BGC ENGINEERING USA INC.
AN APPLIED EARTH SCIENCES COMPANY

WASHINGTON STATE DEPARTMENT OF NATURAL RESOURCES

DEEP-SEATED LANDSLIDE MAPPING AND CLASSIFICATION PROJECT

STUDY DESIGN

FINAL

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Dr. Theryn Henkel
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Dear Dr. Henkel

Re: Deep-Seated Landslide Mapping and Classification Study Design

BGC Engineering Inc. (BGC) is pleased to submit the following Deep-Seated Landslide Mapping & Classification Study Design document. The entire project team at BGC is excited about this meaningful work and feels there is great value contained in the proposed study design outlined herein. We appreciate the opportunity to collaborate with you on this challenging and interesting project.

Yours sincerely,

BGC ENGINEERING USA INC.
per:

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Senior Geoscientist

EXECUTIVE SUMMARY

Understanding present and potential movement of deep-seated landslides (DSLs) in western Washington is a long-studied and difficult problem. In Washington State, DSLs occur within many lithologies, climate regimes, and timescales. Different geographies may be more or less sensitive to natural and anthropogenic landslide triggering mechanisms. Traditionally, DSLs have been studied individually because they are highly variable, and geologists have lacked the tools/technologies necessary to gather information at broader scales (Miller, 2017). However, major advances in remote sensing offer opportunities to classify or group DSLs based on factors such as their geology, failure type, landscape position, and velocity patterns, in conjunction with the application of a variety of statistical analysis techniques, at regional scales (defined as > 1,000 km^2; Woodard, et al., 2023).

This Study Design Report lays out a framework and design guidance for a proof-of-concept pilot study utilizing remotely sensed data in an effort to characterize several thousand landslides within a regional study area. Characterization will occur by combining landslide movement data from interferometric synthetic aperture radar (InSAR) and lidar change detection technologies that measure landslide velocities with other regional datasets (e.g., existing landslide inventories, geological mapping, topography, land use, hydroclimate). This combined effort will facilitate the classification of DSLs into common groupings and characterize regional drivers for landslide velocity changes. The purpose of this study is to develop a landslide classification scheme based on an improved understanding of landslide characteristics and activity levels. It is part of a larger deep-seated landslide research strategy to understand and anticipate landslide behavior and sensitivity to forest management.

The four-county study area proposed by the Upslope Process Scientific Advisory Group (UPSAG) has extensive landslide mapping by the Washington Geologic Survey (WGS), historical synthetic aperture radar (SAR) coverage (covering large periods of the past 30 years) and overlapping lidar acquisitions (over the past 17 years). Relative to other areas around the globe, this is a very high density of data coverages that can assist in developing an understanding of spatial and temporal variations in landslide activity at a regional scale. This study targets specific sub-regions within the proposed four-county area. As originally proposed, the four-county area is likely not practical for a single study because of the significant amount of data and logistical constraints. The smaller sub-regions were identified based on an overlap of high-quality remote sensing data and a representative cross-section of landslide types; particularly the availability of multiple repeat lidar data sets and the spatial and temporal density of archived SAR data that could support generating InSAR deformation data. The following sub-regions have been identified to execute the Mapping and Classification Pilot Study:

- Option 1a and 1b: Western Whatcom County (Mount Baker to Lower Nooksack River) and the Upper Snohomish River System (Snoqualmie and Skykomish Rivers) – 2,700 km^2
- Option 2 (includes 1b): Snohomish County (Sloan Peak to Snohomish) and the Snoqualmie River Valley (Fall City to Monroe) – 3,600 km^2.

Each study area has been selected to provide a cross section of landslide classes and clusters that provide a statistically robust data set to support understanding the sensitivity of landslides to natural processes and human disturbance.

For each of the areas described above, a targeted region-specific program of ground velocity data collection and processing would be undertaken, and these data would be integrated into a structured data schema for mapped landslides in the region. It is expected that the following velocity/displacement data would be integrated at each landslide polygon by a landslide practitioner:

- Confirmation of presence or absence of measurable displacements across the collection period for the data utilized
- Annualized displacements to support screening different relative landslide activity zones across clusters
- Discrete velocity trend data to support variation in velocity in relation to seasonal and multi-year fluctuations in hydroclimatic conditions, surface vegetation change and/or human modification of the ground surface.

The above observations would be entered into a database with schema designed to support integration of these data sets into various modelling efforts for other projects that contribute to the broader programmatic objectives. To develop a data-driven understanding of the linkages between velocity trends and extrinsic factors (such as hydroclimatic influences and human disturbance), the design report outlines key publicly available datasets that could be integrated with velocity data.

The project outlined in this Study Design Report is derived from the Cooperative Monitoring, Evaluation, and Research (CMER) Scoping Document (UPSAG, 2020). However, the intent of the Scoping Document was to investigate *why* landslides with similar characteristics may exhibit differences in activity level. This was envisioned to include an early field effort focused on specific landslides of interest within clusters, with a field methodology developed in an iterative fashion to support the overall DSL classification, including research that has shown that some DSLs are triggered by local subsurface hydrogeological and stratigraphic differences (Miller, 2016, 2017; Iverson et al, 2015). The Study Design takes a slightly different approach and is based on remote sensing techniques that utilize velocity trends to develop a spatial understanding of the variability in landslide activity across the study area. Following the development of a landslide inventory, activity, and velocity time-series database, the study will use statistics to analyze the data. Field work will primarily focus on verification of the insights derived from remote sensing data analysis. The novel hybrid methodology described in the Study Design is untested in this area, as are the mixed methods described in the Scoping Document.

The following comparison between the research objectives listed in the CMER Scoping Document (UPSAG, 2020) and the Study Design offers information on how the original research objectives will be met with a focus on activity level:

Table 1-1. Comparison between the CMER Scoping Document research objectives and the Study Design plan.

Research objectives defined by CMER (UPSAG, 2020)	Study Design	Explanation of Differences
Identify distinguishing characteristics within and between DSLs with similar geomorphic, topographic, stratigraphic, hydrologic, and climate settings.	Section 5.3 provides a methodology that utilizes statistics derived from the existing landslide inventories to support designation of landslide classes and the use of different morphological attributes to define landslide clusters.	The Scoping Document envisioned classifying DSLs by identifying their controlling characteristics through a hypothesis-driven iterative process, including field validation early in the classification process. It makes use of existing qualitative and quantitative data. The study design utilizes statistics throughout the workflow to analyze quantitative inventory and remote regional-scale data in conjunction with movement and velocity technology (InSAR and LiDAR change detection (LCD)).
Investigate why landslides with similar characteristics may exhibit differences in activity level. Can activity levels of individual DSLs within and between clusters be linked to sensitivity to hydrologic or other change?	Section 5.4 describes how data obtained from globally available hydroclimatic models and remote sensing-derived products can spatially and temporally link these transient conditions to differences in landslide activity.	The Scoping Document envisioned a process that relied on identification of clusters and field verification while the Study Design relies on statistical analysis of remote sensing data to investigate the linkage between DSL movement and hydrologic and other data.
Develop causal mechanism hypotheses for individual landslides evaluated in the field. These mechanisms might be evident through hydrogeologic characteristics visible in active landslides.	Temporally and spatially continuous regional velocity and displacement observations will be linked to the landslide inventory polygons that partially inform the designation of landslide classes and clusters. These will be used for modelling with the hydroclimatic and land cover datasets to derive relationships between landslide attributes and these external drivers. After the classification process is complete, differences in landslide activity across similar landslides will be utilized to guide field validation of hypotheses as to what is driving landslide activity change at the local scale.	The Scoping Document has a stronger focus on understanding causal mechanisms at local scales. The Study Design de-emphasizes identifying causal mechanisms for individual landslides, instead focuses on finding relationships across a region.
Determine the best remote sensing tools, field assessment and other methods to classify DSLs in a manner that will improve our understanding of the relative potential for DSL reactivation or accelerated movement. What data are necessary to estimate the relative sensitivity of DSLs within a class?	Section 5.2 provides an overview of the existing remotely sensed data and considerations for integration to best support the classification tasks. The application of the existing remotely sensed data will support understanding as to which tools are most effective in deriving the critical variables and will support the optimization of data collection for future focus areas.	The Scoping Document asks what methods are best for classifying the DSLs to provide new information and insights. The Study Design (section 5.2) is concerned with the efficacy of InSAR and LiDAR Change Detection technologies as useful method to classify DSLs.
Define classes of DSLs within and across clusters using a suite of physical attributes based on critical variables. These classes will also be used to support future phases of the research strategy (i.e., which DSLs are most representative or illustrative for future research and modeling efforts based on the results of the classification project). What are the critical independent (predictor) variables necessary to define DSL classes?	Sections 5.0 and 6.0 provide information about these variables and their integration into future phases.	The Scoping Document intended to define classes of DSLs based on critical independent variables. The Study Design has no distinction made between independent and dependent variables in the statistical analyses. Instead, all variables mentioned in sections 5.0 and 6.0 may be analyzed for correlations, because some dependent variables may be critical to assessing sensitivity.
Evaluate if certain classes of landslides have a high or low potential for instability from forest practices and rank classes based on multiple sources of empirical evidence.	To test an initial hypothesis that DSLs can be effectively ranked and classified based on multiple sources of empirical evidence, and that certain classes of landslides have a particularly high or low potential to experience an increase in instability from forest practices. This document outlines an approach that would subdivide landslides based on attributes such as lithology, size, failure depth, and geomorphic position and correlate these with velocity and extrinsic drivers (hydroclimate, land use, land disturbance) to assess which landforms are most sensitive to human disturbance.	The Scoping Design and the Study Design share the same goal to identify and evaluate landslide classes. However, the methodologies differ, as described above in this table.

5.06.0The work plan outlined in this report is meant to provide a basis to directly inform and support the overall deep-seated landslide research strategy by providing a robust set of data and tools to understand historical trends to calibrate models that will support the understanding of the intrinsic and extrinsic contributions to landform sensitivity.

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LIMITATIONS

BGC Engineering USA Inc. (BGC) prepared this document for the account of Washington State Department of Natural Resources. The material in it reflects the judgment of BGC staff in light of the information available to BGC at the time of document preparation. Any use which a third party makes of this document or any reliance on decisions to be based on it is the responsibility of such third parties. BGC accepts no responsibility for damages, if any, suffered by any third party as a result of decisions made or actions based on this document.

INTENT OF THIS DOCUMENT

This document contains a technically complex and rigorous study design to interrogate deep-seated landslides in Washington, USA. The intent of the document is to guide a qualified consultant in addressing the critical research questions outlined in Section 1.0. The methodology outlined in this report provides a sufficient level of detail to guide a consultant with foundational expertise in the geological and kinematic understanding of deep-seated landslides and the application of remote sensing tools to develop a spatial understanding of the variability in landslide activity across the study area chosen.

The field of leveraging large remote sensing datasets to evaluate spatiotemporal patterns of landslide behavior at scale is a rapidly evolving field. This document provides recommendations based on the authors' current understanding of the state of science. However, it is recommended that the project team carefully evaluate advances at the project outset and alter the scope accordingly should new techniques be demonstrated that can advance the objectives of this study. In some portions of this document, the authors have determined it is premature to offer detailed workflows and instead point to potential frameworks and suggestions for data analysis. The state of the science at the time of evaluation should be brought to bear on the problem of evaluating landslide sensitivity in the context of forestry operations, and a great deal will be learned about the best analytical methods once initial data compilation and analysis is complete.

For these reasons, it is recommended that any organization attempting to undertake this study demonstrates at a minimum the following qualifications:

- The study should be overseen by a qualified geological engineer or engineering geologist with demonstrated understanding of landslide processes in complex glaciated and bedrock environments. As an example, the Washington State Department of Licensing for Geologists provides specific guidelines in Washington State as to the qualifications and experience required to undertake landslide studies. Professionals that have received their Licensed Engineering Geologist specialty license have demonstrated qualifications and experience in the following key areas:
    - Knowledge of the geology of the state of Washington.
    - Skill and ability in use of geotechnical field classification systems for soil and rock.
    - Ability to recognize landforms from surficial and deep-seated geologic processes.
    - Knowledge and ability to evaluate and analyze soil and rock mechanical relationships.
    - Knowledge of the appropriate application of geotechnical laboratory testing methods.
    - Ability to interpret and portray engineering geologic information and data three dimensionally, at a scale appropriate for site-specific applications.
    - Knowledge and understanding of the principles of grading codes, as well as critical areas, shoreline, and other pertinent regulations.

- In addition to the foundational qualifications that an experienced geoscience professional brings to this study, the team executing the study should have demonstrated experience in the following areas:
  - Advanced knowledge of the proposed tools and technologies, including, but not limited to, interferometric synthetic aperture radar (InSAR), lidar, database design, and physical and statistical modeling for landslide processes. This includes demonstrated project experience in the integration of various monitoring technologies to develop hypotheses related to kinematics of shallow and deep landslide processes. Demonstrated experience should include an evaluation of the limitations of each technology for understanding landslide kinematics.
  - Experience with both remote and field-based landslide characterization, including velocity and activity estimates. This includes a demonstration of previous consideration of multi-sensor approaches to characterize local and regional velocity changes. This includes the demonstration of the understanding of the underlaying monitoring technologies and how these measurement techniques can be utilized to characterize landslide velocity trends.
  - Advanced geospatial data analysis capabilities, including demonstrated project experience in generating multi-temporal spatial databases and integrating these databases into statistical and/or physically based landslide models.

1.0 INTRODUCTION

1.1. Project Background

The Washington State Forest Practices Board (Board) approved a comprehensive package of forest practice rules in 1999 (Forests & Fish Report) adopted by the Washington state Legislature in 2001.

The Washington forest practices Habitat Conservation Plan (HCP) lists a key resource objective under sediment as a “Functional objective” to:

Provide clean water and substrate and maintain channel forming processes by minimizing to the maximum extent practicable, the delivery of management induced coarse and fine sediment to streams (including timing and quantity) by protecting stream bank integrity, providing vegetative filtering, protecting unstable slopes, and preventing the routing of sediment to streams (HCP, Schedule L-1, Appendix N).

The Board’s Adaptive Management Program (AMP) is designed to provide science-based, technically sound recommendations and guidance in support of the resource objectives related to aquatic habitats and water quality outlined in the WA forest practices HCP. The Cooperative Monitoring Evaluation and Research (CMER) committee was formed to conduct research in support of the AMP meeting the HCP’s resource objectives, including empirically defining classes of deep-seated landslides (DSLs) based on critical variables controlling the occurrence and failure mode.

In response to the Oso DSL in 2014, the WA Forest Practices Board directed CMER to update their DSL research strategy. To support the initiatives of the Board, the Upslope Processes Scientific Advisory Group (UPSAG) issued the *Deep-Seated Landslide Research Strategy (*UPSAG, 2019) and the *Deep-Seated Landslide Mapping & Classification Project Scoping (Scoping*) (UPSAG, 2020) documents to CMER. The Strategy document outlines a collection of successive and interrelated projects to determine if relative levels of landslide response to forest practices can be predicted by key observable characteristics of DSLs and/or their groundwater recharge areas. The Scoping document outlines a research plan to empirically define and characterize classes of DSLs based on critical variables that control the occurrence and type of landslide failure. This type of classification is part of a unique effort by the Washington State Department of Natural Resources (DNR) to develop a broader understanding of DSLs as they relate to natural processes and human disturbance. For this study a landslide will be classified as “deep” if the slide plane lies below the vegetation rooting zone, which is typically greater than 10 feet (~ 3 meters), as defined in the Washington Forest Practices Board Manual 5/2016 (WFPB, 2016).

To support these efforts, BGC Engineering Inc. (BGC) was retained by the DNR to draft a study design for a mapping and classification project for DSLs in Washington State. This study design is one part of the broader Strategy scheme and combines two parts of the plan, including Project 4.5 - Mapping and Project 4.6 – Classification (Figure 1-1).

1.2. Definitions and Acronyms

The following definitions and acronyms are provided to explain in more detail some of the terminology used throughout this document. Some of the definitions included were sourced from the UPSAG Scoping document.

- ALOS – Advanced Land Observing Satellite.
- AMP – Adaptive Management Program.
- Asc – Ascending satellite orbit (as related to InSAR data collection).
- BDSL – Bedrock Deep-Seated Landslide. A deep-seated landslide with a failure plane within bedrock.
- Board – Washington State Forest Practices Board.
- CMER – Cooperative Monitoring, Evaluation and Research committee.
- Critical ~~Independent~~ Variables – In terms of landslides and in the context of this study design, critical variables are those for which it has been determined through data-driven statistical analysis to have the strongest influence on landslide activity and sensitivity.
- CSA – Canadian Space Agency.
- DEM – Digital Elevation Model.
- Desc – Descending satellite orbit (as related to InSAR data collection).
- DNR – Washington State Department of Natural Resources.
- DSL – Deep-seated landslide. A landslide with a body and failure plane. The failure plane lies below the tree root zone. This depth can range from ten to several hundreds of feet below the ground surface. Simple, rapid failures such as debris flows and debris avalanches are not deep-seated landslides regardless of failure depth.
- ERS – European Remote Sensing satellite.
- ESA – European Space Agency.
- Forest practices – forestry-related activities on lands regulated by the Washington Forest Practices rules (i.e., timber harvest, road construction and rock quarrying).
- GDSL – Glacial Deep-Seated Landslide. A deep-seated landslide with a body and failure plane within glacial deposits.
- GIS – Geographic Information Systems.
- Hydrologic sensitivity – the likelihood of landslide reactivation following a hydrologic change related to the movement and distribution of water.
- Harvesting – In terms of forestry operations, this pertains to different processes by which timber is selected, fallen and removed from the landscape. Common examples of forest harvesting systems are clearcut, seed-tree, shelterwood, and selection harvest. Logging roads are associated with timber harvesting activities, which include original road construction and maintenance.
- InSAR – Interferometric Synthetic Aperture Radar.
- JAXA – Japanese Space Agency.
- Landslide Class – A group of DSLs with similar characteristics. Classes of DSLs can occur in spatially discontinuous areas (i.e., in different clusters).
- Landslide Cluster – A sampling unit encompassing proximal DSLs with similar geomorphologic, topographic, hydrologic, and stratigraphic settings. Preliminary clusters

will be established with GIS tools and may be refined with field data. The intent is that landslides in a cluster are located close together and their critical variables are homogeneous. The DSLs within a cluster are expected to respond to natural and anthropogenic triggers similarly, facilitating an analysis of sensitivity.

- Landslide sensitivity – the likelihood of landslide reactivation or acceleration following a change in condition (e.g., toe erosion, ground disturbance, etc.).
- LCD – Lidar Change Detection.
- Lidar – light detection and ranging.
- LoS – Line of Sight. When using InSAR for deformation measurement, the component of the displacement vector in the LoS of the satellite is being measured (vector between the satellite and the imaged surface).
- LULC – Land Use/Land Cover.
- NiSAR – NASA-ISRO Synthetic Aperture Radar (ISRO - Indian Space Research Organization).
- PALSAR – Phased Array-type L-band instrument.
- R1 – Radarsat-1.
- R2 – Radarsat-2.
- SAR – Synthetic Aperture Radar.
- Scene – In the context of InSAR data satellite coverages, a “scene” is an individual image acquisition of SAR data.
- Scoping – The *Deep-Seated Landslide Mapping & Classification Project Scoping* document.
- SLIP – Streamlined Landslide Inventory Protocol.
- SME – Subject Matter Expert.
- Stack – In the context of InSAR data satellite coverages, a “stack” is a collection of overlapping, repeatedly-collected scenes covering the same spatial footprint over different time periods.
- Strategy – The *Deep-Seated Landslide Research Strategy* document.
- TPI – Topographic Position Index.
- Trigger – The final factor that causes DSL failure at a moment in time.
- USDA – United States Department of Agriculture.
- UPSAG – Upslope Processes Scientific Advisory Group.
- USGS – United States Geological Survey.
- WGS – Washington Geological Survey.

1.3. Problem Statement and Purpose

DSLs in Washington State are complex, and their distribution and activity levels vary greatly because of both intrinsic and extrinsic factors. The Scoping document identifies a range of critical variables such as geologic materials, climate regimes, and timescales, and different geographic locations which may lead to different sensitivities to modern natural and anthropogenic landslide triggers. In particular, the AMP is interested in the potential effects of hydrologic inputs from forestry activities on the different classes of DSLs, especially at sites where landslides have the potential to degrade fish habitat, water quality, or threaten public safety. Based on the complex and diverse context of Washington State and the specific focus of] forest practices rules on DSLs, it is a priority to create an applicable, effective, and geologically sound DSL classification system.

The purpose of the current study design is to empirically classify and define DSLs across Washington which are inferred to represent a range of potential sensitivities to natural and forest practice triggers. The classification scheme will be based on critical variables with controlling influence over the occurrence and type of landslide failure. The landslide classes developed during this study will be used to target a subset of landslides for future focused efforts according to the Strategy: those landslide classes that may be prone to an increase in slope movement activity due to timber harvest or forest road construction.

The overall Strategy (UPSAG, 2019) focuses on the following critical key questions from the CMER Work Plan:

1. Can relative levels of landslide response to forest practices be predicted by key characteristics of deep-seated landslides and/or their groundwater recharge areas?
2. Does harvesting of the recharge area of a deep-seated landslide promote its instability?
3. Are unstable landforms being correctly and uniformly identified and evaluated for potential hazard?

To address these questions, DNR has organized a series of complimentary and interdependent projects that are defined below in Figure 1-1.

Figure 1-1. Conceptual linkages of the projects outlined in the Deep-Seated Landslide Research Strategy (UPSAG, 2020).

1.4. Critical Sub-Questions and Research Objectives

This study design document will provide guidelines and a framework to leverage the rich dataset of mapped DSLs in Washington (e.g., Mickelson et al., 2017, 2019, 2020; Miller, 2016, 2017; Xu et al., 2021; Herzig et al., 2023) and to intersect these mapped regions with both physical (e.g., land cover changes, surface roughness) and velocity characteristics (e.g., velocity estimates from interferometric synthetic aperture radar, lidar change detection, or direct monitoring). This will support DNR in understanding the variability amongst DSLs in the specified study area and allow for an empirically supported and repeatable landslide classification schema which may inform probabilistic estimates on the future variability of landslide behavior, such as sustained movement, reactivation, or cessation. The study area including Whatcom, Snohomish, King, and Pierce Counties will be used to implement a proof-of-concept that will demonstrate how the intersection of mapped DSLs with remotely sensed data could support addressing the critical sub-questions and the research objectives.

1.4.1. Critical Sub-Questions

The critical sub-questions, from the CMER Scoping Document (UPSAG, 2020), specific to this current study design are as follows:

1. What are the distinguishing characteristics among DSLs within similar geomorphic, topographic, stratigraphic, hydrologic, and climatic settings?
2. Can activity levels of individual DSLs within and between clusters be linked to their sensitivity to hydrologic change?
3. What are the critical variables necessary to define DSL classes?
4. What data are necessary to estimate the relative sensitivity of DSLs within a class?
5. Are there particular classes of DSLs that have a greater or lesser potential for instability?

1.4.2. Research Objectives

The outcomes of this study design will specifically address the following research objectives. As outlined in the Scoping document (UPSAG, 2020), these objectives directly explain the outcome of the acquisition and analysis of the data required to answer the key critical sub-questions.

Research objectives defined by CMER (UPSAG, 2020) are as follows:

1. Identify distinguishing characteristics within and between DSLs with similar geomorphic, topographic, stratigraphic, hydrologic, and climate settings.
2. Investigate why landslides with similar characteristics may exhibit differences in activity level. Can activity levels of individual DSLs within and between clusters be linked to sensitivity to hydrologic changes or other?
3. Develop causal mechanism hypotheses for individual landslides evaluated in the field. These mechanisms might be evident through hydrogeologic characteristics visible in active landslides.
4. Determine the best remote sensing tools, field assessment and other methods to classify DSLs in a manner that will improve our understanding of the relative potential for DSL

reactivation or accelerated movement. What data are necessary to estimate the relative sensitivity of DSLs within a class?

5. Define classes of DSLs within and across clusters using a suite of physical attributes based on critical variables. These classes will also be used to support future phases of the research strategy (i.e., which DSLs are most representative or illustrative for future research and modeling efforts based on the results of the classification project). What are the critical independent (predictor) variables necessary to define DSL classes?
6. Evaluate if certain classes of landslides have a high or low potential for instability from forest practices and rank classes based on multiple sources of empirical evidence.

2.0 PHYSIOGRAPHY AND GEOLOGICAL SETTING

2.1. Study Area

As part of the Scoping Document, UPSAG considered several study alternatives focusing on Glacial Deep-Seated Landslides (GDSLs) and/or Bedrock Deep-Seated Landslides (BDSLs) and targeting different geographic areas ranging from four counties up to nine counties in Western Washington. UPSAG's preferred option (Alternative 2) considered the mapping and classification of both GDSLs and BDSLs across Whatcom, Snohomish, King, and Pierce counties (Figure 2-1). The following sections of this report will review the available data sources for coverage and quality and provide recommendations for a smaller area for which to execute a more detailed study.

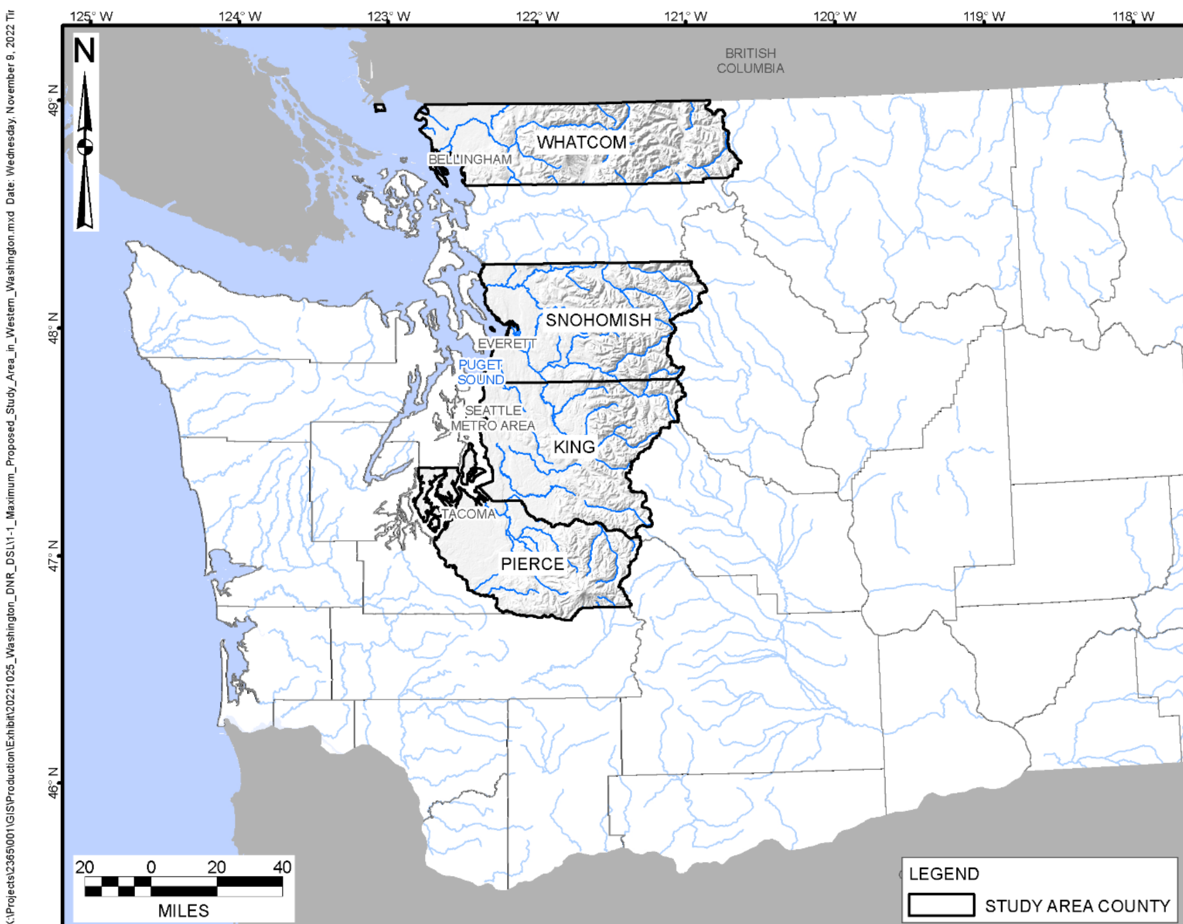

Figure 2-1. Maximum proposed study area in western Washington.

2.1.1. Physiographic Regions and Geological Setting

A rich tectonic, volcanic, and glacial history has developed several distinct physiographic provinces in Washington State. The study area of this project crosses three distinct physiographic regions, the Northern Washington Cascades, the Southern Washington Cascades, and the Puget Lowland, discussed below (DNR, n.d.; Figure 2-2).

2.1.1.1. Northern and Southern Washington Cascades

The Cascade Range, spanning over 500 miles from northern California to British Columbia contains the highest peaks in Washington State and records a complex geologic history spanning the last 400 million years. Within western Washington, the Cascade Range is composed of various terranes that were accreted to North America that were then subsequently folded, buried, faulted, uplifted, and moved to their present location (Brown, 1987; Haugerud & Tabor, 2009; WGS, 2022a; 2022b). This complex assembly of metamorphic mélange, sedimentary, and intrusive igneous rocks was later intruded and partially covered by volcanic deposits of the Cascade volcanic arc (Haugerud & Tabor, 2009, WGS, 2022a).

Despite the shared history of terrain accretion, tectonism, and volcanism, the Washington Cascades can be split into Northern and Southern physiographic regions based upon their geomorphic expressions and surficial geologic compositions (DNR, n.d.). The North Cascades physiographic region, which extends from Snoqualmie Pass in the south to the US-Canadian border in the north, is steep, rugged, and primarily exposes rocks of the various accreted terranes (WGS, 2022a; 2022b). The South Cascades physiographic region which extends south to the Columbia River, however, is dominated by surficial volcanic deposits derived from the Cascade volcanic arc and the Columbia River lava flows. Similar rocks of the older accreted terranes are present within the southern Cascades but are primarily buried by younger volcanic deposits (WGS, 2022a; 2022b). During the late Pleistocene, the Cordilleran ice sheet covered all but the highest peaks of the Northern Cascades (Porter & Swanson, 1998; Thorson, 1980) producing the ruggedness and higher relief within this area relative to the unglaciated southern Cascades. Alpine glaciers persist to this day within both physiographic regions, occupying the high elevation slopes.

2.1.1.2. Puget Lowland

During the Pleistocene, multiple glacial advances and retreats of ice sheets formed the modern-day Puget Sound and associated Puget Lowland, where most of Washington’s population currently resides (Armstrong et al., 1965; Easterbrook et al., 1967; Easterbrook, 1992; Mullineaux et al., 1965; Porter & Swanson, 1998). Sediments and erosional features left behind by the most recent of these glaciers, referred to as the Fraser Glaciation (Armstrong, 1965), dominate the landscape within the Puget Lowland. Deposits associated with the Fraser Glaciation range from coarse tills and outwash to fine-grained glaciolacustrine and glaciomarine deposits (WGS, 2022a; 2022b). These deposits have distinct markings on the landscape in various forms including moraines, flutes, terraces, drumlins, eskers, kettles, and kames. Stratigraphic sequences of different glacial deposits (e.g., outwash overlying till) play an important role in groundwater hydrology (Kahle & Futornick, 2012) and slope stability (e.g., Heller, 1981; Perkins et al., 2017) due the abrupt changes in material properties (e.g., grain size, degree of compaction, hydraulic conductivity).

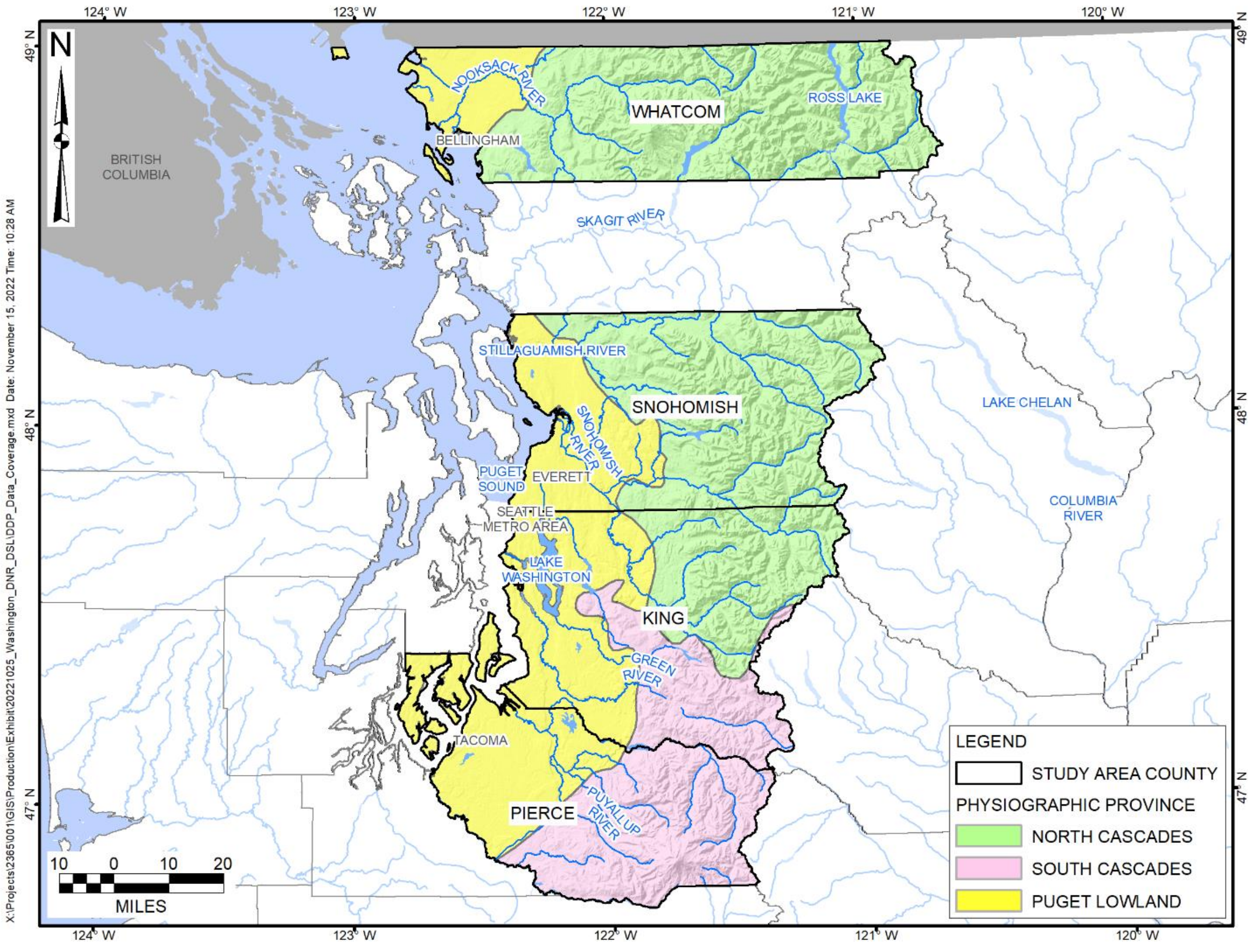

Figure 2-2. Physiographic regions within the proposed study area (Data source: DNR).

