, because soil moisture variations or vegetation growth/removal may have also contributed to the changes.

The offset tracking results confirms that localized but significant deformation was present at the middle lobe between 2017 and 2019. The most notable deformation occurred near the head scarp, which shifted by about 10 m. The riverbank near the mouth of the middle valley also had significant erosion of about 7 m. We did not observe any conspicuous signs that would indicate the movement of a large, centralized block, or main body.
Figure 4.6 Slope deformation captured by LiDAR DEMs. DEM changes (a) from 2005 to 2016, and (b) from 2013 to 2016. Slightly white-shaded regions represent overlaps of two DEMs.
Figure 4.7 Detected active landslides nearby Gold Basin from an ALOS-2 interferogram spanning from 2016 to 2017. Small windows on the right show the close-up of each landslide. One fringe represents a line-of-sight range change of 12.1 cm. The Gold Basin landslide complex is outlined in Red. Black dots are layover and shadow regions in the right-looking SAR data due to steep topography.
Figure 4.8 Intensity changes and tracked displacements of TerraSAR-X images spanning 2017–2018 (left column), 2018–2019 (middle column), and 2017–2019 (right column).
4.4.2 Simulations of Hypothetical Runout Scenarios

We simulated 12 scenarios with varied volume-mobility combinations to assess the potential inundation extents of the Gold Basin landslide complex in the event of a failure. Figure 4.9 and Figure 4.10 depict the simulated runout scenarios as $m_0 - m_{\text{crit}} = 0.02$ and $m_0 - m_{\text{crit}} = -0.02$ respectively. Note that $m_0 < m_{\text{crit}}$ corresponds to relatively mobile debris flows, while $m_0 > m_{\text{crit}}$ corresponds to less mobile ones. Comparison of the two groups demonstrates a large disparity in the risk posed to the campground area, based solely on the debris-flow mobility given the same initial landslide volume: a more mobile debris flow would cause more damages to the campground by increasing both inundation extent and deposit thickness, provided the same landslide volumes.

Differencing of 2005 and 2016 LiDAR DEMs indicates an average cumulative landsliding volume of $1.03 \times 10^5 \text{ m}^3$ per year (see Section “Landslide volume estimations”), which is approximated by the simulated cases of $V=1.1 \times 10^5 \text{ m}^3$. Even the highly mobile simulations with this initial volume pose limited threats to the campground (Figure 4.10). Consequently, collapses of the head scarp with volumes less than $10^5 \text{ m}^3$ are unlikely to be of much concern. The simulations agree well with the field observations from U.S. Forest Services that the campground has never experienced any debris flow events since at least 2005.
Figure 4.9 Maximum campground damages from D-claw simulations with $m_0 - m_{\text{crit}} = 0.02$. $V$ denotes volumes ranging from $5.7 \times 10^4$ to $4.5 \times 10^6 \text{m}^3$, and $t$ is time denoted in hours:minutes:seconds. The highly smooth area near headscarp of the middle lobe is the simulated slip surfaces. See supplementary materials in Xu et al. 2020 for a runout animation of the case $V = 2.1 \times 10^6 \text{m}^3$. 
Figure 4.10 Maximum campground damages from D-claw simulations with $m_0 - m_{crit} = -0.02$. V denotes volumes ranging from $5.7 \times 10^4$ to $4.5 \times 10^6$ m$^3$, and $t$ is time denoted in hours:minutes:seconds. See supplementary materials in Xu et al. 2020 for a runout animation of the case $V = 2.1 \times 10^6$ m$^3$. 
However, once landslide volumes exceed $10^6$ m$^3$, the simulated debris flows run over the entire campground under both mobility assumptions. As expected, larger volumes tend to increase the runout extent as well as the thickness of deposits on the campground. The estimated maximum landslide volume of $2.0\times10^6$ m$^3$ (see Section “Landslide volume estimations”) is most closely represented by our simulations with $V=2.1\times10^6$ m$^3$. As shown in Figure 4.9 and Figure 4.10, our simulations with initial volumes of $V=2.1\times10^6$ m$^3$ produce debris flows which invariably inundate the entire campground, regardless of their simulated mobility (see supplementary materials in Xu et al. 2020 for runout animations). The highly mobile debris flow with this initial volume crosses the campground with an 8 m high flow front. The simulations also suggest that camp sites near the mouth of the middle valley are the most vulnerable to potential runout events.

4.4.3 Simulations of Interactions with the Stillaguamish River

In order to evaluate how the Stillaguamish River located at the landslide toe could affect the mobility and inundation hazards of the landslide-initiated debris flow upon a catastrophic failure, we added a flowing river at the landslide toe and simulated corresponding runout scenarios for both the dilative and contractive cases with landslide volume fixed at $2.1\times10^6$ m$^3$. As depicted in Figure 4.11, the simulated results show that clearly observable debris flow fronts which are primarily comprised of water (solid fraction $\approx 0$) are generated when the landslide-initiated debris flows move downslope and hit the Stillaguamish River for both the dilative and contractive cases. Such scenarios can be explained by the horizontal momentum exchange between the running debris flow front and the waterbody. However, adding the river leads to similar inundation extents in comparison to cases without the river. Potentially, the Stillaguamish River increases the debris volume, but such volume growth ($\sim 6\times10^4$ m$^3$) remains relatively small compared to the landslide source volume ($2.1\times10^6$ m$^3$) and therefore does not enlarge the inundation area considerably.
Moreover, the simulated debris flows start to run uphill after sweeping across the Gold Basin campground, which would rapidly weaken the debris flows’ kinetic energy and hence limit the inundation extent even with slightly increased debris flow volume.

Next, we investigated how the Stillaguamish River might impact the dynamics of the simulated debris flows by comparing the flow depth and solid fraction times series at three checkpoints CP1, CP2, and CP3 on the Gold Basin campground (Figure 4.11). CP1 is the closest checkpoint to the Stillaguamish River whereas CP3 is the farthest one. For the dilative scenario (slow flow), the flow fronts arrive at the checkpoints #1 and #2 (CP1 and CP2) approximately 10 s earlier if the river is included (Figure 4.12). However, such difference in arrival time is negligible at the checkpoint #3 (CP3) which is 340 m distant from the river. Moreover, peak flow thicknesses at all of the three checkpoints are slightly increased by the presence of the river, with a maximum of 0.5 m at the checkpoint #2. The flow thicknesses also drop earlier (~ 50 s) at each checkpoint if including the river. Additionally, interactions with the river reduce the solid fraction of the deposited debris on the campground by 0.04, which may slightly affect physical property of the deposits in a geomorphic view. For the contractive scenario (fast flow), adding the river considerably affects the riverside checkpoint CP1 by increasing height of the first wave of flow front by 2.8 m. However, the river has negligible impacts to the checkpoints CP2 and CP3. To conclude, the presence of the Stillaguamish River affects only the riverside region for a fast debris flow, yet it greatly impacts a slow debris flow in a large spatial extent.
Figure 4.11 Simulations of interactions between the debris flow and the Stillaguamish River. Simulated debris flows with (a) dilative and (c) contractive behaviors. (b) and (d) are close-up visualizations of the yellow boxes depicted in (a) and (c), respectively. CP1, CP2, and CP3 denote checkpoints #1, #2, and #3, respectively.
Figure 4.12 Impacts of the river on landslide runout at different geographical locations. Geographical locations of the checkpoints #1, #2, and #3 are depicted in Figure 4.11. The first and the second rows of the figure show the evolution of flow depth and solid fraction with time for the simulated dilative flow at the checkpoints #1, #2, and #3, respectively. The third and the fourth rows show the simulations for the contractive flow.
4.5 Discussion

Remotely sensed data such as LiDAR DEMs and SAR provide a means for monitoring landslide motion, at a large scale, in an efficient and cost-effective manner. However, these methods may also present technical and practical challenges for particular difficult cases. For instance, available LiDAR DEMs are typically temporally sparse, while the side-looking angle and spatial resolution of SAR data limit their effectiveness for small landslides in steep or heavily vegetated areas.

Different SAR datasets have varied advantages and disadvantages in terms of landslide mapping. For instance, the L-band ALOS and ALOS-2 SAR sensors have great vegetation penetration but temporally sparse acquisitions. The Sentinel-1A/B datasets provide temporally dense sampling yet coarse resolution in azimuth direction (Xu et al., 2019). The TerraSAR-X images have high spatial resolution but poor vegetation-penetrating capability. While using phase information through InSAR provides the best displacement measurement accuracy, it has limited applicability to cases with severe coherence loss. Such decorrelation might be induced by large displacement, long spatial/temporal baselines, or ground feature changes. In contrast, offset tracking of SAR intensity images is more tolerant to large deformation and temporal/spatial baselines despite of the lower accuracy of 1/20 – 1/10 pixels (Hanssen, 2001). Overall, by combining multiple sources of SAR datasets and employing optimal data processing strategies, we have found that it is possible to maximally harness their combined attributes for landslide monitoring.

LiDAR DEMs are able to provide reliable measurements of landslide activity with small spatial extent, such as headscarp collapses of the Gold Basin landslide complex, but the high cost of repeated LiDAR acquisitions and the low sensitivity to slow-moving slides comprise its primary
disadvantages. Nevertheless, we have shown that the challenges with individual remote sensing technologies can largely be overcome through the simultaneous use of multiple data sources and comprehensive data corroboration.

Modeling of landslide dynamics and inundation given an initial mass failure still presents challenges as well, largely resulting from uncertainties about site-specific subsurface conditions and material properties. However, by considering a range of possibilities, inundation bounds can be approximated to a reasonable degree of certainty, at least for general hazard awareness and effective mitigation strategies.

4.6 Conclusions

Applying complementary remote sensing data including LiDAR DEMs and SAR images to surveil stability of the Gold Basin landslide demonstrates that only substantial and localized displacements have occurred at the Gold Basin area between 2005 and 2019. The middle lobe has been the most active, while the eastern-most lobe has been primarily stable during this period. The head scarp of the middle lobe underwent a maximum displacement of approximately 40 m during the past decade, and the western-most lobe has also experienced displacements of about 20 m at the head scarp. Significant erosion was observed at the riverbank near the middle valley after 2017. Average cumulative landsliding volume of the Gold basin landslide complex is 1.03×10^5 m^3 per year. Nevertheless, from 2005 to 2019 there is no evidence indicating movement of a large central block or single deep-seated landslide body.

Our practice of interpreting SAR with multiple approaches demonstrates that offset tracking of high-resolution SAR is an effective alternate approach to detect landslide activity if InSAR cannot yield reasonable results due to coherence loss induced by vegetation or steep slope angles.
D-claw runout simulations with multiple landslide volumes and varied runout behaviors shows that small collapses of the head scarp with volumes less than $10^5$ cubic meters will most likely pose a low threat to the campground, while severely hazardous runout might occur if the initial slide is over $10^6$ m$^3$. The estimated maximum volume of the Gold Basin landslide is $2.0 \times 10^6$ m$^3$, indicating a significant hazard to the nearby campground should slope failure induce a mobile landslide. The runout potential of such a landslide would depend on the landslide mobility, which is dependent on material parameters that are difficult to constrain due to uncertainties about the subsurface conditions. Nevertheless, flow simulations provide evidence about the range of possible outcomes and inform hazard mitigation. In addition, our simulations demonstrate that interactions between debris flow and waterbodies may impact the flow dynamics significantly depending on the flow speed, waterbody volume, and the topographical settings.

In this investigation, we have proven the possibility of using remotely sensed data to measure deformations occurred on a difficult terrain by integrating multiple data sources and comprehensive data processing strategies. Furthermore, we have presented a means of evaluating runout hazards of a landslide by employing the numerical model D-claw. Most importantly, these methods developed for this case study can be easily adapted for other similar landslides globally to assist on landslide hazards prevention and mitigation.
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CHAPTER 5

GEOLOGIC CONTROLS OF SLOW-MOVING LANDSLIDES
HIDDEN NEAR THE U.S. WEST COAST


5.1 Introduction

Landslides are a geologic process crucial for landscape evolution and hydrologic change (Burbank et al., 1996; Kesley and Bockheim, 1994; Roering et al., 2009; Simoni et al., 2013), and as a natural hazard, landslides annually cause 3.5 billion dollars of property loss and 25–50 casualties in the United States alone (Spiker and Gori, 2003). Locating presently active landslides is a critical step towards preventing their future hazards and forecasting their impact on the landscape. However, conventional landslide-identifying approaches that rely on geologic maps and citizen-reported events (Guzzetti et al., 2012; Jones et al., 2019; Highland and Bobrowsky, 2008), could easily miss numerous active yet slowly moving slides that lack readily identifiable features (e.g., fresh headscarps) or occur in rarely accessed lands. Slow-moving landslides persistently damage infrastructure and imply a force imbalance of the hillslope (Highland and Bobrowsky, 2008). Additional forces such as earthquake shaking, coastal and stream erosion,
intense rainfall, and other natural or anthropogenic disturbance could shift their present creeping behavior into rapid movement and cause catastrophic damages (e.g., Kilburn and Petley, 2003; Schulz and Wang, 2014; Intrieri et al., 2018; Xu et al., 2020b). Discovering presently slow-moving landslides for future hazard prevention particularly requires approaches with high measurement accuracy and wide spatial coverage. However, few tools were available until the InSAR (Interferometric Synthetic Aperture Radar) method evolved into an effective means in the last two decades (Intrieri et al., 2018; Xu et al., 2020; Squarzoni et al., 2003; Ye et al., 2004; Xu et al., 2019). InSAR utilizes interferometry of satellite-captured radar images (frequent repeated acquisitions since 1992) to achieve maximal millimeter-level measurements of ground displacement (Ferretti et al., 2007; Nishiguchi et al., 2017).