3.0 DATA SOURCES

The following sections describe suggested geospatial and tabular datasets covering the larger study area (Figure 2-1) which could assist in execution of the proposed study. As additional data sources become available, however, we recommend the evaluation and possible incorporation of those data. Further considerations regarding data assimilation and data analysis are discussed in Section 4.0.

3.1. Geospatial Data

The following provides an overview of the publicly available geospatial datasets that are available to support the project and therefore are considered as part of the design.

3.1.1. Geological Maps

3.1.1.1. Map Scales and Coverage

The WGS offers free, publicly available geologic maps in GIS format across the state of Washington at various scales. Seamless geologic map coverage is available across the state at scales of 1:500,000, 1:250,000, and 1:100,000 (WGS, 2022a; 2022b; 2019; 2016). The WGS also provides 1:24,000 geologic maps across portions of the state and are actively mapping additional quadrangles at 1:24,000 scale each year. Within the study area, 1:24,000 coverage is available across much of the western portions of Snohomish and King Counties but is only available in a small subset of quadrangles in Whatcom and Pierce counties (Figure 3-1). As such, the proposed study will likely rely on the 1:100,000 geologic map series (WGS, 2016) since it is the highest resolution of seamless coverage across the entirety of the study area. However, the study may use 1:24,000 maps where available. Geologic maps provide broad spatial distributions of geologic units. They do not provide site specific stratigraphy or consistent details about geologic heterogeneity.

3.1.1.2. Geologic Attributes

1:100,000 and 1:24,000 geologic maps produced by the WGS (2019; 2016) provide spatially referenced information on the various characteristics of surficial rocks and deposits within the mapped extent. Each map series is comprised of 12 feature classes with the following descriptions:

1. Attitude_points (structural data) – geologic structural attitude measurement points (such as strike and dip of foliation).
2. Contacts – lines representing the boundary between geologic units. Complements the geologic_unit_polygon feature class.
3. Dikes – line representing individual igneous dikes, sills, and descriptive data.
4. Faults – lines representing geologic faults.
5. Folds – lines representing fold axes, showing the location and types of folds in bedrock.
6. Geologic dates – points representing sample sites for geologic age data.

7. Geologic_unit_polygons – polygons defining the extent and label of each geologic unit. The label is an abbreviation that represents the age, lithology, and name of a geologic unit.
8. Map_index – spatial location of all 1:24,000 or 1:100,000 scale data and their sources.
9. Map_line – lines representing linear attributes and boundaries for Washington State. Specifically, the feature class contains arcs representing geologic units that, due to map scale, are too thin to be represented as polygons. It also includes isograds, glacial moraines, eskers, lineaments, paleosols, limits of continental glaciations, limits of alpine glaciations, landslide scarps, landslide arrows, terraces, scarps, cross section lines, streams, intermittent streams, map boundaries, contours, geophysical data collection lines, and strand lines (former shorelines).
10. Map_point – point locations for geologic polygons that are important but are too small to show as polygons at the map scale.
11. Misc_polygons – polygons representing geologic data for features other than geologic units, such as alteration zones, dike swarms, outcrops, geomorphic features, mineral resources, and descriptive data for areas of Washington State.
12. Volcanic_vents – point locations for individual volcanic vents.

Each map series also contains a related unit description table (unit_descriptions) which defines each unit and provides age, lithology, and full unit descriptions.

The map attributes likely to be most useful for the purposes of landslide classification include the descriptions of geologic units and extents (geologic_unit_polygons and unit_descriptions) and structural data (attitude_points, faults, folds).

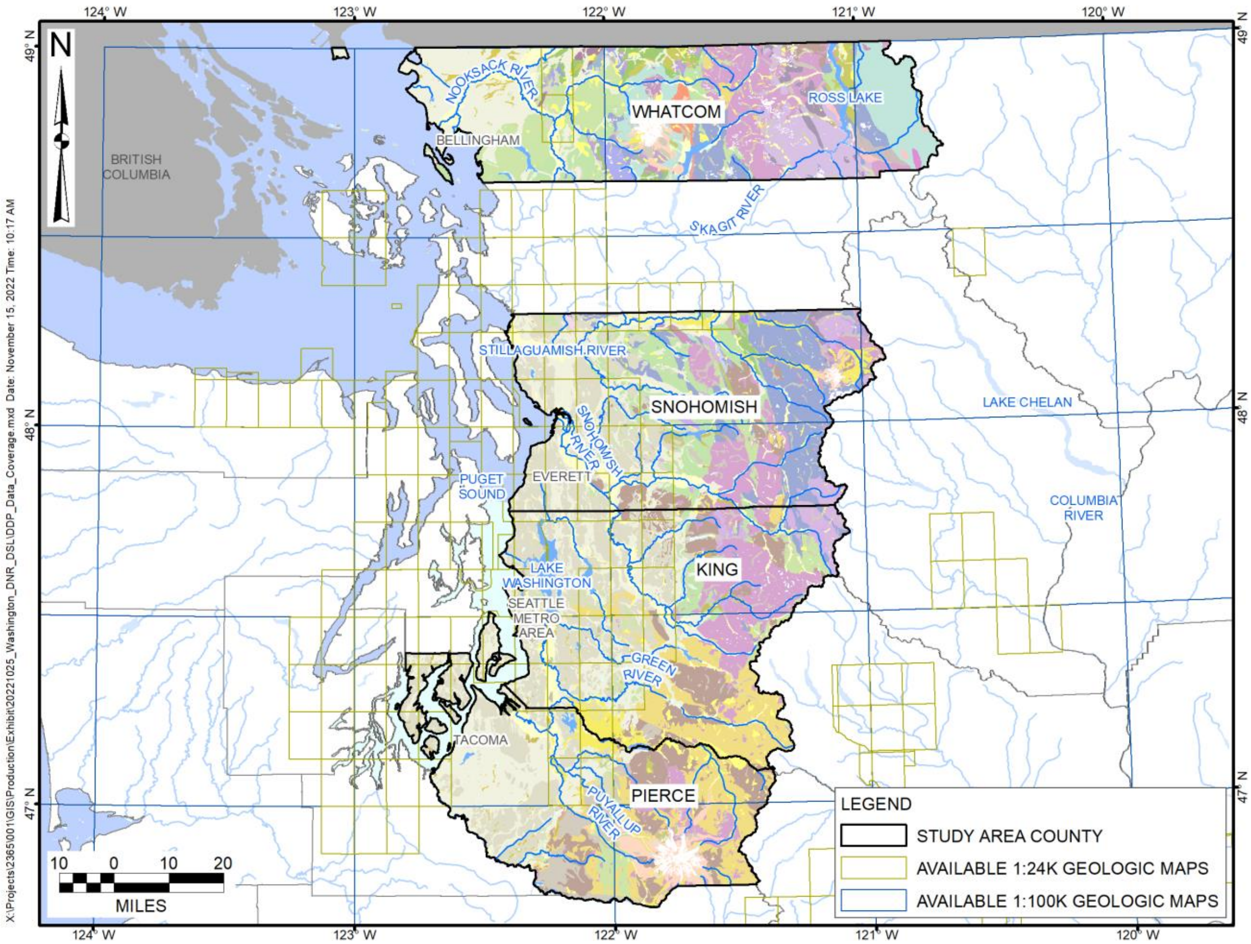

Figure 3-1. Geologic map coverage within the proposed study area. 1:100,000 geologic mapping is shown by the colored regions and is symbolized following the Washington Geological Survey (2019) (Data source: DNR).

3.1.2. Landslide Inventories

BGC has identified seven unique landslide inventory datasets within the study area of this project. Many of these landslide inventories were compiled to accomplish different objectives and, as such, are mapped at various scales, record different landslide attributes, and are constructed using different methodologies (Table 3-1). Detailed landslide mapping from the WGS is considered the primary inventory data source, with other inventories considered supplementary inventory data. The following sections describe each landslide inventory. Recommendations for the integration of all inventories into a single dataset to be used for DSL classification are provided in Section 4.2.1.

Table 3-1. Summary of available landslide inventories and the attributes they provide.

Inventories	Citation	Type	Method	Provided Landslide Attributes			
				Failure Depth	Reported Activity	Cruden and Varnes (1996) Classification	Estimate of Confidence
Primary Landslide Inventory							
WGS Lidar-Based	Mickelson et al. (2017; 2018; 2019; 2020; 2022)	Polygon	Lidar	x[1]		x[1]	x
Supplementary Landslide Inventories							
WGS Compilation	Washington Geological Survey (2022c)	Polygon	Map Compilation				x
Non-Glacial Deep Seated	Miller (2017)	Polygon	Literature Synthesis	x[2]	x	x	
Glacial Deep Seated	Miller (2016)	Polygon	Literature Synthesis	x[2]	x	x	
Slow Moving InSAR	Xu et al. (2021)	Polygon	InSAR		2007-2019		
DNR Recent Landslides	DNR (2022)	Point	Public Reports		2015-2022		
Puget Lowland DSL Inventory	Herzig et al. (2023)	Polygon	Lidar	x[2]			

Notes:

1. SLIP Landslides mapped by the Washington Geological Survey do not contain depth or classification information.
2. Inventory only includes deep seated landslides, but specific depth not assigned.

3.1.2.1. Washington Geological Survey Lidar-Based Landslide Inventory

In 2017, The WGS developed a protocol for lidar-based mapping and characterization of existing landslides (Slaughter et al., 2017) closely following the Oregon Department of Geology and Mineral Industries landslide mapping protocol described in Special Paper 42 (Burns & Madin, 2009). Using this protocol, the WGS has created detailed landslide inventories for the western portions of Pierce (Mickelson et al., 2017), King (Mickelson et al., 2019), Whatcom (Mickelson et al., 2020), and Snohomish (Mickelson et al., 2022a) Counties, and along the northern (Washington) side of the Columbia River Gorge (Mickelson et al., 2018) (Figure 3-2). In these locations, the lidar-based inventory has superseded the WGS statewide landslide compilation (Section 3.1.2.2).

Following Slaughter et al. (2017), lidar-derived products are used to map landslide polygons and assign distinguishing attributes including:

- Landslide material and movement type, following the classification framework of Cruden and Varnes (1996)
- Qualitative confidence of the presence of a landslide (i.e., high, medium, or low)

- Relative age classification of landslide movement (e.g., prehistoric) and year of movement, if known
- Geometry of landslide including the slope angle, headscarp height, failure depth, direction of movement, and volume of landslide material.

In remote portions of the mapping areas, the authors mapped landslide polygons from lidar data but only assigned confidence ratings in a process termed Streamlined Landslide Inventory Protocol (SLIP; Slaughter et al., 2017). SLIP landslide mapping has fewer attributes compared to the more detailed landslide mapping but is faster to complete and generally used in regions with lower population density.

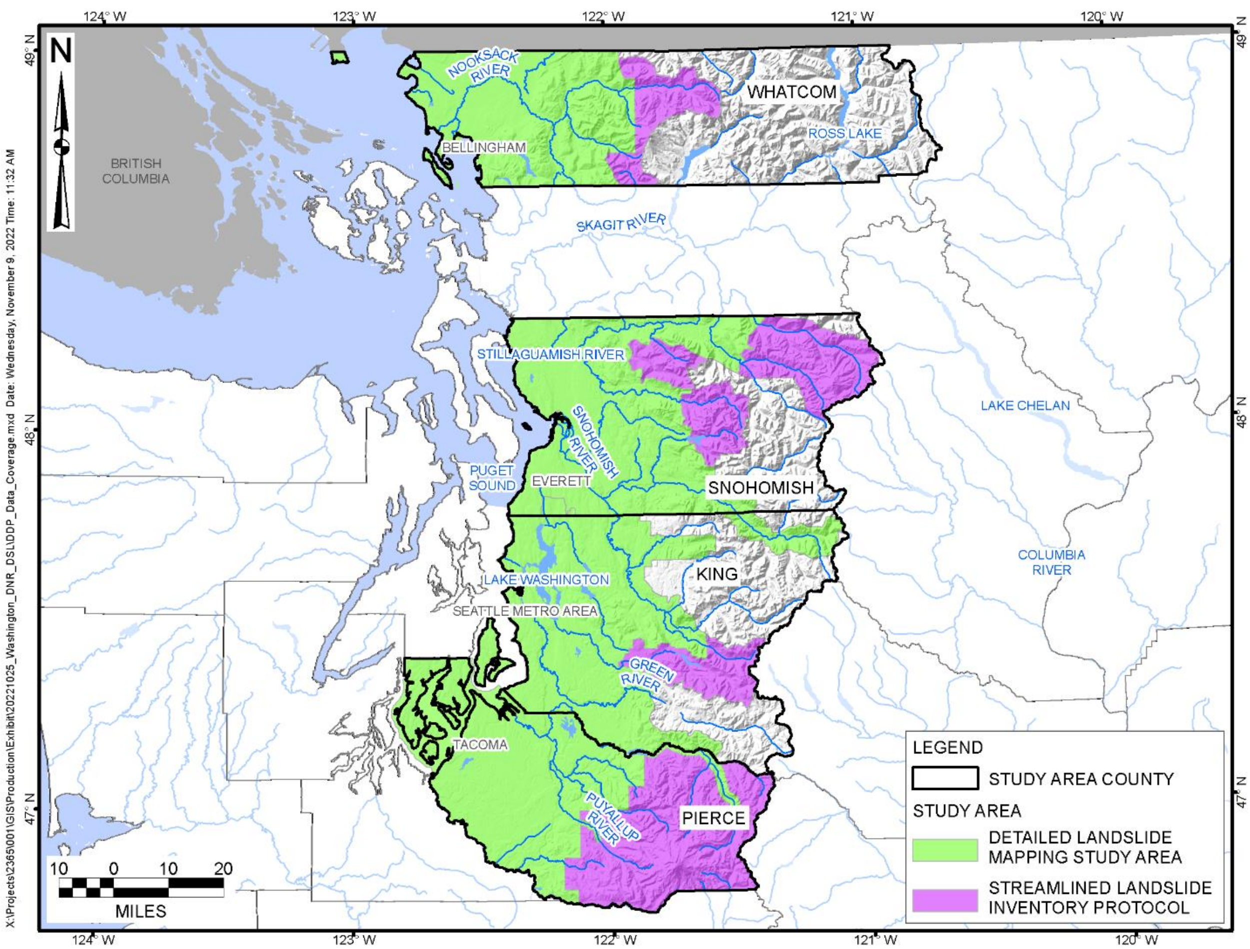

Figure 3-2. Lidar-based landslide inventory mapping extents of Mickelson et al. (2017; 2018; 2019; 2020; 2022).

3.1.2.2. Washington Geological Survey Compiled Landslide Inventory

The WGS provides an inventory of landslides compiled from a variety of mapping efforts across Washington (WGS, 2022c). Landslides within this compilation are derived from the following sources:

- Landslides mapped within 1:24,000-scale and 1:100,000-scale geologic maps.

- Miscellaneous landslide mapping from the WGS, the DNR Forest Practices Division, and other federal and private entities.
- Landslides mapped as part of Watershed Analysis efforts for the Washington Forest Practices Board (2016). Landslides within this dataset were mapped using aerial photographs, soil and geologic maps, field observations, and lidar, where available.
- Large, reconnaissance-scale mapping of landslides following significant precipitation events. Landslides within this dataset are typically mapped using small-aircraft surveillance, aerial photography, satellite imagery, or lidar identification, with minimal field verification.
- A study of near-shore landforms along the Salish Sea that have characteristics of deep-seated landslides but lack the thorough investigation necessary to classify these landforms as landslides.

Because of the variety of datasets and methodologies contributing to this compilation, the detail and quality of assigned landslide attributes are inconsistent across the dataset. Most notably, the compilation does not include a consistent attribution of landslide depth or morphology.

3.1.2.3. Glacial and Bedrock Deep-Seated Landslide Inventories

In the Fall of 2015, UPSAG and CMER were directed by the Washington Forest Practices Board and Timber Fish and Wildlife Policy Committee to develop a scope of work for a focused literature review and synthesis of research assessing the effect of forest practices on groundwater recharge areas and deep-seated landslides in glacial materials. The resulting review and synthesis (Miller, 2016) raised additional questions regarding forest practices effects on the groundwater recharge, reactivation, and runout potential of non-glacial deep-seated landslides. As such, the literature review and synthesis were expanded by Miller (2017) to focus on non-glacial deep-seated landslides. Both works (Miller, 2016; 2017) included a geospatial inventory of deep-seated landslide polygons with attributes indicating the activity level (i.e., relict, dormant, recent), representative material from which the landslide is derived, and the landslide material and movement type following the classification framework of Cruden and Varnes (1996).

3.1.2.4. InSAR-Identified Slow Moving Landslides

Xu et al. (2021) evaluated synthetic aperture radar (SAR) satellite imagery to identify slow-moving landslides across the continental U.S. western coastal states of California, Oregon, and Washington. Landslide movement was detected by evaluating interferograms derived from ALOS PALSAR (Advanced Land Observing Satellite; Phased Array type L-band Synthetic Aperture Radar) images between 2007 and 2011, and ALOS-2 PALSAR-2 images between 2015 and 2019. Within this dataset, each polygon represents the largest active area of the landslide captured by either ALOS PALSAR or ALOS-2 PALSAR-2. Xu et al. (2021) only reported landslides where the line-of-sight (LoS) displacements exceeded 5 mm over the data range processed. Therefore, the results likely do not capture the displacements for very slow moving landslides in the region. Landslide polygon attributes only include which time period showed landslide movement (i.e., 2007-2011, 2015-2019, or both); additional details on the amount or rate of movement are not provided. No displacement time series data are provided with this inventory.

3.1.2.5. Washington Department of Natural Resources Recently Reported Landslides

Beginning in 2015, DNR has collected and continually reported point observations of landslide occurrence statewide (DNR, 2022). Point observations only record the date of the observation and provide a brief description; information on the landslide characteristics or extent is limited. Additionally, the accuracy of the point locations is likely not sufficient for detailed analysis. As such, the information provided by this dataset likely would not contribute to the inventory of deep-seated landslides but may help to confirm the activity level of a landslide already included in the inventory.

3.1.2.6. Puget Lowland Deep-Seated Landslide Inventory

In 2023, Herzig et al. published a new DSL inventory of 1,065 landslides in the Puget Lowlands. The inventory is entirely inside King County and was based on detailed mapping on high resolution lidar (1-meter pixel size) combined with field observations. They classify all landslides in the inventory as deep-seated, with deep-seated landslides defined as those with a slip plane located beneath the rooting depth of trees. They utilized the WGS lidar based inventory for King County (Mickelson et al., 2019) as a starting basis and performed more detailed mapping including field verification visits. This appears to be a quite high-quality inventory in terms of spatial accuracy, though the attributes provided are mostly geometrical (e.g., length, height to length ratio).

3.1.3. Forest Operations Data

Geospatial information on past forest operations is available through records of forest permit applications and orphaned or abandoned forestry roads provided by DNR Forest Practices Division (2022). Extents of previous and current forest applications are provided as polygons while forestry road records are provided as polyline segments. Both datasets provide statewide coverage. These records, corroborated by remote imagery analysis to verify timing of forest practices activities, may be compared with DSL landslide inventories to analyze the spatial and temporal relationships between forestry operations and DSL activity.

3.1.4. Topographic Position

The position of a landslide in the context of hillslopes, ridges, and valleys can have important implications regarding the sensitivity of the landslide. For example, landslides that initiate in upper hillslopes and deposit material on valley floors may be more susceptible to river flows and active undercutting than landslides that do not travel all the way to the valley floor. A metric for assessing landscape position in this manner is known as the Topographic Position Index (TPI), developed by Weiss (2001).

TPI classifies the landscape into valleys, ridges, flat sections, and various portions of the hillslopes (e.g., upper, middle, lower). As topography is a fractal feature, TPI is thus a scale-dependent method that can be used to identify large- or small-scale topographic features depending on variables selected when computing the TPI. For example, Figure 3-3 identifies large features (e.g., major river valleys, major ridges) in western Washington. During study execution, scale parameters for TPI should be explored to determine scales that are most relevant to the inventoried DSLs. Multiple TPI datasets may be warranted to capture landscape features of different scales and assist in the landslide class definitions.

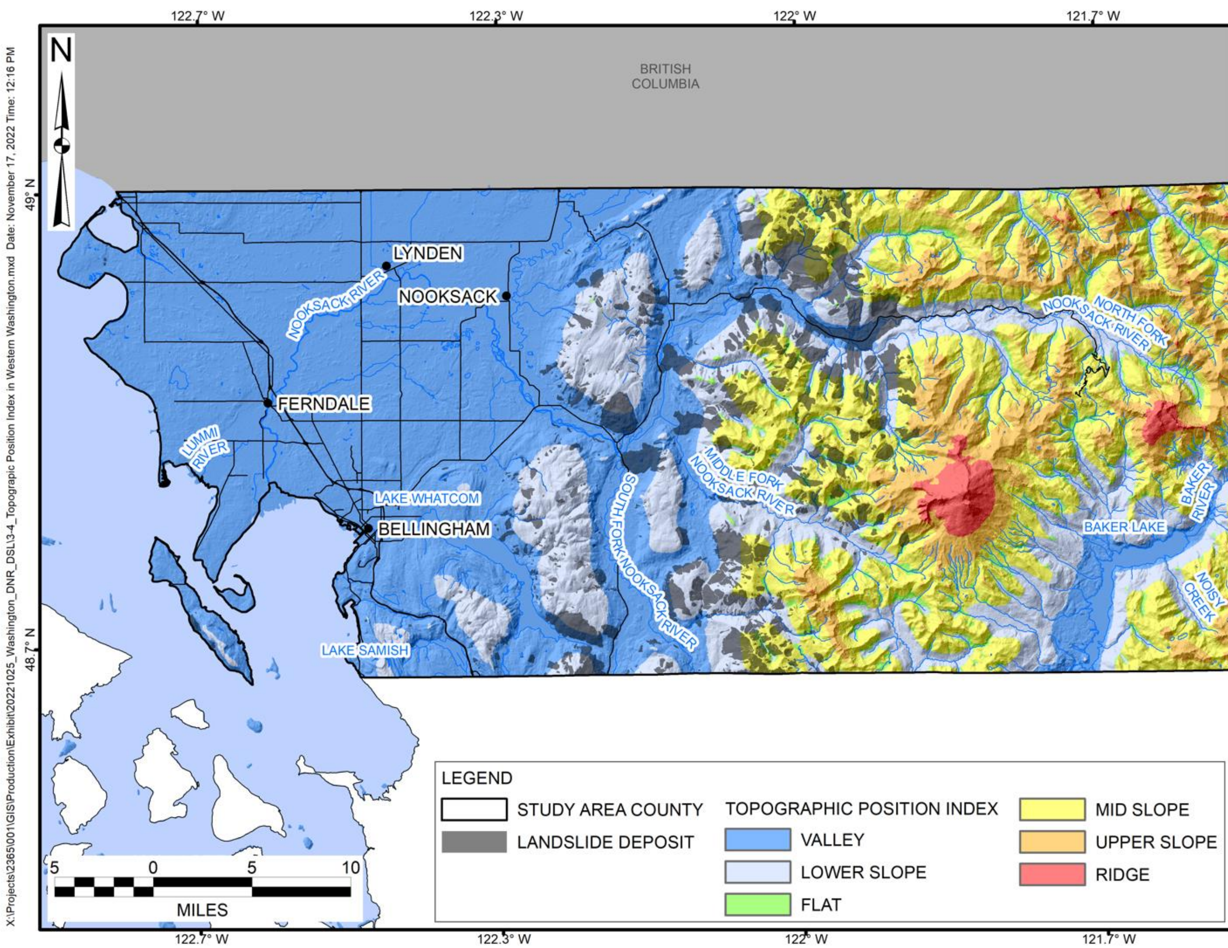

Figure 3-3. Example Topographic Position Index map for western Whatcom County for identifying range-scale features. Landslide deposits of Mickelson et al. (2020) are shown for reference (Data source: BGC, USGS).

3.1.5. Land Use/Land Cover

Land use/land cover (LULC) datasets provide spatially referenced categorical descriptors for each pixel of a satellite image. Common LULC classes include forests, agriculture, or built-up areas (e.g., Figure 3-4). As these data are developed from satellite imagery, they are thereby time-referenced as well, meaning that it is reasonable not only to identify present LULC categories, but also to track change in LULC through time. These types of data could be compared with landslide inventories to evaluate anthropogenic or natural influence on DSL activity. Worldwide, time-enabled, 10-m resolution LULC data derived from the processing of Sentinel-2 satellite imagery are available through Google Dynamic World (Brown et al., 2022). This service provides LULC data from June 2015 to present at a frequency of an updated classification every ~2-5 days.

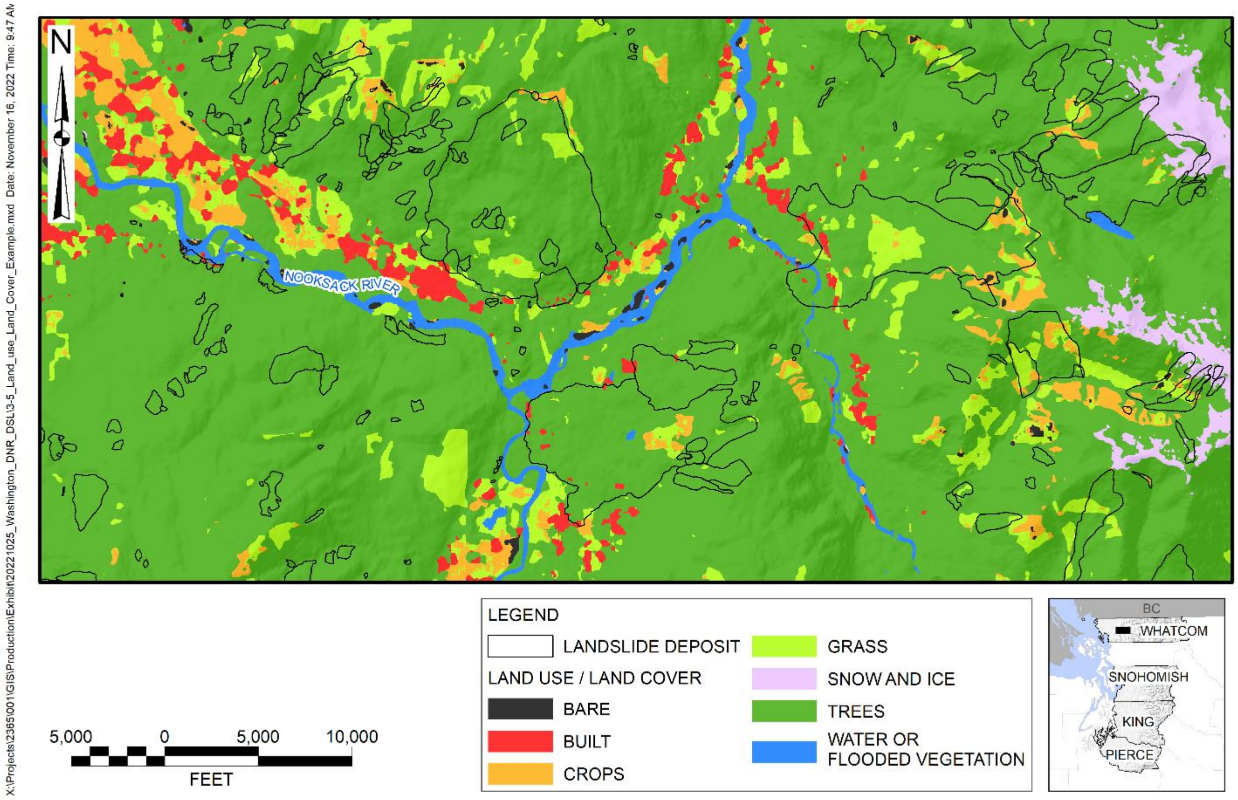

Figure 3-4. Example of LULC in relation to mapped DSLs in western Whatcom County (Mickelson et al., 2020). LULC data is derived from Google Dynamic World (Brown et al., 2022) and represents conditions on June 1, 2021.

3.1.6. Soil Maps

The United States Department of Agriculture (USDA) Natural Resources Conservation Service provides spatial and tabular soil information for most of the United States, including western Washington (USDA, 2022). Soil information from these maps such as the soil type, typical depth of the soil profile, drainage class, and water table depth may be used for landslide sensitivity assessment particularly in relation to hydrologic properties (see Sections 5.2.5 and 5.4).

3.1.7. Lidar Data

3.1.7.1. Lidar in Washington State

Lidar collection started in Washington State in 1996 and spurred the establishment of the Puget Sound Lidar Consortium – the first lidar management organization in Washington (Gleason & Markert, 2020). In 2015, Revised Code of Washington 43.92.025 was incorporated to

State Law, requiring the WGS to conduct lidar based mapping of seismic, landslide, and tsunami hazards in Washington (Gleason, 2016). This law initiated the development of a state-wide lidar collection, analysis, and dissemination program under the guidance of the Washington Office of the Chief Information Officer and the WGS. Using lidar to identify landslides is a well-established technique in the landslide community (e.g., Burns & Madin, 2009; Jaboyedoff et al., 2012) and lidar data have been a key underpinning for landslide inventory mapping by the Washington Geological Survey (Mickelson et al., 2017, 2019, 2020, 2022c) and others in the region (e.g., LaHusen et al., 2016).

Lidar is currently available from acquisition campaigns spanning between 2002-2022 in various portions of Washington. Data quality has generally increased with time and has been consistent with the state of the practice at the time of collection due to close collaboration between Washington agencies and project collaborators such as the U.S. Geological Survey. Current data are collected at Quality Level 1 (QL1) specifications with a minimum aggregate return density of 8 pulses per square meter (ppsm). Additionally, data are processed to digital elevation models (DEM) with a cell size of 0.5 meters. Return classification is consistent with American Society of Photogrammetry and Remote Sensing standard classifications (ASPRS, 2019). Based on preliminary, proof-of-concept, lidar analysis, lidar collected at least as long ago as 2006 is suitable for lidar change analytics (Section 5.2.3).

3.1.7.2. Lidar Coverage in the Study Area

In 2022, lidar is generally available over all portions of the study area where landslide mapping has been conducted. Multi-epoch data are also available, with between one and 10 epochs available for any given location in the study area. Figure 3-5 illustrates individual blocks of lidar data acquired by Washington State or partner agencies and in the Washington State Lidar database. Most frequent coverage is generally available along major river valleys in the study area such as the Nooksack (Whatcom Co.), North Fork Stillaguamish (Snohomish Co.), Snoqualmie and Cedar (King Co.), and Puyallup rivers (Pierce Co.). However, for virtually all landslides in the WGS Landslide Database (Section 3.1.2), at least two epochs of lidar are available.

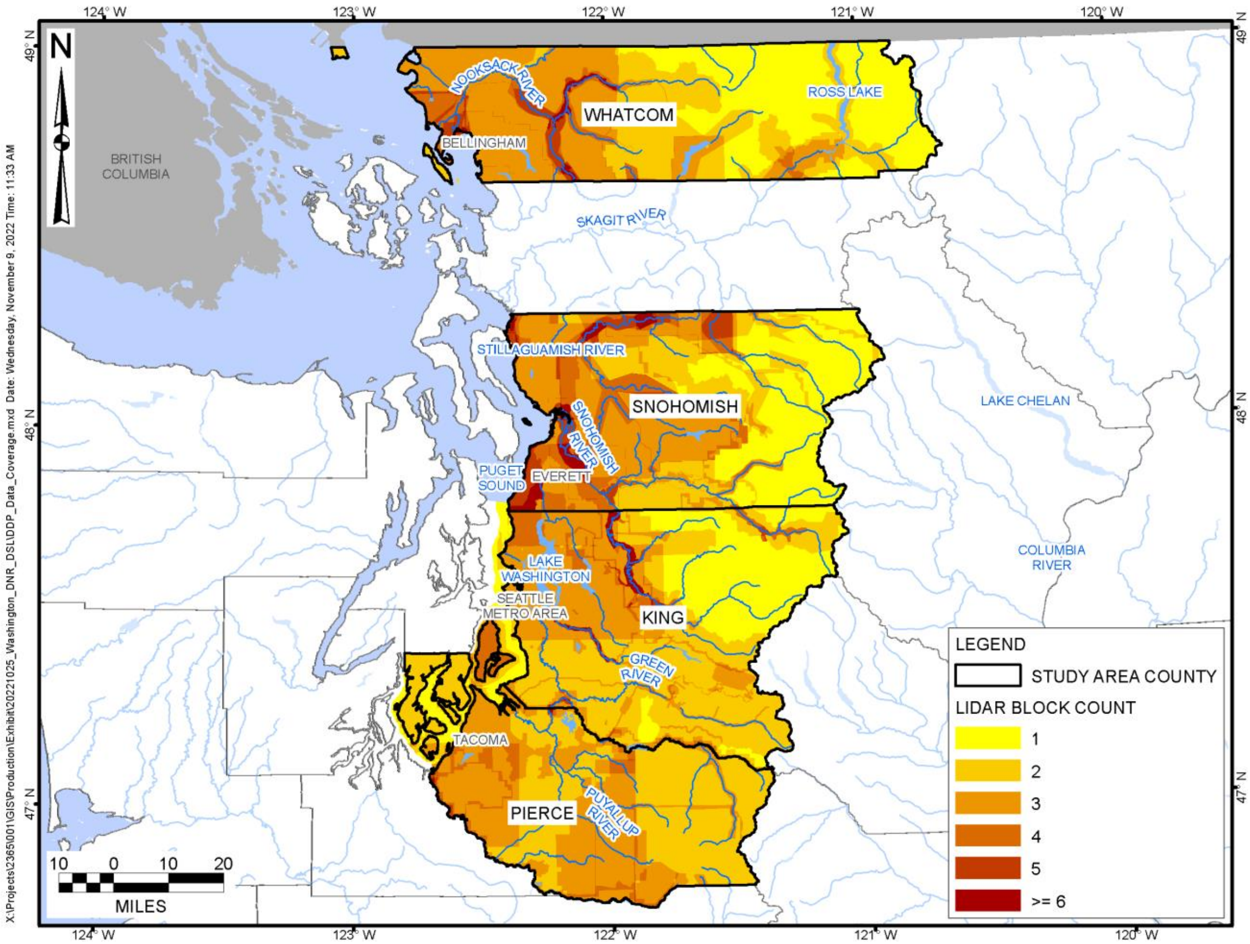

Figure 3-5. Lidar coverage within the proposed study area. Warmer colors represent more epochs of collocated lidar (Data source: DNR).

3.1.8. Synthetic Aperture Radar (SAR) Data

3.1.8.1. InSAR Coverage Considerations

Since 1991, a series of satellites with synthetic aperture radar (SAR) sensors, launched by several international space agencies, have collected coverages of data that can be utilized to support monitoring of ground deformation (Figure 3-6). These SAR data, when processed utilizing a technique called SAR Interferometry (InSAR), can in many cases map ground displacements as small as millimeters per year. While the ability to map this level of ground deformation is dependent on many factors related to the sensing parameters, the processing techniques, error introduced by atmosphere and topography, impacts of ground cover/vegetation and attributes of the ground movement itself, these data theoretically can provide a time history of deformation going back 30 years.

Some of the key requirements to support building long term time histories of ground displacement using InSAR is that SAR data had to have been systematically collected and archived and must be accessible to download and process. At this time the only systematically global coverage of freely available and easily accessible SAR data that is still operational has been obtained via the European Space Agency's (ESA) Sentinel 1A and 1B satellites, which were launched in 2014 and 2016, respectively. Historical data obtained by ESA's ERS 1 and 2 (1991 to 2011), and Envisat-1 (2002 to 2012) are also freely available and accessible through ESA. Radarsat-1 (1996-2013) and ALOS-1 (2004-2011) are also freely available but did not acquire standard coverages and therefore data are not always suitable for building an InSAR time series. There are also other satellites with SAR sensors that were launched by international space agencies where areas have been imaged based on government priorities or tasked on an on-demand basis for commercial purchase. With these satellites there are only existing stacks of data present if acquired for the above purposes and therefore data is not consistently available globally.

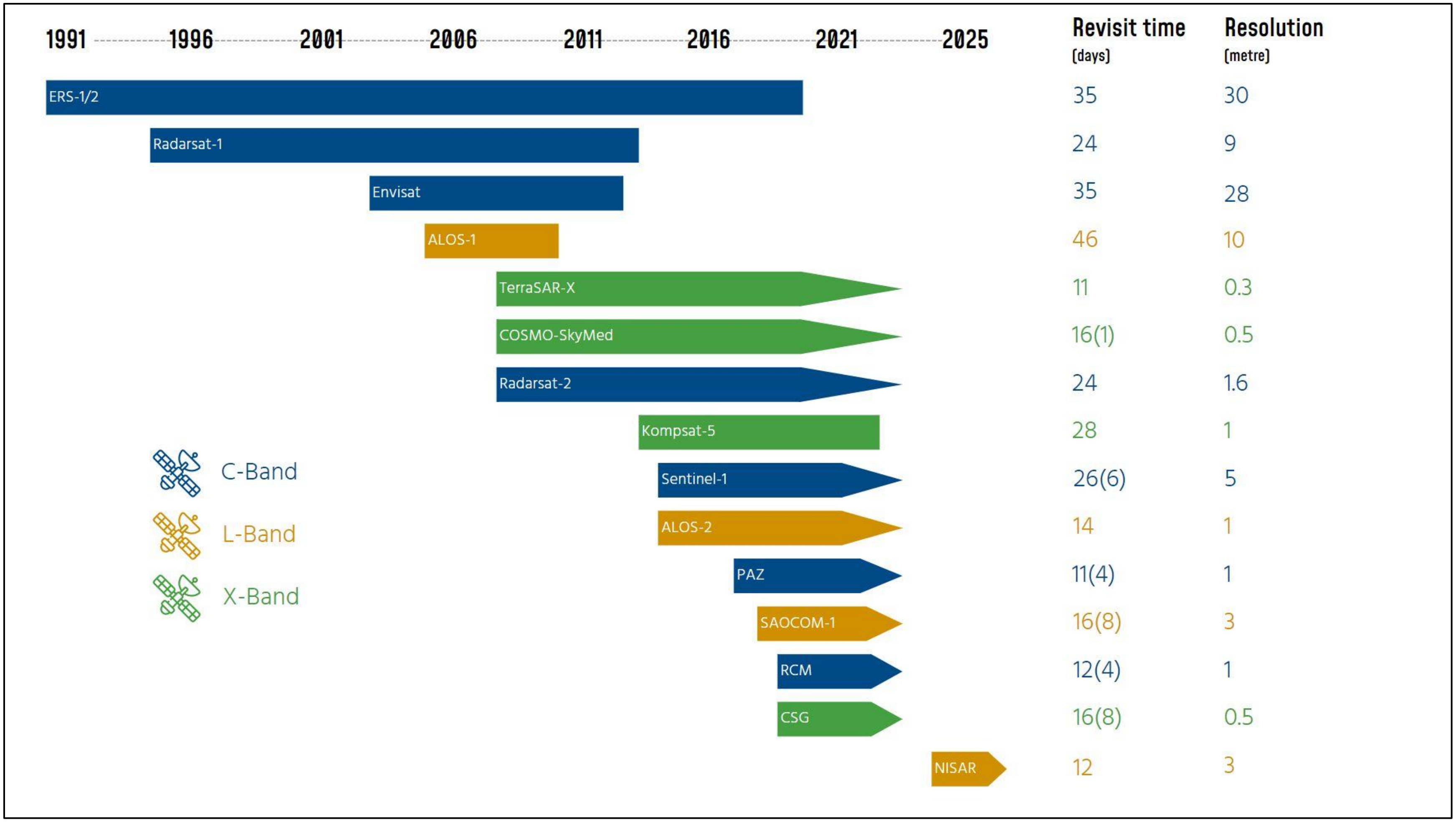

Figure 3-6. Overview of the historic, current, and upcoming SAR satellites launched by various international space agencies. A pointed right-end on the bars shown indicates ongoing data collection, whereas a square end indicates a cessation in satellite acquisition.

The SAR sensors operate in different wavelengths and acquire data in different orbital configurations and, potentially, imaging modes. These configurations have implications on the ability to quantify ground motion. The high-level considerations impacting the overall suitability of these SAR data to support mapping regional ground deformation will be discussed in more detail in Section 5.2.4.

3.1.8.2. SAR Data Coverage for Study Areas

The western coast of the United States is exceptionally data rich in terms of the availability of historical archives of SAR data coverages. These coverages include both C-Band and L-Band SAR data and often provide both ascending and descending look directions. When used together, these datasets provide opportunities to maximize spatial coverage and the ability to quantify ground displacement in terms of displacement direction and rates of movement. When discussing satellite coverages, each acquisition of SAR data is referred to as an individual “scene” while overlapping, repeatedly collected scenes covering the same area over different time periods is referred to as a “stack”. Typically, when assessing the feasibility of SAR data to generate time series data, discussion focuses on whether there are enough SAR scenes available for that analysis, which is referred to as the “stack depth”.

The following provides an overview of the spatial and temporal attributes of the available C-Band and L-Band coverages over the specific counties. X-Band coverages are not currently considered as they are broadly not considered to be suitable to quantify ground movement in vegetated terrain. The details in relation to the available data coverages (footprints) and acquisitions are included in Appendix A and summarized in the following sections.

3.1.8.2.1 C-Band (1992 to Present)

3.1.8.2.1.1 ERS-1 and 2 (1991 to 2011)

Launched by the European Space Agency (ESA) the ERS program consisted of two satellites, ERS-1 (launched in 1991) and ERS-2 (launched in 1995). These satellites had identical sensors and shared the same orbit, making the data suitable for interferometric processing. A significant amount of ascending and descending data, captured between 1992 and 2011, are available over the study area. Although this coverage is not temporally consistent, different footprints can be chosen to optimize the InSAR processing results. An overview of the spatial coverages of the ERS-1 and ERS-2 data in relation to the study area is provided in Appendix A, with the temporal properties of these coverages provided in Table 3-2.

Table 3-2. Overview of temporal characteristics of existing ERS-1 and ERS-2 coverages.

County	Ascending	Descending
Whatcom	Complete coverage of study areas with sporadic acquisitions obtained between early 1993 to late 2011. Maximum stack depths of up to 25 scenes.	Complete coverage of study area with relatively consistent acquisitions (gaps in 2003-2005). Deep stacks available (>30 scenes).
Snohomish		
King		
Pierce		

3.1.8.2.1.2 Radarsat-1 (1996 to 2013)

Launched in late 1995 by the Canadian Space Agency (CSA), Radarsat-1 (R1) was a hybrid sovereign/commercial SAR satellite that acquired data in areas of strategic need for the Canadian Government and allowed for the tasking of on-demand images commercially via MacDonald, Dettwiler and Associates (MDA). Based on this tasking arrangement, no standard coverages were typically available in areas outside of Canada. However, the review of the R1 archives encountered relatively good spatial and temporal coverage over portions of the study areas. An overview of the spatial coverages of the R1 data in relation to the study area is provided in Appendix A, with the temporal properties of these coverages provided in Table 3-3.

In April 2019, the R1 archives were made freely available by the Canadian Space Agency and therefore there is no cost associated with obtaining the SAR data for processing.

Table 3-3. Overview of temporal characteristics of existing Radarsat-1 coverages.

County	Ascending	Descending
Whatcom	Existing coverages for southern half of county with temporally dense image stacks available between late 2004 to early 2008.	Large portions of area covered by various footprints. Image stacks are typically less than 10 images and sporadically collected.
Snohomish	Partial coverage with various footprints with deep image stacks between early 2005 to early 2008.	Partial coverages by various footprints with deep image stacks between early 1999 and early 2008
King	Consistent coverage for large portions of the study area with consistent acquisitions between early 1999 and early 2008.	Consistent coverage for large portions of study area with consistent acquisitions between early 1999 and early 2008.
Pierce		

When reviewing the temporal coverage, it is apparent that there are areas where more frequent acquisitions have been targeted and therefore the utility of this data will vary based on the targeted areas prescribed in this design.

3.1.8.2.1.3 Radarsat-2 (2007 to Present)

The second of Canada's Radarsat satellites, Radarsat-2 (R2) was launched in late 2005 with a similar acquisition model as R1. Therefore, SAR data was only collected over areas of strategic importance for the Canadian government, or areas where acquisitions were tasked for commercial purposes. When reviewing the R2 archives, only sporadic coverage primarily focused over the western portion of Pierce County has been collected. If this area is one of the areas chosen for more detailed study, then the suitability of this data for InSAR processing would be evaluated with consideration that this data is currently only available on commercial basis through MDA.

3.1.8.2.1.4 Sentinel-1A and 1B (2014 to Present)

ESA's Sentinel-1A and 1B missions provided the first systematic global acquisition of C-Band SAR data which is easily accessible and freely available. Similar to the ERS program, Sentinel 1A and 1B provided identical imaging characteristics and were launched on the same orbital path.

An overview of the spatial coverages of the Sentinel-1 A and B data in relation to the study area is provided in Appendix A, with the temporal properties of these coverages provided in Table 3-4.

Table 3-4. Overview of temporal characteristics of existing Sentinel-1 coverages.

County	Ascending	Descending
Whatcom	Complete coverage of all areas with consistent 12-day temporal revisit between early 2017 and late 2021. Deep stacks of data (>30 scenes)	Complete coverage of all areas with consistent 12-day temporal revisit between late 2017 and late 2021. Deep stacks of data (>30 scenes)
Snohomish		
King		
Pierce		

3.1.8.2.2 L-Band

3.1.8.2.2.1 ALOS-1 (2006 to 2011)

The Advanced Land Observing Satellite (ALOS) was an earth-imaging satellite launched by the Japanese Space Agency (JAXA) in January 2006 and collected imagery until May 2011. The ALOS satellite featured 3 instruments, including the Phased Array-type L-band SAR (PALSAR) instrument. While the ALOS satellite featured a systematic global observation strategy, the acquisition plans were targeted for systematic coverage by all 3 instruments. The PALSAR instrument acquisition strategy featured routine observations for 4 instrument modes, all of which are not interferometrically compatible. Nevertheless, the PALSAR acquisition strategy allowed for the collection of ScanSAR (30 m resolution) stacks of data suitable for InSAR processing for most areas of the globe. For the areas of interest, there are relatively good coverages of ALOS-1 data (shown in Appendix A) that are outlined below on Table 3-5.

Table 3-5. Overview of temporal characteristics of existing ALOS-1 coverages.

County	Ascending	Descending
Whatcom	Complete ScanSAR coverage 2007-early 2011 (some gaps in 2008-2009) with some stacks over 20 scenes deep.	Majority of area covered with ScanSAR data but stack depths range from 3 to 6 scenes and are likely not suitable for building displacement time-series.
Snohomish	Complete ScanSAR spatial coverage with intermittent coverage between early 2007 and 2011. Stack depths range between 9 to 12 scenes.	Majority of area covered with ScanSAR data but stack depths limited to a maximum of 7 scenes.
King		
Pierce		

In September 2015, the ALOS-1 archived data were made freely available for download and are accessible through JAXA and various distribution centers.

3.1.8.2.2.2 ALOS-2 (2014 to Present)

JAXA's second satellite of the ALOS mission, ALOS-2, was launched in May 2014, with priority coverages focused on the Japanese government requirements and commercial acquisitions available on a fee-for-tasking basis. With this model, consistent global coverages were not obtained, however, there were relatively consistent acquisitions of coarser ScanSAR data collected over the study areas, as shown in Appendix A and described in Table 3-6.

Table 3-6. Overview of temporal characteristics of existing ALOS-2 coverages.

County	Ascending	Descending
Whatcom	Regularly spaced coverages between late 2014 to 2022 with stack depth of up to 12 scenes.	Regularly spaced coverages between late 2014 to 2022 with stack depths of up to 12 scenes. Image stacks of lower resolution ScanSAR data up to 64 scenes deep.
Snohomish		
King		
Pierce		

The archived images over the study areas are available for commercial purchase through JAXA's reseller, PASCO (https://alos-pasco.com/en/offer/).

3.1.8.3. InSAR Feasibility for Study Area

The design of the data acquisition and processing strategy will maximize the potential for accurately measuring true ground displacements. As discussed previously, the key considerations include the spatial coverage of data, the number of scenes that can be utilized for InSAR processing (stack maturity), and the wavelength of the data. Table 3-7 provides a preliminary assessment of the suitability of the data presented in Section 3.1.7.2 and Appendix A to provide high fidelity InSAR timeseries data for each of the counties in question. The data are rated as high (H), Medium (M) and Low (L) suitability based on the following criteria:

Likelihood of Success:

- High (Green): Complete spatial coverage of the study area and deep stacks of data (>15 scenes of L-Band data or >30 scenes of C-Band data) that likely can be utilized to generate near-continuous displacement time series
- Moderate (Yellow): Study areas are mostly/completely covered with some stacks that have at least 10 scenes of L-Band data or 20 scenes of C-Band data that could be utilized to generate displacement time series
- Low (Red): Either there is poor spatial coverage, or the stack depths are insufficient to generate useful displacement time series.

Even though areas are marked as having a High to Moderate likelihood of success based on spatial and temporal data coverages, there are other reasons why data may not be suitable for use, such as large orbital baselines, which may reduce the stack depth. Furthermore, C-band data will result in lower measurement point densities in the presence of vegetation. This being considered, any area marked as High to Moderate likelihood of success should be considered for acquisition and processing of data, especially for freely available data sources such as ALOS-1 ScanSAR, ERS-1 and 2, Radarsat-1 and Sentinel-1. For ALOS-2 ScanSAR data, which is commercially available, it is recommended that only areas marked as High likelihood should be considered for acquisition and processing.

Table 3-7. Summary of the Feasibility (High, Medium, Low) of Utilizing Existing SAR archived data to generate time series InSAR.

Band	Coverage	Date Range	Whatcom		Snohomish		King		Pierce	
			Asc	Desc	Asc	Desc	Asc	Desc	Asc	Desc
L	ALOS-1	2006 - 2011	H	L	M	L	M	L	M	L
	ALOS-2	2014 - 2022	M	H	M	H	M	M	M	H
C	ERS-1/2	1992 - 2011	M	H	M	H	M	H	M	H
	Radarsat-1	1996 - 2008	M	M	M	M	M	H	M	H
	Radarsat-2	2012 - 2022	L	L	L	L	L	L	L	L
	Sentinel-1	2017 - 2022	H	H	H	H	H	H	H	H

Notes:

1. Asc: Ascending.
2. Desc: Descending.

3.2. Site-Specific Studies

Site-specific studies of DSLs within the project area may provide additional details on the landslide properties beyond what is included within existing landslide inventories. These studies are available as published papers, academic theses, or geotechnical reports (either from government agencies or consultants) and may contain valuable information from instrumentation monitoring (e.g., slope inclinometers, extensometers, GPS, survey monuments). Comparison of a subset of landslide classes and clusters (Section 5.2.5) with site specific studies, where available, may provide verification of the DSL classification schema proposed within this document. In our experience, long-duration site-specific instrumentation data are relatively rare, with few large landslides monitored with a regular temporal frequency. Where available, these data will also be site-specific and it will be important to not apply too great of an emphasis on monitoring data from one landslide. Because of these issues, site-specific data will be supplementary to the overall study. They will be very useful where available, and if sufficient data exist, using them to correlate remote-sensing derived findings will be a value-add to the program. However, the overall results of the study should not hinge on instrumentation data availability.

Miller (2016; 2017) includes references to geotechnical reports or published works in his inventories of glacial and non-glacial DSLs and, as such, may serve as a starting point for seeking site-specific information. Because these works only include active DSLs identified before 2017, other means of identifying site specific studies should be utilized for DSLs which contain more recent information.

Additionally, where available, forest practice applications (FPA) should be consulted for further evidence of activity state or field-based observations that can be useful in the classification. These reports may contain evidence of landslide activation that are missed via remote-sensing methods alone. Further, they may contain precursors to landslide activation such as ponding of water or changes in surface water drainage patterns.

4.0 DATA CONSIDERATIONS

4.1. Dataset Size and Completeness

Historically, studies aiming to evaluate factors influencing DSL activity were conducted on a single to a few DSLs that are studies in detail at a site-specific scale. This is because these studies were generally heavily field-oriented and often included subsurface investigations such as drilling or monitoring (e.g., soil moisture probes, piezometers, inclinometers). While useful, these methods are not applicable at a regional scale and can quickly become prohibitively expensive to conduct on a large population of landslides. It is not feasible to undertake detailed field investigations of the over 9,000 DSLs known in Washington, for example. Although this is true, these detailed studies are important to support extrapolation of the site-specific models developed across similar landslides within associated landslide groupings (classes or clusters).

Satellite-derived remote sensing data is an increasingly viable alternative to study large populations of landslides. The spatial continuity and increasingly dense temporal coverage of these data give the alternative a great advantage of being able to interrogate large populations of landslides over the last 2-3 decades (as far back as 1992 depending on the availability of archived data), resulting in the ability to remotely capture many “landslide-years” of observations. For example, recent works by Xu et al. (2021) and Handwerger et al. (2022) use InSAR to make observations on the activity state of 617 and 38 landslides over a period of 13 and 6 years, respectively. These works resulted, therefore, in several thousand landslide-years of observations regarding the activity of DSLs in space and time.

This current study design approach supports the collection of thousands to tens of thousands of landslide-years of observations to be used in the evaluation of landslide sensitivity to forestry activities. This may allow the further subdivision of the overall population into classes and clusters of landslides, following the expectation that in different regions or at different times, sub-populations of landslides may respond differently than others. This study will likely not be successful if only landslides that can be investigated with field methods are used in the analyses contained in this design. Furthermore, the spatial definition of key areas from the remotely sensed data will allow for targeted site-specific studies and/or monitoring to support subsequent program phases.

Quality control of all data sources will be critical throughout the study execution. Errors could be propagated and, thus, should be considered wherever possible. Errors may be categorical (e.g., landslide type, mapped lithology) or numerical (e.g., LCD or InSAR derived velocities) and may come from original data sources or from those generated during the study execution. Throughout the study design, project members should routinely be checking for data accuracy. Part of this program includes manual analyst review of landslide polygons, specifically during the LCD and InSAR characterization work. This is an ideal time in the program to assess the accuracy of other attribute data associated with landslide polygons. Additionally, project check-ins with UPSAG and associated agencies and data transmittals should be shared to facilitate gathering others’ perspectives on classifications and methods.

4.2. Organization and Structure

Since the modern computational revolution of the 1990s to present, dataset size and complexity has increased exponentially. Extracting meaningful information from these “big data” can be exceedingly difficult without appropriate planning. It also can pay dividends to plan for future unknowns when designing a large-scale study such as this one.

This section describes some considerations in designing the data architecture for this program. The objective of this planning is to adequately prepare for the known program objectives but also provide a flexible framework to account for future potential uses of these data. These future potential uses could include application of the program to new geographic areas (e.g., additional areas inside or outside Washington), new data sources, and perhaps most importantly, new analytical techniques.

4.2.1. Landslide Inventory Integration Procedure

For this study design, we suggest integrating the landslide inventories described above into a single dataset that can be used to classify landslide properties and assign velocity classes. The most relevant attributes readily provided by available inventories for landslide classification include the depth of landslide movement, representative source material, movement type classification (Cruden & Varnes, 1996), activity level, and confidence in the landslide interpretation.

The purpose of integrating inventories is not to suggest what areas of the landscape are experiencing landslides in modern day (e.g., are “active”). Instead, the effort aims to identify the maximum likely extent of present-day and geologically recent (i.e., since the last glacial period) landslides, and thus, to conservatively estimate areas of the landscape that may be sensitive to external perturbations such as forestry disturbances. This base layer of possible DSL locations will serve as the basis for where to perform further analysis.

Given the variability in scale, quality, and coverage of the available landslide inventories, careful consideration should be paid to the landslide attributes and the methodology of the original source. In many locations, landslide polygons from different inventories may overlap and provide conflicting information on landslide attributes. Recognizing that virtually every landslide inventory is developed with slightly different methodologies, it can be useful to provide a quality score to each inventory when performing an integration of these different datasets. A quality score can capture different components of the mapping methodology. For example, was the inventory generated through mapping on high resolution lidar or only on coarse resolution topographic data (e.g., SRTM)? Was the inventory field verified or is it primarily composed of media reports? A quality ranking, thus, provides a basis for deciding which inventory takes precedent when overlaps occur or when conflicting information is provided by the different inventories. Further, it can provide the basis to omit data entirely or to warrant further confirmation of landslides from a given inventory prior to analysis. Mirus et al. (2020) provide a framework for this quality metric and we would encourage a similar methodology be used in this study. In Mirus et al. (2020), the authors use a ranking score of 1-8 (Fibonacci sequence, i.e., 1, 2, 3, 5, 8) according to factors such as the presence (or lack thereof) of field observations, the resolution of topography data used for mapping, the use of aerial imagery, the reliance on media reports, and more). The WGS inventory provides a separate confidence level attribute for each polygon (low, moderate, or high). This indicates how confident the mapping geologist was that the identified feature was a landslide, considering the clarity of the landslide headscarp, flanks, toe/deposit, and morphology (Slaughter et al., 2017). This WGS ranking may be used in conjunction with the Mirus et al. (2020) ranking system. One suggestion is to carry the Mirus et al. (2020) assigned score of 8 through to only "high" confidence WGS polygons. For "moderate" WGS polygons, perhaps a score of 5 is assigned, and for "low" confidence WGS polygons, perhaps a score of 3. Careful consideration here should attempt to carry all confidence metrics through to the final compiled inventory.

We suggest that the detailed, lidar-based inventory provided by the WGS (Mickelson et al., 2017; 2018; 2019; 2020; 2022) be the primary contributor to the overall landslide inventory because it is mapped using lidar at a scale appropriate to this work and contains relevant information on landslide depth, materials, and movement type. The WGS also field verifies a percentage of their polygons and uses aerial imagery where available. Mirus et al. (2020) ranks the WGS lidar based inventories as highest quality (score = 8). That said, more recent work by Herzig et al. (2023) overlaps areas also mapped by the WGS in the Puget Lowlands and in many cases, the Herzig et al. data overlap with WGS mapping (see Figure 4-1). We bring this up here to illustrate that even amongst high quality inventories, sometimes decisions will need to be made on an inventory by inventory basis and a simple quality score is only a guiding metric and does not provide a complete workflow. These quality ratings may be used by DNR in further assessments, whether they be office- or field-based. For example, DNR may opt to perform a more rigorous review of low-confidence features and a less rigorous review of high-confidence features.

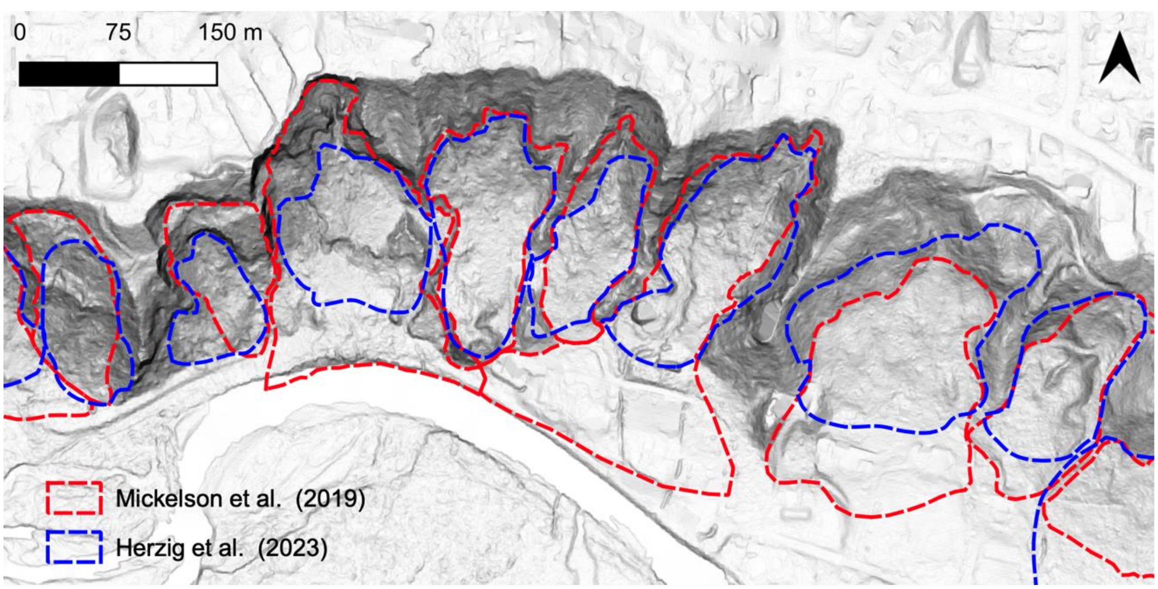

Figure 4-1. Comparison of two recent high quality landslide inventories from Herzig et al. (2023) and Mickelson et al. (2019) in King County, WA. Slopeshade base derived from DNR, King County Lidar 2021.

Other inventories may be used to supplement the WGS lidar-based inventory, depending on their methodologies and attributes provided. A suggested procedure for how to integrate the landslide inventories is shown in Figure 4-2. Comments on how the supplemental inventories may contribute relevant landslide information is described below:

1. WGS Compiled Landslide Inventory (WGS, 2022c) – Because the WGS lidar-based inventory supersedes the WGS compiled inventory, the only landslides within this compilation that should be included within this study are those that fall outside the mapping areas of Mickelson et al. (2017; 2018; 2019; 2020; 2022). The attributes within the WGS compilation are highly variable aside from the confidence in the landslide existence. Therefore, the subject matter expert (SME) performing the proposed study will need to check that the polygon reasonably delineates a deep-seated landslide, estimate the landslide depth, representative source material, Cruden and Varnes (1996) classification, and activity level based on their professional judgement using contextual information such as geometrical relationships, available lidar datasets, geologic maps, or additional landslide inventories.
2. Glacial and Non-Glacial DSL Inventories (Miller, 2016, 2017) – These datasets provide high-quality information on DSL source materials, movement type, and activity level but are limited in their extent and spatial coverage because they are primarily derived from landslides reported in several external data sources. Where landslides within this compilation overlap with the WGS lidar-based landslides, if appropriate, polygons may be merged to conservatively represent the deep-seated landslide extent.
3. InSAR Derived Slow Moving Landslides (Xu et al., 2021) – These datasets provide information on the timing of landslide movement that may be incorporated with other existing inventories. Our preliminary review shows that all slow-moving landslides identified through InSAR (Xu et al., 2021) overlap with DSLs mapped by the WGS using lidar-based methods (Mickelson et al., 2017; 2018; 2019; 2020; 2022) within the WGS mapping extent. Similar to overlapping glacial and bedrock DSL inventories discussed above, we suggest that InSAR-identified landslides that overlap landslides from other inventories be merged to conservatively represent the potential area of landslide sensitivity. Landslide activity information provided by the InSAR datasets should be maintained within the database.
4. DNR Recent Landslides (DNR, 2022) – The DNR recent landslide database would likely not contribute to the inventory compilation as it only provides point data of landslide observations and accuracy of the point locations are questionable due to the sourcing of these data from a variety of reporting agencies including media networks. This data, however, may be useful for determining the activity history of landslide polygons that intersect the recent landslide points features. Our preliminary review shows that 29 DSLs within the WGS lidar-based inventory intersect point observations of recent landslide activity. When reviewing the various landslide activity data obtained from LCD and InSAR these data points will be considered to gather additional insights into the timing of sudden landslide activity changes at the point locations.

Puget Lowlands Landslide Study (Herzig et al., 2023) – Researchers from Washington, Oregon, and California produced an inventory of 1,065 deep seated landslides in the

Puget Lowlands of western King County, WA. In many instances, the inventory overlaps with the WGS inventory for King County (Mickelson et al., 2019). The mapping was performed on 2021 vintage lidar (1-meter pixel size) and the resulting inventory includes several geometric attributes (e.g., height, length). The inventory does not include any field observations, though the authors did field verify some landslides.

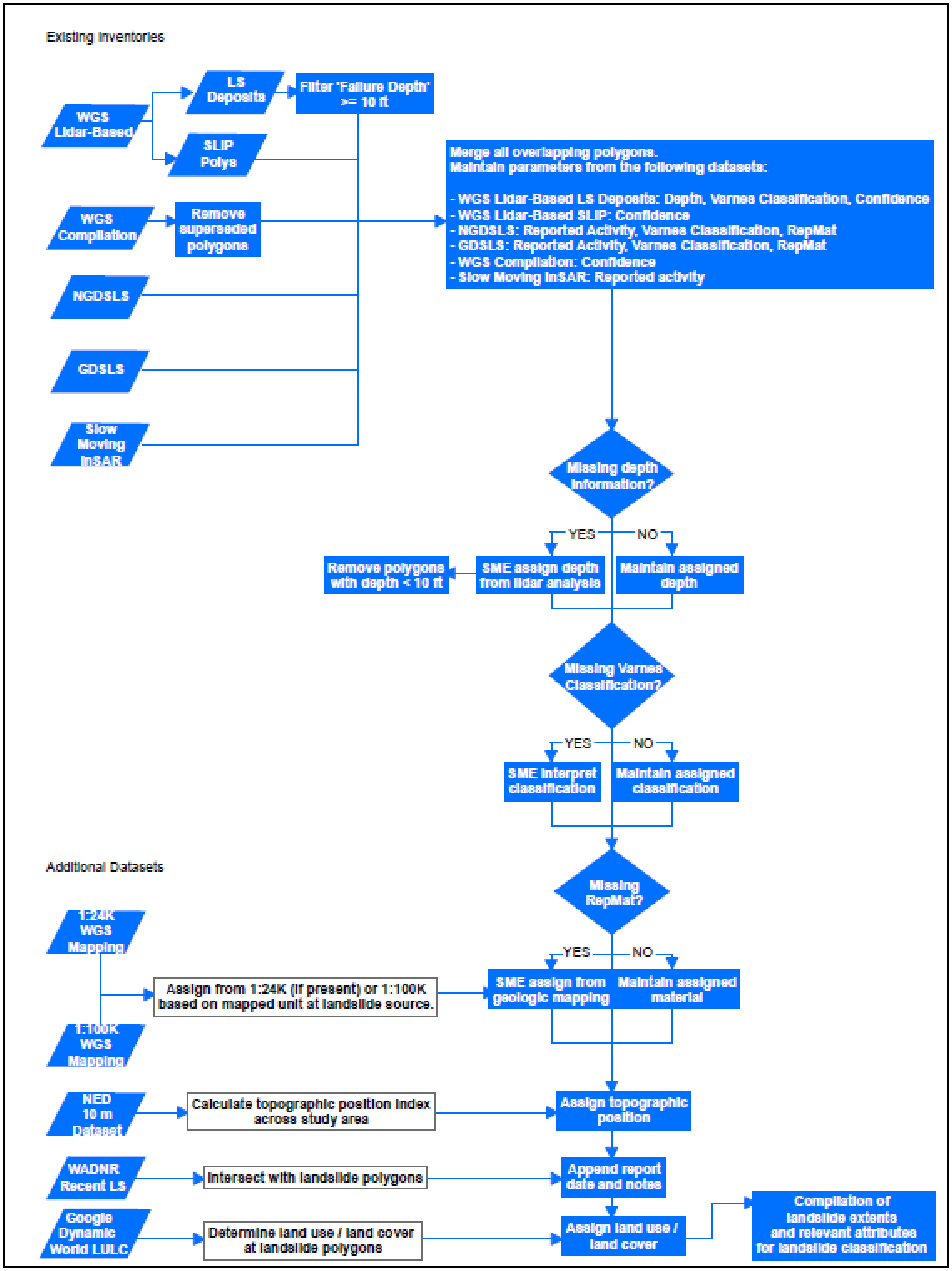

Figure 4-2. Suggested approach to integrating various landslide inventories and additional geospatial datasets.

4.2.2. Addition of Time-Stamped Attribution

In addition to integrating already cataloged data, the present study will include time-enabled tabular attribution of landslide velocities and potential LULC data. These data should be stored in tables containing at least the following attribute data:

- Landslide unique identifier number
- Date
- Annualized displacement (i.e., velocity) or LULC classification (e.g., forest)
- Method of estimating the attribute (e.g., lidar change detection, InSAR, instrumentation).

The current schema of the WGS detailed landslide inventory does not account for this addition, however, with careful consideration, these data could be appended in a fashion suitable for future analysis. A simple solution is a table of date and inferred velocity or LULC classification that will be joined to the main database by use of a landslide unique identifier (e.g., object ID or landslide ID). A common field such as the landslide ID will ensure that many time-stamped data types and formats could be tied to individual landslides. Additional time-enabled attributes could be appended this way by developing additional joined tables.

4.2.3. Flexibility for Future Modeling Efforts

This effort and future projects in the DSL Strategy will require robust statistical modeling (e.g., logistic regression, principal component analysis, machine learning, and other exploratory statistical techniques). To support this, all components of data storage and architecture should be designed in a way that will support future modeling efforts. This means structuring data in a manner suitable for querying and quantification wherever possible and minimizing qualitative data such as free text fields and one-off considerations. It is imperative that data assimilation and compilation is structured from the beginning of a multi-year study like this one with such an end goal in mind.

Focusing on integrating a single source of landslide attribute information with geolocation information and time-enabled tabular datasets will increase the utility of the data organization and assimilation tasks discussed in this study. Additionally, this will increase the flexibility of the dataset for future research and modeling efforts that may be part of the larger Strategy.

5.0 RECOMMENDED METHODOLOGY

This section describes the methodology for further study refinement and execution of the proof-of-concept study. A summary of the steps included is shown in Figure 5-1 below and discussed in more detail in subsequent sections.