Multiple recent studies have focused on the precipitation-driven short-timescale dynamics of presently active, slow-moving landslides (e.g., Squarzoni et al., 2003; Ye et al., 2004; Xu et al., 2019); however, knowledge of their geologic controls is still poorly known owing to a lack of detailed, large-scale evidence, but such knowledge is essential for deciphering their characteristics and for preventing future hazards. Spatially large, slow-moving landslides are generally deep-seated (meters to hundreds of meters) (Highland and Bobrowsky, 2008; Larson et al., 2010; Bonzanigo et al., 2007) and may have been active for hundreds to thousands of years (Kesley and Bockheim, 1994; Bonzanigo et al., 2007; Bovis and Jones, 1992; Varnes and Savage, 1996; Mackey et al., 2009). Hence, their occurrence could be controlled by the lithology and structure of the underlying bedrock and by geologic processes (Clarke and Burbank, 2010; Roering et al., 2005; Cruden and Varnes, 1996; Lambe and Whitman, 1969). In addition, vertical uplift (i.e., any upward movement of the land surface) in a geologic time scale ($10^3$–$10^5$ years) could deliberately alter the force balance of hillslopes and regulate the denudation process (Burbank et al., 1996; Larsen and
Montgomery, 2012; Bennett et al., 2016a; Roering et al., 2015), thereby potentially modulating occurrence and kinematics of long-term creeping landslides.

Here we apply the high-accuracy InSAR method over the entire U.S. west coast states (~8.6×10^5 km^2) to discover large, presently active landslides hidden in both the high mountains and coastal neighborhoods inhabited by 47.8 million people (2019 census; USCB, 2019). Based on the large-scale observations, we tested our hypotheses that the spatial density and size of slow-moving landslides are significantly controlled by bedrock type and that their occurrence and persistent motion reflect long-term land uplift.

5.2 Materials and Methods

5.2.1 SAR Interferogram Generation and Unwrapping

We used radar interferometry of both the ALOS PALSAR (Advanced Land Observing Satellite–Phased Array type L-band Synthetic Aperture Radar) images from 2007 to 2011 and ALOS-2 PALSAR-2 images from 2015 to 2019 for identifying landslides near the U.S. west coast. SAR interferograms were generated by differencing the phase measurements of two SAR images. For each SAR interferogram, the interferometric phase of a SAR resolution element, φ, is composed of multiple independent components:

\[
\phi = W\{\phi_{def} + \phi_{dem} + \phi_{orb} + \phi_{atm} + \phi_n\}
\]

where \(\phi_{def}\) is the phase change due to movement of the pixel in the satellite radar line-of-sight (LOS) direction; \(\phi_{dem}\) is the DEM error sourcing from the difference between the DEM height and the elevation of average scatterers in the resolution element; \(\phi_{orb}\) is the residual phase due to orbit errors; \(\phi_{atm}\) is the difference in atmospheric phase delay between passes; \(\phi_n\) is the phase noise due to both temporal variability in scattering and thermal noise; and \(W\{\cdot\}\) is the wrapping
operator that drops whole phase cycles (2π), as only a fractional part of a cycle can be measured with SAR interferometry. In order to obtain $\phi_{\text{def}}$, other contributing terms including $\phi_{\text{dem}}, \phi_{\text{orb}}, \phi_{\text{atm}},$ and $\phi_{n}$ must be removed or reduced.

We set multi-looking factors of 3×7 (range by azimuth) and 2×4 for ALOS PALSAR and ALOS-2 PALSAR-2 images, respectively, in order to reduce the approximately Gaussian-distributed data noise $\phi_{n}$ (Hanssen, 2001). We also minimized the DEM contributions $\phi_{\text{dem}}$ by using the 1-arcsec SRTM DEMs (Farr et al., 2007) and reduced the orbit-related artifacts $\phi_{\text{orb}}$ using the quadratic fitting (Fattahi and Amelung, 2014). The stratified atmospheric artifacts related to regional topography were reduced by using a linear fitting, and other large-spatial-scale phase artifacts such as tropospheric noises were largely reduced by selecting localized, stable, and highly coherent reference regions near the landslides. We unwrapped the SAR interferograms using the minimum cost flow approach (Costantini, 1998) and set a coherence threshold of 0.4 for both ALOS and ALOS-2 interferograms. Accuracy of the InSAR measurement can be quantified based on the Cramer-Rao bound (Rodriguez and Martin, 1992):

$$
\sigma = \frac{\lambda}{4\pi} \sqrt{\frac{1}{2NM} \frac{(1 - \gamma^2)}{\gamma^2}}
$$

(5.2)

where $\sigma$ is the uncertainty of InSAR measurements, $\lambda$ the radar wavelength, $N$ and $M$ the window sizes for the coherence estimation, and $\gamma$ the coherence. We used a 32×32 moving window for the coherence estimation, which consequently corresponds to a minimum measurement uncertainty of ~1.4 mm for both ALOS and ALOS-2 data.
5.2.2 Identification of Active Landslides

Active landslides were identified based on the ground motion captured by SAR interferograms. All of the interferograms with good coherence (greater than 0.4) and various temporal (maximal two years) and perpendicular baselines were utilized to cross-validate the identified landslides. We also used the 10-meter-resolution DEMs (USGS, 2020b) from the U.S. Geological Survey and the high-resolution true color image time series from Google Earth to exclude non-landsliding displacement signals dominated by processes such as vegetation regrowth after clear cut, water level change in wetlands, underground oil exploitation, and urban construction. Note that rapid landslide activities such as rock avalanche and debris flow that alter original ground features significantly leading to complete coherence loss are not identifiable from SAR interferograms.

5.2.3 Bedrock of the Landslides

Bedrock formations of the identified landslides were derived from the State Geologic Map Compilation (SGMC) geodatabase of the conterminous United States (ver. 1.1, August 2017) (Horton et al., 2017). We combined the results for essentially repeated geologic formations (e.g., multiple “basalts”) and used adjacent hillslope material to revise the formation for eleven landslides that were supposedly in alluvium but actually appeared to have deposited thereon (Table 5.1).
<table>
<thead>
<tr>
<th>Name abbreviation</th>
<th>Full name</th>
<th>General Type</th>
<th>Description with major constituents (USGS 2020a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Franciscan Schist</td>
<td>Franciscan schist</td>
<td>Metamorphic</td>
<td>Blueschist and semi-schist of Franciscan complex. Major - Mica-schist (Blueschist). Strongly deformed quartz-mica schist containing blueschist-facies minerals</td>
</tr>
<tr>
<td>Pre-Upper Jurassic</td>
<td>Pre-Upper Jurassic metamorphic rocks of the low-grade zone</td>
<td>Metamorphic</td>
<td>Greenschist, phyllite, and slate; includes some limestone, quartzose phyllite, schistose metaconglomerate, breccia, and basic igneous rocks. Includes schist locally. Major - Phyllite- (Glaucophane-schist) Darrington Phyllite metamorphosed in blueschist facies</td>
</tr>
<tr>
<td>Ultramafic Mesozoic Unit 3</td>
<td>Ultramafic rocks, chiefly Mesozoic, unit 3 (Coast Ranges and Western Klamath Mountains)</td>
<td>Mélange</td>
<td>Ultramafic rocks, mostly serpentine. Minor peridotite, gabbro, and diabase. Chiefly Mesozoic unit 3. Major - Serpentinite - Formed by alteration of peridotite. Also forms sheared matrix of serpentinite mélange</td>
</tr>
<tr>
<td>Franciscan Complex Unit 1</td>
<td>Franciscan Complex, unit 1 (Coast Ranges)</td>
<td>Mélange</td>
<td>Cretaceous and Jurassic sandstone with smaller amounts of shale, chert, limestone, and conglomerate. Includes Franciscan melange, except where separated. Major - Sandstone - Mostly graywacke; commonly contains blueschist-facies metamorphic minerals. Mudstone - Generally sheared. Commonly forms matrix of mélange. Also described as shale and argillite</td>
</tr>
<tr>
<td>Paleozoic Marine Unit 9</td>
<td>Paleozoic marine rocks, undivided, unit 9 (Western Klamath Mountains)</td>
<td>Mélange</td>
<td>Undivided Paleozoic metasedimentary rocks. Includes slate, sandstone, shale, chert, conglomerate, limestone, dolomite, marble, phyllite, schist, hornfels, and quartzite. Major - Mélange - (mélange) Disrupted chert, argillite, volcanic rocks, and clastic sedimentary rocks containing blocks of limestone, marble, and amphibolite</td>
</tr>
<tr>
<td>Ultramafic Ophiolite</td>
<td>Ultramafic and related rocks of ophiolite sequences</td>
<td>Mélange</td>
<td>Predominantly harzburgite and dunite with both cumulate and tectonite fabrics. Locally altered to serpentinite. Includes gabbroic rocks and sheeted diabasic dike complexes. Major - peridotite, serpentinite (Pluton). Includes basal parts of ophiolites</td>
</tr>
<tr>
<td>Ultramafic Mesozoic Unit 2</td>
<td>Ultramafic rocks, chiefly Mesozoic, unit 2 (Western Sierra Nevada and Klamath Mountains)</td>
<td>Mélange</td>
<td>Ultramafic rocks, mostly serpentine. Minor peridotite, gabbro, and diabase. Major -Serpentinite - Forms matrix of mélanges; also occurs as alteration product of ultramafic rock slabs in mélange. Peridotite - Commonly occurs as blocks and slabs of harzburgite-dunite tectonite in serpentinite-matrix mélange</td>
</tr>
<tr>
<td>Name abbreviation</td>
<td>Full name</td>
<td>General Type</td>
<td>Description with major constituents (USGS 2020a)</td>
</tr>
<tr>
<td>--------------------------------------------------------</td>
<td>----------------------------------------------------</td>
<td>--------------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Tertiary-Cretaceous Coastal Belt</td>
<td>Tertiary-Cretaceous Coastal Belt Rocks</td>
<td>Mélange</td>
<td>Sandstone, shale and minor conglomerate in coastal belt of northwestern California; included by some in Franciscan Complex. Major - Mudstone (Bed) Penetratively sheared; commonly forms matrix of mélange enclosing other rocks of unit. Sandstone (Bed) Feldspathic to arkosic. Commonly cut by laumontite veins; commonly contains fine-grained prehnite and pumpellylite. Ranges from partially disrupted to mélange.</td>
</tr>
<tr>
<td>Paleocene Marine Unit 2</td>
<td>Paleocene marine rocks, unit 2 (Northern California)</td>
<td>Sedimentary</td>
<td>Sandstone, shale, and conglomerate; mostly well consolidated. Major - Sandstone (Bed, Arkosic) Arkosic to feldspathic; locally lithic. Thin- to thick-bedded to massive. Interpreted as turbidites. Mudstone (Bed) Silty; thinly interbedded with sandstone.</td>
</tr>
<tr>
<td>Sedimentary Dothan Formation</td>
<td>Sedimentary rocks of Dothan Formation and related rocks</td>
<td>Sedimentary</td>
<td>Sandstone, conglomerate, graywacke, rhythmically banded chert lenses. Includes western Dothan and Otter Point Formations in Curry and southern Coos Counties. Major - Graywacke (Bed) turbidite facies. Mudstone (Bed)</td>
</tr>
<tr>
<td>Mesozoic-Tertiary Marine, undivided</td>
<td>Mesozoic-Tertiary marine rocks, undivided</td>
<td>Sedimentary</td>
<td>Dark-gray, massive to poorly bedded gray-wacke of the interior Olympic Peninsula; commonly with interbedded slate, argillite, volcanic rocks, and minor arkosic sandstone. Major - argillite, slate, graywacke (Bed)</td>
</tr>
<tr>
<td>Pliocene Marine</td>
<td>Pliocene marine rocks</td>
<td>Sedimentary</td>
<td>Sandstone, siltstone, shale, and conglomerate. Major - Mudstone (Bed). Sandstone (Bed)</td>
</tr>
<tr>
<td>Eocene-Oligocene Volcanic</td>
<td>Eocene-Oligocene volcanic rocks</td>
<td>Igneous</td>
<td>Predominantly light-green, bedded andesite breccia with interbedded andesite and basalt flows, mudflows, and tuff beds; becomes more tuffaceous near top of unit. Includes tuffaceous and arkosic sandstone, shale, and carbonaceous shale beds in central and southern Cascade Mountains. hyodacite and quartz latite flows in northwestern Ferry County. Major - Basalt (Flow, Pyroclastic-tuff). Andesite (Flow, Pyroclastic-tuff, Volcaniclastic-volcanic breccia)</td>
</tr>
<tr>
<td>Oligocene-Miocene Volcanic</td>
<td>Oligocene-Miocene volcanic rocks</td>
<td>Igneous</td>
<td>Andesite flow breccia, andesite flows, and minor tuff beds; includes some basalt flows and flow breccia. Commonly more massive and less altered than similar-appearing Eocene-Oligocene volcanic rocks. Clastic flows and flows of black glass, and course to fine-grained clastic and pyroclastic rocks in the Republic and Curlew areas of Ferry County. Major - Andesite (Flow, Pyroclastic-tuff, Volcaniclastic-volcanic breccia)</td>
</tr>
<tr>
<td>Name abbreviation</td>
<td>Full name</td>
<td>General Type</td>
<td>Description with major constituents (USGS 2020a)</td>
</tr>
<tr>
<td>-------------------</td>
<td>-----------</td>
<td>--------------</td>
<td>-----------------------------------------------</td>
</tr>
<tr>
<td>Upper Eocene Volcanic</td>
<td>Upper Eocene volcanic rocks</td>
<td>Igneous</td>
<td>Predominantly andesite flows and breccia; includes some basalt flows. Contains basaltic conglomerate, pyroclastic rocks, tuff beds, and sandstone in Chehalis-Centralia coal district, Lewis County. Major - Andesite (Flow, Pyroclastic, Volcaniclastic-volcanic breccia). Basaltic-andesite (Flow)</td>
</tr>
<tr>
<td>Miocene Volcanic</td>
<td>Miocene volcanic rocks</td>
<td>Igneous</td>
<td>Dark-gray to black, dense aphanitic basalt flows; commonly columnar jointed, less commonly irregularly and platy jointed; some flows vesicular, grading to scoriaceous; includes minor pillow lava, palagonite beds, and interbedded soil profiles and sedimentary beds; contains diatomite beds locally. Maximum thickness in south-central Washington may be in excess of 10,000 feet; much thinner in western Washington, where flows are mostly associated with marine sedimentary rocks. Includes acidic and intermediate volcanic rocks in northern Cascade Mountains. Major - Basalt (Flow, Pyroclastic-tuff, Dike or sill, Volcaniclastic-volcanic breccia)</td>
</tr>
</tbody>
</table>
5.2.4 Landslide Area-volume Scaling and Average Slope Angle

A power-law relationship between landslide volume, $V$, and landslide surface area, $A$, was used to estimate landslide volumes in varied bedrock (Larson et al., 2010):

$$ V \propto A^{\gamma} $$

(5.3)

where $\gamma$ is a scaling exponent. We used $\gamma = 1.6$ for the identified large, deep-seated landslides (Larson et al., 2010). Surface areas of landslides were computed from the landslide boundary (Xu et al., 2020b) outlined from SAR interferograms.

The slope angle of each DEM cell element was derived from the 10-meter-resolution DEMs. Each identified landslide spatially covers multiple DEM cell elements, and we define the average slope angle of a landslide as the arithmetic mean of all cell elements within the landslide boundary.

5.2.5 Land Uplift Rate

Land uplift rates in the U.S. west coast states were obtained by evaluating published literature on geologically and historically recent vertical land movement. This literature (Table 5.2) includes studies emphasizing land surface surveying (Amos et al., 2014; Hammond et al., 2016; Levy, 2019; Yousefi et al., 2020) during recent times, or geologic studies generally extending from recent times into the Quaternary and Neogene Periods (Bennett et al., 2016a; Amos et al., 2014; Levy, 2019; Yousefi et al., 2020; Anderson, 2008; Barth and May, 1992; Hellwig, 2010; House, 1999; Jones, 1987; Kesley and Bockheim, 1994; Kobor and Roering, 2004; Lock et al., 2006; Machette et al., 1984; Muhs et al., 1992; Pazzaglia and Brandon, 2001; Penserini et al., 2017; Reiners et al., 2002; Schweickert, 2009; Spotila et al., 1998; Unruh, 1991). Longer-term studies emphasized fluvial and coastal geomorphology, often with cosmogenic nuclide and/or radionuclide dating, thermochronology, and modeling. We interpolated these pointwise uplift data into a gridded raster.
file using inverse distance weighting, and we clipped the gridded data to within 100 km of the points, to land sloped more steeply than 5°, and by the geographical boundary of the U.S. west coast states.

Table 5.2 Source literature of the uplift data for the U.S. west coast.

<table>
<thead>
<tr>
<th>Literature</th>
<th>Primary time period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amos et al., 2014</td>
<td>Recent</td>
</tr>
<tr>
<td>Anderson, 2008</td>
<td>Neogene – recent</td>
</tr>
<tr>
<td>Barth and May, 1992</td>
<td>Cretaceous</td>
</tr>
<tr>
<td>Bennett et al., 2016</td>
<td>Neogene – recent</td>
</tr>
<tr>
<td>Hammond et al., 2016</td>
<td>Recent</td>
</tr>
<tr>
<td>Hellwig, 2010</td>
<td>Pleistocene – recent</td>
</tr>
<tr>
<td>House, 1999</td>
<td>Cenozoic</td>
</tr>
<tr>
<td>Jones, 1987</td>
<td>Neogene – recent</td>
</tr>
<tr>
<td>Kelsey and Bockheim, 1994</td>
<td>Quaternary</td>
</tr>
<tr>
<td>Kobor and Roering, 2004</td>
<td>Quaternary</td>
</tr>
<tr>
<td>Levy, 2019</td>
<td>Recent</td>
</tr>
<tr>
<td>Lock et al., 2016</td>
<td>Neogene – Quaternary</td>
</tr>
<tr>
<td>Machette et al., 1984</td>
<td>Quaternary</td>
</tr>
<tr>
<td>Muhs et al., 1992</td>
<td>Quaternary</td>
</tr>
<tr>
<td>Pazzaglia and Brandon, 2001</td>
<td>Quaternary</td>
</tr>
<tr>
<td>Penserini et al., 2017</td>
<td>Recent</td>
</tr>
<tr>
<td>Reiners et al., 2002</td>
<td>Tertiary – recent</td>
</tr>
<tr>
<td>Roering et al., 2015</td>
<td>Recent</td>
</tr>
<tr>
<td>Schweickert, 2009</td>
<td>Pliocene – recent</td>
</tr>
<tr>
<td>Sportila et al., 1998</td>
<td>Neogene – recent</td>
</tr>
<tr>
<td>Unruh, 1991</td>
<td>Neogene – recent</td>
</tr>
<tr>
<td>Yousefi et al., 2020</td>
<td>Holocene</td>
</tr>
</tbody>
</table>
5.3 Results

5.3.1 Discovery of Hidden Landslide Hazards

We processed 6589 scenes of ascending ALOS PALSAR (Advanced Land Observation Satellite–Phased Array type L-band Synthetic Aperture Radar) images acquired between 2007 and 2011, and 484 scenes of ALOS-2 PALSAR-2 images acquired between 2015 and 2019 using the InSAR method to discover large, active landslides over the entire U.S. west coast states (the left panel in Figure 5.1). Active landslides during the observation period were identified from deformation signals captured by the differential InSAR interferograms, assisted by 10-meter-resolution DEMs (Digital Elevation Models) (USGS, 2020b) and high-resolution optical satellite images.

We identified 630 landslides in total, of which 379 were active between 2007 and 2011, 476 were active between 2015 and 2019, and 225 were active during both the 2007–2011 and 2015–2019 periods (the exact active areas might slightly vary) (Figure 5.2). Spatially, the landslides are spread out over the U.S. west coast states, yet with concentrations in mountain ranges of western Washington, southwestern Oregon, and northwestern California (Figure 5.2). Multiple towns and roads especially in northern Washington, northwestern California, and the vicinity of the coastline are within 0.5-5 km to the identified landslides (Figure 5.2; the right panel in Figure 5.1), and could be threatened by future failure events that initiate rapid slides and flows that might travel kilometers (Legros, 2002) downslope/downstream. Moreover, comparison with Google Earth optical images reveals numerous infrastructures which are located on the identified active landslides. We also identified 89 active rock glaciers that are predominantly distributed along the high mountain ridges in eastern California (Figure 5.2). Overall, these InSAR-captured active landslides are spatially large and some are on relatively steep slopes, which imply high hazard
potentials to the vicinity during possible future runout events. Spatial sizes of the identified landslides range from $4 \times 10^4 \text{ m}^2$ to $13 \times 10^6 \text{ m}^2$, and 88.7% are larger than $10^5 \text{ m}^2$. The majority of the landslides (97.1%) have slope angles between 5 and 30 degrees, and 16.8% (106 slides) are steeper than 20 degrees (Figure 5.3).

Figure 5.1 The left panel – coverage of the processed satellite radar images. Gray shaded rectangles illustrate spatial extent of the ascending ALOS PALSAR images used (2007–2011), and the white shaded rectangles represent spatial coverage of the ALOS-2 PALSAR-2 images (2015–2019). The ALOS images spatially cover the entire U.S. West Coast, and the ALOS-2 images are primarily distributed over the western regions and cover 97.6% of the identified landslides. The right panel
comparison of InSAR-captured landslides and the national landslide inventory. The InSAR-captured landslides denote active landslides detected by ALOS (2007–2011) and/or ALOS-2 (2015–2019) radar images. The landslide inventory (Jones et al. 2019) was compiled from multiple sources and includes landslides recorded between 1932 and 2018, but only as point locations.

Figure 5.2 Active landslides detected by radar satellites. The states are annotated as WA=Washington, OR=Oregon, CA=California. Geographical locations of towns were obtained
from U.S. Census Bureau (2017 data; USCB, 2020). Topographic maps were produced based on the 10-meter-resolution DEMs (USGS, 2020b).

Figure 5.3 Surface geometry of the identified landslides. Left, probability distribution of active areas of the 630 slow-moving landslides. The figure in the upper-right corner is an enlarged illustration of landslides larger than 4 km$^2$. Right, probability distribution of average slope angles of the identified landslides.

Of the 630 detected landslides, only 29 (comprising 4.6%) are included in the national landslide geodatabase (Jones et al., 2019), which is a compilation of multiple global, national, and state-level landslide inventories (the right panel in Figure 5.1). The 89 active rock glaciers were also absent. A key reason that most of our identified landslides are missing from the geodatabase is that these landslide inventories source from human-reported events and geologic maps (Jones et al., 2019), yet only landslides with historical failures or obvious geomorphic signatures would typically have been noticed and reported. Consequently, long-term, slow or creeping landslide movement are less readily recognized (Highland and Bobrowsky, 2008; Keefer and Johnson,
1983) so are relatively infrequently discovered. Indeed, our results show that many landslides that we discovered are nearly indistinguishable from their neighboring stable hillslopes on the high-resolution optical images, but their active slow motions (4–17 cm/yr along radar line-of-sight direction) were clearly captured and measured by the InSAR interferograms (e.g., Figure 5.4). Note that the free and frequently acquired SAR datasets (3–60 repeated acquisitions per year since 1992) also allow identifying the presently active section of a landslide, which are less achievable from LiDAR hillshade maps. In addition, many landslides recorded in the existing geodatabase (Jones et al., 2019) since 1932 were one-time failures such as flows and avalanches that will not recur (Cruden and Varnes, 1996), while the InSARaptured large, slow-moving slides are likely to remain active in the near future (Kesley and Bockhein, 1994; Bovis and Jones, 1992; Mackey et al., 2009; Varnes and Savage, 1996) and pose continued threats.

5.3.2 Bedrock Control of Slow-moving Landslides

Using the SGMC (State Geologic Map Compilation) geodatabase of the conterminous United States (Horton et al., 2017), we statistically analyzed the bedrock underlying and likely involved in the identified 630 slow-moving landslides. Over the entire study area, 102 out of the total 398 bedrock formations had landslides, and 16 formations had more than 10 landslides. We selected only these 16 formations for detailed statistical analyses and categorized them into four distinct types: metamorphic rocks, mélangé, sedimentary rocks, and igneous rocks. Particularly, we investigated the spatial density (defined as the area ratio of overlying landslides by a lithology) and spatial size of the landslides with regard to various lithology.
Figure 5.4 Examples of hidden active landslides discovered by SAR interferograms. This figure illustrates ten exemplary pairs of presently active slow-moving landslides that were generally unidentifiable from submeter-resolution optical images (columns 1 and 3), but were clearly revealed by SAR interferograms (columns 2 and 4). These ten landslides were distributed over Washington, Oregon, and California (Geographical coordinates are shown in degrees beside each landslide). Red polygons outline the landslide extents, and white arrows mark the downslope directions. All the optical images were acquired in 2019 and accessed from Google Earth. All the SAR interferograms were produced from ALOS-2 SAR images acquired between May 2018 and August 2019. One fringe (changes from $-\pi$ to $\pi$) on the SAR interferograms represents a line-of-sight movement of 12.1 centimeters.
Figure 5.5 Landslide spatial density by bedrock. Left, average landslide spatial densities by the 16 different formations on which more than ten landslides were identified. Descriptions of the bedrock formations refer to Table 5.1. Right, average landslide spatial densities by the four general bedrock types.