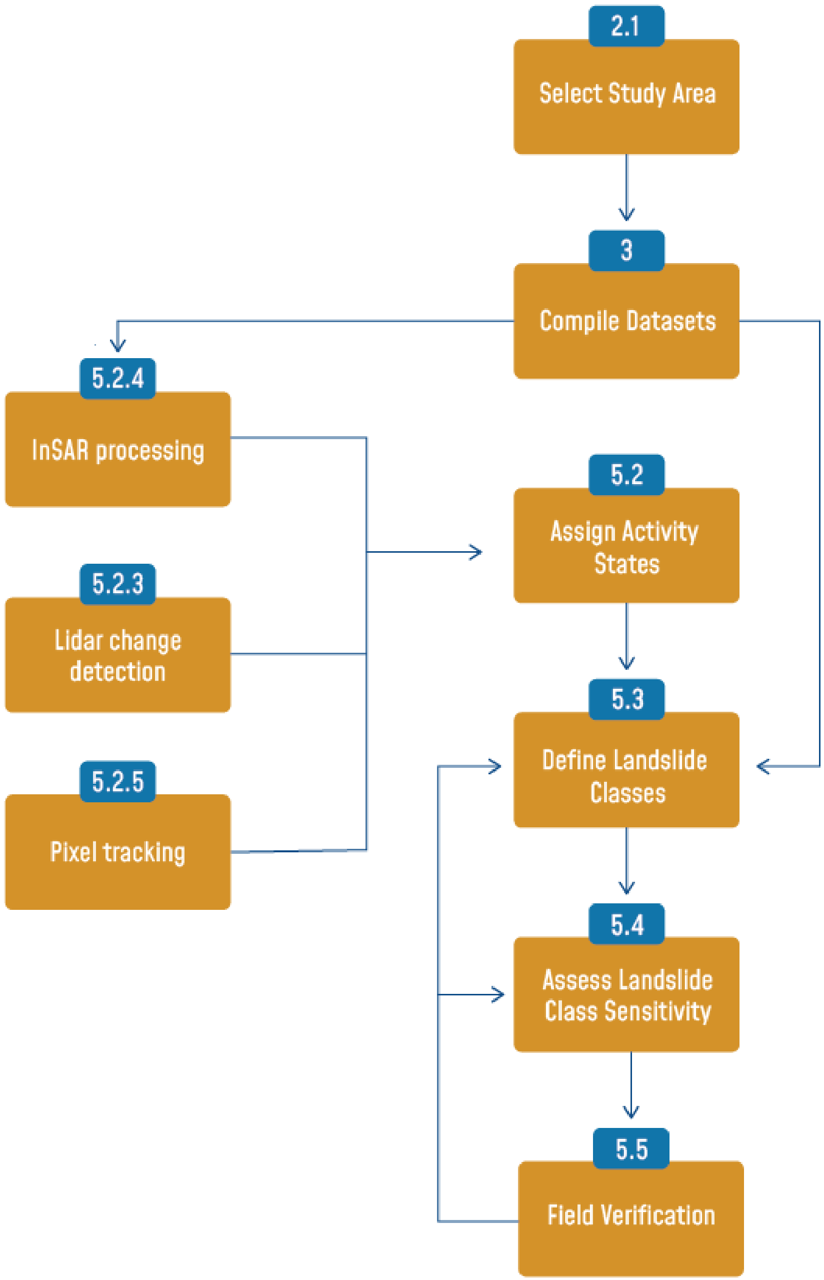

Figure 5-1. Study execution summary.

5.1. Selection of Area for Proof-of-Concept Execution (Pilot Study)

A significant part of this initial study focuses on the identification of data sources and their spatial and temporal coverage of the study area. Alternative 2 from the Scoping document included four counties in western Washington. These counties coincide with the areas of detailed landslide inventory mapping from the WGS (Mickelson et al., 2017, 2019, 2020). With that in mind, this section discusses additional considerations in data coverage which may be useful to further define a targeted study area for this initial proof-of-concept. If linkages between forestry activities and DSL activity levels are identified, the developed workflows may be calibrated and tested to evaluate additional areas beyond this initial study area.

The initial study area should include an overlap of high-quality data sources where it is expected that statistically robust relationships can be identified (Section 4.0). This design has considered the overall spatial and temporal coverage of the following key data sets:

- Landslide inventory data: Focusing on the completeness of mapping utilizing modern techniques and high quality lidar base maps (Section 3.1.2.3) and the temporal resolution and value of mapping (e.g., InSAR derived slow moving landslides, Section 3.1.2.4).
- Lidar data: Focusing on the largest number of epochs of data coverage, as well as optimizing where higher resolution point cloud data is available to support maximizing the resolution of detectable displacements (Section 3.1.5).
- SAR data: Assessing where a combination of multi-look and multi-frequency data sets are available that provide spatial coverage of key landslide populations but also allow for longer term InSAR time series to be generated for a select subset of sites. Focus on L-band data for resolving displacements in vegetated environment of western Washington (Section 3.1.6).
- Types of deep-seated landslides: Focus on a representative process type (e.g., slide, flow) and geomorphic position (e.g., valley, mid slope, upper slope) for the broader population of landslides in western Washington.
- Other vector data such as geological mapping and scale, forestry operations, instrumentation, and geotechnical information.

The coverage maps and discussion provided in Section 3.0 illustrate the relative spatiotemporal coverage of the available datasets. Based on these coverages, the following table identifies two potential initial study area locations (within the original Alternative 2 extents) for consideration. The areas outlined below should undergo further consideration prior to implementation of this study and are only provided here to illustrate how one may approach determining trial areas. The maps provided here (Figure 5-2) are insufficient for the level of detail required to make this determination, and an iterative review process with DNR should fine tune these areas with the selected contractor to implement the study design.

Table 5-1. Example targeted study areas and rationale. Additional areas should be considered based on data availability during study execution.

<table>
<tr><th>Area</th><th>Description</th></tr>
<tr><td>1</td><td>Western Whatcom County (Mount Baker to Lower Nooksack River) and the Upper Snohomish River System (Snoqualmie and Skykomish Rivers, including Upper Tolt and North Fork Snoqualmie) – 2,700 km^2, >3,000 mapped DSLs</td></tr>
<tr><td colspan="2">Rationale: Western Whatcom County experiences a relatively high density of medium to large sized bedrock landslides and both detailed and supplementary landslide mapping is available. The area also encompasses geological diversity, including landslides initiating in glacial deposits, alluvial deposits, metamorphic rocks, sedimentary rocks, and igneous rocks. This area contains representative landslide types and geomorphic positions except for river valley landslides where undercutting may be a significant contributor to activity state. Adding the Snohomish River system, where these landslides are more numerous will address this deficiency. By itself, however, the upper Snohomish River system would not capture the landslide and geological diversity of western Whatcom. Additionally, up to six epochs of lidar coverage and stacks of ascending and descending ALOS-1 and ALOS-2 L-Band SAR data dating back to 2004 are available. Active historical and recent forestry operations are also recorded in the area.</td></tr>
<tr><td>2</td><td>Snohomish County (Sloan Peak to Snohomish) and the Snoqualmie River Valley (Fall City to Monroe, including Upper Tolt and North Fork Snoqualmie) – 3,600 km^2, >4,350 mapped DSLs</td></tr>
<tr><td colspan="2">Rationale: Snohomish County has a relatively high density of small to large sized glacial and bedrock landslides and both detailed and supplementary landslide mapping is available. This area includes the SR-530 corridor and the Oso landslide. The area also encompasses geological diversity, including landslides initiating in glacial deposits, alluvial deposits, metamorphic rocks, sedimentary rocks, and igneous rocks. This area contains representative landslide types and landscape positions except for river valley landslides where undercutting may be a significant contributor to activity. Adding the Snoqualmie River Valley, where these landslides are more numerous will address this deficiency. Additionally, up to six epochs of lidar coverage and stacks of ascending and descending ALOS-1 and ALOS-2 L-Band SAR data dating back to 2004 are available. Active historical and recent forestry operations are also recorded in the area.</td></tr>
</table>

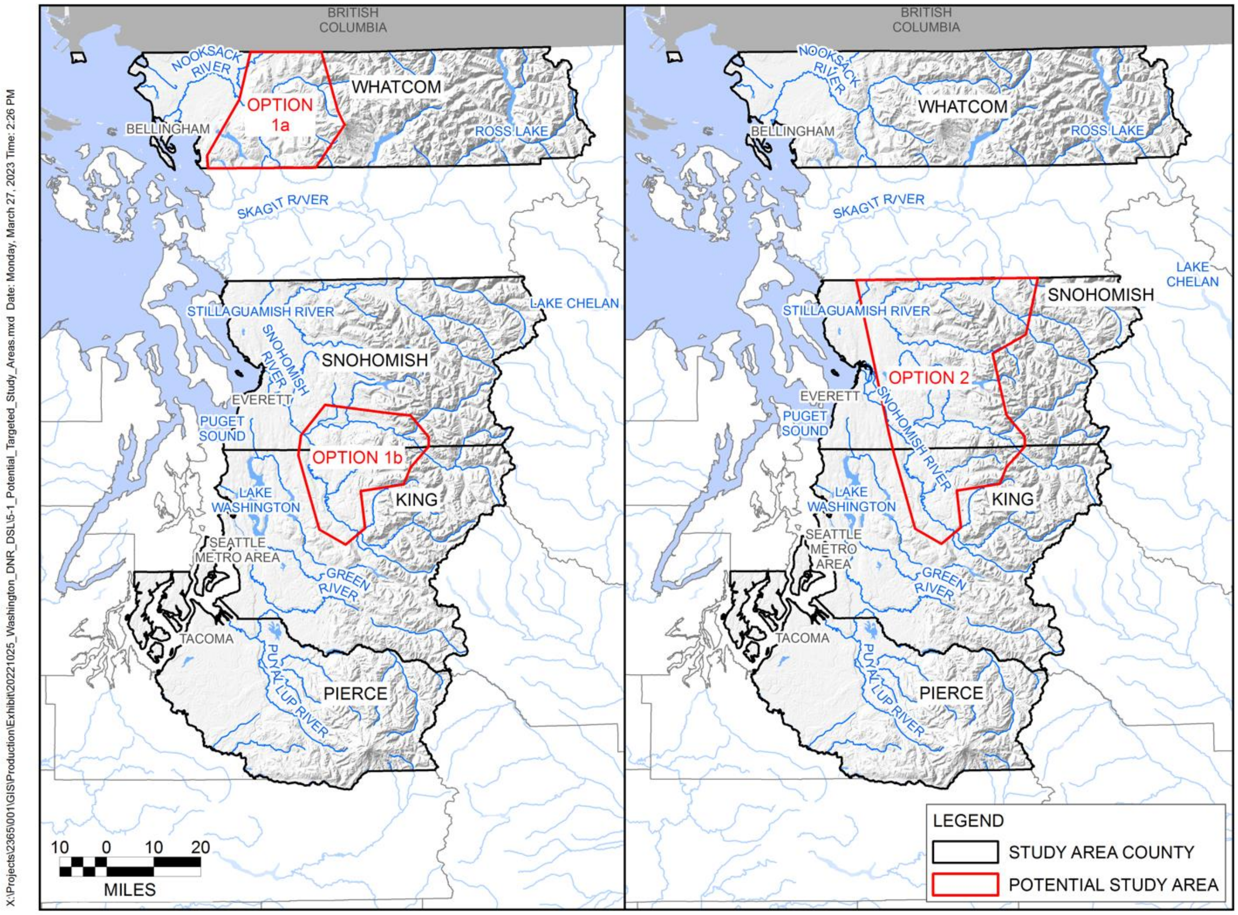

Figure 5-2. Potential targeted study areas in western Washington.

The cost of study execution in terms of financial and human resources will scale proportionately with the size of the initial study area. The scope of the study, as coordinated with UPSAG, will therefore inform practical size limitations of the initial study area. A smaller study area will be both faster and less expensive to evaluate, though may lack statistical rigor and diversity to adequately characterize DSL sensitivity to both natural and forest practice triggers. During study execution, data availability should be updated and changes to available datasets should be considered when selecting a targeted study area.

5.2. Velocity Characterization

5.2.1. Background and Objectives

A key objective of this Study Design is to investigate why DSLs with similar morphological and/or geological characteristics may exhibit differences in activity level and/or differences in response due to climate, weather, or forest management activities. The primary relationships of interest are between landslide triggering conditions (e.g., a wetting period, changes to surface water drainage) and changes in landslide displacement (e.g., Handwerger et al. 2022). This can be thought of as the response rate of a landslide and is typically related to depth to the sliding plane of the landslide, material composition, and the ability for water to infiltrate at the surface. Shallower landslides originating in coarse grained material or highly fractured bedrock will likely respond fastest to changes in conditions, whereas deeper landslides originating in fine grained material or massive bedrock will typically respond slowest (Miller, 2017).

Quantifying relationships between triggering conditions and landslide activity changes and providing a mechanistic explanation for it is one of the most formidable challenges in landslide science and is usually only resolved case-by-case (e.g., Lacroix et al., 2020). However, recent advances in remote sensing have allowed monitoring of landslide movement and velocities at a regional scale and may provide insights to spatial and temporal landslide activity characteristics for a population of landslides (e.g., Handwerger et al., 2022; Cignetti et al., 2023). To isolate these effects, it is necessary to understand the velocity of the inventoried deep-seated landslides. This may include a real velocity estimate (e.g., mm/yr), an estimate of the annualized displacement, or the status of the deep-seated landslide activity (e.g., active, dormant/relict). Regardless, an understanding of the activity state will be required to answer the stated research objectives. Where such data as LCD or InSAR is available, those landslides will be assigned an estimated activity level as can be determined utilizing each measurement technique.

Precursory deformation prior to DSL collapse has been successfully identified using remote sensing technologies presented in this study design. The following are four examples of such works: Lato et al. (2019) used lidar change detection to identify precursory deformation in the vicinity of the Oso headscarp prior to the 2014 collapse. Morris et al. (2023) use InSAR and optical image pixel tracking to identify movement starting in 2015 at the release zone of the 2022 Chaos Canyon Collapse in Colorado. Van Wyk de Vries et al. (2021) used InSAR and optical image correlation to identify pre-collapse movement in the five years prior to the ultimate slope collapse in 2021 in Uttarakhand, India. Lacroix et al. (2020) identify precursory movement via InSAR over three years prior to a collapse of the Maoxian Landslide, China.

5.2.1.1. Response Rate

Luna and Korup (2022) recently completed a study in the Pacific Northwest where they investigated lag time between seasonal precipitation fluctuations and shallow landslide occurrence. Using Bayesian inference models, they found shallow landslide occurrence to lag seasonal increases in precipitation by three months for the aggregate dataset of five different landslide inventories in Oregon and Washington (Luna & Korup, 2022). Their models compared estimated rainfall conditions from the Parameter-elevation Regressions on Independent Slopes Model (PRISM, University of Oregon) with landslide date from five inventories, one of which was the WGS compiled landslide inventory described in this document.

Their methods may be reproducible for smaller subsets of landslides and particularly for increases in displacement rate as opposed to the rapid failure date as was typically recorded for the shallow landslides they evaluated. While Luna and Korup (2022) relied only on a reported day of movement of a landslide, we understand DSLs are often moving for many days (or months or years), at varying rates. In other words, can we identify accelerations in persistently or episodically moving DSLs and evaluate for lag relative to longer term hydroclimatic patterns or land use? Additionally, Luna and Korup (2022) evaluated precipitation only, whereas we also understand soil moisture may play a role in the onset of landslide activity.

Initial studies conducted for DSLs in Western Canada by Froese et al. (2022) and in Western Europe by Distefano et al. (2023) have highlighted the potential application of large spatiotemporal hydroclimatic data sets to support understanding of landslide activity changes. This gives us an additional advantage in that we can compare precipitation and soil moisture data (see Section 5.4.3) to higher resolution displacement patterns to understand lag time of landslide classes and potentially individual landslides. Exploratory work will need to be conducted as a part of this study design to assess the feasibility of determining these lag times.

5.2.1.2. Representative Landslide Velocity

Assigning a single velocity value to a DSL will typically oversimplify the true deformation field. Instead, it is likely more accurate to establish a distribution of velocities. A three -dimensional velocity field is difficult to quantify and contains large uncertainties. Most work in the published literature to date relies on surface velocity fields from remote sensing (e.g., Booth et al., 2020) or point measurements from field instrumentation (e.g., Froese et al., 2022). Further complicating the characterization, the components of velocities can often be one-dimensional (e.g., horizontal, vertical) and not representative of the true three-dimensional movement vectors.

These sources of uncertainty and inconsistency can be partially limited by assigning velocity classes to landslides instead of individual velocity values. Similar to evaluating a velocity time-series, variations in landslide velocity class through time can also illustrate inflection points between periods of acceleration, deceleration, or steady state activity. This is a poorly studied subject, and the present study will require new methodologies to be developed. However, the objective here is relatively straight forward: Design a workflow to calculate surface velocity fields, ideally with three-dimensional movement vectors, for thousands of landslides from remote sensing data (i.e., lidar, InSAR). This seems to be the most reasonable objective given the technologies discussed in this document and the scale of the program. For example, the proposed lidar change detection methods (Section 5.2.3) result in three-dimensional change vectors and InSAR can be used to decompose deformation into three-dimensional components (e.g., Sharifi et al. 2023).

Recent work by Porter (2021), Porter et al. (2022), and van Veen et al. (2022) has made progress in categorizing landslide activity states and landslide types for the purposes of integrating into models that support the estimation of the likelihood of transition between velocity classes (condition states) utilizing Markov-Chain techniques. To model landslide velocity probability distributions, the authors related the landslide velocity condition states to the Cruden and Varnes (1996) landslide velocity classification (Table 5-2). In the original Cruden and Varnes classification, the Very Slow velocity class corresponds to landslides with a velocity ranging from 16 mm/year to 1.6 m/year. Porter (2021) and Porter et al. (2022) subdivided the Very Slow velocity class into Class 2a (> 16 mm/year) and 2b (>160 mm/year) to facilitate better characterization of the range of potential impacts from slides moving within this velocity range. The landslide velocity classes in Table 5-2 have been defined in terms of total annual landslide displacement criteria listed in the fourth column of the table. Further details about the proposed modified landslide velocity classification can be found in Porter et al. (2022).

Table 5-2. Modified landslide velocity classification after Cruden and Varnes (1996).

Class	Description	Typical velocity	Proposed annual displacement criteria (m)	Proposed mean annual displacement (m)
7	Extremely rapid	>5 m/sec	---	---
6	Very rapid	>3 m/min	---	---
5	Rapid	>1.8 m/hr	---	---
4+	Moderate	>13 m/month	>16	64
3	Slow	>1.6 m/yr	>1.6	6.4
2b	Very slow	>160 mm/yr	>0.16	0.64
2a	Very slow	>16 mm/yr	>0.016	0.064
1	Extremely slow	<16 mm/yr	>0	0.005
0	Dormant	0 mm/yr	0	0

Recent work by van Veen et al. (2022) describes the application of regional remote sensed data to support the development of a landslide activity inventory for large slowly moving landslides along the Peace River in northeastern British Columbia. In this study lidar acquired in 2006, 2015, 2019, and 2021 were utilized to detect changes. The LCD methodology utilized by van Veen et al. (2022) was able to estimate gross displacements with detectable limits between 15 and 50 cm between acquisitions separated by at least two years. The combination of this detection limit and time difference was typically able to characterize displacements in the velocity Class 2b or faster. Van Veen et al. (2022) also utilized ALOS-2 L-Band InSAR data collected over the study area during snow free periods for 2020 and 2021.

For a given landslide, the annualized displacement is estimated by normalizing the measured displacement (via LCD or InSAR) by the time duration between acquisitions. One of the main findings by van Veen et al. (2022) is while the LCD data was able to provide definition for Velocity Class 2b and higher, the L-Band InSAR data better supported the velocity characterization for activity states 1 to 2a (<160 mm/year). Furthermore, temporal resolution of LCD or InSAR based methods are commensurate with the observational record of lidar or SAR acquisition, respectively. In other words, activity state estimates derived from LCD provide an activity state integrated over the duration between lidar acquisitions, which are typically a few years in Washington State. When lidar epoch acquisition spans two or more years, for example, it can be quite difficult to estimate the timing of activity state changes between collection dates and therefore, to estimate the conditions that may have triggered the change. Because InSAR provides much more closely spaced temporal observations, activity state changes from InSAR-based methods are often much better constrained compared to LCD derived methods.

More recently, Cignetti et al. (2023) used C-band InSAR in Italy to characterize the velocity patterns of 279 landslides and assess if InSAR could reliably characterize movements and then assign relative landslide activity classes to existing mapped DSLs. The methodology applied by Cignetti et al. (2023) is explored further in Section 5.2.2.

5.2.2. Methodology

To best link various landslide classes and clusters in terms of current activity state and velocity transition sensitivity, a combination of complimentary data types is considered for this current design. The following sections will provide an overview of the specific data available over the study area and how, depending on the approach to processing the data, the results can be utilized to provide the most complete picture of the variability in landslide activity. The following staged approach is recommended:

1. Characterizing Measurable Landslide Displacement: An initial stage would be to generate a multi-decadal picture as to which of the existing, mapped landslides have exhibited measurable displacement. This work would likely be completed in phases, beginning with comparison of one of the earlier lidar epochs with the most recent epoch to determine if any topographic change can be detected; where change is observed, processing of additional datasets could be completed in a subsequent phase. Based on the availability of high-quality Lidar and L-Band InSAR data, the focus would be as follows:
    a. Lidar Change Detection: Utilize available epochs of lidar data to generate overall displacement rates and annualized velocities for each combination of epochs. The specific lidar epochs should be considered for this phase of the study:
        i. Area 1a: 2005, 2006, 2009, 2013, 2017, 2022.
        ii. Area 1b: 2003, 2004, 2005, 2009, 2011, 2013, 2014, 2022.
        iii. Area 2: 2003, 2005, 2006, 2013, 2014, 2017, 2022.
    b. InSAR Processing: While there are both C-Band and L-Band coverages available, the processing of the ALOS ScanSAR L-Band data should be prioritized. Should there be sufficient budget, the processing of the Sentinel-1 C-Band data could also be considered. Where available the use of multi-look (ascending and descending) ALOS-1 and ALOS-2 data obtained between 2004 to 2011 and 2014 to 2022, respectively, should be utilized to provide definition as to velocity change trends between the lidar epochs to further define the temporal variability of velocities over time. From a costing perspective the initial priority would be to process the freely available archives of ALOS-1 data and then consider processing the commercially available ALOS-2 data. Based on the discussion regarding SAR data availability in Section 3.1.8.3, the following data sets warrant consideration for this task:
        i. Area 1a:
            1. ALOS-1 ScanSAR: Multiple image footprints cover this area for the Ascending track where between 12-20 images have been obtained

with relatively regular spacing between early 2007 and early 2011. The Descending footprints only have stack depths of up to 6 images and are not considered suitable to utilize to build InSAR time series. The ALOS-1 data is freely available, however there will be processing costs involved with generating the InSAR time series results.

2. ALOS-2 ScanSAR: The primary ALOS-2 ascending and descending footprints that are centered over Area 1 consist of 12 and 14 images, respectively, collected between late 2014 and mid-2022. While these stacks are not considered to be deep enough to provide high quality InSAR time series results there are likely valuable insights that can be gained to support the LCD analysis in mapping landslide activity. In addition, deep stacks (up to 64 images) of lower resolution ScanSAR data may be found to provide valuable data at a lower cost than the ALOS-2 Fine data.
3. Option - Sentinel-1: While the C-Band Sentinel-1 data is not considered to be ideal for application in vegetated terrain, the fact that both the ascending and descending image stacks collected over this area are exceptionally deep (>50 images) for the time period between 2017-2022 provide additional data that can support the L-Band InSAR and LCD. As this data is freely available only the processing costs require consideration.

ii. Areas 1b and 2:

1. ALOS-1 ScanSAR: The ascending ALOS-1 coverages are spatially extensive over this area with stack depths ranging between 12-15 images. While these stacks are not considered to be mature the fact that they are freely available makes them worthy of acquiring and processing. The spatial coverages of the descending footprints and the low number of images remote the processing of these data from consideration.
2. ALOS-2 ScanSAR: There are both complete coverages of ascending and descending footprints over the study area with stack depths ranging between 12 and 15 images respectively. As there is a cost to acquire and process these data further work on feasibility (as discussed in Section 5.2.4.2 should be conducted prior to committing to purchase this data. As discussed for Area 1a, the use of the deep stacks (up to 64 images) of lower resolution ScanSAR data should also be considered.
3. Option - Sentinel-1: As with Area 1a, there are very mature (>50 images) stacks of C-Band Sentinel-1 images available in both the ascending and descending look directions. While there are limitations in the ability of the C-Band SAR data to penetrate

vegetation, the freely available nature of the data and stack maturity warrant consideration to support characterization of activity between 2017 and 2022.

2. Defining Velocity Trends: Once the landslides with measurable displacement have been identified, both the LCD results and L-Band InSAR can be utilized at the landslide specific scale to further delineate landslide displacement for DSLs in terms of the following groupings:
    a. No measurable displacement: Either InSAR data cannot be utilized based on geometrical considerations or displacements are below measurement thresholds for InSAR or LCD.
    b. Measurable displacement with no trend data: InSAR cannot be utilized based on geometrical considerations but total displacement over a time can be characterized by LCD.
    c. Measurable displacement trend below a defined threshold: InSAR expected to be able to reliably measure displacement based on geometrical considerations, but rates are below detectable limits for InSAR and LCD.
    d. Consistent and measurable displacement trend: InSAR measured displacements are above thresholds (clear signal) and are linear.
    e. Seasonal and measurable displacement trend: InSAR measured displacements above thresholds with consistent seasonal variability.
    f. Highly variable and measurable displacement trend (externally drivers): InSAR measured displacements with trends observed above the seasonal background.

The above characterization will support the further delineation of landslide velocity condition states in relation to specific landslide types (Section 5.4.4.3).

5.2.3. Lidar Change Detection (LCD)

5.2.3.1. Background

As multiple acquisitions (epochs) of lidar are completed through time over the same area, the ability to identify changes between datasets can add yet more detail to the timing and extent of landslide activity, in some cases facilitating the identification of precursor movements to larger landslide events (e.g., Lato et al., 2019) or of landslides yet to be identified through typical single vintage lidar analysis.

The quality of lidar differencing results is highly dependent on the quality and resolution of the input datasets. In the change detection analysis, the dataset collected first (earlier in time) is referred to as the ‘baseline’ dataset, and the more recent dataset is referred to as the ‘active’ dataset. Data resolution is reported as average points per square meter in each dataset. Factors that contribute most significantly to variable point resolution across a scan region include the density of vegetation and slope angle. Areas with a greater density of vegetation typically have a lower density of bare-earth points than non-vegetated areas. Steeper slopes will typically have a lower point density than flat surfaces.

5.2.3.2. Methodology

There are several methods for differencing lidar datasets that range in complexity and computational efficiency. Methodology can greatly influence the amount of noise and the quality of the results. Methods that describe 3-dimensional movement vectors should be employed for this study. Three common methods are described below:

- The simplest method for lidar differencing is computing the difference in a pair of DEM, often referred to as a DEM of Difference (DoD). This method requires two homologous DEMs. Most modern DEMs are interpolated surface representations of corresponding lidar point clouds. The first source of error with this method is the interpolation that occurs when reducing a complex point cloud to a regularly spaced DEM. Additional error is introduced because a DoD represents vertical offset between two DEMs, even when surface change is not only in the vertical plane.
- Surface based methods compute 3D distances between two surfaces or between a surface and a point cloud can increase accuracy and decrease noise in the lidar comparison process, but this typically comes at the expense of increased computational demand. Some common methods include:
  - Cloud-to-mesh distance (Cignoni et al., 1998).
  - Mesh-to-mesh distance (Aspert et al., 2002).
- Point based methods increase accuracy further, decreasing noise and increasing the quality of the result. 3D point-based lidar differencing calculates the difference between two bare earth point cloud datasets along vectors representing the local normal of each individual point in the dataset (multiscale model-to-model cloud comparison, M3C2, Lague et al., 2013), or the shortest Euclidean distance between two datasets (cloud-to-cloud, Girardeau-Montaut et al., 2005). These methods are computationally expensive and have traditionally required datasets to be subdivided into smaller zones (typically less than 30 million points per zone) for processing. This method produces enhanced results over DEM differencing or surface comparisons as the results represent a 3D change based on the full resolution of the point-cloud data.

For highest accuracy of point-based comparisons, point clouds are typically co-registered via the iterative closest point alignment algorithm (ICP; Besl & McKay, 1992) before comparison. This reduces bias by minimizing systematic differences between the two datasets due to ground control and georeferencing errors at the time of data acquisition.

Performing the ICP alignment and change detection is a very computationally expensive workflow. Most lidar change analysis today is conducted sequentially on computer processing units (CPU). An example of this is using Cloud Compare on a personal computer to perform the ICP alignment and then to implement the M3C2 algorithm. For small geographic extents, this method works well. Scaling the workflow to broad geographic regions such as the present study area (see Section 5.1), however, can quickly reach the limit of modern CPU architecture. Because the described workflow involves multiple independent calculations (e.g., calculating normal) and spatial queries (e.g., which points correspond between the two point clouds), moving the workflow to a parallel-optimized architecture decreases processing time by three orders of magnitude

(Weidner et al., 2022). Recent work by BGC has developed an approach to parallelize these computations on a graphics processing unit (GPU; Lato & Ferrier, 2022), increasing both efficiency and quality of results.

5.2.3.3. Interpretation and Limitations

Positive model differences can be interpreted as gain of material (e.g., material accumulation, bulging), and negative model differences can be interpreted as a loss of material (e.g., material removal, erosion). Figure 5-3 illustrates the relative loss and accumulation of material through a simplified active landslide mass. Figure 5-4 illustrates a simplified example of riverbank erosion and how this process is reflected in lidar change detection results.

There are several limitations with lidar change detection. One limitation is the inability to detect translational movement where the ground and slip surfaces are parallel; in this instance, the ground surface appears unchanged between the two datasets (Figure 5-3). Because the lidar data represents the surface topography at each date, the analysis reflects surface changes only and cannot necessarily be extrapolated to interpret slide movements at depth.

Positive changes reflected in lidar change detection analysis represent the amount of change that occurred along the shortest distance vector between the two datasets, and not necessarily the maximum magnitude of the deformation (Figure 5-3 inset). For example, a landslide with a slope angle of 35° showing a measured shortest distance vector of 0.5 m in the zone of positive topographic change would imply an equivalent true horizontal change of 0.90 m. This limits our ability to detect deformation on some landslides using lidar change detection analysis. For areas of significant riverbank erosion, the shortest distance change measurements are often an underestimate of the total horizontal magnitude of erosion.

Change detection results are limited by the temporal and spatial resolution of the datasets and the relative accuracy of the lidar points between each dataset (also referred to as data precision, or local accuracy).

- Temporal Limitations: Because LCD results indicate change between the date of acquisition for each point cloud, the magnitude of results must be considered in concert with the time range between epochs and with the landslide process. A common method for assessing rate of change with LCD data is to normalize the magnitude of change by the number of years between acquisitions. This provides an annualized velocity estimate (e.g., mm/yr). In some cases, such as large, deep-seated landslides, this may be a fair approximation of the actual rates of movement of the landslide. In other cases, such as a rapidly moving debris flow, this annualized estimate may underestimate the actual velocity of the landslide when moving. This limitation in Washington, where most lidar acquisitions are separated by at least one year, will preclude this method from identifying seasonal velocity changes.
- Spatial Limitations: The assessment of topographic change between lidar datasets of different point density can result in spurious change. For example, in regions of steep topography, ridges and valleys may not be well defined in the lower resolution lidar datasets but are mapped in the higher resolution datasets. The difference in data

resolution, and resultant interpretation of the topology between datasets, is mapped as 'change' by the algorithms used. These regions are considered erroneous. Erroneous results may also occur where data quality is reduced due to heavy vegetation on slopes. Because landslides are not programmatically identified based on LCD results, these erroneous results can typically be identified during landslide identification by trained analysts. Noise derived from heavy and dense vegetation typically appears as an irregular ground movement signature and does not match the expected ground movement signature related to landslide activity.

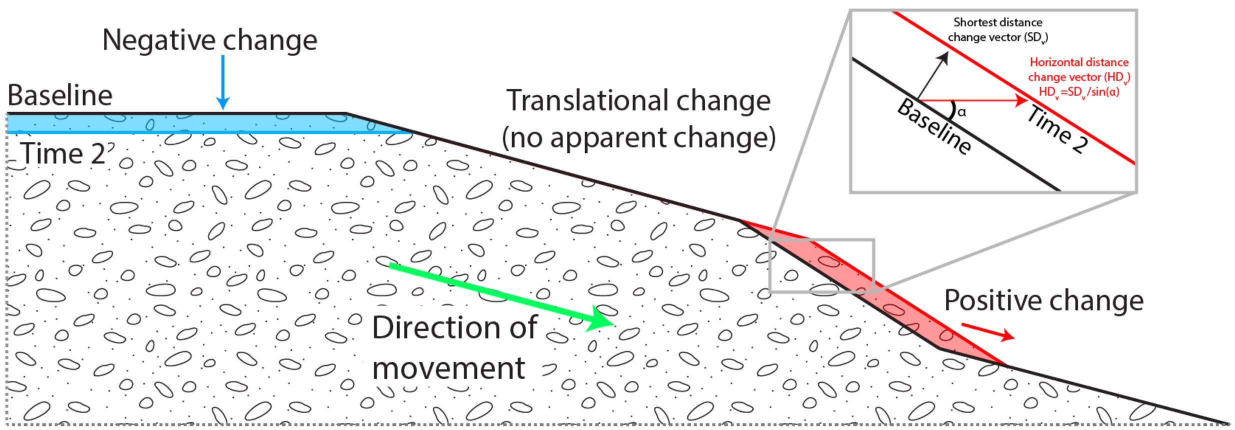

Figure 5-3. Simplified schematic diagram of translational landslide showing positive change in the direction of movement. The amount of change along the shortest distance vector can be used to calculate the true horizontal change.

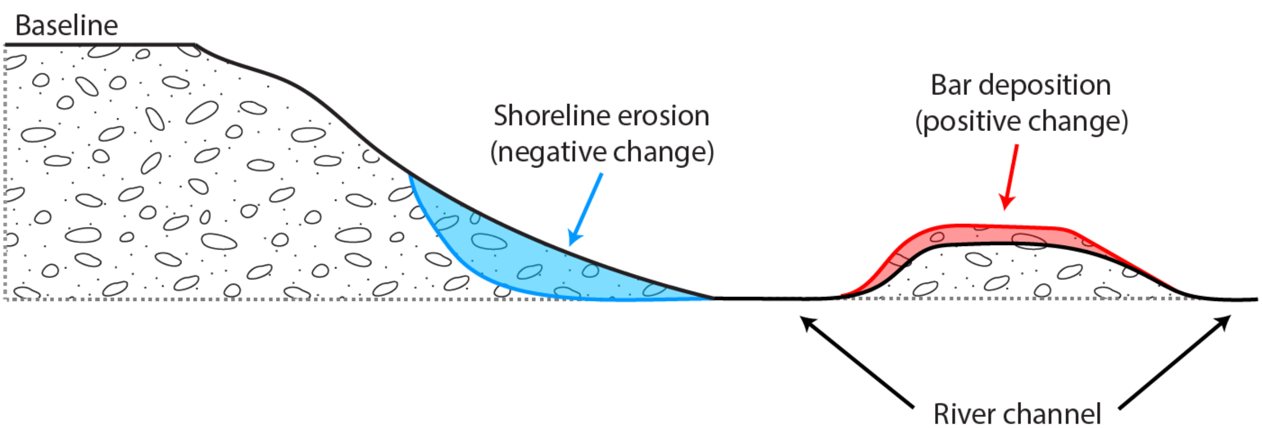

Figure 5-4. Simplified schematic diagram of riverbank erosion (negative change) and deposition of material.