Figure 5.6 Landslide size by bedrock. Left, average landslide size by the 16 formations. Descriptions of the formation refer to Table 5.1. Right, average landslide size by the four general bedrock types.
Our results demonstrate that both spatial density and size of the identified slow-moving landslides were strongly controlled by their lithology. By bedrock type, the greatest spatial density was found in metamorphic rocks \( (15,300 \text{ m}^2/\text{km}^2) \), followed by mélange \( (5400 \text{ m}^2/\text{km}^2) \), sedimentary rocks \( (3200 \text{ m}^2/\text{km}^2) \), and igneous rocks \( (1300 \text{ m}^2/\text{km}^2) \) (Figure 4). Similar trends were also found in their spatial sizes. The largest mean size was in metamorphic rocks \( (1.52 \text{ km}^2) \), then mélange \( (0.6 \text{ km}^2) \), and similar in sedimentary \( (0.44 \text{ km}^2) \) and igneous rocks \( (0.43 \text{ km}^2) \) (Figure 5). Overall, landslides were largest and most frequent in metamorphic rocks followed by mélange, and the spatial density and mean size were 3 to 12 times greater in metamorphic rocks than in sedimentary and igneous rocks. The results also indicate that these presently active landslides are presenting hazards from and modifying landscapes of mélange bedrock to the greatest extent. Assuming similar area-volume scaling (Larson et al., 2010) for landslides in each of the bedrock types, the results indicate that slow-moving landslides in mélange have mobilized 1.4, 8.6, and 10.6 times the sediment of landslides in metamorphic, igneous, and sedimentary rocks, respectively.

The greater size and density of slow-moving landslides in metamorphic rocks and mélange compared to igneous and sedimentary rocks may partly result from generally lower rock mass strength due to pervasive discontinuities in foliated and tectonically sheared metamorphic rocks and mélange (Cruden and Varnes, 1996), as well as the relatively high abundance of clay minerals in these altered rocks (Lambe and Whitman, 1969; Schmidt and Montgomery, 1995). In addition, igneous rocks in which landslides were identified were mostly andesite and basalt flows (Table 5.1). Flows and sedimentary rock are likely to have spatially extensive discontinuities between beds and flow units, and relatively high anisotropy of material properties because of their layered nature (Jaeger et al., 2009). Such discontinuities and anisotropy are relatively lacking from most
metamorphic and mélange rock formations (Jaeger et al., 2009). Shallower and therefore smaller landslides are more likely in materials with such anisotropy (Cruden and Varnes, 1996), whereas deeper and therefore larger landslides are more likely in more isotropic materials (Cruden and Varnes, 1996), such as mélange and metamorphic rocks.

5.3.3 Landsliding Contributed by Land Uplift

We investigated how vertical land motion may relate to the identified slow-moving landslides by incorporating vertical motion data for the study area from radioisotope dating, modeling and recent observations (Table 5.2). We expect that land uplift results in and sustains continuous landsliding because uplift creates topographic relief resulting in stream downcutting and hillslope instability (Burbank et al., 1996; Roering et al., 2005; Cruden and Varnes, 1996; Lambe and Whitman, 1969; Larson and Montgometry, 2012; Bennett et al., 2016a). Slow-moving landslides identifiable from InSAR may be very long lived ($10^2$–$10^4$ years) (Bovis and Jones, 1992; Varnes and Savage, 1996; Mackey et al., 2009; Keefer and Johnson, 1983) and usually continue moving during dry periods or reactivate thereafter (Bovis and Jones, 1992; Bennett et al., 2016b; Skempton et al., 1989; Coe, 2012), thus their occurrence and persistent long-term creeping motions most likely have been greatly contributed to and/or sustained by geologically recent ($10^3$–$10^5$ years) uplift. However, although less sensitive to recent rainfall than small landslides, large landslides are strongly modulated by precipitation on a short timescale such as seasonal movement (Coe, 2012; Bennett et al., 2016b). Here we only focus on the potential contributions from long-term land uplift, and the short-timescale hydrological contributions are detailed in the Discussion section.
Land surface uplift measurements from a total of 79 sites over the study area were converted to gridded data using the inverse distance weighted interpolation in order to compare uplift rates at landslide locations to those at stable regions. We excluded the regions with slope angle less than 5° in the analysis as our observations show that landslides barely occur in such flat terrain (Figure 2). Our analyses reveal that the 630 landslides and the 89 rock glaciers were geographically related to geologic uplift. Overall, the rapidly uplifting northwestern Washington, southwestern Oregon, northwestern California, coastal regions of southern California, and high mountains of middle-east California all saw a great number of active landslides or rock glaciers, while the subsiding middle-west Oregon, middle-west California, and the southern end of Sierra Nevada Mountains (middle-east California) were barely involved with any identified landslides (Figure 6). Quantitatively, the uplift rates at the active landslides and rock glaciers average 0.83 mm/yr, three times higher than the mean rate of 0.27 mm/yr for the whole region (Table 5.3). The results are also insensitive to the excluded flat regions: thresholding slope angles at 0°, 10°, and 16° would yield mean uplift rates of 0.79 mm/yr over 0.12 mm/yr (landslides versus the whole region), 0.83 mm/yr over 0.30 mm/yr, and 0.82 mm/yr over 0.32 mm/yr, respectively (Table 5.3). All of the results provide evidence that the identified slow-moving landslides were preferentially located in areas with accelerated geologically recent uplift. We expect that rapid and/or small landslides similarly collocate with accelerated uplift, but InSAR does not well resolve rapid and/or small landslides.
Table 5.3 Uplift rates by excluding flat regions. Regions with slope less steep than the slope angle threshold were excluded from the corresponding results.

<table>
<thead>
<tr>
<th>Slope angle threshold (°)</th>
<th>Regions</th>
<th>Minimum rate (mm/yr)</th>
<th>Maximum rate (mm/yr)</th>
<th>Mean rate (mm/yr)</th>
<th>Standard deviation (mm/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Landslides</td>
<td>-0.62</td>
<td>2.86</td>
<td>0.79</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td>All regions</td>
<td>-3</td>
<td>5</td>
<td>0.12</td>
<td>0.65</td>
</tr>
<tr>
<td>5</td>
<td>Landslides</td>
<td>-0.62</td>
<td>2.86</td>
<td>0.83</td>
<td>0.58</td>
</tr>
<tr>
<td></td>
<td>All regions</td>
<td>-2.99</td>
<td>4.72</td>
<td>0.27</td>
<td>0.57</td>
</tr>
<tr>
<td>10</td>
<td>Landslides</td>
<td>-0.62</td>
<td>2.86</td>
<td>0.83</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td>All regions</td>
<td>-2.96</td>
<td>4.72</td>
<td>0.3</td>
<td>0.56</td>
</tr>
<tr>
<td>16</td>
<td>Landslides</td>
<td>-0.62</td>
<td>2.86</td>
<td>0.82</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>All regions</td>
<td>-2.95</td>
<td>4.72</td>
<td>0.32</td>
<td>0.55</td>
</tr>
</tbody>
</table>

5.4 Discussion and Conclusions

5.4.1 Landslide Identification Using Radar Interferometry

We revealed 630 active, large, potentially dangerous landslides hidden in the U.S. west coast states, 601 of which are missing from existing landslide inventories that source from geologic maps and citizen reports (Jones et al. 2019). These actively moving landslides are the most significant agents for regional landscape modification and are potential hazards to residents and infrastructure in the vicinity. We found that the high-accuracy InSAR tool could be effective in uncovering their locations, boundaries, and motions.

InSAR is relatively less sensitive to landslide motions that are orientated perpendicular to the radar look direction. However, mountain ranges near the U.S. west coast are dominantly north-south orientated and has formed landslides which are mostly visible from the approximately west/east looking radar sensor. Moreover, we utilized SAR interferograms spanning as long as two
years for landslide identification, and such long timespan allow landslides to accumulate a large
displacement that is clearly identifiable on SAR interferograms.

Figure 5.7 Vertical land motions near the U.S. west coast. Left, vertical uplift (green) and
subsidence (red) rates of the 79 sites shown in solid circles. Right, an interpolated map produced
from the point-wise measurements. Only hillslopes steeper than 5° and within 100 km distant from
the measurement sites are shown in the figure.
5.4.2 Geologic Impacts on Landslide Character and Kinematics

We found that bedrock lithology exerts significant control on both the spatial density and size of the slow-moving landslides. Metamorphic rocks and mélangé that have relatively homogeneous composition, discontinuity distribution, and high clay content, while also having relatively low shear strength, are most likely to bear widespread, deep, and large slow-moving landslides. In contrast, sedimentary and igneous flow rocks that have strength and hydrologic anisotropy and relatively high shear strength tend to produce relatively sparse, shallow, and small slow-moving landslides.

Our observations also provide evidence that geologic uplift is a crucial contributor to the occurrence and long-term creeping behavior of the slow-moving landslides. Both the identified active rock glaciers and slow-moving landslides are predominantly distributed over hillslopes with geologically recent \((10^3–10^5\text{ years})\), accelerated uplift, but barely observed in geologically subsiding terrains, implying a fundamental control from vertical land motion. The contributions from land uplift are a gradually cumulative effect, and such signal could be overwhelmed and clouded by other short-timescale factors (particularly precipitation). Long-term land uplift creates mountains resulting in hillslope instability, and landslide is the process to restabilize a hillslope. Hence, it is essentially land uplift that results in mountain landslides, though precipitation is often seen being the “trigger” for landslide initiation and seasonal acceleration.

5.4.3 Hydrological Impacts on Landslide Motion

On an annual scale, precipitation is widely recognized as the driver for seasonal acceleration and deceleration of slow-moving landslides (Xu et al., 2020; Squarzoni et al., 2003; Ye et al., 2004; Xu et al., 2019; Bennett et al., 2016b; Handwerger et al., 2019). However, precipitation may not be the only reason to initiate a landslide or keep a slow-moving landslide constantly active for
hundreds of years (Kesley and Bockheim, 1994; Bonzanigo et al., 2007; Roering et al., 2015). We compared 30-year average precipitation (1981-2010) relative to observed landslide locations (Figure 5.8) and found that precipitation amount at those locations is highly variable. Overall, 75% of the identified large and slowly moving landslides are located in the mountain ranges that receive relatively rich rainfall ($\geq 2000$ mm). However, numerous exceptions were found in central Washington and south-western California, where relatively dry lands (approximately 400 mm annual rainfall) produced about 90 landslides. Moreover, the rainfall-abundant (over 2500 mm) southern Cascade ranges and northern coastal ranges of Oregon only included 12 landslides, far fewer than the north-western California where 1800 mm of annual rainfall produced 484 landslides (Figure 5.8). In addition, we compared the identified landslides with the average excess precipitation between 2016 and 2019 (the right panel in Figure 5.8). Here excess precipitation is defined as the difference between annual precipitation and the 30-year average. The results show that numerous landslides in particularly southern Washington and southwestern Oregon were captured active during even the historically dry years between 2016 and 2019. Therefore, precipitation alone cannot well explain the spatial distribution of the identified slow-moving landslides.

The precipitation distribution near the U.S. west coast is not independent from land uplift. In fact, annual precipitation positively correlates with elevation (Daly et al., 2017) because the warm air coming from Pacific Ocean condenses to form cloud droplets while climbing up the high mountains and produces precipitation. As evidenced in Figure 5.8, heavy precipitation dominantly falls on the high mountains of the coastal ranges, Cascade Ranges, and the Sierra-Nevada Ranges. Consequently, land uplift not only leads to landsliding by creating high relief, but also contributes to hillslope instability by increasing precipitation over a geological timescale. In addition, the
precipitation-elevation relationship indicates that landslide locations’ correlation with precipitation may result from the correlation with mountain topography, where relatively steep hillslopes reside (also see Figure 5.2).

Figure 5.8 Comparison of landslide distribution and precipitation near the U.S. west coast. Left, 30-year average precipitation from 1981 to 2010. The depicted red polygons include both landslides and rock glaciers captured by ALOS and ALOS-2 images. Right, excess precipitation
(average annual precipitation subtracts the 30-year average) from 2017 to 2019. The green polygons only depict landslides which were active between 2017 and 2019.