5.2.3.4. LCD-Based DSL Velocity Estimates

The utility of LCD should be evaluated across the study area with all available vintages of Washington State lidar (Figure 5-5). LCD should be performed at least where multiple acquisitions of lidar intersect mapped landslide polygons. LCD results will be used to provide annualized velocity estimates for landslide polygons (Section 3.1.3), or potentially for areas of landslide polygons where differential movement is identified. Velocity classes will be designated according to Table 5-2. Landslide process (e.g., slide, flow) should not inform the annualized velocity estimates, however, the landslide class for a given landslide polygon (see Section 5.2.5) can be used in conjunction with velocity estimates for further analysis.

For this study design, BGC conducted a proof-of-concept lidar change detection analysis on data from 2006, 2013, and 2017 along the Nooksack River just south of Whatcom County. The intent of the proof-of-concept was to show an example of results obtained from processing Washington State lidar with the BGC patented GPU-based methodology (Lato & Ferrier, 2022), including data from an earlier epoch (i.e., 2006). Results illustrate the ability of these methods to detect landslides of different process types and geomorphology. Results were generally good with a limit of detection of approximately 1-3 feet (0.3 - 0.9 m) and are only expected to increase in precision with newer epochs of lidar.

In mid-2023, BGC expanded this proof of concept to a contracted project for the DNR, completing approximately 11,000 km^2 of lidar change detection between four epochs of lidar (2006, 2013, 2014, 2017; BGC, 2023). The work was aimed at identifying landslides and providing situational awareness for land managers.

Although BGC is currently advancing similar work in northeastern British Columbia and preliminary results are encouraging, to date, we are not aware of projects that have successfully demonstrated using LCD to programmatically characterize landslide velocity for thousands of landslides. We expect the present study will have to work to develop a new methodology to consistently and efficiently perform this. Our recommended approach would be to exploit statistics of LCD distributions inside each landslide polygon to estimate the rate (absolute or relative) of movement. In most cases, even in lidar -rich regions such as western Washington, LCD will only be able to estimate landslide velocity in several change detection periods. This will likely miss considerable nuance in developing a full velocity time series for each landslide but should identify landslides that are active versus inactive, and this understanding alone should help with sensitivity estimates (e.g., landslides that are already moving are likely more sensitive to further disturbance). For further consideration of LCD derived velocity time series, see Section 5.4.4.3.

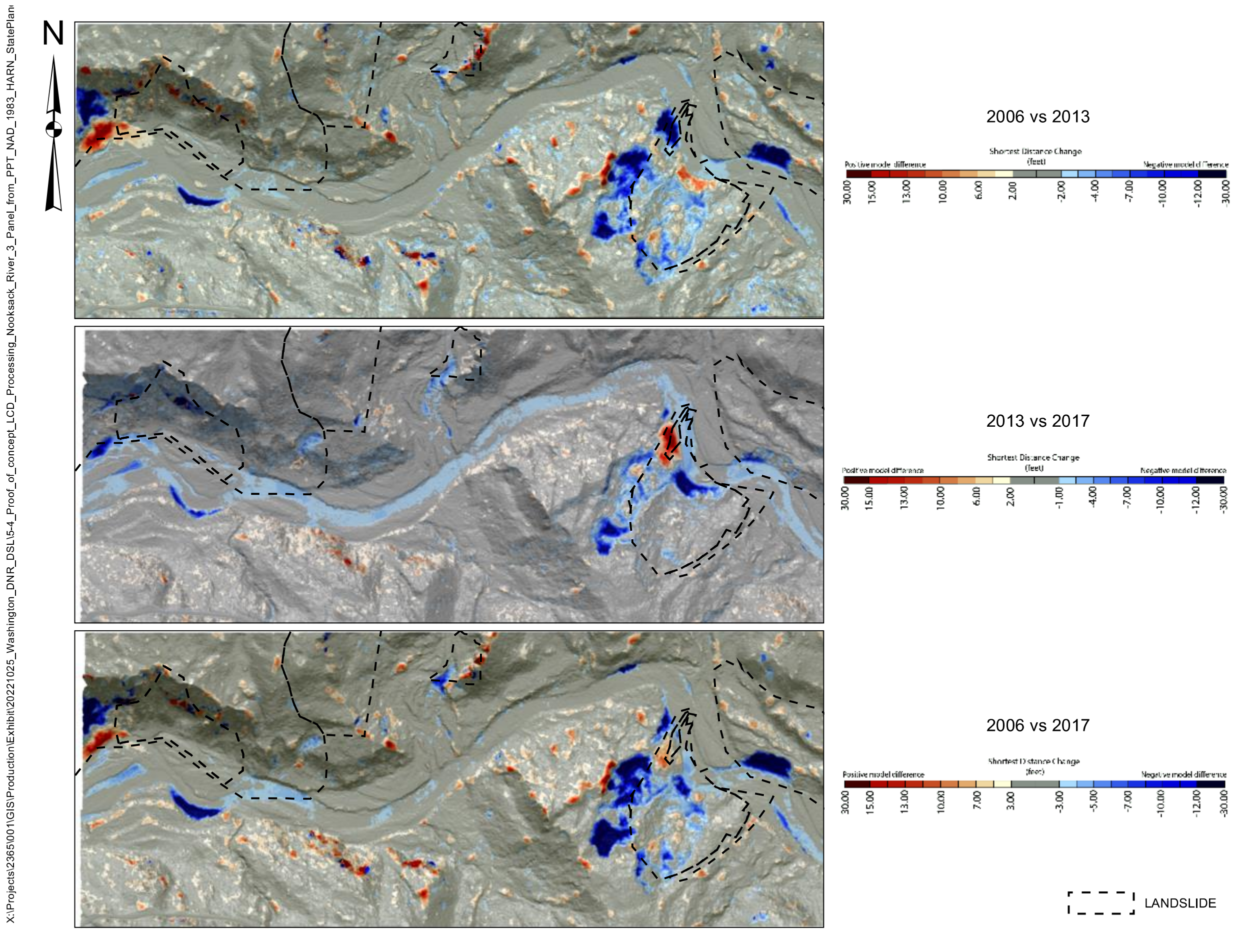

Figure 5-5. Proof-of-concept of lidar change detection with Washington lidar along the Nooksack River, Skagit County (Data source: Washington Lidar Portal). Dashed black lines indicate landslides mapped as a part of the Forest Practices landslide geodatabase (Section 3.1.2).

It is likely that an approach based on a non-parallelized (i.e., sequential) computational method will be greatly hindered with respect to processing time and accuracy. For this reason, we recommend a GPU-based approach or similar and significant consideration be given to the ability of a proposed method to perform large-scale LCD. Requesting a proof-of-concept example may be prudent during a request for proposal period to assess for efficiency and accuracy of any proposed approach.

5.2.4. Interferometric Synthetic Aperture Radar (InSAR)

5.2.4.1. Applications, Considerations, and Limitations

Satellite InSAR is a technique by which radar satellite images can be used to track ground displacements with millimeter level precision. When satellite radar images are collected, electromagnetic microwaves are transmitted from the sensor and the backscattered waves are returned to the satellite. By collecting a stack of radar images over time, the difference in the phase of the returned electromagnetic wave (Figure 5-6) at each data point (scatterer) can be used to calculate surface displacements (Pepe & Calo, 2017). The InSAR technique can only resolve movement magnitudes smaller than half the radar wavelength between two repeat images and between adjacent scatterers (Baek et al., 2020; Figure 5-6). The spatial data resolution, wavelength, and the time period between radar image acquisitions can vary depending on the satellite used. The precision of the displacement measurements depends on the number of processed images, (typically 15 images or more) and the temporal continuity of acquisitions.

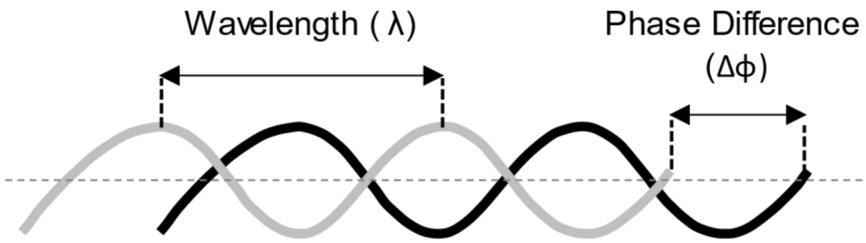

Figure 5-6. Radar phase difference measured between consecutive radar images.

Although InSAR is a mature technology used to monitor displacement, the suitability for obtaining reliable displacement data for DSLs in Washington State will need to consider the following:

- Geometry: The operational SAR sensors are in polar orbit, following a path between the North and South poles (also called the satellite heading or azimuth) (Figure 5-7a and b). The sensors are designed to look either to the left, or to the right with some satellites having the ability to switch between left and right-looking configurations. The SAR sensor transmits the signal, at an incidence angle, measured from vertical, with the surface (Figure 5-8c and d). The vector between the satellite and the imaged surface is known as the satellite Line-of-Sight (LoS). When using InSAR for deformation measurement, it is important to note that only the component of the displacement vector in the LoS of the satellite can be measured (Figure 5-9). The ability to detect displacement is therefore dependent on the orientation of the slope of interest with respect to the satellite LoS. Slope movements orientated perpendicular to the LoS direction will not be measurable by InSAR, and therefore the satellite imaging geometry needs careful consideration depending on the orientation of the slope of interest. The LoS geometry also makes the interpretation of the movement direction ambiguous. For example, in an ascending orbit with right-looking sensor, positive LoS values are consistent with movement predominantly upward or towards the west, and negative values are consistent with movement predominantly downward or towards the east (Figure 5-8c). For a descending orbit, positive values are consistent with movement predominantly upward or towards the east, and negative values are consistent with movement predominantly downward or towards the west (Figure 5-8d). By combining ascending and descending acquisitions, the vertical and east-west components of the real displacement vector can be resolved. The more detailed processing and screening methodology described in Section 5.2.4.2 provides a process for determining which geometries of landslides can be expected to have InSAR displacement points that are able to represent mean velocities to support initial stages of classification. Considerations for utilizing LoS measurements to more reliably characterize velocities of DSLs in terms of hypothesized kinematics are discussed in more detail in Section 5.2.1.2.

- Vegetative Cover: In vegetated regions, longer wavelength L-band SAR data is recommended since it provides an improved ability to see through vegetation resulting in higher precision measurements. However, commercial L-band data archives are currently only available from two platforms (ALOS-1 and ALOS-2) which means that data coverage is sparse and not necessarily available for locations and timeframes of interest for landslide activity characterization. Although Sentinel-1 and Radarsat Constellation Mission (RCM) SAR data can also be used for InSAR measurements, the data are captured at shorter C-band wavelengths. While the C-band data have been used extensively for monitoring surface deformation using InSAR timeseries approaches, successful use-cases are generally confined to areas characterized by low vegetation densities. More recently, L-Band data from both ALOS-2 and the Argentine SAOCOM satellite have been utilized to successfully detect landslides and generate time series for DSLs in mountainous and vegetated terrain along the Columbia River in British Columbia. While these results are not yet reported in the peer-reviewed literature the findings have been reported publicly by BC Hydro (BC Hydro, 2021) and presented to the international landslide community (Mitchell et al., 2023). As part of the characterization of a specific large DSL along the Columbia River, called the St. Cyr Rockslide, the authors have reviewed the relative ability of C-Band and both fi and coarse L-Band data to provide both spatial and temporal coverage of displacement data but have also coupled this data with lidar-derived surface morphology and structural measurements to support development of a hypothesized kinematic model this DSL. Figure 5-7 shows a comparison of the spatial data coverages obtained from Sentinel-1, ALOS-2 Fine and ALOS-2 ScanSAR to demonstrate the potential spatial coverages that could be obtained utilizing the existing data archives described in Section 3.1.8.2. Note that for the proposed study design, the use of ALOS-2 ScanSAR is prescribed as the primary data set and has stack depths of over 60 scenes of data. In comparison, the ALOS-2 ScanSAR results show on the far right image below comprise of a series of less than 15 scenes, therefore the spatial density of displacement points would be expected to be significantly improved when compared to the results shown below.

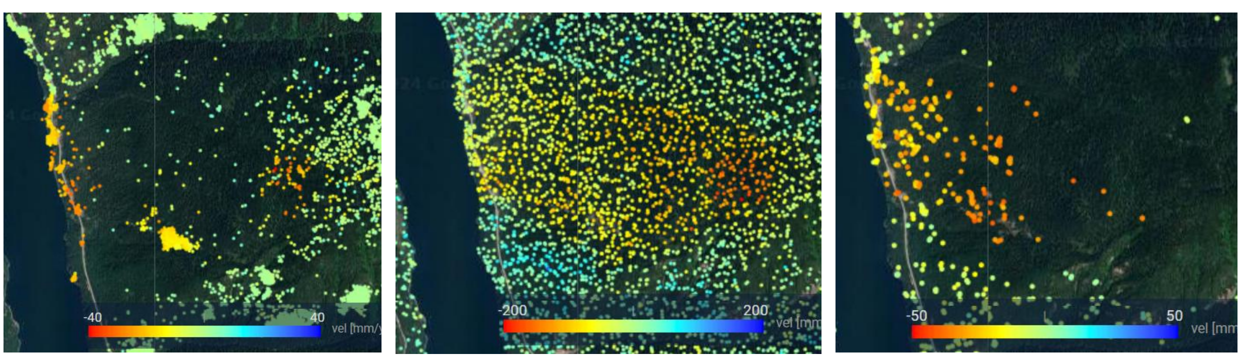

Figure 5-7. Spatial displacement data coverage for a large rock slide along the Columbia River in British Columbia for (left to right) Sentinel-1 C-Band, ALOS-2 Fine L-Band, ALOS-2 ScanSAR L-Band data.

- Changing Ground Conditions (Coherence Loss): InSAR can measure displacement only in areas on the ground that have the same surface conditions between all image acquisitions. Such areas are said to be 'coherent'. InSAR analysis will result in noise and/or "no data" where the ground surface is disturbed between two acquisitions (e.g., construction activities, surface material raveling, agricultural activities, snow cover, etc.). It is important to note that the presence of snow introduces signal noise and limits the ability to extract InSAR measurements. Therefore, annual data acquisitions are usually limited to periods that were deemed snow free which implies that the monitoring of slope movement in periods of snow cover will not be possible. In addition, land use change products (discussed in Section 5.4.2.8) could also be utilized to determine where ground conditions have changed significantly between SAR acquisitions in order to assess potential impacts on coherence and over which periods displacement could more reliably be characterized.
- Rate of Displacement: In addition to the sensitivity to the presence of vegetation, the wavelength of the sensor also dictates the measurement precision and maximum and deformation rates measurable by InSAR. Using SAR data, line-of-sight surface movements between successive image acquisitions is measured as a fraction of the wavelength of the SAR signal. The accuracy of this phase measurement is dependent on the signal-to-noise ratio of the sensor, which tends to be higher for shorter wavelengths (Hanssen, 2003). Therefore, if no external sources of noise are present, shorter wavelength data are more sensitive to small scale movements. The wavelength of the sensor also informs a fundamental condition for radar interferometry, which is the maximum detectable deformation gradient. If deformation at the surface induces a phase difference greater than half the wavelength of the sensor, the deformation cannot be measured unambiguously. Any surface movement between successive image acquisitions that exceeds this maximum will result in phase noise and the movement will not be measurable by InSAR. As only a half of a wavelength of change can be quantified between successive scenes, the choice of wavelength is an important consideration depending on the anticipated deformation rates. The theoretical maximum measurable deformation between successive scenes equates to ~1.5 cm, ~2.8 cm and ~11.8 cm for X-band, C-band and L-band sensors respectively. Considering the best possible revisit intervals of SAR satellites, the maximum deformation rates measurable by operating sensors are 25.7, 42.5, 127, and 87 cm/year for TerraSAR-X, Sentinel-1, RCM, and ALOS-2 respectively (after (Crosetto et al., 2016)). This makes TerraSAR-X and Sentinel-1 only suitable for measuring the very slow to extremely slow landslide classes identified in Cruden and Varnes (1996). In contrast, the (theoretical) higher revisit frequency provided by RCM and the longer wavelength provided by ALOS-2 makes it suitable for the monitoring of slow to very slow velocity classes. As part of the study design, the use of ALOS-2 ScanSAR data is expected to provide the highest spatial density of displacement data points and be able to characterize slope displacements with rates up to those as reported above. For displacement rates above the maximum detectable limit it is expected that the LCD data will support understanding where these more active areas are and where future more detailed phase unwrapping may be required. For displacement

rates below the detectable limits for L-Band, consideration for processing of the Sentinel-1 data stacks should also be considered. While the spatial coverage of data will not be as dense as for the L-Band data, it may provide more information on the landslides moving in the range of millimeters to tens of millimeters per year.

- Steep Slope Distortions: Another consideration for regional InSAR monitoring programs is the potential impact of geometric distortion of SAR data in steep mountainous terrains (Dai et al. 2022). Due to the side-looking geometry of the SAR sensors, steep slopes facing away from the radar look direction may result in a radar shadow if the slope angle is greater than 90° - the incidence angle of the data. These slopes will not be measurable with data captured in that geometry and data from a different look-direction will be needed. Similarly, for steep slopes facing toward the radar, if the incidence angle of the signal is smaller than the slope angle, the signal returns from the slope bottom and the top is reversed, resulting in an effect known as layover (e.g., Dai et al. 2022). Slope movements in these situations will also not be measurable with InSAR data. The areas affected by geometric distortions for a particular SAR acquisition geometry can be modelled using an external digital elevation model. These geometric masks should be provided with any InSAR results as it will be important to understand where no data was available compared to where no movement was detectable.

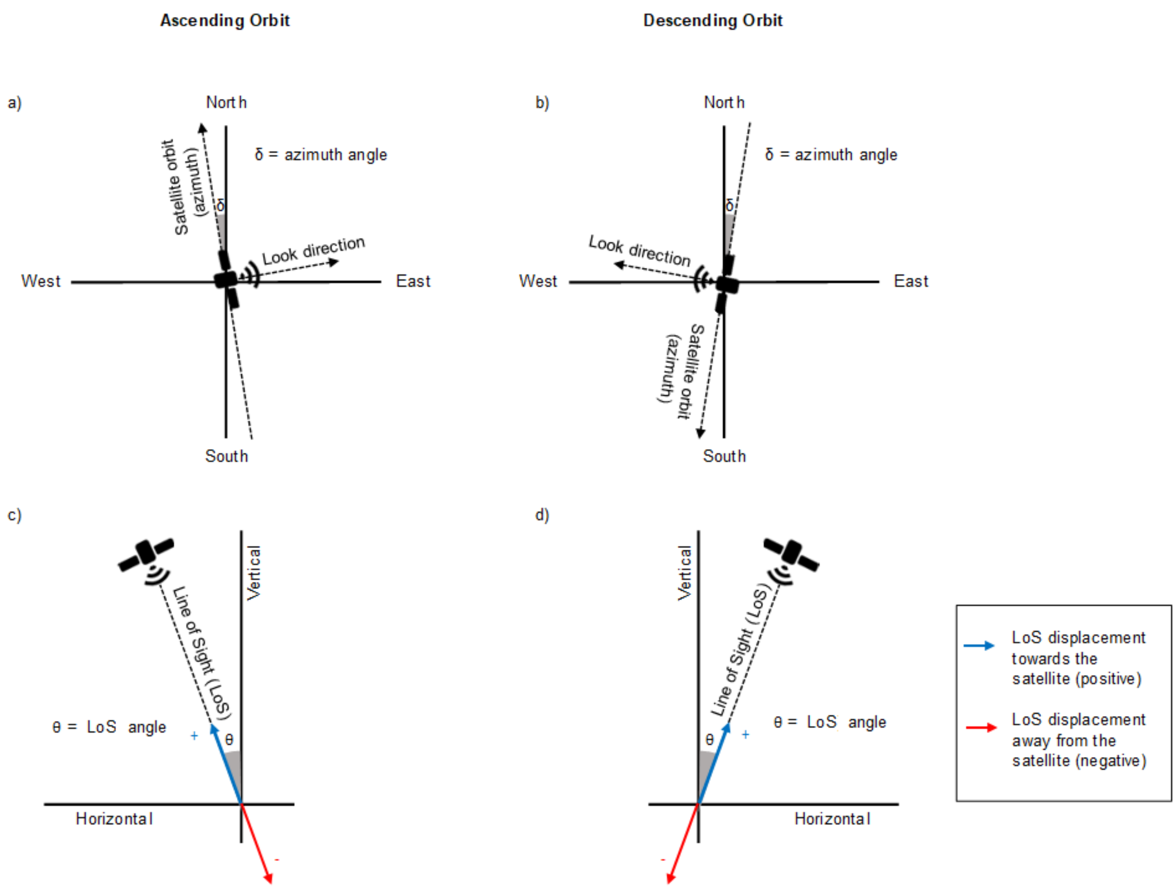

Figure 5-8. Satellite acquisition geometries and sign of the measured displacement relative to the satellite for the ascending orbit (“a” and “c”) and descending orbit (“b” and “d”).

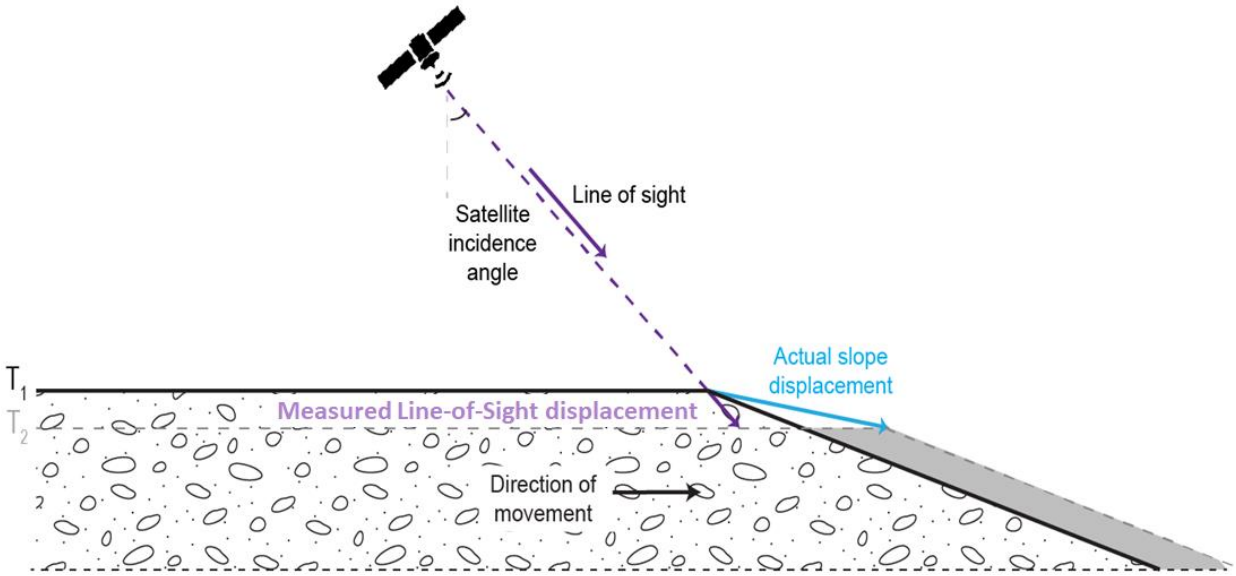

Figure 5-9. Simplified schematic diagram illustrating the line-of-sight measurement of the true displacement.

5.2.4.2. InSAR Processing and Slope Activity Classification

While it is critical that the data coverages are collected with consideration of the above, the approach to the interferometric processing of the data will also be key as there are two primary requirements to support mapping of ground displacements:

- Maximizing the spatial density ground displacement data over the chosen study area
- Providing regularly spaced and reliable time series data to discern multi-year, seasonal and event driven displacements for the maximum number of landslides possible.

When considering InSAR as a tool for the extraction of the ground movement history of an area of interest, the operational limitations of InSAR data and data acquisition implications need to be considered. These include the following and are discussed in more detail in Section 5.2.4:

1. The selection of sensor wavelength, which has a bearing on the maximum measurable displacement and the influence of vegetation.
2. The consideration of the satellite image acquisition geometry and look direction in relation to the anticipated surface displacement orientation.
3. The satellite revisit frequency and archive data availability which has a bearing on applicability for historical assessments and/or ongoing (future) monitoring.
4. Geometric distortions in steep terrain preventing InSAR measurement.

The Study Design proposes to utilize a staged approach to characterize spatial and temporal velocity patterns following a methodology recently applied to DSLs in Northern Italy and outlined by Cignetti et al. (2023). This technique uses a combination of InSAR processing techniques, existing mapped landslides, and topographic data to provide initial broad screening of activity. To promote statistically robust characterizations, they used a multi-criteria exclusion procedure to evaluate for 1) the number and distribution of persistent scatterers, 2) number of voids, and 3) skewness of the first-order nearest neighbor distance prior to assigning a velocity characterization to a given DSL polygon. The results categorized landslide velocities into inactive, low, medium or high velocity (less than 2.5 mm/yr, 2.5-5 mm/yr, 5-10 mm/yr, and greater than 10 mm/yr, respectively). Pattern of movement was categorized into bimodal, heterogeneous, or homogeneous. The pattern designation was a subjective measure attributed by the authors. Figure 5-9 provides an overview of the process flow for the methodology proposed by Cignetti et al. (2023).

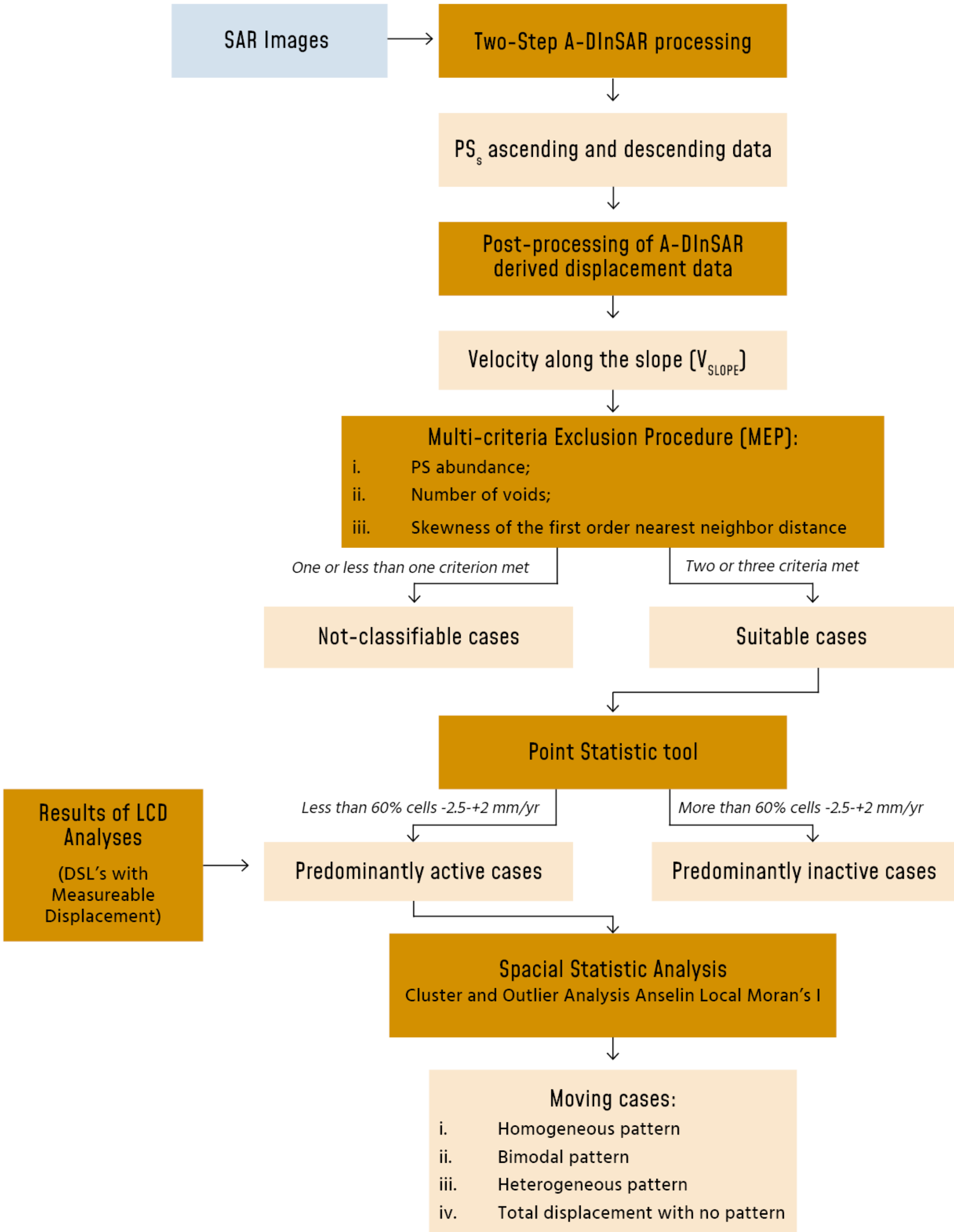

Figure 5-10. Flowchart for InSAR Activity Classification modified after Cignetti et al. (2023).

The following section more specifically describes the Cignetti et al. (2023) approach, as it could be applied to the regional DSL pilot study. The Implementation Team could consider differing approaches to processing that achieve similar objectives but the Cignetti et al. (2023) approach is provided for initial guidance:

- Two Step Advanced-DInSAR Processing: The objective of this phase is to a) utilize the entire SAR time series to characterize broad displacements over the period of record and b) define where higher quality Persistent Scatterers (PS) are present that can adequately describe spatiotemporal displacement trends. The approach demonstrated by Cignetti et al. (2023) involves first undertaking a broad Small Baseline Subset processing methodology on the data to estimate atmospheric and small-scale non-linear deformation and then apply a full resolution analysis utilizing Differential SAR Tomography to detect and estimate topography and residual deformation of the PS. The results of these two different processing techniques are combined to provide large scale deformation measurements. Specific considerations related to processing accuracy and phase unwrapping are described in more detail by Cignetti et al. (2023).
- Post-Processing of A-DInSAR Derived Displacement Data: In some cases, the LoS InSAR displacement data may not be suitable for use in characterizing landslide velocities based on poor alignment of the SAR imaging geometry with the displacement vector of the DSL (Section 5.2.4.1). To understand where this is the case, post processing is undertaken to calculate which component of movement can (or cannot) be characterized on a slope. Results from this work should be used to remove PS data that are unlikely to accurately characterize deformation on a slope.
- Definition of Velocities Along Slope: For DSLs that contain suitable geometries for evaluation, available topographic data is utilized to support projection of the LoS InSAR data onto the fall line of the slope. Sharifi et al. (2023) provide a review of various methodologies and associated limitations related to the projection of InSAR LoS data that should be reviewed and considered for this process. Processing both L-Band and C-Band SAR data from different look geometries may improve along-slope velocity projections. Although the projection of a mean velocity along slope may seem an over-simplification, it will allow for the relative understanding of landslide activity across various landslide classes and clusters.
- Multi-Criteria Exclusion Procedure: For the PS that are expected to be able to reliably support characterization of slope activity, Cignetti et al. (2023) propose evaluating the number of PS points present in each DSL, the distribution of the PS points within the DSL, and the clustering of PS points. The objective of this procedure is to determine whether an activity state can accurately be assigned to a DSL. For example, a) few PS points or b) poor distribution of PS points on a DSL would preclude accurate activity state characterization.
- Point Statistical Analysis: Following application of the multi-criteria exclusion procedure, the mean along-slope projected velocities are used to classify each DSL as Predominantly Active (PA) and Predominantly Inactive (PI). This is achieved by utilizing a GIS-based Point Statistics tool and comparing groupings of neighboring PS points to review deviations from mean velocities within a DSL. DSLs with deviations of -2.5 mm to

+2 mm/year were classified as PI and those outside of this range were classified as PA. While this section is focused on integration of the InSAR data, this stage of the assessment would also benefit from the integration of the regional LCD data. For DSLs where the LCD was able to characterize displacement, these DSLs would also be classified as PA.

- Spatial Statistical Analysis: DSLs that have been defined as PA are then subjected to a GIS-based “Cluster and Outlier” analysis to start identifying statistically significant spatial clustering of DSLs with similar activity states.

At the end of this process, the following products could support next levels of the assessment:

- Map of DSLs with mean velocities projected along the slope fall line. DSLs where InSAR is not suitable for characterizing velocities will also be highlighted so there is not an assumption that these DSLs are moving slowly, but rather that there is not data available.
- Map of all DSLs showing the number of threshold screening criteria defined in the multi-criteria exclusion analysis that have been met. This will support definition of a relative quality parameter for each DSL in terms of how representative the InSAR data are of the overall velocity trends for a DSL.
- Map of DSLs classified based on their state of activity (PA or PI) with an indication of variability in temporal velocity trends for PA-DSLs.

These outputs will support subsequent phases of the analyses as follows:

- The magnitude and variability of velocities obtained from the PA-DSLs will be coupled with the slope classification (Section 5.3.1) to support the definition of clusters of DSLs with similar velocity classes.
- The PA-DSLs will be used to identify DSLs where there are time series data that can be considered for integration into a displacement database to support initial exploration of trends, as discussed in Section 5.4.4.3.

5.2.4.3. Application of InSAR Velocity data to Higher Sensitivity DSLs

Following the above process, DSLs that have been defined as having adequate PS coverage and that have been classified as having varying displacement patterns with moderate to high variability will be evaluated in more detail. Each DSL will require careful consideration to ensure that the LoS measurement is coupled with the expected ground deformations to accurately describe the velocities. Important considerations will be as follows:

- What are the hypothesized kinematics of the DSL at this location?
- What are the hypothesized or known vectors of displacement for the DSL based on either site-specific monitoring or based on interpretation of surface morphology?
- How is the satellite LoS aligned in relation to the hypothesized displacements across the DSL?
- Is there shallower deformation superimposed on the DSL that would mask the movements of the DSL? In this case, are the InSAR LoS measurements reflecting deformation of the shallower movement, rather than the DSL? This can be resolved by comparing the deformation results with landslide inventory and lidar elevation data. For example, if

InSAR-derived displacements are identified only inside a mapped shallow landslide feature that occurs within a larger DSL, then it would be assumed that the shallow landslide is moving even though the larger DSL is not.