5.4.4 Implication on Landslide and Geomorphic Studies

Failure events initiated from slow-moving landslides have caused considerable socioeconomic loss globally in recent decades (Schuster and Highland, 2001; Froude and Petley, 2018; Kilburn and Petley, 2003; Intrieri et al., 2018; Xu et al., 2020b), and many damages (especially casualties) could have been avoided if the precursory slow motions were revealed prior to the catastrophes. The routinely acquired (optimal every 6 days; ESA, 2020) and globally covered satellite radar images could prove valuable in uncovering such hidden landslides for mitigating future hazards, especially in response to the predicted increasingly frequent landslide activities owing to global climate change and expanding anthropogenic activities (Gariano and Guzzetti, 2016; Froude and Petley, 2018). In addition, the fundamental controls of slow-moving landslides by bedrock and vertical land motion could offer novel insights for landslide susceptibility forecasting and landform evolution studies. Globally, the geologically recent uplifts in the Himalayan mountains (Asia) (Ader et al., 2012), Alps mountains (Europe) (Sternai, 2019), Pacific West Coast (North America) (Muhs et al., 1992), and Andes mountains (South America) (Armijo et al., 2015) are expected to fuel continued landslide hazards and intensify geomorphological change. However, regional tectonic subsidence within these mountain ranges may conversely attenuate local landslide activities.
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The ALOS PALSAR data are freely accessible from the Alaska Satellite Facility (https://asf.alaska.edu/), and the ALOS-2 PALSAR-2 data are obtainable from Japan Aerospace Exploration Agency (https://auig2.jaxa.jp/). The 10-meter-resolution DEMs covering the U.S. west coast states are freely available from U.S. Geological Survey (http://usgs.gov/NationalMap/data/), and the high-resolution true color images are available from Google Earth. Shapefiles of towns and state boundaries of the U.S. west coast states are downloadable from U.S. Census Bureau (https://www.census.gov/cgi-bin/geo/shapefiles/). The State Geologic Map Compilation (SGMC) geodatabase of the conterminous United States is available from U.S. Geological Survey (USGS, 2020a). The PRISM precipitation data are freely available from the PRISM Climate Group (https://prism.oregonstate.edu/). Shapefiles depicting
landsides identified during this study are available from the U.S. Geological Survey ScienceBase repository (Xu et al. 2020a).
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CHAPTER 6

KINEMATICS OF IRRIGATION-INDUCED LANDSLIDES IN A WASHINGTON DESERT: PRELIMINARY RESULTS


6.1 Introduction

Landslides are a natural gravity-driven geomorphic process that transports unstable materials from hills downslope and modifies landscape in both short and long timescales depending on landslide motion rate (Highland and Bobrowsky, 2008; Mackey and Roering, 2011; Simoni et al., 2013). Moreover, landslides as a frequent natural hazard in mountainous regions annually claim thousands of human lives and cause billion dollars of property loss on a global basis (Froude and Petley, 2018; Spiker and Gori, 2003). Common natural triggers of landslides include seasonal precipitation, earthquakes, and coastal and stream erosion (Highland and Bobrowsky, 2008); however, anthropogenic activities are becoming an increasingly frequent trigger for slope failures in the recent decades (Froude and Petley, 2018). Particularly, agricultural irrigation has emerged into a new activator to many large landslides in arid and semi-arid regions due to increased popularity of irrigation farming since 1950s (Garcia-Chevesich et al. 2021). Monitoring
irrigation-triggered landslides helps to evaluate how irrigation water impacts slope stability and provide insights for mitigating such landslide hazards.

Post-failure behaviors of landslides significantly affect their hazard level. Slow landslides consistently damage infrastructures in their near vicinity, whereas catastrophic landslides pose escalated hazards to both infrastructures and human lives with extended spatial extents. For instance, landslide-initiated debris flows may travel several kilometers downstream/downslope and cause a catastrophe along its path (Legros, 2002). Deciphering the main factors that control landslide post-failure kinematics is critical for understanding and mitigating landslide hazards. Landslide kinematics are potentially regulated by multiple hydrogeological factors such as rainfall infiltration, soil dilation and contraction, and basal geometry, which modulate landslide basal pore pressure (Terzaghi, 1950); however, isolating and quantifying the contribution of each element for a natural landslide have always been challenging. Unlike landslides in wet climates whose motion dynamics are complicated by delayed basal pore-pressure variation from seasonal precipitation (Handwerger et al., 2013; Xu et al., 2019; Xu et al., 2020), landslides in arid climates offer a unique opportunity to naturally exclude the impacts of rainfall and enable examining other independent factors such as basal geometry. Consequently, a desert with irrigation-induced landslides provides such a natural laboratory for assessing impacts of basal geometry.

This investigation is focused on landslides induced by agricultural irrigation in a desert near Hanford, Washington. Satellite optical and radar images are utilized to identify both creeping and catastrophic landslides in the study region and to measure their post-failure motion dynamics. Filed photos and compiled soil laboratory tests data help to explain how excessive irrigation water led to widespread landslide activities along the desert valley. The life cycle of both slow landslides and catastrophic landslide are characterized by capturing and integrating concurrent landslides in
variable life stages. Moreover, by incorporating groundwater and basal topography data of multiple landslides, the critical impacts of basal topography on landslide post-failure motions are evaluated from integrating satellite observations and numerical modeling.

Our investigation provides important understandings on how agricultural irrigation destabilizes hillslopes, how groundwater level modulates landslide motions, and how basal topography regulates landslide post-failure kinematics. The knowledge can be widely applied to not only irrigation-triggered landsides but also many natural hillslope failures globally for future landslide hazard reduction.

6.2 Study Area

Prior to 1950, the arid lands near Hanford, south-central Washington with an annual rainfall of ~180 mm (Figure 6.1) was dominated by dryland farming (Schuster et al., 1989; Peel et al., 2007). Since 1950, continuous development of the Columbia Basin Project has transformed this region into one of the most productive agricultural fields in the United States (Drost, 1993) by importing irrigation water from the upstream Columbia River to the arid lands through dams and canals. About 1500 mm of irrigation water was diverted annually to the farmlands east of the Columbia River (Schuster et al., 1989; Figure 6.1). However, such successful agricultural transformation had unforeseen consequences: widespread landslides were triggered along the desert valley near Hanford (Figure 6.1) which damage roads and houses near the desert valley and harm salmon spawning in the Columbia River by transporting considerable amount of sediments downstream (Drost, 1993).
Figure 6.1 Geographical location of the study area near Hanford, Washington. A scaled-down map is shown at the bottom-left corner. The groundwater level data were modified from Drost et al. 1993.

The eastern banks of the Columbia River in the study area are composed of steep, 45 m to 170 m high bluffs. Geologically, these bluffs comprise of dominantly the Ringold Formation which overlays rocks of the Columbia River Basalt Group and is capped by Quaternary fluvial and
windblown sediments (Schuster et al., 1989). The Ringold Formation is termed for the nearly horizontal, soft rock layers (locally dipped towards the Columbia River by 1°) composed of weakly indurated claystone, siltstones, and sandstones near Hanford (Schuster et al., 1989). Mechanically, the soft rocks of the Ringold Formation are relatively strong when dry yet becomes weak when wetted. Laboratory tests of undisturbed soil samples from the bluff (Bareither et al., 2012) show that saturating the soil sample decreases the friction angle from 32.9° to 19.8° and the cohesion from 274 kPa to 46 kPa in the vertical orientation. Along the horizontal orientation, it reduces the friction angle from 22.7° to 21° and the cohesion from 368 kPa to 16.7 kPa.

From 1950 to March 1983, excessive agricultural irrigation elevated the groundwater level of the study area by 40 to 140 m (Figure 6.1) from unlined canal leakage and wastewater drainage (Drost, 1993). In addition, the irrigation water vertically infiltrates into the farmland subsurface and evolves into horizontal flows along the fine-grained, low-permeability layers to produce extensive water seepage on the bluffs (Bjornstad and Peterson, 2019). Elevated basal pore pressure and weakened soil shear strength together contributed to widespread landslide activities at the steep bluffs along the Columbia River and other hillslopes in the study region (Figure 6.1).

### 6.3 Data and Methods

This investigation was aimed at mapping active landslides and measuring their time-series displacements using satellite optical and radar images and the Interferometric Synthetic Aperture Radar (InSAR) technique. Moreover, numerical modeling and topographical maps were incorporated to decipher mechanisms of the contrasting post-failure slow and rapid motions of the observed variable types of landslides.
6.3.1 Data

The Sentinel-1 SAR images from the ascending track A166 (January 2016 – September 2020) and the descending track D42 (August 2015 – September 2020) were used to discover slow landslides and measure their time-series displacements. Google Earth images from 1996 to 2020 were utilized to identify catastrophic landslides and measuring time-series motion of a fast landslide. A 1924 topographical map and the National Elevation Datasets (USGS, 2021a) and a 2010 lidar DEM from Washington Department of Natural Resources were employed to produce pre-landslide and/or post-landslide topography of selected landslides. Daily water level of the Columbia River was obtained from a river gauge located immediately below the Priest Rapids Dam (38 km upstream of the Locke landslide in Figure 6.2b) (USGS, 2021b). Daily precipitation data of the study area were obtained from a meteorological station at the Saddle Mountain (18 km west of the Locke landslide in Figure 6.2b) (WRCC, 2021). Groundwater records from 1964 to 1983 were collected at a well 1 km east of the Johnson landslide by U.S. Bureau of Reclamation. (Figure 6.2b; Schuster et al., 1989).

6.3.2 Multitemporal InSAR Processing

SAR interferometry is a technique that utilizes the phase information in satellite radar images to achieve displacement measurement of ground objects in millimeter-level accuracy (e.g., Ferretti et al., 2007). A SAR interferogram is produced from two repeat-path SAR images that are usually separated by several days. Multiple SAR interferograms spanning varied observation periods can be used to generate time-series measurements of a ground target.

In this investigation, we utilized both ascending and descending Sentinel-1 SAR images from 2015 to 2020 to obtain InSAR time-series measurement of the target slow landslides. The National Elevation Datasets (USGS, 2021a) covering the study area were used during SAR interferogram
generation from the GAMMA software (Werner et al., 2000), and the stratified tropospheric artifacts associated with surface topography were removed before phase unwrapping. Stable, high-coherence (coherence > 0.7) reference regions (300 m × 300 m) within 1 km distant from each target landslide were selected to remove potential artifacts sourcing from regional soil moisture changes and turbulent troposphere in the interferograms. The Sentinel-1 SAR images were multi-looked using factors of 5×2 (range by azimuth) before interferometric processing, and the generated interferograms were unwrapped with the minimum cost flow method (Costantini, 1998). Measurement accuracy of each pixel in an individual SAR interferogram can be quantified from the estimated coherence (Rodriguez and Martin, 1992):

\[
\sigma = \frac{\lambda}{4\pi} \sqrt{\frac{1}{2NM} \frac{(1 - \gamma^2)}{\gamma^2}}
\]  

where \(\sigma\) is the uncertainty of InSAR measurements, \(\lambda\) the radar wavelength, \(N\) and \(M\) the window sizes for the coherence estimation, and \(\gamma\) the coherence.

Multitemporal InSAR processing was achieved by using a coherence-weighted small baseline subset (SBAS) method (see details in Section 3.3.2 or Xu et al., 2020). We selected only interferograms spanning the two closest dates for the time-series inversion and set the minimum coherence threshold as 0.4, which consequently leads to a minimum measurement uncertainty of ~ 0.35 mm for the time-series displacements.

6.3.3 Forced Water Circulation on A Wavy Sliding Surface

Field and laboratory evidence shows that many clayey, slow-moving landslides deform with dominant displacements (commonly > 70%) concentrated on the millimeters to centimeters thick basal shear zones (Hutchinson, 1983; Skempton and Petley, 1968; Morgenstern and Tchalenko,
Slow landslides commonly move in steady rates accompanied by very short periods of acceleration and deceleration, and sustained acceleration resulting in rapid motion never occurs (Keefer and Johnson, 1983; Baum and Johnson, 1993). The steady movements could be explained using the forced pore fluid circulation (Baum and Johnson, 1993) on an irregular basal surface which reduces basal pore pressure and obstructs downslope landslide movement (Figure 6.2). Physically, it can be understood as that water is squeezed out of soil on upstream side of bumps ($\theta > 0$) whereas sucked into swelling soil on downstream sides of bumps ($\theta < 0$). The forced water circulation model simplifies slow landslides as a porous elastic solid sliding over a wavy, impermeable, rigid surface with an average rate $\bar{v}_x$ along the x direction (Figure 6.2), and the stress and pore water movement in the landslide materials are governed by four equations (Baum and Johnson, 1993; Rice and Cleary, 1976):

$$\frac{\partial T_{xx}}{\partial x} + \frac{\partial T_{zx}}{\partial z} + \gamma_s \sin \alpha = 0 \quad (6.2)$$

$$\frac{\partial T_{zx}}{\partial x} + \frac{\partial T_{zz}}{\partial z} + \gamma_s \cos \alpha = 0 \quad (6.3)$$

$$\nabla^2 \left( T_{xx} + T_{zz} + \frac{1 - 2\mu}{1 - \mu} P \right) = 0 \quad (6.4)$$

$$\frac{2K \gamma_w (1 - \mu)}{\gamma_w (1 - 2\mu)} \nabla^2 (T_{xx} + T_{zz} + 2P) = \frac{\partial}{\partial t} (T_{xx} + T_{zz} + 2P) \quad (6.5)$$

where $T_{xx}, T_{zz}, T_{zx}$ are the stresses as shown in Figure 6.2. $\gamma_s$ is the unit weight of the saturated soils, $\alpha$ is the slope angle, $\mu$ is the Poisson’s ratio for drained deformation, $P$ is the pore-water pressure, $K$ is the hydraulic conductivity, $G$ is the shear modulus, and $\gamma_w$ is the unit weight of
water. Equations 6.2 and 6.3 are the stress equilibrium equations, equation 6.4 is the compatibility equation, and equation 6.5 is the stress diffusion equation.

Figure 6.2 Sketch of a landslide block sliding on a wavy surface. (a) The x-axis is along the average slope of the slip surface, and the z-axis is perpendicular to x. A and L are the amplitude and wavelength of the sine-wave slip surface. \( \alpha \) is the slope angle measured from the x-axis to the horizontal. \( \theta \) is the angle measured counterclockwise from the x-axis to a line tangent to the slip surface at any point x. Local coordinates \( n \) and \( s \) are normal and tangential to the slip surface. The blue arrows indicate that that water is flowing away from the upstream sides of the bumps and is
flowing toward the downstream sides of the bumps. (b) Stresses acting on an arbitrary element shown in (a). All the arrows point to the positive orientations of the stresses. The figure was modified from Baum and Johnson, 1993.