- If no InSAR points are observed on the DSL but the surface morphology represents an active feature, are displacements too fast for the InSAR? Confirm this by reviewing LCD data.
- If only one look direction of SAR data is available, is it possible to resolve the 1D LoS InSAR data onto the hypothesized DSL displacement vector to obtain a representative velocity condition date value?
- If there is 2D InSAR data available, do the horizontal (East/West) and vertical components of the displacement support the hypothesized kinematic model for the DSL? Can these data support a more refined projection of the InSAR data onto the actual DSL displacement vector?

These considerations will need to be made at each of the moderate to high variability DSL polygons to ensure that the velocity data obtained from the InSAR is projected appropriately to provide a realistic representation of the velocity along the true displacement vector for the DSL. It will also be imperative that the LCD data is utilized in conjunction with the InSAR results to support the understanding of the kinematic model and to ensure that the displacement results obtained from the two different technologies paint a common picture of the velocity trends at each site. As these technologies are complimentary, utilizing the results of each to support validation of the other will be an important component of this program.

5.2.5. Pixel Tracking

For DSLs where a review of displacement data obtained from LCD and InSAR identify phase jumps that don't allow for characterization of higher velocity displacements, pixel tracking could be considered to quantify these displacements. Pixel tracking can be applied to SAR imagery, optical imagery (e.g., aerial, satellite), and lidar based digital elevation models to identify sub-pixel offsets between subsequent images of the same ground area. For the Pilot Study, a key consideration will be whether there are existing archived data sources available with spatial and temporal coverage suitable for application of pixel tracking to DSLs in the study areas.

Pixel Tracking has been applied to glacier motion studies for decades (e.g., Bindschadler & Scambos, 1991; Strozzi et al., 2002; Berthier et al., 2005). Image co-registration and correlation methods have provided a means for estimating co-seismic horizontal deformation from imagery for nearly the same period (e.g., Van Puymbroeck et al., 2000; Leprince et al., 2007). SAR-based pixel tracking has been used to produce long duration (e.g., years) time series estimates for landslide displacements, even in densely vegetated terrain (e.g., Singleton et al., 2014; Raucoules et al., 2020). Mazzanti et al. (2020) demonstrates the utility of pixel tracking from satellite imagery to provide a nearly year-long, short interval (days to weeks) displacement time series at the Rattlesnake Hills landslide in Yakima, WA. Booth et al. (2020) provides a framework for applying phase correlation techniques to subsequent DEMs for identifying predominantly horizontal landslide deformations. These technologies are proven in the literature at estimating ground deformation and their application to landslides is increasing as the spatiotemporal resolution of available imagery and computational capabilities increase.

In both academia and industry, pixel tracking is not utilized as intensively as LCD or InSAR methods for landslide displacement studies and the methodologies are not immediately operational to the same scale of LCD or InSAR. However, methods for extracting glacier velocities at scale do exist (e.g., Dehecq et al., 2015), giving promise that these methods could be refactored and applied specifically for landslide displacement estimates. A key consideration is the size of the features of interest, where DSLs in western Washington tend to be smaller than most studied glaciers.

Methods for producing pixel tracking based displacement estimates vary according to the base dataset, however, all styles of pixel tracking fundamentally rely on image correlation:

- SAR based pixel tracking is based on correlation of coherence or intensity images
- Optical imagery-based pixel tracking is based on phase correlation between Fourier transformed images
- DEM based pixel tracking is based on phase correlation between subsequent lidar derived DEMs.

Developing a methodology to programmatically characterize many (e.g., thousands) landslides in terms of 1D or 3D velocity components would be a significant contribution to landslide science. Notably, the accomplishment of this task could complement LCD and InSAR limitations. Following are specific examples of how a robust pixel tracking program could compliment these other change detection techniques:

- Accurately characterizing horizontal deformation from pixel tracking could complement the stated limitation of LCD in estimating pure translational movements (Section 5.2.3.3). This is especially notable in the current study given the rich lidar datasets available across western Washington.
- Producing long duration, short interval displacement time series from SAR or optical imagery could complement the stated limitation of LCD in identifying seasonal or sub-seasonal velocity signals (Section 5.2.3.3).
- Utilizing optical imagery-based pixel tracking could complement the stated limitation of InSAR analysis in identifying landslide displacements in landslides that are aligned roughly north or south, and orthogonal to look-directions of SAR sensors (Section 5.2.4).

There are several relevant references that should be considered in developing this framework. A few examples are listed below with a short summary of their relevant workflows.

- SAR based: Raucoules et al. (2020) provide a framework for utilizing ALOS-2 SAR imagery in a heavily vegetated environment for tracking deformation of a large landslide moving at approximately 1m/yr
- Optical based: Mazzanti et al. (2020) provide a workflow for evaluating landslide displacement from high spatiotemporal resolution optical imagery in eastern Washington (more arid and less vegetated than the present study site)
- DEM based: Booth et al. (2020) provide a framework for identifying low-magnitude and predominantly horizontal deformation estimates from subsequent lidar-derived DEMs.

Once completed, we expect the DSL velocity characterization workflows from pixel tracking based methods would be quite similar to the workflow summary from Cignetti et al. (2023; Section 5.2.4.2 and Figure 5-9). This follows that the results will include a series of points on a landslide have been characterized in terms of displacement through time. Similar consideration should be given to the quantity and distribution of points in terms of how to classify the DSL.

5.3. Development of DSL Class Designations

The sensitivity of a given landslide to external perturbations (e.g., slope or surface water flow modifications) is fraught with nuance and likely only resolvable by a site-specific detailed subsurface study. Therefore, the present study aims to characterize populations of landslides into *Classes*, which should maintain homogenous characteristics such as mapped lithology, area, volume, failure depth, geomorphic position, and recharge area. *Clusters* of landslides should be identified as subsets of classes. Clusters should be proximal in the landscape and would be expected to respond to external perturbations similarly. This study aims to develop estimates of sensitivity of both DSL classes and clusters.

5.3.1. Landslide Classes

Classes of landslides should be derived through data analysis and expert interpretation. Classes may be spatially discontinuous and present across larger regions. So long as the data support the definitions, there is no upper limit to how many classes could be defined. However, we expect the number of defensible landslide classes to likely be around ten and would primarily be defined based on the nature of the originating parent material, the degree of structural modification, the topographic position on the slope, the exposure to active processes (such as toe erosion), slope aspect and distributions of systematically mapped landslides. The statistical distribution of variables from existing landslide inventories will be helpful in identifying classes. With appropriate data management and organization, it may be feasible to apply machine learning approaches to aid in defining landslide classes (e.g., the k-means clustering algorithm; Likas et al., 2003).

In Figure 5-9, we show the distribution of landslide area, estimated failure depth, and ground slope as reported by the WGS for over 9,000 landslides in western Washington. The results are displayed as a function of the geological class of the source zone material for each landslide (based on data from Section 3.1.2 and 3.1.3). These results illustrate that landslides initiating in alluvial and glacial deposits tend to be smaller in area with shallower failure depths than those landslides initiating in surficial bedrock or lightly weathered bedrock materials. This is consistent with the expected lower shear strength and generally low-lying topographic position (i.e., in valleys) of alluvial and glacial materials. The data do not, however, suggest that slope in the upper portion of the landslide is influenced by source zone material type. Because shallower and smaller landslides respond more quickly to external perturbations (Miller, 2016, 2017), it may follow that landslides initiating in alluvial or glacial deposits may similarly respond more quickly to external perturbations compared to landslides initiating in bedrock materials. Landslides initiating in alluvial and glacial materials, therefore, might be considered more sensitive, though further work (such as field investigations or local scale monitoring) would be required to support this claim and herein, we show this only as an example of a data interrogation approach that could be considered when conducting the study. Further landslide characteristics that could be considered, along with their rationale, are discussed in Section 5.4.2.

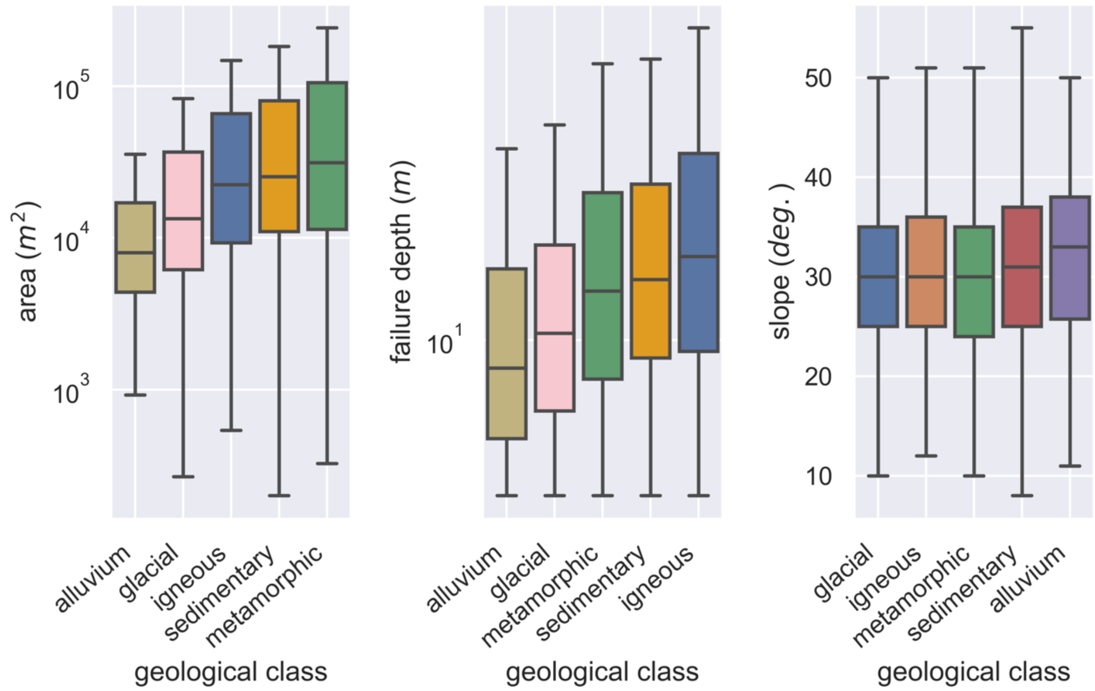

Figure 5-11. Boxplots illustrate area, estimated failure depth, and slope for landslides in five different geological classes. Each box extends vertically from the first quartile to the third quartile, with a line at the median. One takeaway from this figure is that landslides initiating in alluvium and glacial deposits are typically smaller in size and shallower than those initiating in more competent bedrock materials.

For one example, Porter et al., (2022) subdivided deep-seated landslide types typically encountered in glacial sediments and flat-lying shale and mudstone bedrock into five class designations (Classes A-E, Table 5-3). Class designations were largely based on morphological interpretation of landslide size, process type, the presence of toe erosion, long-term weighted average displacement rates, and evidence of episodes of relatively more rapid movement. The designation did not include other variables like geology, land use, or topographic slope angle. These definitions are provided for example only and may or may not be applicable to DSLs in Washington State.

Table 5-3. Example class designations from Porter et al. (2022).

Behaviour Type	Type A	Type B	Type C	Type D	Type E
Typical geology	Relatively intact shales, mudstones	Relatively intact shales, mudstones, residual soils, over consolidated glacial deposits	Relatively intact glacial deposits, colluvium derived from shales, mudstones, residual soil and glacial deposits	Colluvium derived from shales, mudstones, residual soil and glacial deposits	Colluvium derived from shales, mudstones, residual soil and glacial deposits
Typical failure mechanism	Translational block slides and spreads	Translational block slides and spreads	Translational block slides and spreads, rotational slides, complex earth slides-earth flows	Translational slides, rotational slides, earth flows, complex earth slides-earth flows	Translational slides, rotational slides, earth flows, complex earth slides-earth flows
Typical inclination of basal shear surface	Sub-horizontal (0 to 5 degrees)	Sub-horizontal (0 to 5 degrees)	Similar to the residual friction angle	Similar to the residual friction angle	Sub-parallel to the ground surface
Typical toe condition	No toe erosion	Toe erosion usually absent	Toe erosion may be active	Toe erosion often active	Toe erosion almost always active
Long-term annual probability of Class 4+ velocities	1 in 20,000	1 in 6,500	1 in 2,000	1 in 650	1 in 200

5.3.2. Landslide Clusters

Clusters are most simply proximal landslides of a particular landslide class. For example, if one class of landslides was defined as a DSL initiating in alluvial materials due to river undercutting, then a grouping of these landslides in a particular river valley will constitute a cluster. Due to spatial proximity, these populations will likely respond similarly to external forcings such as hydroclimatic conditions or river flows. This becomes useful in sensitivity analysis when hydroclimatic conditions may cause a decrease in the sensitivity of a cluster of landslides in a drought-stricken area, even though the sensitivity of the overall class of landslide may not change.

Present-day landslide velocity may further define a landslide cluster as this attribute is indicative of sensitivity of the landslide to further perturbation (Section 5.6). Therefore, a cluster of a particular landslide class may function similarly regarding displacement and activity state. For initial screening, the criteria provided in Section 5.4 would be utilized to assess activity state.

Following the definition of landslide classes, clusters should be identified using spatial- and data-clustering techniques (e.g., kernel density estimates, k-means). Spatial- and data-clustering methods will provide first order groupings of spatially proximal landslides and landslides with similar attributes. From these initial clustering results, subject matter experts should revise cluster definitions. Clusters and potential outliers may be visited in the field, as needed. Landslide classes and clusters will drive the sensitivity assessment efforts described in Section 5.4.

5.3.3. Consultation with Experts

Landslide practitioners have been working in western Washington for many years and have a rich level of experience with observing behavior and characteristics of DSLs. Selected geologists and geotechnical experts in western Washington should be consulted following the development of landslide classes to determine if based on their experiences, any populations of DSLs do not fit in a recommended class. This consultation phase will aim to incorporate the collective experience of the landslide community in class designations.

5.4. Assessment of Landslide Sensitivity

To assess how likely a landslide is to respond to future hydroclimatic events or human activity, an important first step is to understand past behavior. The focus is to assess both the spatial and temporal aspects of landslide activity at regional scale with a sufficient time sampling to evaluate a variety of natural and human-induced events and their impacts on landslide activity. The following sections outline a methodology that considers the spatial variation of landslide types and characteristics and couples these with spatially continuous data sets that characterize historical displacement trends for DSLs. These data sets will be integrated with regional hydroclimatic and land cover data to assess drivers for landslide activity change.

5.4.1. Historical Displacement Trends

Once landslide classes have been identified, the next step will involve building an understanding of how these various landslides have moved historically to form the basis to assess how sensitive they will be to future disruption. This will also support the definition/refinement of clusters. By utilizing the results obtained from the LCD and InSAR analysis, the goal of this phase would be to represent the absolute movements over time periods and/or extract velocity trends over time to assign to each polygon. The following spatial representations of velocity trends could support the sensitivity:

- DSLs with no measurable displacements (InSAR and LCD): Any DSLs that have either no measurable displacement from the LCD analysis or have been classified as PI--DSLs during the InSAR assessment will be considered as relict or dormant features (e.g., Velocity Class 0, or possibly near the lower limit of Class 1).
- DSLs with measurable displacements but no seasonal trend data (LCD): These would be DSLs where displacement has been characterized with LCD but were excluded from the InSAR assessment based on geometrical considerations.
- DSLs with consistent displacement trends (InSAR): Any DSLs that have been identified as PA-DSLs in Section 5.2.4.2 and exhibit low variability in velocity.
- DSLs with seasonal displacement trends (InSAR): These would be PA-DSLs that are described as having seasonal and low-magnitude velocity variations.
- DSLs with a high variability in movements (InSAR): These would be PA-DSLs with moderate to high velocity variation that may correspond to more focused external drivers, such as hydroclimatic events or human activities. These DSLs may be representative of landslides that are highly sensitive to disturbance. More specifically this would be

characterized as very well-defined, shorter-term acceleration of landslide activity following observed disturbance of the landslide by toe erosion or human alteration of surface water/vegetation. It is likely that this set of landslides would be the initial focus on time series extraction to support the next phases of assessment.

While each polygon in the inventory should be assigned with one of these broader classifiers, this does not preclude integrating the discrete velocity trends that can be extracted over the period for which displacement data is available.

5.4.2. Landslide Characteristics for Sensitivity Assessment

When reviewing the displacement data, it is likely that there will be variations in activity that may correlate with different landslide characteristics. These characteristics may be useful for both defining landslide classes (Section 5.3.1) and/or assessing the sensitivity of landslide classes. This section will describe if and how others in the literature have leveraged these landslide characteristics to assess sensitivity and how they may be most useful to the present study. During study execution, it is possible that limited or no relationships with some of these variables will be found. However, we believe there to be enough scientific merit and precedent that is worth cataloguing and evaluating the following variables in terms of landslide class sensitivity.

5.4.2.1. Geology and Soils

Geologic unit (surficial or bedrock) and soils units of a given landslide can have far reaching impacts on the response of a landslide to changing conditions. These include, for example, hydraulic conductivity parameters, structural characteristics such as the presence and orientation of discontinuities that could promote landsliding, or compositional properties such as enhanced clay content that can promote landsliding. For the purposes of this study, mapped geologic and soils units could assist in developing landslide classes. Once cataloged, geologic and soil materials should be ranked in terms of stability parameters and used in sensitivity assessments as a relativistic variable. For example, all things being equal, landslides originating in glacial materials will likely be more sensitive to changes in hydroclimate or surface drainage than large rockslides originating in metamorphic rocks. This is of course not a rule, but a relationship to be explored during data analysis.

5.4.2.2. Slope and Aspect

While slope is often reported as the single most important factor in shallow landslide initiation (e.g., Budimir et al., 2016), it is much less important in studies of deep landslide initiation and should generally be considered in context with the myriad other factors influencing DSL initiation (Burns & Mickelson, 2016). However, because DSLs occur at various positions within the Washington landscape, from river valleys to steep mountain flanks, we expect that slope may be useful in differentiating landslide classes (Section 5.3.1) and potentially landslide class sensitivity estimates.

Topographic aspect is another related factor that may assist in both DSL class definition and sensitivity assessment. The primary mechanism by which aspect can influence DSL behavior or sensitivity includes evaluating the geometric relationships between the downslope preferred direction of movement (i.e., the “fall line” direction) and any available geologic mapping that includes fracture, foliation, or other discontinuity information (Burns & Mickelson, 2016; Wooten et al., 2022). For example, if foliation or another weakness plane is dipping to the southwest, and a slope is similarly oriented such that the fall line of the topography is to the southwest, then perhaps this is an ideal geometric alignment for continued DSL activity and increased sensitivity. This relationship should be assessed for populations of DSLs in the present study with varying activity states but otherwise similar characteristics.

5.4.2.3. Surface Roughness

After activation, landslides are quite rough in texture and through time, natural geologic weathering processes smooth out topography across the landslide scar. Authors working in Washington and Oregon have successfully exploited this phenomenon to utilize surface roughness, as estimated from high resolution lidar, as a proxy for age -dating DSLs (LaHusen et al., 2016; Booth et al., 2017; LaHusen et al., 2020; Herzig et al., 2023).

Surface roughness can be approximated by utilizing several methods to quantify heterogeneity in topographic variables (e.g., slope). For example, authors have explored the use of standard deviation of slope, root mean square height, direction cosine eigenvalues, Ricker wavelets, and others (Berti et al., 2013; Goetz et al., 2014; LaHusen et al., 2016).

Most recently in Washington, Herzig et al. (2023) estimated the age of last activity of >1,000 DSLs in the Puget Lowlands using a calibrated surface roughness-age relationship. Nine radiocarbon dates collected by Herzig et al. and six dates collected by Booth et al. (2017) were used to calibrate the relationship within this inventory. Most ages clustered between approximately 200 and 2,000 years before present. Therefore, the ages of more recent landslides (<100 years) are quite poorly constrained. This is typical of the literature, and to present, authors employing a surface roughness-age calibration approach (e.g., LaHusen et al., 2016; Booth et al., 2017; LaHusen et al., 2020) have primarily shown success at using the method to investigate only long term (10^2 to 10^5) landslide activity trends. However, these same studies often show a low degree of confidence in using the method to estimate more recent (<100 years) landslide activity trends (Figure 5-10).

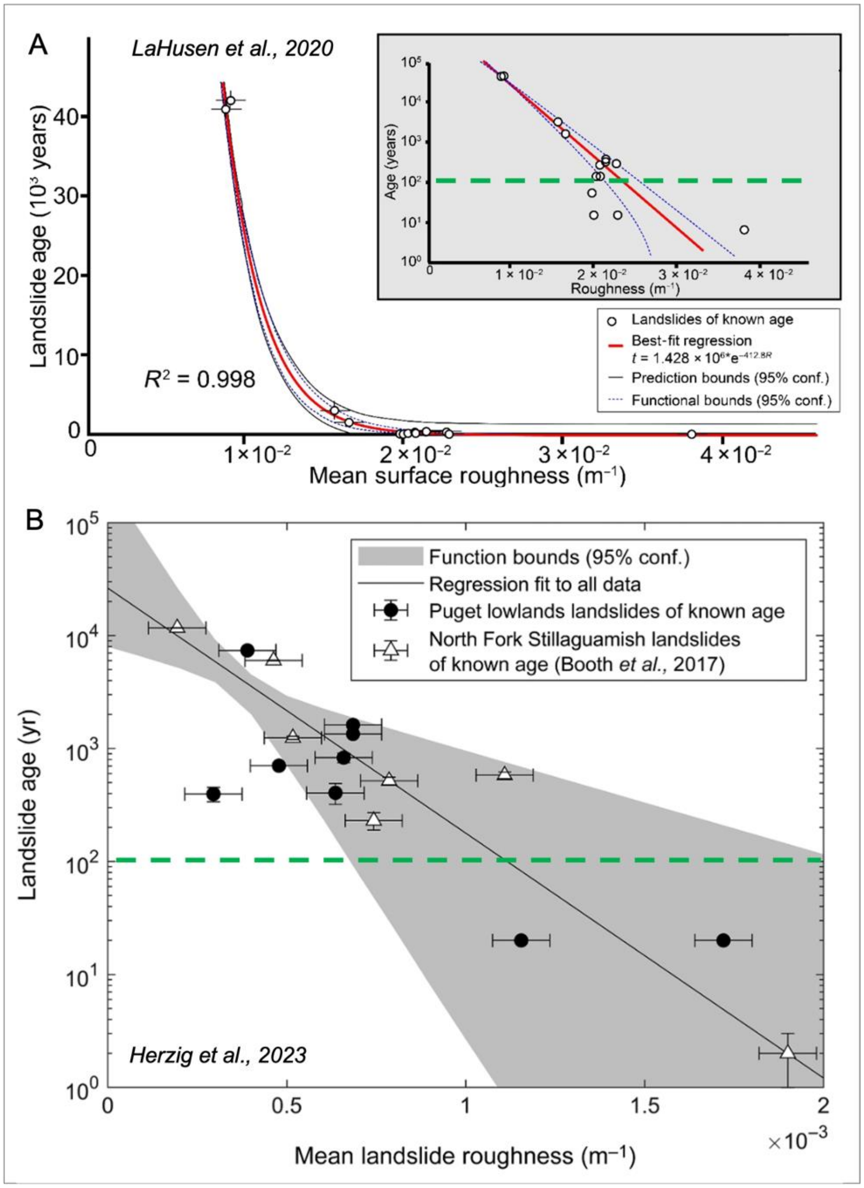

Figure 5-12. Results from previous studies (LaHusen et al., 2020 and Herzig et al., 2023) illustrate the typical timescale of study for surface-roughness based methods for identifying landslide activity states. A dashed green line is shown at a landslide age of ~100 years. Note that below this value (0-100 years), the confidence bounds for both studies increase markedly.

Given the high degree of variability in landslide morphology immediately following failure and the weathering characteristics in the immediate aftermath of a landslide, the methods are unlikely to provide significant insight into landslide activity along human timescales. Therefore, for this study, we propose to consider a surface roughness-age relationship (utilizing data from the previously referenced studies in Washington and Oregon) for the purpose of clustering dormant or relict landslides. However, it is unlikely this method will provide meaningful information regarding the present-day activity states of DSLs.

5.4.2.4. Depth to Rupture Surface

As the depth of the rupture surface of a DSL increases, the rupture surface tends to become more disconnected from surface activities such as increased runoff or infiltration. This can increase lag time between disturbance and activity or can reduce the sensitivity of the landslide to changes in activity state. However, depth to rupture surface is a notoriously difficult parameter to estimate from surface observations alone. Of the compiled landslide inventories (Section 3.1.2), only the WGS inventory contains an estimate on failure depth. Failure depths in this inventory are estimated as a function of ground slope angle and head scarp height (Burns & Madin, 2009), however these methods are not widely agreed upon as a preferred solution (Burns & Mickelson, 2016).

Jaboyedoff et al. (2020) provides a review of existing methods for estimating depth and does not converge on a single preferred method, but instead, suggests future efforts toward an adequate depth (and volume) estimation technique should include surface velocity data to facilitate a conservation of mass approach. This is encouraging, given the present study intends to catalog a rich dataset of surface velocities. During study implementation, consideration should be given to investigating the feasibility of integrating geometrical relationships with surface velocity fields to better estimate failure depth. We expect this would provide a great input in terms of landslide class sensitivity and would be a great contribution to the landslide community. However, as this is a formidable problem in landslide science, the project team should carefully consider the level of effort to do so and if the expected outcomes are worth the investment.

5.4.2.5. Topographic Position

For the present study, we expect the TPI could be useful for assisting in defining landslide classes. For example, this metric may assist in identifying DSLs that are in valleys or along lower slopes compared to those that are within middle to upper slope regions. The TPI algorithm can be applied to landscapes at various scales and the hyperparameter tuning will greatly influence results (De Reu et al., 2013). An example is shown in Figure 3-3, where we evaluate TPI at a broad scale (e.g., across tens of miles) across western Washington. Landslides that initiate and arrest in alluvial materials are expected to be most sensitive to river flows and due to their statistically shallow failure depths and small areas Figure 5-10), may respond relatively quickly to surface disturbances. Conversely, landslides that initiate and arrest in upper slopes underlain by more competent geologic materials may respond more slowly to surface disturbances. These relationships should be explored once landslides are attributed in terms of velocity and topographic position.

5.4.2.6. Toe Condition

Toe condition is a subjective measure of how actively the toe is exposed to erosional forces, most often in the form of active river erosion. An example of how this measure can be used in landslide class definitions is shown in Table 3-3. As to sensitivity, landslides actively undergoing toe erosion (e.g., Figure 5-4) are likely more sensitive to further perturbations compared to those that are not actively undergoing toe erosion. The kinematics of how modern-day toe erosional processes can influence landslide sensitivity are similar to the influence glacial debuttressing can impart on historic landslides (e.g., Lacroix et al., 2020 and references therein).

5.4.2.7. Forestry Activities

Though the literature is rich with works pertaining to forestry activities' influence on shallow landsliding (e.g., Jakob, 2000; Imaizumi et al., 2008; Goodman et al., 2023), virtually no work has been published to date on the influence of forestry activities on DSL activity. In his review, Miller (2017) did not identify any studies that investigated the causal relationships between forestry activities and DSL activity. As of 2024, we did not identify any studies that have been added to the literature since Miller's review.

However, several factors that influence DSL behavior (e.g., soil hydrology and overland flow patterns) are indeed influenced by forestry activities (Miller, 2017 and references therein). This gives weight to the hypothesis driving this study design – that forestry activities can and do impart an influence on DSL behavior.

It is well established in the shallow landslide community that there is a period after logging ceases when elevated risk of landsliding is present (e.g., Goodman et al., 2023). This tends to be due to root decay processes and loss of hydrologic contributions made by local ecology (e.g., evapotranspiration, canopy interception). It perhaps is reasonable to expect a similar relationship to hold in the potential effects of forestry activities on DSL behavior, however, the duration of influence is likely different.

For this study design, forestry operations data (Section 3.1.3) should be considered in terms of landslide class definitions and sensitivity assessments. Landslides that are proximal to documented forestry operations may be considered more sensitive to further disturbance. The date of forestry operations will be important, and much is unknown about these effects, their timing, and their mechanics. Findings from this work will be a strong contribution to the understanding of DSL behavior in the face of forestry operations both in Washington and the greater Pacific Northwest.

5.4.2.8. Land Use/Land Cover Change

LULC (Section 3.1.5), and particularly anthropogenic changes to LULC, is an increasingly discussed topic in terms of shallow landslide susceptibility (Pacheco Quevedo et al., 2023). However, very little work has been published to date in terms of the effects of LULC change on DSL behavior. This study should consider identifying LULC patterns proximal to active and inactive landslides to assess for correlations. No correlation may be found and LULC data may not be overly useful in assessing sensitivity, however, the easy availability of LULC data may provide insights to how LULC is influencing DSL behavior in Western Washington.

5.4.3. Evapotranspiration and Hydrology

Hydroclimate and land cover drive landslide activity by influencing surface and subsurface hydrologic conditions. It will be important to establish correlations between seasonal or multi-year fluctuations in velocity to hydrology of these landforms. While it is not practical to quantify the surface and near surface hydrogeology at any single location, there are publicly available geospatial data sets that can be utilized to develop qualitative/semi-quantitative correlations with historical landslide activity. Some of the key publicly available datasets that can be considered to support this assessment include the following:

- Hydroclimatic Data: Globally continuous modelled hydroclimatic data sets dating back to 1950 are available from the European Center for Medium-Range Weather Forecasting (ECMWF) and NASA. These data sets integrate satellite-derived data with ground and aerial observations to model a wide array of hydroclimatic, atmospheric and ground conditions over time. Froese et al. (2022) provides an example as to how these types of data have been utilized to support understanding of the sensitivity of different landslides to broader decadal and seasonal soil moisture change and these data sets are likely considered to be foundational to support the development of regional correlations in the study area.
- Precipitation Data: Developed and made available by the National Oceanographic and Atmospheric Administration (NOAA) the NCEP North American Regional Reanalysis (NARR) data set provides a high-resolution combined model and assimilated dataset of precipitation data over North America that is available back to 1979. While there are many different parameters reported in this dataset, key parameters driving water infiltration, such as precipitation and snowmelt are expected to be key data sets to support the sensitivity analyses.
- Topographic Recharge Area: Area of the land surface that is draining to the upper portions of a DSL will also be a consideration in understanding how regional hydroclimate and precipitation drive landslide processes at the local level. Figure 5-10 provides a distribution of recharge areas to over 6,000 DSLs in western Washington. We understand that the groundwater recharge area often differs from topographic recharge areas for DSLs, however, topographic drainage area serves as a proxy for recharge area and is a metric that can be computed at scale with existing datasets. By combining geological and soils maps (see bullet below) with these data, we may be able to further subdivide watersheds based on an estimate of recharge potential. As the percentage of a watershed that is harvested increases, so does the annual water yield of the basin, given the loss in evapotranspiration and canopy interception (Moore & Wondzell, 2005; Miller, 2017). This increase in yield can increase subsurface drainage, especially in geologic materials that have high permeabilities, and potentially destabilize DSLs (Miller, 2017).
- Land Cover/Land Use: As discussion in Section 3.1.5, there are extensive global data sets available that provide change in relation to lands use and land cover that can be assessed both qualitatively and quantitatively in conjunction with other data sets to assess the relative impact of these surface changes on landslide activity. Variables such as vegetative cover (in terms of quantity and quality) and human disturbance, when integrated into the same spatial and temporal frames as the other data sets can allow for quantification as to the relationships between these factor and other extrinsic drivers and assess the relative importance in relation to landslide activity changes.

- Soils Data: It is expected that national and state soils data, such as publicly disseminated by the USDA will provide important information as to the types and drainage characteristics of near surface soils which will also support understanding the relative susceptibility of landslides to water infiltration and impacts on landslide activity. Coarser and shallower soils are likely to communicate hydrologic signals more rapidly to the subsurface, potentially increasing the sensitivity of DSLs initiating in these soils.

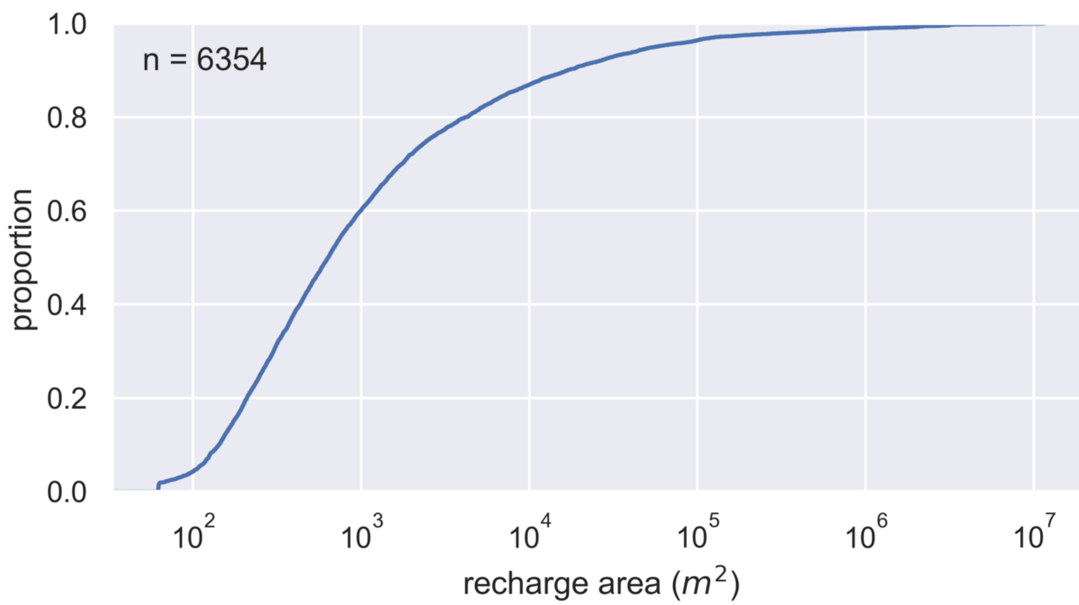

Figure 5-13. Distribution of DSL recharge area illustrates most landslides drain between 100-100,000 m^2. Drainage area computed via TauDEM in OpenTopography (Tarboton, 2005) DEM source: USGS.

The above publicly available datasets can be used to illustrate how different temporal and spatial scale hydroclimatic variables can influence landslide activity. Figure 5-10 and Figure 5-11 provide spatial and temporal depictions of modeled soil moisture obtained from the ECMWF's ERA-5 dataset and precipitation and snowmelt obtained from NOAA's NARR data set in relation to the multi-year period around the Oso landslide in March 2014.