Solving equations 6.2 to 6.5 requires three boundary conditions based on physical assumptions embedded in the model:

\[
[v]_{z_0} = \bar{v}_x \left( \frac{dz_0}{dx} \right) \tag{6.6}
\]

\[
[T_{z\xi}]_{z_0} = 0 \tag{6.7}
\]

\[
\left[ \frac{\partial^2 \bar{P}}{\partial \xi^2} \right]_{z_0} = -\left( \frac{\bar{v}_x \gamma_w}{K} \right) \left[ \frac{\partial \bar{e}}{\partial \xi} \right]_{z_0} \tag{6.8}
\]

where \( z = z_0(x) \) and \( z = z_1(x) \) are the ground surface and the basal slip surface, respectively (Figure 6.2). \([v]_{z_0}\) is the first-order derivative of the landslide motion rate on the slip surface along the \( z \) direction. \( \xi = x - \bar{v}_x t \) is introduced as a new coordinate system which moves parallel with \( x \) in order to simply the problem as independent of time (Rosenthal, 1946). \([T_{z\xi}]_{z_0}\) is the first-order shear stress on the slip surface, \( \bar{P} \) is the first-order pore-water pressure, and \( \bar{e} \) is the volumetric strain. Equation 6.6 states that the landslide is sliding tangential to the slip surface \( z_0(x) \). Equation 6.7 sources from the assumption that the first-order shear stress is zero everywhere on the basal slip boundary. Note that this assumption differs from the Coulomb friction which considers shear dilation and contraction on the slip surface. Equation 6.8 relates fluid flow to volume change at the slip surface by using the continuity equation.
Using the above three boundary conditions to solve equations 6.2 to 6.5 and drop several non-significant high-order terms, the average resistance $R$ which results from the slip surface roughness and acts parallel to $x$ can be obtained (Baum and Johnson, 1993):

$$R = -\bar{v}_x (Al)^2 \gamma_w \frac{(1 - 2\mu)^2}{4kI(1 - \mu)^2}$$  \hspace{1cm} (6.9)

where $l = 2\pi/L$ is the wave number, $L$ is the wavelength of sinusoidal bumps on the slip surface, $Al$, the product of the amplitude and the wave number, is the maximum local slope of the slip surface with respect to $x$. Equation 6.9 shows that the sliding resistance $R$ resulting from forced water circulation increases linearly with the average landslide motion rate $\bar{v}_x$. It would consequently contribute to stopping slow landslides from infinite acceleration after the shearing failure instigates.

6.4 Preliminary Results

6.4.1 Mapping Slow and Catastrophic Landslides

Using SAR interferograms from both the ascending Sentinel-1 track A166 and the descending track D42 between August 2015 to September 2020 as well as satellite optical images from the Google Earth between 1996 to 2020, we identified 12 concurrently active slow large landslide complexes and 13 catastrophic landslides in the study region near Hanford, Washington (Figure 6.3). These identified landslides dominantly occurred at the bluffs along the eastern bank of the Columbia River. Currently, active landslide regions (31.3 km) occupy 50.2% of the eastern Columbia River bank in the study region (62.1 km).
Figure 6.3 Irrigation-triggered landslides in a desert near Hanford, Washington. (a) S1 – S13 denote the slow landslides identified from SAR interferograms between 2015 and 2020. C1 – C11 mark catastrophic landslides identified from Google Earth true color images. Some catastrophic landslide and slow landslides may overlap. The background hillshade map was produced from the 10 m resolution National Elevation Datasets (USGS, 2021). (b) A Google Earth true color image acquired in 2020 that covers the same geographical extent as (a). The irrigated farmlands are mostly in green color.

The largest active landslide complex in the region is the Wiehl Ranch landslide complex (S2), which are composed of multiple landslides and stretches by ~ 7.5 km along the Columbia River bank (Figure 6.3). Each landslide within the complex measures ~ 750 m in the longitudinal direction and 200 – 750 m in the width direction. The Wiehl Ranch landslide complex has also
been rapidly expanding south from 1996 to 2020 which potentially resulted from water infiltration from the wastewater pond 4 km east of the landslide headscarp (Figure 6.3b). The largest catastrophic runout landslide (C1) occurred near the Savage landslide complex in June 2017, which inundated a 940 m by 830 m (length by width) region along the hillslope. The formed earth flows remain active with slow motions by September 2020 (Figures 6.3 and 6.4). This also explains the overlaps among polygons of the identified slow and catastrophic landslides in Figure 6.3. Moreover, the 2020 true color image (Figure 6.3b) illustrates that vast farmlands in green colors exist on the eastern side of the Columbia River where the active landslides reside. In contrast, the dry lands in the western side of the Columbia River were not irrigated and did not include any identified landslides.

Annual movement rates at different locations within a same landslide complex vary significantly, which indicates that the landslide complexes are composed of multiple relatively independent landslides moving towards the Columbia River. For example, the northernmost section of the Locke landslide complex (S1) had a 3.3 cm/year Line-of-Sight (LOS) motion rate between 2015 and 2020 from the ascending Sentinel-1 SAR images, whereas the central section moved at 1.5 cm/year and some sections remained almost stable (Figure 6.4a). Similarly, the Savage landslide complex (S5) experienced most deformation (2 – 3 cm/year along A166 LOS direction) at the northernmost and the southernmost sections, whereas the central section only moved at 0.4 cm/year (Figure 6.4a). The individual landslides within a complex are also distinguishable from their separate, curve-shaped headscarsps ((Figure 6.4). The identified large catastrophic landslides (e.g., C1, C6, C12) were commonly initiated at their steep headscarsps beside the irrigated farmlands (Figure 6.4b) and were instigated in irrigation seasons (April to
October), which indicates that irrigation water was their primary failure trigger. The inundation extents vary depending on the source volume and basal topography (Figure 6.4b).

Figure 6.4 Landslides observed from space. (a) Stacking SAR interferograms from 2016 to 2020 for six typical slow landslide complexes. For each slow landslide, the left SAR interferogram was produced from ascending Sentinel-1 images (track 166), and the right one was from descending images (track 42). A full color fringe from red to violet on the SAR interferograms represents a LOS displacement of 33.6 cm. The white “+” symbols mark the selected points for time series analyses. (b) Google Earth true color images of six catastrophic landslides. Note that the image size is not scaled up by the real landslide extent. Landslide motion directions are marked with red arrows.
6.4.2 Kinematics of Slow Landslides

6.4.2.1 The slow life cycle from initiation to deposition

In order to characterize the life cycle of slow landslides trigged by agricultural irrigation near Hanford, Washington, we measured and integrated the motion dynamics of the Locke landslide (S1) and the southernmost section of the Savage landslide (S2) to establish a typical showcase. During our satellite observation period from 1996 to 2020, the Locke landslide has already stepped into the relatively later stage as motion cessation and final deposition (Figure 6.5), whereas the Southern Savage landslide were freshly instigated and subsequently stepped into gradual deceleration (Figure 6.6). Both landslide complexes were initiated in a highly similar amnner by water infiltration from nearby wastewater ponds, progressed similarly by advancing forward towards the relatively flat Columbia River bed, and began to slow down afterwards.

Figure 6.5 illustrate the 2020 landscape of the Locke landslide complex. This landslide complex was initiated by irrigation water which was diverted to a wastewater pond ~ 1 km east of the landslide in late 1960s for enhancing wildlife habitat (Bjornstad and Peterson, 2019). The landslide block slumps began in 1970s, peaked around 1985. The wastewater pond was completely drained in mid-1990s in an effort to stop the landsliding; however, landslide creeping continues to the present day at maximum 9.3 cm/year along the downslope direction (Figure 6.4a). From 1924 to 2020, the advancing landslide toe has shifted the western Columbia River bank eastward by maximum 260 m (Figure 6.5b), which also exacerbated river erosion of the Locke Island by up to 42 m since 1994 (Bjornstad, 2006). Aeolian sand covers the large unirrigated lands east of the landslide (Figure 6.5a; Figure 6.3b) whereas water seepage and sagged ponds are clearly present near the landslide headscarp, which clearly evidences irrigation water infiltration as the primary landslide trigger.
Similar to the Locke landslide complex, the southern Savage landslide complex shares analogous geological and topographical settings and was also triggered by irrigation water infiltration. The primary water source was potentially from the wastewater pond 3.1 km east of the landslide headscarp (Figure 6.3b and Figure 6.6). Active landslide activities were initiated in 2003 at the very southern end of the landslide complex. The motion rates peaked at 22.5 m/year between
2003 and 2006, followed by subsequent gradual rate decrease to 17.3 m/year by 2009, 12.4 m/year by 2011, 10.3 m/year by 2013, and 6.1 m/year by 2020. Note that estimations of the shoreline position are more sensitive to river level fluctuation after 2015 as the landslide toe started to advance nearly horizontally and more slowly. Following the deceleration trend, it can be estimated that the movement of the southern Savage landslide will reduce to 9.3 cm/year (current maximum rate of the Locke island) in 40 years by using an exponential fitting

\[ v_r = 22.65 e^{-0.09755 \times t_r} (R^2=0.998) \]

where \( v_r \) is the motion rate and \( t_r \) the time. The estimation is comparable to the 35 years for the Locke landslide complex during which the landslide motion dropped from peak rate to the current state.

Figure 6.6 Landscape evolution at the southern end of the Wiehl Ranch landslide complex (landslide S2). (a) Advancing front of the landslide toe above the Columbia River from 1996 to 2020. The background image was acquired in July 1996 and accessed from Google Earth. (b) The advance of landslide toe and the retrogression of landslide headscarp. The background image was acquired in August 2020 and accessed from Google Earth.
By integrating motion dynamics of both the Locke landslide and the southern Savage landslide, it can be concluded that the irrigation-triggered slow riverside landslides near Hanford move with an exponentially decreasing rate after rapid instigation and acceleration to the peak rate.

### 6.4.2.2 Slow motion modulated by external force disturbances

Over a long timescale (e.g., tens of years), the slow landslides present motion dynamics composed of a short-period acceleration and a subsequent period of slow motion 10 times longer (Figure 6.6). However, in a short timescale (e.g., weeks to months), external forces such as groundwater variation from irrigation water and the Columbia River strongly modulate landslide motions. Note that surface precipitation mostly evaporates and does not contribute to groundwater in the desert climate near Hanford (Peel et al., 2007).

Figure 6.7 shows the time-series LOS displacements of seven slow landslides from ascending and descending Sentinel-1 InSAR measurements between 2015 and 2020. The ascending and descending InSAR measurements of the slow landslides S1, S2, S3, and S12 correspond to exactly the same pixel (25 m × 25 m), whereas the measurements for landslides S3, S4 and S5 correspond to slightly different neighboring pixels (within 100 m) because of coherence loss in one or more of the selected SAR interferograms. For the landslide S4, a runout event occurred in June 2017 which caused severe coherence loss and consequently broke the InSAR time-series measurements into two halves. We manually bridged the pre-event and post-event displacement times series together using the average motion rates immediate before and after the June 2017 runout event.

As can be seen from Figure 6.7, the annual motion rates of different slow landslides vary considerably. The landslide S2 moved the fastest with a mean ascending LOS rate of 8 cm/year and a descending LOS rate of 14 cm/year, whereas the landslide S5 moved the slowest with a mean ascending LOS rate of 1.2 cm/year and a descending LOS rate of 3.6 cm/year. However, landslides
with similar geographical settings share anomalous movement fluctuations. For example, the four riverside landslides (i.e., S1, S2, S3, and S12) with landslide toes in the Columbia River manifested simultaneous acceleration in February 2017, April 2018, April 2019, and April 2020 though their absolute motion rates vary (Figure 6.7). A detailed comparison of their motion rates with water level of the Columbia River demonstrates that the observed four major accelerations were primarily associated with water level rise of the river (Figure 6.8). Accelerations occurred when the river water level reach a threshold of approximately 5 m.

In contrast, the landslides distant from the Columbia River (i.e., S4, S5, and S7) presented motion dynamics unrelated to the river water level. The short-term accelerations of the away-from-river landslides S4, S5, and S7 mostly likely resulted from irrigation water seepage as these landslides are all located at the margin of the irrigated farmlands and the major accelerations occurred during the irrigation season (April to October). Note that exact irrigation schedules (time and amount) might vary depending on crop types. The long-term motion trend of the away-from-river landslides (S4, S5, S7) exhibited linkages to the surface topography. For instance, the landslides S4 and S7 with long and nearly planar basal slopes maintain nearly constant motion rates after 2018, whereas the landslide S5 with a concaved-up basal slope gradually slowed down as advancing downslope from 2015 to 2020. In addition, unlike many slow-moving landslides near the U.S. west coast which are strongly regulated by seasonal precipitation (e.g., Handwerger et al., 2013; Xu et al., 2019; Xu et al., 2020), ground precipitation in the desert near Hanford shows no contribution to the landslide motions (Figure 6.8d).
Figure 6.7 Time-series displacements of seven slow-moving landslides between July 2015 to October 2020 from Sentinel-1 InSAR measurements. Geographical locations of the selected...
measurement points for the landslides are depicted in Figure 6.3. (a), (b), (c), and (g) show displacement measurements of a same geographical point from ascending (A166) and descending (D42) SAR data for each individual landslide. (d), (e), and (f) show measurements at slightly different locations (within 100 m) on a landslide from ascending and descending data because of coherence loss in one of the SAR datasets. Positive LOS displacements denote distance shortening between ground targets and the satellite.