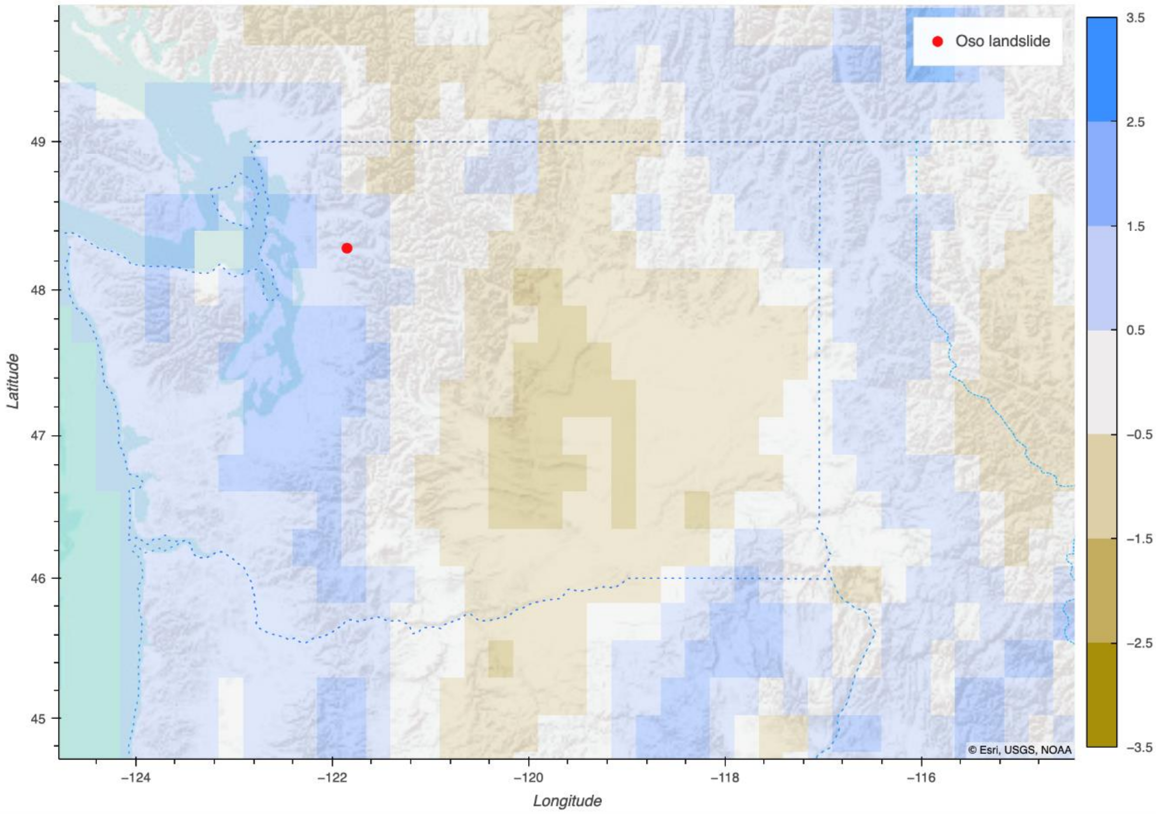

Figure 5-14. ERA-5 (Level 4) Standard Deviations from Historical Monthly Mean Soil Moisture for March 2014 (Data source: Hersbach et al., 2020).

Figure 5-14 provides a spatial representation of ERA-5 derived soil moisture for March 2014 in terms of standard deviation from monthly mean (1950 to present) of modeled soil moisture. Based on this review, the near surface soil conditions (modelled at 1-3 meters below ground surface) were wet of normal (0.5 to 1.5 Standard Deviations from Mean) related to the 72-year record.

Figure 5-13 provides a time series extracted from the same data set at the location of the Oso Landslide and provides a time series view of the soil moisture in terms of standard deviation from the monthly mean soil moisture and the 2-year rolling average of the same metric. Also provided are the modelled precipitation (24-hour and 60 day cumulative) and snow melt (daily and 60-day cumulative). When reviewing the soil moisture data, monthly soil moisture values are 1.5 standard deviations above mean, but not the highest observed during this period. Perhaps the most interesting observation is provided by the 2-year rolling standard deviation from mean which illustrates that the four-year period (2010-2014) preceding the Oso landslide event (Washington) was a prolonged period of above average soil moisture. This type of analysis may be useful in suggesting causal mechanisms between hydrologic conditions and landslide activity. However, it will be important to evaluate potential causal mechanisms with regard to groundwater flow pathways between near surface zones and DSL failure zones which may be deep and/or within confined aquifer zones.

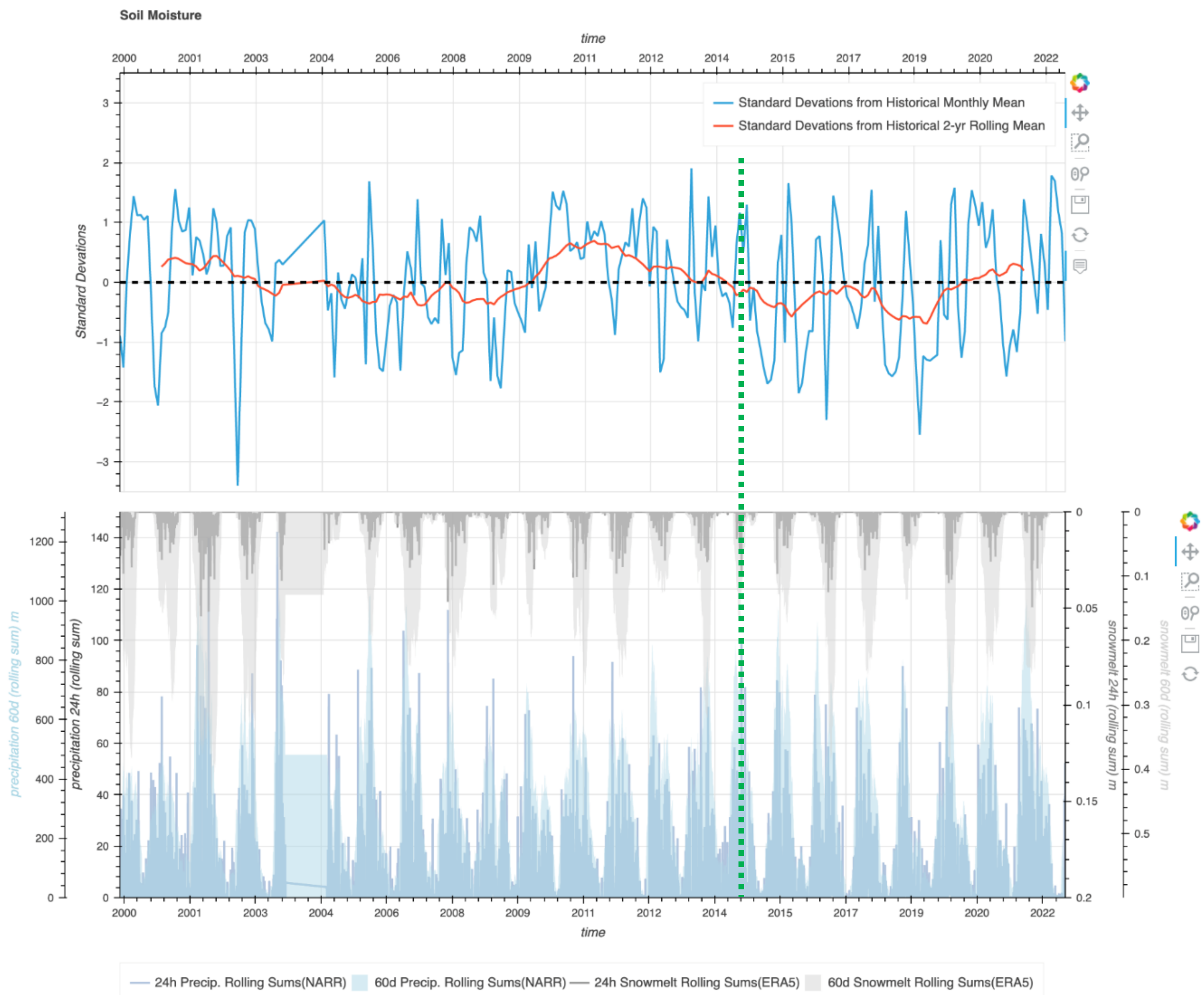

Figure 5-15. Hydroclimatic Data time series at the Oso Landslide. (Top) ERA-5 (Layer 4) soil moisture depicting the monthly standard deviation from mean (Blue line) and the 2-year rolling deviation from the monthly mean (Red Line). (Bottom) Precipitation (24-hour and 60-day cumulative) and Snow Melt (24-hour and 60-day cumulative). The green dotted line represents March 2014 (Data Source: Hersbach et al., 2020).

When coupled with soil moisture data, available precipitation and snowmelt data can further contribute to the understanding of landslide activity states in addition to rainfall-only thresholds (e.g., Iverson et al., 2015). Figure 5-15 provides an overview of a subset of the precipitation (24-hour and 60 day cumulative) and snow melt (daily and 60-day cumulative) to understand whether there were any “pulses” of water infiltration that would coincide with the March 2014 landslide in this example. When reviewing Figure 5-15, there is a local maximum in both cumulative snow melt and precipitation in March 2014 that likely contributed to a significant increase in water infiltration at this location. This focused pulse of water infiltration, coupled with the historically high antecedent soil moisture may have played a role in the timing of the landslide at Oso.

While the above graphics and description are meant to highlight how these publicly available datasets can be utilized to support understanding as to the drivers of activity change on a qualitative basis, they may also be harnessed, along with robust displacement data sets to attempt to quantify these relationships.

5.4.4. Assessment of Combined Impacts

The preceding sections have outlined how various critical variables influence sensitivity of landslides. The determination of the sensitivity of landslides to external variables may be conducted at various scales (landslide classes, clusters, or even individual landslides). The goal of this section is to describe considerations and methods for assessing sensitivity of landslide classes or clusters, as defined in Section 5.3.

5.4.4.1. Data Compilation and Organization

The next step of the assessment is to compile spatial and temporal data to support cluster sensitivity assessment (Section 5.4.4.4). The database (Section 4.2) should be populated with attributes collected thus far in the study and with velocity-based condition states and time series results. Datasets in Table 5-4 have been described elsewhere in the document and Table 5-4 should not be used as an exhaustive attribute list. We provide this simply to illustrate a potential attribute list and corresponding options.

Table 5-4. Potential attribute list and categories for compiling information on each DSL.

Data Category	Subcategories	Relevant Study Design Sections
Geology	Unit Lithology Proximity to Faults Degree of Metamorphism	3.1.1, 5.4.2.1
Topography	Roughness Convexity Aspect Slope	3.1.3, 3.1.7, 5.4.2.2, 5.4.2.3, 5.4.2.4

Data Category	Subcategories	Relevant Study Design Sections
Landslide Attributes	Location Dimensions Topographic Position	3.1.2, 3.1.4, 5.4.2.5
Landslide Classification	Class Cluster	5.3
Activity Classification	Active/Inactive (A/I) Mean Velocity (mm/yr) Variability (L, M, H)	5.4.1, 5.2.3.4, 5.2.4.2, 5.2.4.3
Displacement	Time Series	5.2
Hydroclimate	Precipitation (mean) Soil Moisture (mean)	5.4.3
Land Use	Category	3.1.5, 5.4.2.8
Forestry Activities	Distance Date	3.1.3, 5.4.2.7

Table 5-4 provides only a sample of what we expect would be many tens of attributes and corresponding categories. Following analysis, this attribute list should be considered by the project team and stakeholders as it will serve as the basis for the sensitivity assessments.

5.4.4.2. Data Visualization and Exploration

Once data are organized and accessible to landslide subject matter experts on the project team, exploratory data analysis should be conducted to explore relationships such as:

- Bi-variate relationships: Comparing variables such as Activity State or Mean Velocity directly to independent variables such as geological unit, topographic position, surface roughness, slope aspect to assess strength of relationships
- Multi-variate relationships: Comparing combinations of independent variables to review the relationship with Activity State or Mean Velocity to visually identify trends that may support further review.

The focus of the above exploratory analysis is to test a series of hypotheses that have been developed in relation to the linkages between landslide activity and the suite of independent variables (and combinations of variables) defined during the study to assess which trends or outliers require more specific study and more robust statistical review.

5.4.4.3. Velocity Time Series Analysis

Velocity time series data, based on methods described in this report thus far, will fundamentally consist of a series of points within landslide polygons that describe the velocity for a given time step. In the case of InSAR or pixel tracking, there may be displacements for many time steps, facilitating the development of a long duration, short interval time series. In contrast, LCD results will only contain displacements for up to a few time steps, commensurate with the number of lidar datasets available for any given location.

From these velocity time series data, there are several useful outcomes and potentially more information to extract from time series analysis. The simplest metric to extract from these data is a binary classification of if a landslide has moved faster than the lower limit of detection for a given method. This classification would indicate to DNR which landslides have already fallen below a factor of safety of one and are therefore likely susceptible for further disturbances and are the most highly sensitive landslides in the inventory. These data, even in the case of LCD derived time series, would be useful in the same context as presented in Cignetti et al. (2023).

More advanced analysis should seek to identify temporal clusters of accelerations or decelerations in landslide velocity. In terms of the temporal component, Urgilez Vinueza et al. (2022) offer a framework for identifying accelerations or decelerations in InSAR displacement time series data that is fundamentally based on fitting piecewise linear functions to cumulative displacement time series (Figure 5-16.) The example shown from Urgilez Vinueza et al. (2022) is from a single pixel within a landslide. However, the present study should consider statistically valid methods of performing a similar analysis for all pixels in a landslide or on an aggregate cumulative time series dataset (e.g., the mean of all pixels in a landslide). In an appropriate computational environment, this could provide a scalable method for identifying the timing of accelerations and decelerations for a large population of landslides. If SAR or optical image pixel tracking is successful (Section 5.2.5), we expect similar methods could be applied to those displacement time series data.

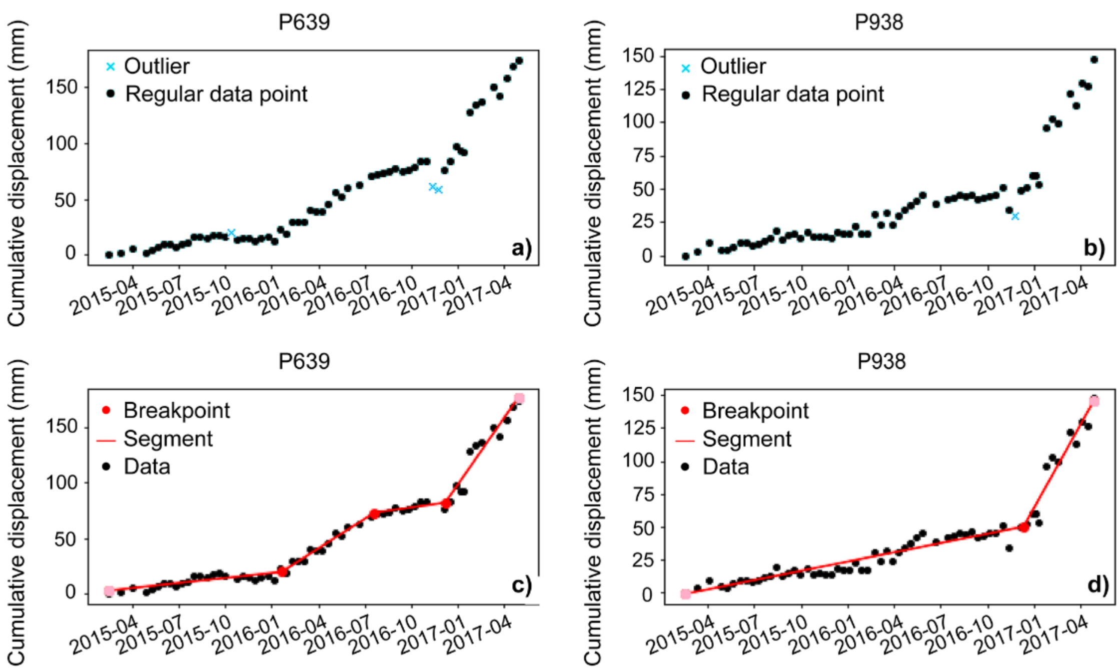

Figure 5-16. Example from Urgilez Vinueza et al. (2022) illustrating a two-stage method for detecting accelerations or decelerations from cumulative displacement InSAR time series data. The first stage includes omitting outliers (blue crosses in panels a-b). The second stage includes fitting a piecewise linear function to the data as shown in panels c-d).

The temporal analysis of lidar-derived time series data (i.e., from LCD or lidar -derived pixel tracking) will be much simpler, given the much coarser resolution of the time series. For example, it is unlikely that lidar-derived displacement data will contain more than several velocity estimates over the period of record, given the number of epochs of lidar available in western Washington (generally less than 10). However, temporal analysis of lidar-derived data is still important because it will be a critical resource for evaluating movement patterns of landslides that moving faster than is suitable for InSAR analysis and will still have several useful outcomes:

- Confirm if landslides are moving at velocities that exceed the capability of InSAR analysis and require application of another processing approach, such as pixel tracking, to develop time series data.
- At generally 1- to 3-year intervals, determine the velocity class of landslides and see if landslides are consistently moving or are experiencing accelerations and decelerations, even though details on these changes will be slightly subjective and open to interpretation.
- Provide estimates on velocity for landslides that are poorly oriented given the geometry of InSAR.
- Corroborate the InSAR derived temporal analysis for landslides moving at approximately velocity class 2a, a rate that others have shown can be detectable by both InSAR and high-quality LCD (Section 5.2.1.2).
- A key outcome of the temporal analysis is to provide the means to then identify spatial and temporal clusters of landslide accelerations or decelerations. This will be fundamental to testing the hypothesis that regional hydroclimatic drivers are causing regional activity changes to landslides (with an unknown lag time).

5.4.4.4. Cluster Sensitivity Analysis

There are many approaches that could be used for further qualifying the influence of landslide attributes discussed herein. Perhaps the simplest approach would rank the influence of velocity trends, material properties, geomorphic setting, or evapotranspiration/hydrology on landslide sensitivity to external perturbations. This relativistic ranking may allow DNR to estimate which landslides are most sensitive to a proposed project when the project may impact many landslides. The following steps are recommended to support this approach:

- Once displacement data is available, each existing landslide polygon would be reviewed, and the following validation and data entry completed:
    - Landslide extents, area, and estimated volume are entered into the database. This would be completed utilizing the information available in the existing inventories and checked with basic DEM-based volume estimation techniques (e.g., Jaboyedoff et al., 2020).
    - Source zone/parent material is confirmed in relation to position of landslide, available mapping, and expert judgement. To support this step, the highest point of any mapped landslide polygon would be reviewed in relation to both the estimated depth to the failure plane and the mapped geological unit to estimate which unit the landslide initiated in.

   - Observations of external modification due to natural toe erosion or human activity would be noted based on a visual review of landslide toe conditions and the temporal land use and land cover data sets.
   - Each mapped landslide would be assigned a screening activity level based on the observations from the LCD and InSAR data using the criteria outlined in Section 5.4.1.
   - Each existing landslide polygon would be assessed with the context of the displacement data obtained from the LCD and InSAR to assess whether any modifications to the polygon boundaries would be required (reduction or expansion) to ensure that a representative landslide volume is entered into the database. This delineation will be based on activity level and expert judgement using knowledge of the geological framework, surface morphology and spatial deformation trends.
- Following the validation and update of the polygon data, initial visual observations and/or spatial analysis would be undertaken to delineate broad landslide classes based on geologic parent material, structural controls, and spatial densities of mapped landslides.
- Within each broad landslide class, attributes such as external modification, surface roughness, and the initial activity screening may be utilized to subdivide the classes into clusters based on proximity and activity level.
- As a next phase, each of the various broad activity categories outlined in Section 5.4.1 would then be reviewed to assign specific velocity condition states across the timeframe for which displacement is available, such that velocity trend data is accessible in the database.
- For the activity trends observed in the classification above, cluster-specific analysis would build on this displacement trend data and couple it with available hydroclimatic, precipitation, land cover and land use data (with the ability to review spatial and temporal changes for all data sets) in order to break out relationships observed.
- Each polygon in clusters defined as being most sensitive to disturbance would then be assigned velocity condition states that would be used as the basis for analyses outlined in Section 5.6.

Pending an understanding of data organization and completeness (Section 4.0), quantitative data driven approaches, such as applied for regional landslide correlations in Norway (Krogli et al., 2018) may be applicable for identifying statistically meaningful landslide attributes or correlations between intrinsic and extrinsic landslide factors and landslide activity. Additional evaluation would be afforded by nearly continuous time-series information on landslide velocity and extrinsic factors such as hydroclimatic conditions.

The sensitivity of DSLs to surface modifications (e.g., changes to surface drainage, land cover, or vegetative removal) or hydroclimatic patterns (e.g., increased rainfall or snowmelt) can be estimated by observing high temporal resolution displacement data such as that from InSAR. These data are key to understanding the latency or memory of DSLs and to estimate how quickly or easily they may start to respond to surface changes. As discussed in Section 5.3.1 and Miller (2016, 2017), large and deep landslides in fine grained materials are likely the slowest to respond to hydroclimatic trends or surface modifications. This follows from the fact that the shear surface in these landslides is physically more distant from the ground surface and fine-grained materials act as a buffer in transmitting hydrologic response from the ground surface. Conversely, DSLs initiated in coarse-grained or loosely consolidated materials and with a relatively shallow failure depth may experience the most rapid response to surface changes. The present study should assess the rate of velocity change (i.e., acceleration) in relation to these extrinsic perturbations.

Forestry activities may influence the observed lag time between hydroclimatic changes and landslide activity. This could be due to the effects of forestry on local hydrology, such as reducing evapotranspiration, canopy interception capacity, or removing structural root masses. Landslide accelerations should be assessed in the context of historical forestry activity data (e.g., Section 3.1.3 or 5.4.2.6) and historical hydroclimatic trends. If velocity patterns of a landslide within or adjacent to forestry operations are consistent with velocity patterns of nearby landslides of a similar morphology (i.e., within the same landslide cluster), it could be possible that the forestry operations did not have much influence on the landslide activity. However, if the landslide within or adjacent to the forestry operations showed a greater acceleration compared to other landslides in the cluster, further interrogation should be performed. Examples of this further analysis could include using SAR-derived soil moisture trends (e.g., Bauer-Marschallinger et al., 2018) to assess if the removal of vegetation coincided with a commensurate increase in soil moisture over a duration significant enough to potentially destabilize the landslide. If the cluster of the given landslide had previously been shown to have a lag time of months, then a very short duration increase in soil moisture (e.g., days) following forestry activities may not be significant enough to activate the landslide. Soil moisture is but one variable in the equation of landslide activity and, thus, findings from Section 5.4.3 should be included in this assessment.

While the above sections describe how geospatial data and office-based assessment would be utilized to classify and organize landslides, the areas that are determined to be most sensitive to disturbance will likely benefit from field verification. It is expected that field verification would consider the hypotheses derived from the office-based assessments and review local conditions to assess validity of assumptions.

5.5. Field Verification

The field verification of the insights derived at the cluster-level from existing mapping and remotely sensed data will be important to provide confidence in the classification and support the development of field data collection procedures. As an example, as visual observations as to landslide velocity are extremely difficult to accurately quantify for velocity classes lower than Class 3 (Table 5-2) the DNR may choose to identify clusters that have been historically active and/or demonstrated to be sensitive to disturbance, to review field-based activity indicators that had been collected previously, or select DSLs with no prior field observations for field verification, in order to assess how correlated these visual indicators were to the actual activity levels. Conversely, if there are areas for which decades of field observations indicate that a landslide is active, but the remote sensed data does not reflect this, the ability of these techniques to measure displacement in certain conditions would also require evaluation.

Once specific areas have been classified, it is expected that landslide clusters will be prioritized by UPSAG and will require some level of field validation by DNR to have confidence in the classification. In addition, the remote sensing analyses may identify areas with outliers that may require field data to clarify. During the study execution, each of the DSLs will be classified based on a collection of geological and morphological attributes and documented landslide activity (discussed in Section 5.2). To confirm that conditions on the ground agree with the office-based classification, the visual observations listed in Table 5-4 will be considered to support the classifications. Note this verification is not intended to verify individual features (e.g., ponded water or vegetation type), but instead to support the remote sensing-based DSL class assignment.

Table 5-5. Sample visual observations to support validation of slope classification.

Slope Dimensions	Slope Morphology	Lithology/ Stratigraphy	Vegetation	Water	Human Modification	Ground Movement
Angle Total length	Smooth Undulating Benched Ridged	Geologic origin or parent material, degree of lithification (bedrock, glacial sediments) Fine grained (clay or silt) Coarse grained	Cover type and density Observations of distressed and/or curved trees	Ponded water on slope Quality of slope drainage. Disruption of natural drainages	Observations of vegetation removal Any road construction Any material stockpiling	Stepped/Benched Slopes Hummocky Ground Actively moving slopes in area

As part of the ground-based validation of the landslide classification by DNR (or their consultants), a structured digital field data collection form and protocol would be developed and used to confirm that ground conditions are as expected and whether there are any site-specific conditions that require further consideration or modifications to the sensitivity analysis.

5.6. Interim Methods to Estimate Future Behavior (Markov-Chain Analysis)

A goal of the broader UPSAG DSL Strategy is to understand the potential sensitivity of DSLs to forestry related activities relative to other trigger mechanisms, and thus the probability that DSL activity and velocity will increase with surface disturbances. In the interim, however, data aggregation techniques discussed in this study may be useful for extracting information regarding future landslide behavior.

Markov-Chain analysis can be used to combine landslide behavior type and current velocity to assign velocity class probability distributions for annual model timesteps. The model outputs can be used to support landslide hazard and risk assessments and lifecycle cost models. This method can be implemented where a velocity history of a given DSL is known or can be reasonably inferred (Section 5.2). Results of the analysis indicate the probability that a DSL class will transition to faster or slower velocity class over a given future time period, generally decadal in scale. The approach has been successfully applied to several engineering consulting assignments in central British Columbia and across the Western Canada Sedimentary Basin (e.g., Porter, 2021; Porter et al., 2022, van Veen et al., 2022). The suitability of implementing this method regionally across western Washington will be understood following the data assimilation and velocity characterization tasks described above.

It is expected that landslides that are observed to be moving slowly near the beginning of the study period of record will exhibit more frequent transitions to higher velocity classes over the period of record when compared to landslides that do not appear to be moving at the beginning of the period of record. In other words, it is more common for landslides that are already moving to accelerate compared to those that are dormant or relict. Furthermore, the expectation is that the observed frequency of velocity class transitions will be greater for faster moving landslides compared to slower moving landslides. If the study results validate these expectations, they will provide good justification for using landslide velocity as a key variable to predict the relative sensitivity of landslides to disturbance from timber harvesting using Markov Chains.

Relying on expert interpretation from local landslide subject matter experts, Markov-Chain velocity class transition matrices represent the probability of transitioning from one landslide velocity class to another (or staying in the same velocity class). In the present study, these matrices could be developed for the representative landslide classes (Section 5.2.5). This could be done by first estimating the long-term average distribution of the velocity classes for each type of landslide as determined by InSAR and lidar change detection (i.e., the total number of “landslide years” spent in each velocity class over the period of record). This provides a representation of the target limiting state vector that should be generated by a reasonably well-calibrated Markov Chain transition matrix when the model is run for several hundred annual timesteps. Next, for each mapped landslide and each year of record, the number of observed transitions from and to each possible velocity class could be counted. These provide a first estimate of the transition probabilities that form the transition matrix for each type of landslide. Next, the models derived from the preliminary transition matrices could be run for several hundred timesteps and the model outputs compared with the target limiting state vectors. And finally, through experience, judgement, and trial and error, the transition probabilities in the preliminary transition matrices could be adjusted to improve the calibration of each model.

If implemented here, DNR may gain access to a tool to generate meaningful probability estimates regarding the likely future condition state of DSLs while continuously working toward future goals for the research program (e.g., physically based or statistical slope stability models).

6.0 ADDITIONAL DATA CONSIDERATIONS

This section provides a brief discussion of potential additional data considerations that may be explored during the execution phase of the study to support the various linked projects as part of the larger Strategy. An example of potential additional data includes landslide and slope stability inventories and studies by other agencies, for instance the compilations of the Washington Department of Transportation Unstable Slope Management Program (WSDOT USMP). BGC understands the WSDOT USMP has been active for many years, and although the data would be constrained to transportation corridors and is intentionally different, the information could provide patterns and indications of sensitivities to natural attributes and anthropogenic changes. The study should incorporate all relevant and applicable data sources available at the time of execution, including those not listed in the following sections.

6.1. Targeted Site-Specific Data Collection

While the remotely sensed data will provide a temporally and spatially continuous regional representation as to deformation trends, recent studies by Froese et al. (2022) highlight the importance of gathering site-specific displacement data to link external drivers with velocity state transitions. The daily to weekly observations provided by ground sensors, such as slope inclinometers or Global Positioning System (GPS) sensors, at instrumented landslides can provide critical understanding as to the sensitivity of local scale landslides to inputs such as increased moisture. To supplement the remotely sensed data, the team conducting the project execution is advised to assess whether site specific data exists or could be installed in the future that can better represent the transient conditions at more sensitive landslide clusters/locations and the following data sources could be considered:

- Continuous displacement records – Froese et al. (2022) has demonstrated the utility of integrating near-continuous displacement data obtained from Slope Acceleration Arrays (SAA) with global hydroclimatic data coverages to assess the correlations with different rates/amounts of gross water infiltration with the onset of slope accelerations. These continuous data would be important to confirm hypotheses regarding the differing contributions of snow melt, precipitation, and longer-term soil moisture trends in relation to accelerations of different types of landslides in the study area.
- Local climate stations – As discussed above with respect to displacement data, it would be of value in the project execution phase to select more highly sensitive landslide locations/clusters to provide actual ground measurements of near surface hydrology/soil moisture. This could be achieved with the installation of climate stations that collect data on precipitation, snow depth, temperature, and soil moisture to support calibration with regional data models.

Both types of point source data would provide significant benefit to additional project phases, specifically Projects 4.8, 4.9 and 4.10 from the Strategy (Figure 1-1). Regional data and insights would be utilized to target locations for local data collection. These local data would then be utilized to increase site specific understanding of water infiltration and potential slope destabilization. These local models can then further inform regional modeling efforts, forming a recurring cycle of regional to local understanding of DSL dynamics in western Washington.

6.2. Future Data Availability and Project Integration

The current study design considers technologies and data that are available at the time of the presentation of this report but there are significant advances in data availability that will likely evolve future application of the study guidance for other areas within Washington. One significant advancement will be the availability of freely available standard coverages of L-Band SAR data obtained from the NASA-Indian Space Research Organization (ISRO) NiSAR satellite. This satellite currently has a launch window that opens on January 29, 2024, and could have up to six months of data coverages available for processing in the fall of 2024. By having both ascending and descending standard coverages of L-Band data, more sensitive landslide clusters could likely be monitored and reassessed on a more regular manner to support more detailed characterization.

In addition, the ability to continually integrate continuously collected displacement data into analytical models to refine the understanding as to the linkages between hydroclimate, land use, and displacement will allow the evolution of the models to enhance the ability to support seasonal decision making around activities in sensitive terrain. It is considered that these new data sets would provide specific value to Projects 4.7, 4.8, 4.9 and 4.10 (Figure 1-1).

7.0 TECHNICAL LIMITATIONS

The critical research questions being addressed in this study (Section 1.4) are very challenging relative to the state of the science in 2023. Any study attempting to provide insight into these questions will include an inherent level of uncertainty. This is particularly true when attempting to address the questions for landslide populations that span large geographic areas.

A large component of this uncertainty stems from the fact that the study has yet to be undertaken and there are a great many unknowns in what the study will uncover about the velocity characterizations of known deep-seated landslides. Rapid increases in landslide activity or velocity are relatively rare. That is, the activity of a given landslide typically remains constant through time, punctuated by small and relatively short duration changes to activity. This study attempts to identify these relatively rare transitions within the limited time frame of the available remote sensing data. The more of these transitions the study can identify, the more opportunity we will have to interrogate the relationship between the transition and external variables (e.g., hydroclimate, geology). If the available InSAR, lidar, and other datasets do not identify many transitions, our opportunities for further evaluation will be limited. The likelihood of success of this approach, therefore, is unknown at present, because the velocity characterization work has yet to be performed. BGC undertakes similar evaluations of regional landslide activity across Western Canada on an on-going basis utilizing a combination of LCD, InSAR, and field data to support regional understanding of landslide activity in relation to operational decision making. Based on the similarity of the ground conditions and relatively rich coverage of data, BGC considers that the approach outlined in this study design would provide significant value for the application proposed in western Washington. The architecture of this study aims to begin at the broadest grouping of the landslide population (e.g., >2500 landslides in proposed Study Area 1) and then to subdivide based on various attributes into landslide classes and ultimately clusters. The working thesis underpinning this approach is that the characterization work will provide sufficient detail around landslide activity patterns such that subdivisions can yield additional insight into the potential for increased landslide activity. For example, if a cluster of landslides is identified to respond similarly to changing hydroclimatic conditions, perhaps in the future, if a transition is identified at one of the landslides in the cluster, the remaining landslides in the cluster may be nearing a similar transition.

Further uncertainty is due to the complex interplay between driving and resisting forces for a deep-seated landslide. Even intensive studies of single landslides are fraught with nuance to the landslide in question (e.g., Badger & D’Ignazio, 2018). Therefore, uncertainties around an evaluation of many thousands of deep-seated landslides must be considered carefully in the use and utility of the results. Primary sources of uncertainty in regard to driving and resisting forces include, but are not limited to, the following:

- Site-specific hydrogeologic considerations including the presence, absence, or condition of geological units that may promote or impede groundwater flow
- Unknowns regarding the site-specific history of a given landslide at geologic timescales
- Spatial resolution of available data including geological maps and hydroclimatic data.

Executing this study will provide a more informed basis around uncertainty in the results and in how to best apply the results to assessing deep-seated landslide susceptibility in Washington.

8.0 PROJECT DELIVERABLES AND NEXT STEPS

A complete list of project deliverables should be agreed upon between the qualified contractor selected to complete the study and DNR, but should at minimum, consist of:

- A report describing the study execution and findings
- Digital data transmittal including the project final database (Section 4.2) in a format preferred by DNR (e.g., ESRI Geodatabase).

Findings of the Study should be integrated into the larger Strategy. The Study was designed with a forward-looking approach to assessing sensitivity of landslides (see item 4.7 in Figure 1-1). This is likely a GIS-based geospatial workflow that will need to be designed in a future effort and is not covered here. The objective of designing and populating the database for this Study, however, is to facilitate future statistical estimates on the sensitivity of landslides and to aid selection of DSLs for field-based testing of forest practice treatments and calibration of hydrologic models.

Specifically, by undertaking the Study as outlined in this report, the qualified contractor should be able to provide guidance in relation to other portions of the overall program, including:

- Project 4.7: GIS-Based Stability and Sensitivity Tool Kit – It is expected that the assembly of the structured landslide database and the satellite-derived hydroclimatic data to support the Study can be used as a foundation to build analytical tools to support modeling sensitivity of landslide classes or clusters.
- Project 4.9: Physical Modeling Project – The classification of landslide classes and clusters in the study are expected to highlight differences in landslide performance that may help focus localized studies that integrate a deeper understanding of the subsurface conditions and external drivers to develop physical models that are able to replicate the observed performance.
- Project 4.10: Monitoring Project – The application of the various remote sensing technologies to characterize landslide activity will provide important learnings to inform the design of future monitoring programs. This may include providing guidance on future lidar acquisitions, selection of targeted local monitoring programs, or development of plans for the integration of data from future SAR missions, such as NiSAR.
- Projects 4.11: Modeled Evapotranspiration Refinement Project – The assembly of the satellite-derived hydroclimatic datasets can be utilized to support further evapotranspiration modeling to support landslide sensitivity assessments.