Figure 6.8 Relationship of landslide movement with regard to rainfall and groundwater level for the riverside slow landslides S1 and S2. (a) Orange circles denote LOS displacements of the landslide S2 from the Sentinel-1 descending track D42. The green polyline shows the corresponding movement velocity as scaled by the green labeling on the right. (b) Movement measurements of the landslide S1, with same labeling rules as (a). (c) Water level of the Columbia
River from a river gauge below the Priest Rapids Dam. (d) Gray bars depict daily precipitation at the Saddle Mountain meteorological station (18 km west of the landslide complex S1). The pink polyline shows cumulative rainfall starting from September 1 of each year, and follows the vertical labeling on the right. The red vertical lines between (b) and (c) mark the time when the landslide S1 started to accelerate each year, and the green vertical lines mark the time when the landslide began to decelerate.

6.4.3 Kinematics of Catastrophic Landslides

Different from the prolonged life cycle of slow landslides (e.g., tens of years), catastrophic landslides undergo a full life cycle from initiation to deposition within several days with dominant movements completing within minutes to hours.

Figure 6.9 shows photos of three catastrophic landslides (C12, C1, and C6) occurred between 2006 and 2017 in the study region. The catastrophic landslide C12 failed on 20 August 2008 at the Basin Hill (Figure 6.3). It traveled downslope by up to 580 m after an abrupt failure at the headscarp and inundated a region of $2.4 \times 10^5$ m$^2$. The formed debris flow buried a 390 m long segment of a busy county road (Road 170) and almost wiped out local farm workers’ home at the bottom-right corner of the debris in Figure 6.9a. Landslide C1 occurred in early June 2017 and evolved into a typical “hourglass” shaped earth flow which traveled downslope by ~ 580 m. The formed flow deposits remain active by September 2020 (Figure 6.7d). Before the largest June 2017 runout, multiple small debris flows occurred from retrogressive failures at the same headscarp since 2003 as captured by Google Earth optical mages. These headscarp failures were directly triggered by excessive water from the sprinkler irrigation at and near the landslide headscarp, which was also evidenced by the large amount of water seeping out of the bluff (Figure 6.9b, Bjornstad and Peterson, 2019). Similarly, the landslide C6 was triggered by water seepage from irrigated farmlands near the Johnson landslide complex (Figure 6.9c). It failed abruptly on 13 May
2006 and evolved into a mobile debris flow which transported a large amount of sediments downslope into the Columbia River. The sediments traveled further south as powered by the average 1.5 m/s water flow of the Columbia River (USGS, 2021c) and formed clearly observable silt plumes at least 7.2 km downstream of the landslide toe (Figure 6.9d).

Figure 6.9 Post-failure photos of catastrophic landslides at Basin Hill (C12), the Savage landslide complex (C1), and the Johnson landslide complex (C6). (a) – (c) depict the post-failure debris flows of the three catastrophic landslides, respectively. (d) shows the silt plume produced by the landslide C6. Photos in (a), (c), and (d) were adapted from Bjornstad and Peterson, 2019.

To summarize, the catastrophic landslides C12, C1, and C6 vary in geographical locations but were all similarly triggered by irrigation water seepage at their steep headscarps. They all failed abruptly and evolved into relatively mobile debris flows which inundated areas over 10 times
larger than the landslide source. Compared to the prolonged life cycle of slow landslides, these catastrophic landslides completed the process from initiation to deposition within one day (potentially in a few hours but no temporally dense observations are available for the verification).

6.4.4 Landslide Motion Regulated by Basal Topography

6.4.4.1 Basal topography regulates slow landslides by forced water circulation

Here we take the Loke landslide complex as a typical example to investigate the potential regulation of slow landslide motions by forced water circulation on a wavy surface. As introduced in Section 6.4.2.1, the Locke landslide complex was initiated by water infiltration from a wastewater pond which was later completely drained in mid-1990s. Ground precipitation is also not a factor that contributes to groundwater in the desert climate (Peel et al., 2007). Hence, the groundwater level within the Locke landslide complex was dominantly controlled by water level of the Columbia River where 44% of the landslide body resides (approximately 250 m long). This was also verified by piezometer measurements from ten boreholes drilled on and near the landslide complex in 1998 and 1999 (Bennett et al., 2002). Four boreholes were drilled in 1998 along a north-south orientated line approximately 500 m east of the landslide headscarsps, four were drilled much farther east of the landslide complex (over 1 km) in 1998, and two others were drilled on the landslide toe (Figure 6.5b). The borehole piezometer measurements suggest that the far east side of the landslide were completely dry from 1988 to 2002, whereas the groundwater level within 500 m east of the landslide complex was almost the same as the Columbia River surface at 114.6 m above sea level. Moreover, the borehole drilling revealed that landslide thicknesses at the toe were 16.6 m (the northern one) and 14.8 m (the southern one), respectively (Bennett et al., 2002).
Figure 6.8 shows that the Locke landslide (at a measurement point representative of the landslide complex) began to accelerate when the water level rose to approximately 5 m every year between 2015 and 2020, which can be attributed to the elevated basal pore pressure within the landslide body. However, the interesting fact is that the landslide started to decelerate when the water level was still over 5 m (i.e., 5.8 m in 2016, 6.4 m in 2017, 8.2 m in 2018, 5.3 m in 2019, and 6.9 m in 2020) at the water level dropping limb, which is in contradiction to the simple infinite slope assumption that landslides keep accelerating when the driving force exceeds shear resistance. Here we attempt to explain the observed phenomenon using forced water circulation as introduced in Section 6.3.3. Following Newton’s second law of motion, the force imbalance of the landslide body leads to a positive or negative acceleration $a_t$ along the downslope direction at time $t$:

$$z \gamma_s \sin \alpha - [(z \gamma_s - h \gamma_w) \cos \alpha \tan \phi + c - R] = z \gamma_s \cdot a_t$$

(6.10)

where $z$ is the average thickness of the landslide material (Figure 6.2), $\phi$ is the internal friction angle, $c$ is the cohesion, $h$ is the hydraulic head on the slip surface, and $R$ is the average resistance acting along the downslope direction as shown in equation 6.9. Note that equation 6.10 is expressed in a general vertical-horizontal Cartesian coordinate system rather than a slope-normal one. The first term on the left in equation 6.10 denotes the downslope driving force, and the second term on the left denotes the resistance resulting from normal stress, hydrostatic water pressure, soil cohesion, and the resistance from forced circulation on an irregular basal surface. Combining equations 9 and 10 yields that:

$$\bar{a}_t = \left[ \sin \alpha - \cos \alpha \tan \phi - \frac{c}{z \gamma_s} \right] + \left[ \frac{h \gamma_w \cos \alpha \tan \phi}{z \gamma_s} - \frac{\bar{v}_t (A_l)^2 \gamma_w}{z \gamma_s} \left(1 - 2\mu^2\right) \right] \frac{1}{4 K_l (1 - \mu)^2} \left(6.11\right)$$

where $\bar{a}_t$ and $\bar{v}_t = \sum_{t=0}^{t} \bar{a}_t$ are the average acceleration and velocity of the landslide material along the downslope direction at time $t$, respectively. We set $\bar{v}_t \geq 0$ to meet the physical constraint that landslides do not move upslope. The first term on the right side of equation 6.11 is a constant if
assuming that slope angle and soil mechanical properties do not change during the movement. Hence, the landslide acceleration is essentially controlled by the dynamic, simultaneous evolution of water level rise and the induced resistance increase.

Equation 6.11 can well explain the observed “premature decelerations” of the riverside landslides shown in Figure 6.7 and Figure 6.8. Every year, seasonal water release from the upstream Priest Rapids Dam elevates water level of the Columbia River and increase basal pore pressure of the riverside landslides near Hanford, thereby causing these slow landslides to accelerate. However, the increased movement velocity strengthens the forced water circulation on the irregular landslide basal surface, which tends to stabilize the landslide by enhancing shear resistance and therefore requires a much higher hydraulic head (water level of the Columbia River) to keep the landslide moving (Figure 6.8). Because the forced water circulation induced a significant pore pressure reduction which cannot be fully compensated by the elevated water level, the landslide started to slow down. According to equation 6.11, the slowing-down periods were not impacted by the forced water circulation. Consequently, the landslides stopped once the water level dropped below the 5 m threshold until another wave of high water level to reactivate the landslide movement (Figure 6.8).

6.4.4.2 Basal topography bifurcates slow and catastrophic movements

Our satellite observations show that slow landslides and catastrophic landslides coexist in some of the landslide complexes near Hanford (Figure 6.4). We therefore investigated the potential factors which might have contributed to their contrasting post-failure motion behaviors. As a typical example, the Johnson landslide complex contains six catastrophic landslides (C6 – C11) and multiple large, slumping landslide blocks (Figure 6.10). Except for the landslide C6 which occurred in 2006, all of the other slow landslides and catastrophic landslides instigated before
1996. The entire Johnson landslide complex was activated by a nearly linear groundwater level rise after 1971 due to excessive agricultural irrigation (Figure 6.11). By 1983, the groundwater level has risen to 3.3 m below the ground surface at the monitoring well 1 km east of the Johnson landslide complex and started to level off.

Figure 6.10 Landscape of the Johnson landslide complex (S12 and C6 – C11). The background photo was adapted from Bjornstad and Peterson, 2019.

As can be seen in Figure 6.10, all of the slow-moving landslides are composed of large, deep-seated (steep headscarp angle), and relatively intact slump blocks, whereas the catastrophic landslides typically source from small failures at the steep headscarsps. Therefore, the basal topography (defined as basal surface and the topography of the runout path) might have been a decisive factor that bifurcates the post-failure kinematics of these landslides. To further elucidate the potential impacts of basal topography on landslide post-failure behaviors, we analyzed the basal topographies of five slow landslides and five catastrophic landslides over the entire study
region by differentiating their topographical characteristics. As shown in Figure 6.12, we plotted elevation profiles of the selected ten landslides along their commensurate downslope directions under identical geographical scales. First, a straightforward comparison of basal slope angles of the slow landslides and the catastrophic landslide reveal that catastrophic landslide are dominantly seated on much steeper basal surfaces than the slow landslides. Second, catastrophic landslides have steeper topographical settings immediately below the landslide toe than slow landslides. Third, slow landslides tend to be deep-seated and involve movement of a large amount of soil mass. Mechanically, steep basal surface and runout path allow landslide materials to gain more kinetic energy from potential energy drop when moving the same downslope distance, which are more likely to keep up the landslide velocity and less affected by highly localized small bumps. The magnitude of landslide volume is essentially controlled by pre-landslide surface topography with other contributing factors being equal.

Figure 6.11 Groundwater level changes near the Johnson landslide complex from 1964 to 1984. The dashed lines denote that observations were unavailable and were extrapolated from data observed in adjacent years.
Figure 6.12 Comparison between basal topography of slow landslides and catastrophic landslides near Hanford. Pre-slide topography of the three transects at landslide complex S1 were obtained from USGS topographical maps in 1924. Post-slide topography of the three transects were from lidar DEM acquired in 2010. Surface topography of other landslides are obtained from either the 2010 lidar DEM or the National Elevation Datasets (USGS, 2021). The headscarp location of each landslide was used as the reference point (x=0, y=0) for each panel, and the absolute elevation of the headscarp above sea level was given in the top-right corner of each panel.
Basal topography also strongly affects motions of slow landslides. For example, the landslide S5 has been slowing down from 2015 to 2020 (Figure 6.7e), potentially because the landslide toe touches an adversely sloped hill that would effectively resist the landslide’s downslope motion (Figure 6.12). The landslide S12 (here referring to the landslide slightly north of the landslide C6 in Figure 6.10) formed steep and large headscarps yet did not failed abruptly as the neighboring landslide C6, potentially because it has a deep-seated and gently sloped basal surface at especially the toe section.

6.5 Discussion

6.5.1 Satellite Imagery for Landslide Identification and Monitoring

Satellite imagery has evolved into an effective and efficient tool for identifying and monitoring landslide activities especially for the past a few decades. In particular, high-resolution satellite optical images are widely used for identifying runout landslides which caused significant surface color changes, whereas satellite radar images are especially sensitive and suitable for detecting and measuring landslide slow motions through radar interferometry processing (e.g., Xu et al., 2010a). In comparison to conventional filed inspection and instrumentation, the all-day, all-weather, global-coverage observation capability of satellite imagery can significantly enhance the efficiency for landslide monitoring across large spatial scales (e.g., Zhao et al., 2012; Xu et al., 2021).

Ground vegetation and surface soil moisture change are the primary factors that cause decorrelation of SAR images and hence decrease accuracy of InSAR measurements for monitoring landslide displacements in a regional scale. Such impacts are common in global climate regions abundant in precipitation, such as the Tropical Wet, Tropical Wet and Dry, Mediterranean, Marine West Coast, Humid Subtropical, and Humid Continental climates (Peel et al., 2007). In contrast,
InSAR measurements are less affected in the Semiarid or Desert climates due to the lack of precipitation and rain clouds. Consequently, the arid region near Hanford in this study offered a great opportunity for obtaining accurate InSAR measurements to characterize the landslide movements. Moreover, the diverse types of landslides occurred near Hanford, Washington further allowed the possibility to decipher impacts of other factors such as topography through mutual comparisons by naturally excluding the influence of precipitation.

6.5.2 Human-Induced Landslides and Potential Prevention Measures

Landslides are a natural geomorphic process driven by gravity (Highland and Bobrowsky, 2008); however, recent decades have witnessed increasingly frequent landslide activities resulting from global climate change and expanding anthropogenic activities (Garino and Guzzetti, 2016; Froude and Petley, 2018). Urban expansion, underground and surface mining, road and reservoir construction, and irrigation farming are typical human activities that have caused numerous landslides worldwide in the latest decades (Froude and Petley, 2018). In particular, intensive irrigation farming which gained increased popularity in semiarid and arid regions since 1950s has brought in considerable unexpected landslide problems besides the expected agricultural production (Garcia-Chevesich et al., 2021). Moreover, seasonal water release from dammed rivers and reservoirs which support the irrigation systems significantly controls the dynamics of riverside landslides. Widespread landslide activities exacerbate soil erosion and farmland loss, transport sediments to streams harming aquatic lives, and endanger life and property safety of local residents. However, irrigation-induced landslide activities could be largely reduced with improved irrigation measures.

We found in this investigation that landslides in the Washington desert near Hanford were primarily triggered by excessive irrigation water which was not fully absorbed by crops and
therefore infiltrated into the subsurface layers. Water leakage from unlined canal and wastewater ponds is another major factor that triggered landslides distant from the irrigated landslides. Consequently, practicing efficient crop irrigation using controlled sprinkler systems is a potential way to save water and reduce irrigation-induced landslide activities. Furthermore, canal lining could be an effective measure to prevent water leakage and therefore the triggered landslides.

6.5.3 Implications of Basal Topography Control on Landslide Behaviors

Landslides initiate from basal shearing failure and may present diverse motion dynamics at the post-failure stage. Deciphering what impacts landslide post-failure mobility could offer critical understanding for mitigating life and property loss from a highly mobile landslide. In this study, we found that basal topography exerts fundamental controls on landslide kinematics in three distinct ways. First, an irregular basal slip surface could produce significant resistance through forced water circulation to obstruct slow landslide motion after failures instigate on a relatively gentle slope. Second, steep basal surface and runout path are more likely to produce catastrophic landslides due to the rapid kinetic energy gain from potential energy drop during the downslope movement. Landslide blocks breaking apart and forming debris flows under large deformation are another potential factor to enhance the landslide mobility. Third, slow landslides could source from debris deposits from a previous catastrophic landslide, and the dynamics of their slow motions are strongly regulated by the basal topography in particularly the toe section. These fundamental controls on landslide motion from basal topography apply to not only the irrigation-induced landslides, but also many other slow and catastrophic landslides around the globe.
6.6 Conclusions

Landslides in the dry climate triggered by agricultural irrigation is a typical type of human-induced geohazard. Monitoring the dynamics of these landslides and decipher their kinematic controls are essential for understanding and reducing their potential hazards. In this investigation, we utilized both satellite optical and radar imagery to discover both slow and catastrophic landslides from 1996 to 2020 in a Washington desert near Hanford.

We retrieved the time-series displacement of seven slow landslides in the study region using radar interferometry of both ascending and descending Sentinel-1 SAR images between 2015 and 2020. Our analyses reveal that the riverside landslides were triggered by agricultural irrigation yet were strongly regulated by water level variation of the Columbia River where the landslide toes reside. Moreover, the seasonal instigation and cessation of the riverside landslides were not controlled by a single fix threshold of groundwater level, which can be explained by the forced water circulation on an irregular slip surface where accelerated landslide velocity enhances basal resistance and in turn contributes to slowing down the landslide movement. By integrating of satellite observations of two highly similar irrigation-triggered slow landslides, we revealed the prolonged life cycle of a typical slow landslide in the study region: a rapid acceleration to the peak rate within 3 years followed by slow decelerations with exponentially decreasing rates for about 40 years.

We further investigated how basal topography could bifurcate the identified slow landslides and catastrophic landslides. By comparing longitudinal topographical profiles of five typical slow landslides and five catastrophic landslides in the study region, we found that steep basal slip surface and runout path are more likely to produce catastrophic landslides with a long runout
distance, whereas gentle surface and basal slopes at particularly the toe region tend to produce deep-seated, slow landslides.

Our findings in this study could contribute to understanding and mitigation of irrigation-induced landslide around the globe. Moreover, the impacts of basal topography on landslide post-failure kinematics are widely applicable to many slow and catastrophic landslides globally for future hazard mitigation.
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CHAPTER 7

CONCLUDING REMARKS

The work presented in this dissertation was motivated to characterize the landslide processes from initiation to deposition and generate insights regarding how landslides initiate and move and what controls their motion behaviors. In particular, these studies were focused on measuring landslide motion time series from multisource remote sensing and deciphering the underlying mechanical mechanism from integrating field measurements and hydromechanical modeling.

In this dissertation, the case studies of variable types of landslides over the U.S. west coastal states demonstrate the capability of integrating remote sensing (especially InSAR) and hydromechanical modeling for discovering slow-moving landslides, measuring landslide surface motion, inferring landslide basal geometry, estimating landslide hydraulic parameters, forecasting the timing of seasonal landslide acceleration and major movements, deciphering basal geometry impacts on landslide motion kinematics, quantifying land uplift and bedrock lithology controls on landslides activity, gauging landslide runout interaction with waterbodies, and evaluating potential runout hazards upon a catastrophic landslide failure. These studies were also aimed to motivate similar efforts globally for landslide evaluation and hazard mitigation.
7.1 Highlights

Chapter 2: This chapter was focused on a constantly (2007-2019) slow moving landslide in Oregon. 1) Retrieving landslide motion time series from 2007 to 2011 and from 2016 to 2019 by combining InSAR processing of both the L-band ALOS and the C-band Sentinel-1 SAR datasets. 2) Inverting pseudo-3D surface motion vectors of the landslide from both ascending and descending InSAR measurements by assuming a dominant downslope direction (azimuth angle only) at each SAR pixel. 3) Estimating landslide thickness from the pseudo-3D surface motions based on volume conservation by assuming a subsurface rheology. 4) Employing an independent limit equilibrium analysis to validate the estimated landslide thickness from surface motion vectors. 5) Integrating landslide motion time series and satellite-sensed shallow soil moisture to obtain time lags between the onset of wet season and the seasonal acceleration of landslide movement. 6) Incorporating rainfall infiltration and pore-pressure diffusion models to estimate hydraulic conductivity and diffusivity.

Chapter 3: This chapter was focused on a coastal landslide in Oregon with alternating slow and rapid motions. 1) Combining sub-pixel offset tracking measurements of both the Sentinel-1 SAR images and the Sentinel-2 optical images to reconstruct 3D surface motion vectors of a 2019 major landslide movement. 2) Integrating InSAR processing of the ALOS and Sentinel-1 imagery and sub-pixel offset tracking of LiDAR DEM gradients to retrieve a 12-year motion time series of the landslide. 3) Proposing a novel three-factor threshold that relies on water-year and previous 3-day and daily precipitation to temporally forecast major landslide movements. 4) Revealing that coastal erosion has been accelerating the landslide motion from 2007 to 2019 by eroding the landslide toe.
**Chapter 4:** This chapter was focused on a potentially catastrophic landslide near a popular campground in northern Washington. 1) Integrating multisource remote sensing datasets (LiDAR DEM, SAR, optical images) and techniques (DEM differencing, sub-pixel offset tracking, radar interferometry) to monitor recent landslide activity. 2) Combining remote sensing measurements and 3D limit equilibrium analyses to constrain the potential landslide volume. 3) Incorporating the D-claw runout model to evaluate potential landslide runout hazards. 4) Simulating a naturally flowing river at the landslide tor and evaluating the river’s impacts on landslide mobility and the corresponding runout hazards.

**Chapter 5:** This chapter was focused on discovering slow-moving landslides over the entire U.S. west coastal states and deciphering their geologic controls. 1) Discovering 601 active, large landslides that were previously unknown in Washington, Oregon, and California using SAR interferometry from 2007 to 2011 and from 2015 to 2019. 2) Revealing that bedrock lithology controls size and spatial density of the identified active landslides. 3) Discovering that land uplift in a geologic scale might contribute to landslide occurrence and activity.

**Chapter 6:** This chapter was focused on landslides in a Washington desert induced by agricultural irrigation. 1) Uncovering 13 active, slow-moving landslide complex and 12 catastrophic landslides along a Washington desert valley from satellite radar and optical images. 2) Verifying that agricultural irrigation induces landslides by reducing soil shearing strength and elevating groundwater level. 3) Discovering that landslides with toes in the Columbia River were strongly impacted by water level of the river, whereas the landslides far away from the river primarily depended on irrigation water seepage and the induced groundwater changes. 4) Revealing that basal topography fundamentally impacts motion kinematics of slow landslides through forced water circulation, and affects catastrophic landslides through kinetic energy gain.
7.1 Future Work

Based on the knowledge and experience gained from the completed landslide case studies, my future research work will be focused on the following five aspects:

1) **Discovering active landslides over the entire conterminous United States using InSAR.** Active landslides consistently damage infrastructures such as highways and buildings and cause constant repair and maintenance costs to state and federal agencies and homeowners. Moreover, active landslides indicate a force imbalance of the hillslopes and could evolve into a future catastrophic disaster under disturbances from such as earthquake shaking, intense rainfall, and anthropogenic activities. Locating these unstable slopes is the first step and a critical step to reduce their future hazards. I will use InSAR processing of primarily the free L-band ALOS SAR images to identify active landslides over the conterminous United States.

2) **Using P-band SAR for uncovering landslides hidden under dense forests.** Our multiple case studies of mapping landslides near the U.S. west coast show that the data acquired by SAR sensors with longer wavelength perform better in discovering landslides in densely vegetated regions. For example, the L-band (~ 23.6 cm wavelength) ALOS and ALOS-2 images were able to produce SAR interferograms with lower background noises than the C-band (5.6 cm wavelength) Sentinel-1 images, because the longer-wavelength SAR sensor possesses better vegetation penetration capability. However, the spaceborne L-band SAR data still suffer from considerable coherence loss in very densely forested regions near the U.S. west coast, which could potentially render some landslides undetectable. To address this problem, we are collaborating with National Aeronautics and Space Administration (NASA) to fly airborne P-band SAR (70 cm wavelength) over multiple selected densely vegetated areas in Washington, Oregon, and California.
to investigate if P-band SAR could be an effective solution for discovering landslides hidden under the dense forest canopy.

3) **Assessing impacts of the interaction between debris flow and waterbodies.** Our case study at the Gold Basin landslide complex show that the interaction between landslide-initiated debris flow and a flowing river could affect landslide mobility and hence the runout hazards. Such interactions may have variable implications depending on the geological, hydrological, and topographical settings of a specific landslide. For example, a giant landslide failing into a lake could generate a tsunami and propagate the hazard by tens of kilometers to the other side of the lake bank. A failed landslide body interacting with a reservoir could cause a dam breach and lead to disastrous flooding down the stream. Consequently, it is critical to evaluate not only the landslide failure itself but also the potential secondary hazards from interacting with waterbodies. I will continue to work with Dr. David George to understand and numerically simulate how the interactions between landslide-initiated debris flow and variable waterbodies could affect landslide post-failure hazards.

4) **Deciphering the length of the precursory motion period for variable landslides.** My recent InSAR studies of multiple catastrophic landslides show that some landslides underwent months-long continuous precursory slow motion preceding the catastrophic failure (e.g., the 2013 Cape Meares landslide in Oregon, the 2020 Elliot Creek landslide in Canada, and the 2021 Chunchi landslide in Ecuador), whereas some experienced no precursory motion within 12 days ahead of the failure (e.g., the 2019 Brumadinho dam failure in Brazil). Deciphering why variable landslides have different time length of precursory motion is critical for establishing effective landslide early warning systems. I will retrieve precursory motion time series of multiple catastrophic landslides
occurred after 2016 around the globe, and utilize mechanical models to understand what potential factors determine the precursory time length of different catastrophic landslides.

5) Developing a pipeline for landslide early warning from InSAR derived precursory 3D motions. For catastrophic landslide with continuous precursory motions for at least 24 days preceding the final failure, I will develop a pipeline to evaluate their post-failure runout hazards from InSAR derived 3D precursory motion. Note that I have discovered at least three catastrophic landslides with months-long precursory motions (e.g., the 2013 Cape Meares landslide in Oregon, the 2020 Elliot Creek landslide in Canada, and the 2021 Chunchi landslide in Ecuador). In particular, I will use both ascending and descending InSAR to derive 3D surface motion vectors of a landslide, and then estimate the active landslide volume from precursory surface motions using thickness inversion models, and then input the inverted landslide basal surface into the D-claw runout model to estimate its potential runout hazards. Moreover, another line of this work will be focused on temporally forecasting landslide failures based on their precursory motion time series. Mechanical modeling will be incorporated to interpret and predict the failure time.