9.0 CONCLUSIONS

The contribution of both intrinsic and extrinsic factors to deep-seated landslide mapping and classification is a complex subject. An understanding of landslide velocity transitions, the availability of emerging remotely sensed data sets and developments in data integration platforms and analytical techniques are allowing the geoscience and engineering communities to better understand trends in activity and sensitivity. This Study Design Report lays out a framework and specific design guidance for a regional proof-of-concept Pilot application that would provide statistical rigor around understanding regional drivers for velocity changes and which specific landslide classes and clusters are more sensitive to different external drivers. The focus of the study is to develop linkages that support the understanding of the landslide types and characteristics that are sensitive to forestry activities and related ground disturbance and could lead to velocity transitions for these types of landslides.

Study areas proposed by DNR are relatively data-rich in relation to the availability of existing geological and landslide mapping and publicly available remotely sensed data (both airborne and satellite-based). An approach to mapping and classification has been proposed and specific sub-regions identified to maximize the likelihood of developing robust relationships. These locations have been chosen based on the quality of existing landslide inventory coverage, the density of mapped landslides, the amount of repeat lidar data sets available, and the spatial and temporal density of archived SAR data that could support generating InSAR deformation data. Based on these criteria, the following subregions have been identified as options for where to potentially execute the Mapping and Classification Pilot:

- Area 1a and 1b: Western Whatcom County (Mount Baker to Lower Nooksack River) and the Upper Snohomish River System (Snoqualmie and Skykomish Rivers, including Upper Tolt and North Fork Snoqualmie) – 2,700 km^2
- Area 2 (includes 1b): Snohomish County (Sloan Peak to Snohomish) and the Snoqualmie River Valley (Fall City to Monroe, including Upper Tolt and North Fork Snoqualmie) – 3,600 km^2.

Each of the above study areas has been selected to provide a cross section of landslide classes and clusters that provide a statistically robust data set to assess the sensitivity of landslides to natural processes and human disturbance. For each of the potential targets, a strategized region-specific program of velocity data collection and processing would be undertaken, and these data would be integrated into a structured data schema for mapped landslides in the region. It is expected that the following velocity/displacement data would be integrated at each landslide polygon:

- Confirmation of presence or absence of measurable displacements across collection period for data utilized
- Annualized displacements to support screening different relative landslide activity zones
- Discrete velocity trend data to understand potential correlation to seasonal or multi-year trends in hydroclimatic conditions, surface vegetation change and/or human modification of the ground surface.

The above observations would be entered into a database with an architecture designed to utilize these data sets into various modelling efforts for the DSL Mapping and Classification Project and other projects that contribute to the broader Strategy. To develop a data-driven understanding of linkages between the velocity trends and extrinsic factors (such as hydroclimatic influences and human disturbance), the design report has outlined key publicly available datasets that could be integrated with velocity data and provided a high-level example of how these data could be utilized in Washington State.

Should the project be executed as outlined in this Study Design, it is expected that the products derived from the project would contribute to the overall study objectives as follows:

1. To identify distinguishing characteristics within and between DSL classes in the study area: Section 5.2.5 provides a methodology that uses statistics derived from the existing landslide inventories to support designation of landslide classes and the use of different geological and morphological attributes and measured landslide activity to define landslide clusters.
2. To determine why landslides with similar characteristics may exhibit differences in activity level: Section 5.4 provides suggestions on how to integrate and evaluate spatial and temporal data to link both physical and transient conditions to differences in landslide activity state.
3. To develop causal mechanism hypotheses for individual landslides evaluated in the field. These mechanisms might include hydrogeologic characteristics visible in active landslides: In Section 5.4.1 there is an overview provided as to a stepwise process outlining how high-quality velocity and displacement observations will be linked to landslide inventory polygons and organized by landslide classes and clusters. The collated data will be integrated with hydroclimatic and land cover datasets to attempt to identify relationships between landslide attributes and these external drivers. Section 5.5 reviews where field verification can be utilized to support validation of causal mechanisms inferred from the remote sensed data assessment.
4. To determine the best remote sensing tools, field assessment and other methods to classify DSLs in a manner that will aid our understanding of the greater or lesser potential for DSL reactivation or accelerated movement: Sections 3.0 and 5.0 provide an overview of the existing remotely sensed data and considerations for integration to best support the classification tasks. The application of the existing archived remote sensing data will support understanding as to which tools are most effective in deriving the critical variables and will support the optimization of data collection for future focus areas.
5. To define classes of DSLs within and across clusters using a suite of physical attributes based on critical variables. These classes will also be used to support future phases of the research strategy (i.e., which DSLs are most representative or illustrative for future research and modeling efforts based on the results of the classification project): Sections 5.0 and 6.0 provide significant detail around these variables and integration into future phases.
6. To test an initial hypothesis that DSLs can be effectively ranked and classified based on multiple sources of empirical evidence, and that certain classes of landslides have a particularly high or low potential for instability from forest practices. This document outlines

an approach that would subdivide landslides based on attributes such as lithology, size, rupture depth, geomorphic position, and correlate these with velocity and extrinsic factors (hydroclimate, land use, land disturbance) to assess which landforms are most sensitive to human disturbance.

When considering the overall research Strategy (UPSAG, 2020), the workplan outlined in this report is meant to provide a basis to directly inform and support the overall Strategy by providing a robust set of data and tools to understand historical trends to calibrate models that will support the understanding of the intrinsic and extrinsic contributions to landform sensitivity. Some of the other applications of the study inputs would be to:

- Support planning data acquisition and mapping to support expanding these methodologies to other regions
- Assessing how new technology advances and data availability, such as NASA’s upcoming NiSAR mission, can be integrated into future studies
- Targeting specific landslide clusters or landslides where more detailed studies could be undertaken to understand the interaction between hydroclimate, hydrology and landslide activity.

10.0 CLOSURE

We trust the above satisfies your requirements at this time. Should you have any questions or comments, please do not hesitate to contact us.

Yours sincerely,

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APPENDIX A
HISTORICAL ARCHIVED SAR DATA COVERAGES

A.1. INTRODUCTION

As part of the assessment into the feasibility of utilizing satellite interferometric synthetic aperture (InSAR) to support mapping landslide velocities in western Washington, a review of the available SAR data archives over the study area provided by the Washington State Department of Natural Resources (DNR) has been completed. Figure A-1 provides an overview of the existing SAR satellites that have been collecting data since late 1991. These coverages include both C-Band and L-Band SAR data which have different strengths and weaknesses when considering integration into the project design.

A sufficient number of SAR scenes over the imagery time period are required for time-series processing of ground displacements. Some coverages listed below lack sufficient temporal density in some areas to create a meaningful displacement time series. Please refer to the accompanying report for more information regarding the number of images required for a given duration and further considerations in leveraging InSAR processing for displacement estimates.

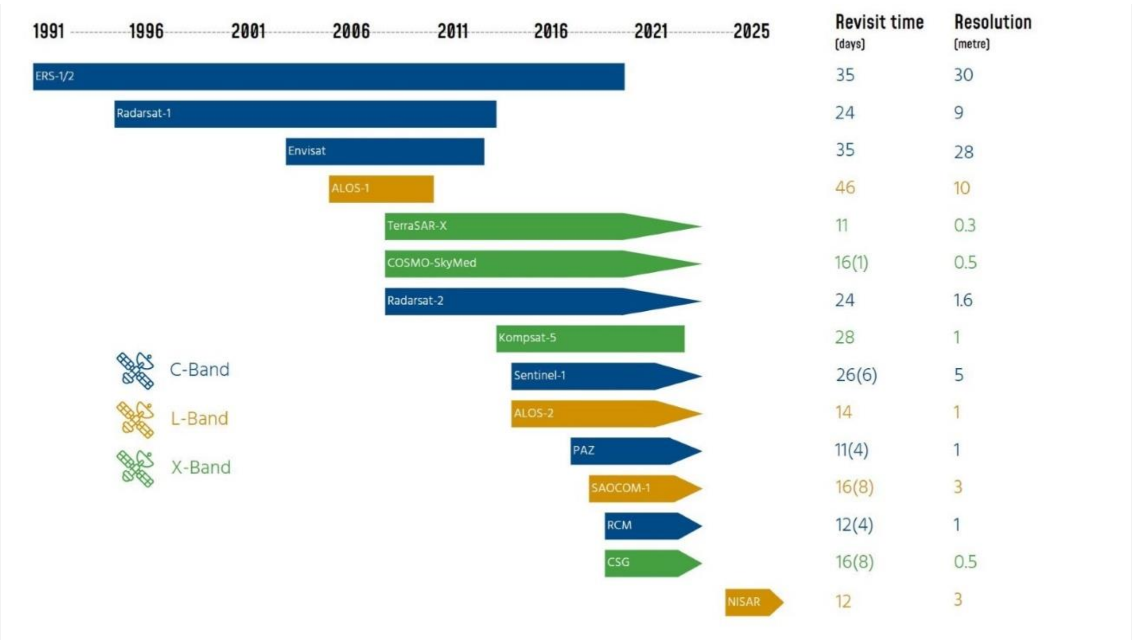


Figure A-1. SAR coverages considered for study design.

Whether any of these data can be utilized to undertake InSAR processing over the study area is dependent on both the spatial and temporal coverages of these data. The following provides an overview of the existing SAR data coverages available over Whatcom, Snohomish, King and Pierce Counties for the period between 1992 and present.

A.2. C-BAND COVERAGES

A.2.1. ERS-1 and ERS-2 (1992 to 2008)

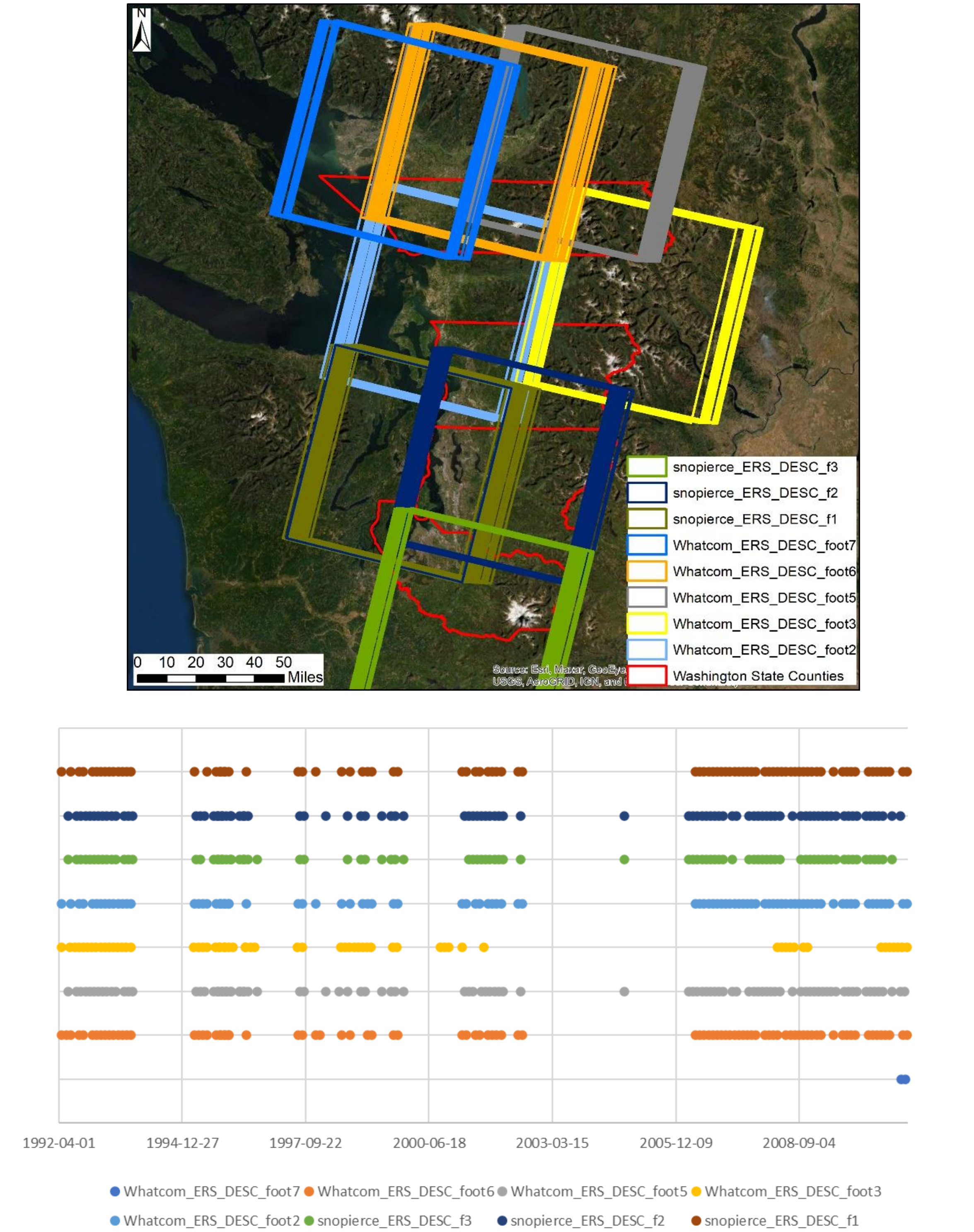
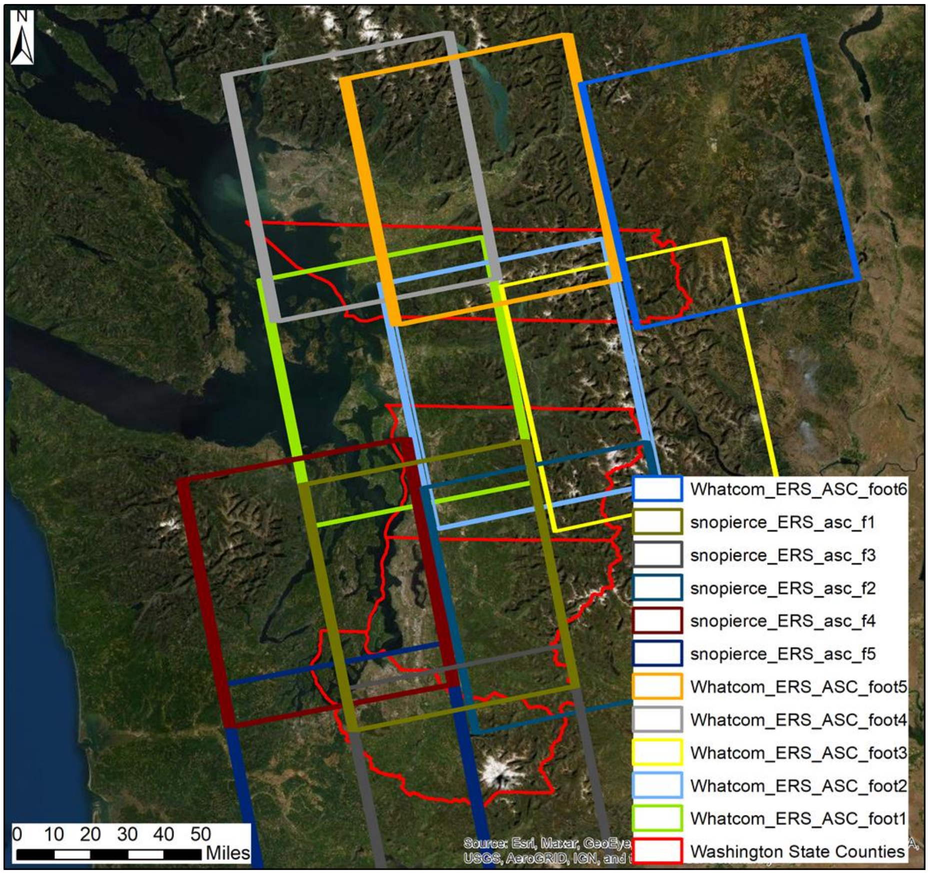


Figure A-2. Descending ERS spatial (top) and temporal (bottom) coverage of the study area.



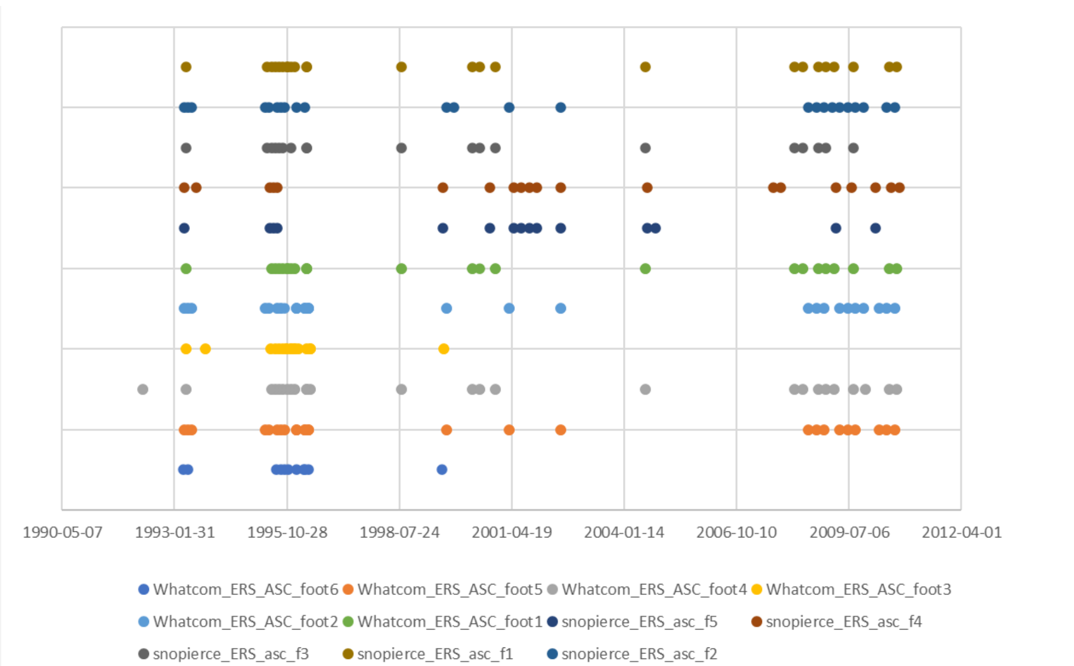


Figure A-3. Ascending ERS spatial (top) and temporal (bottom) coverage of the study area.

A.2.2 Radarsat-1

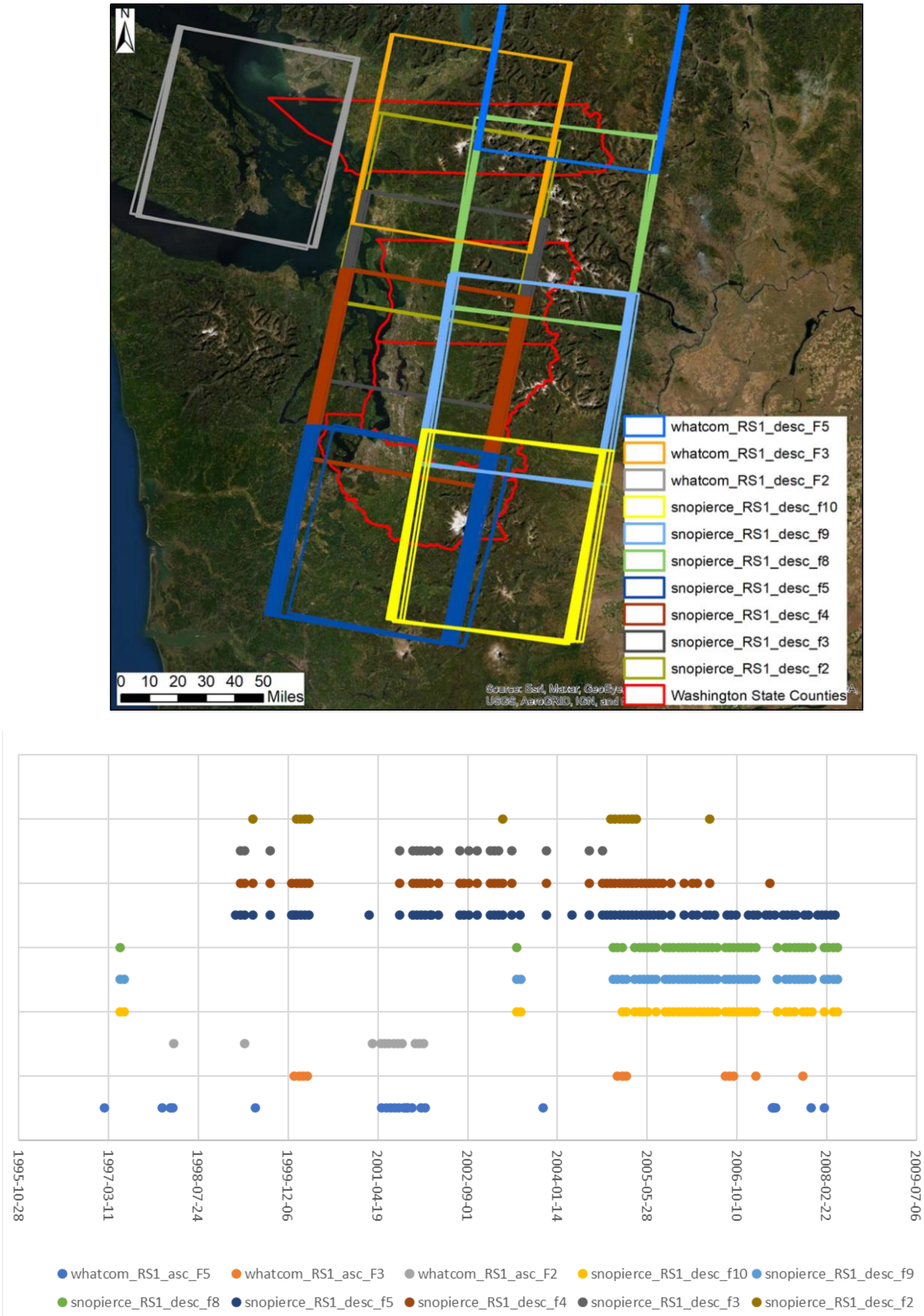
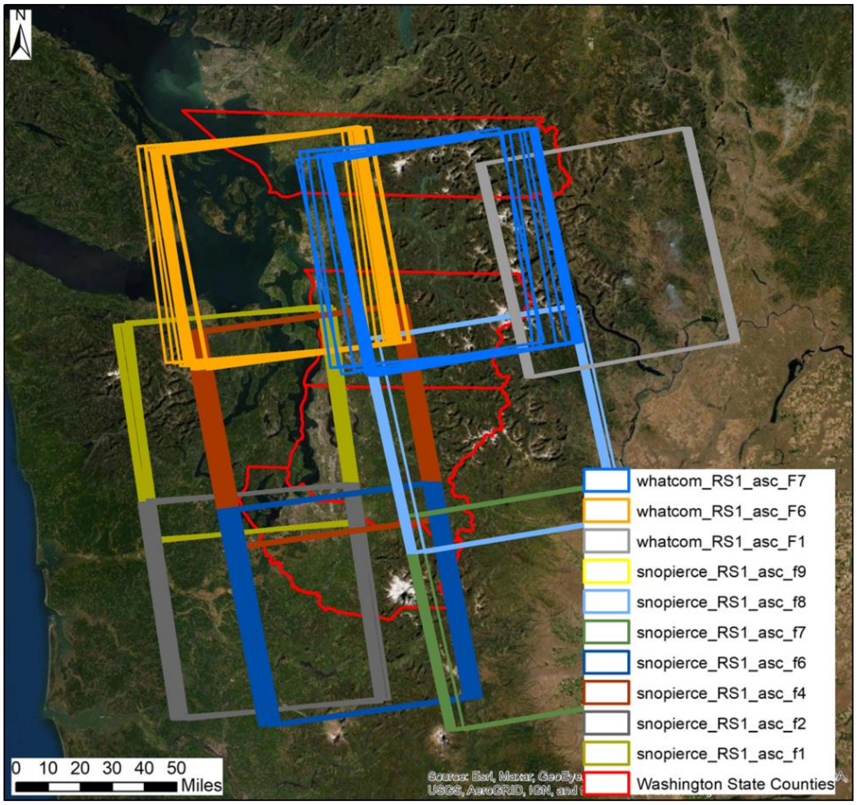


Figure A-4. Descending Radarsat-1 spatial (top) and temporal (bottom) coverage over the study area.



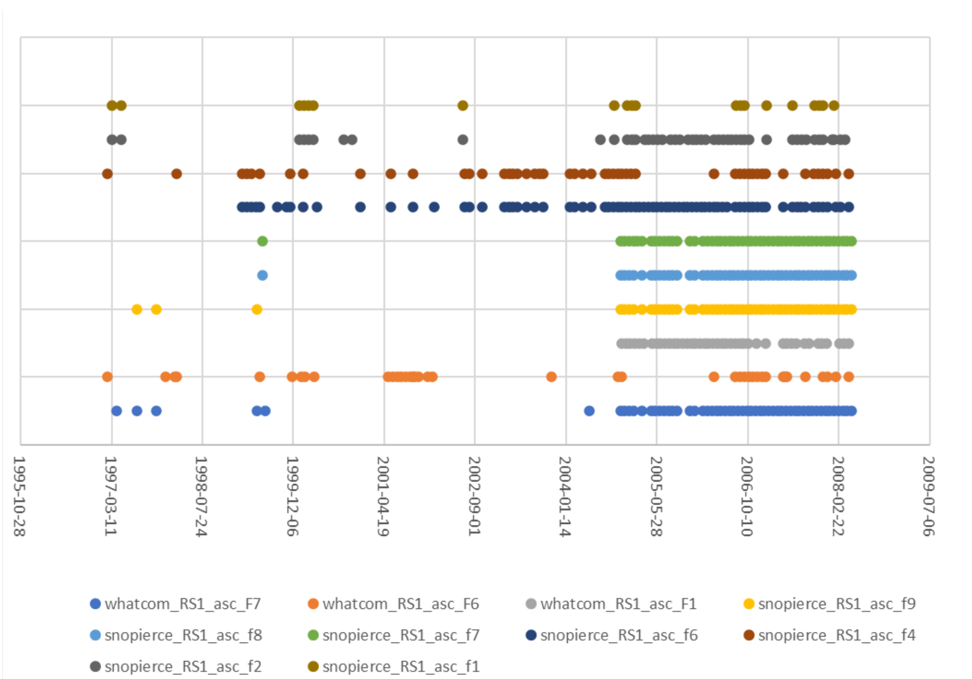
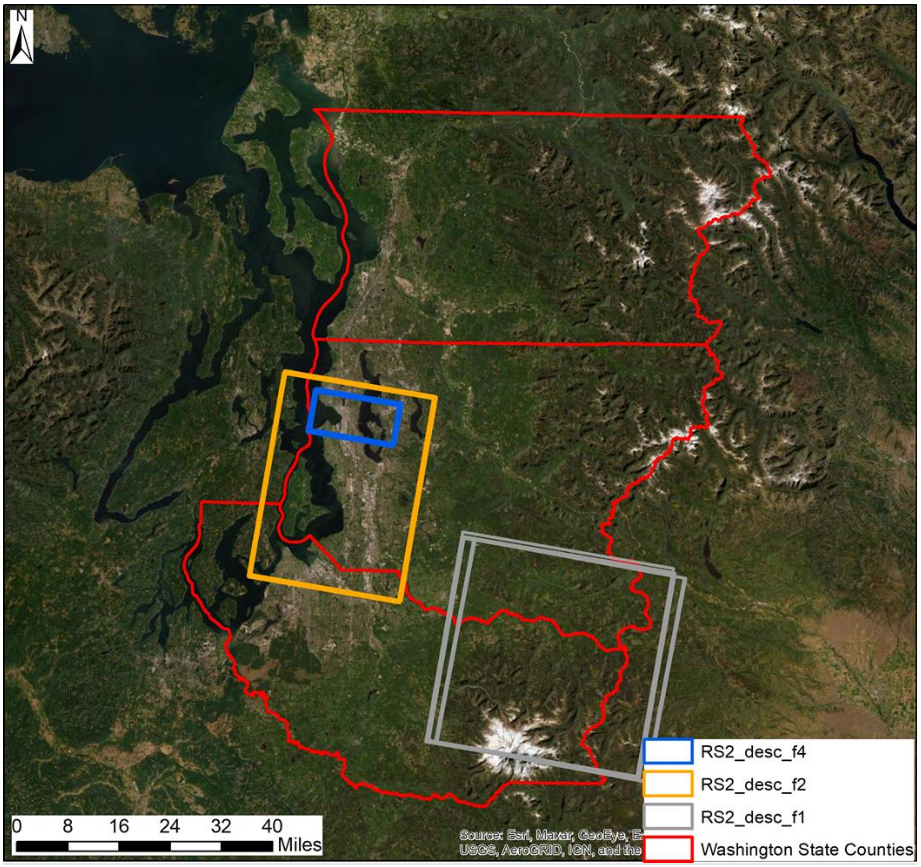


Figure A-5. Ascending Radarsat-1 spatial (top) and temporal (bottom) coverages of the study area.

A.2.3 Radarsat-2



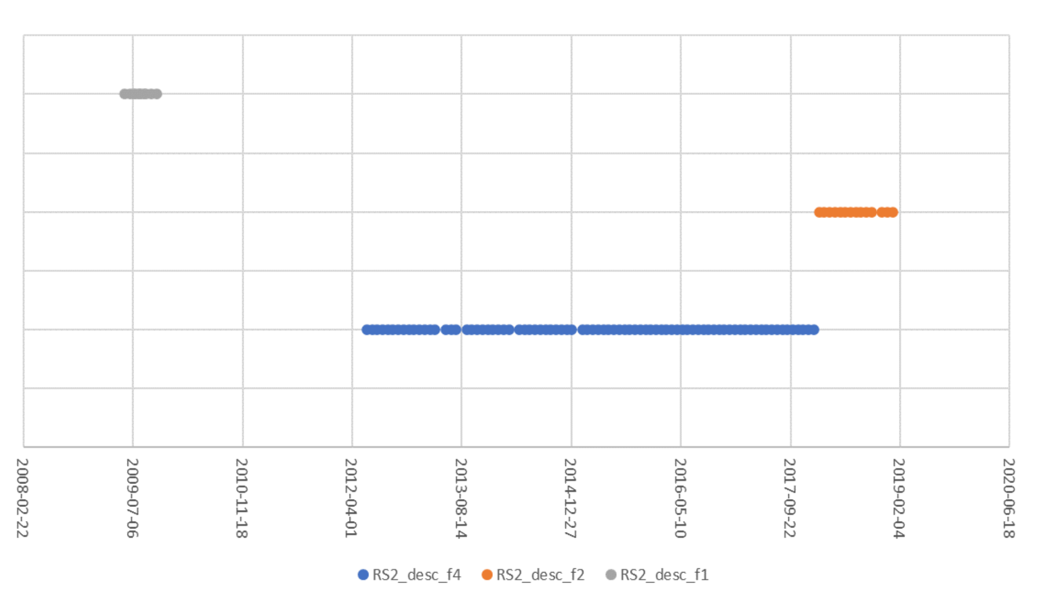


Figure A-6. Descending Radarsat-1 spatial (top) and temporal (bottom) coverage of the study area.

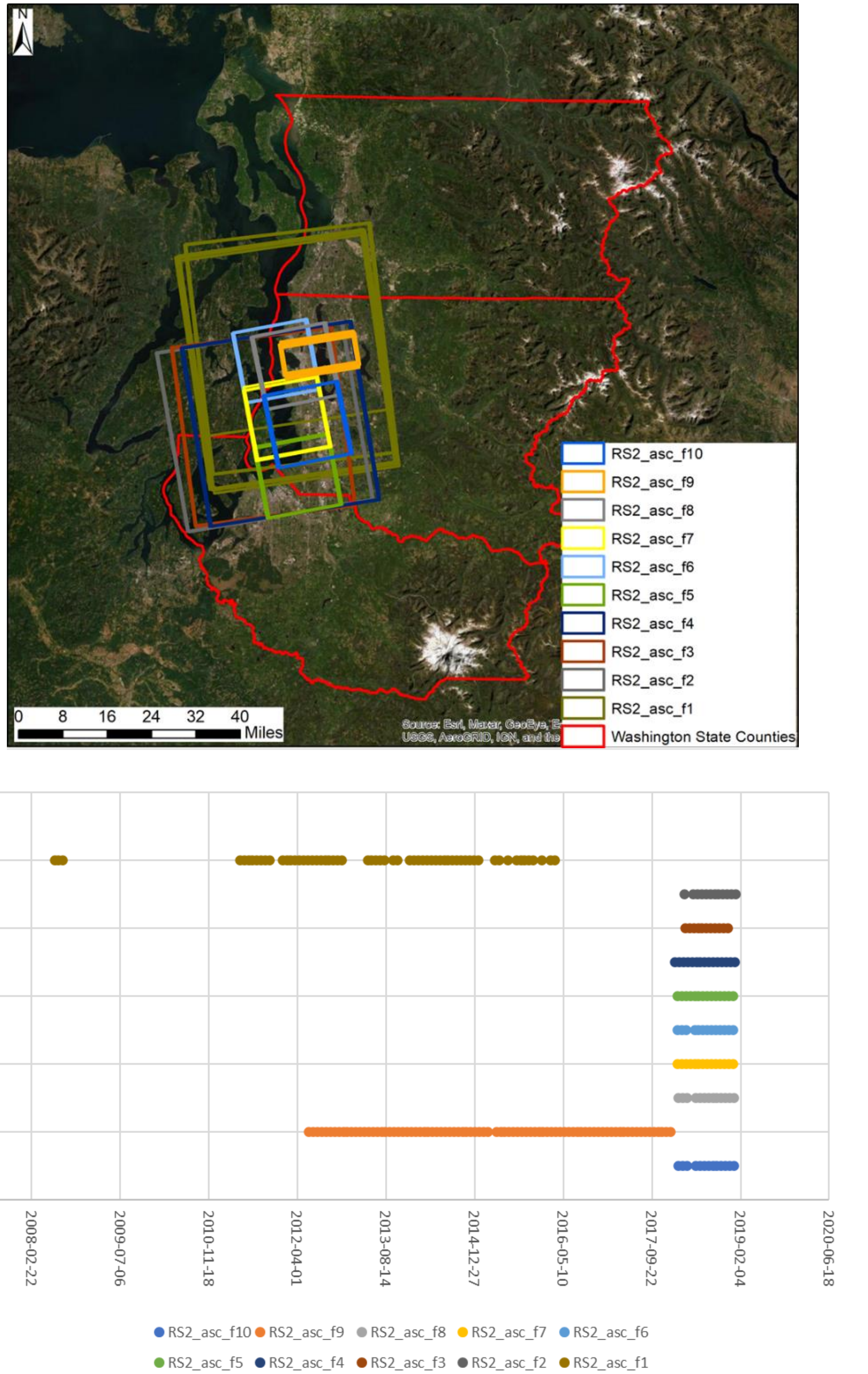
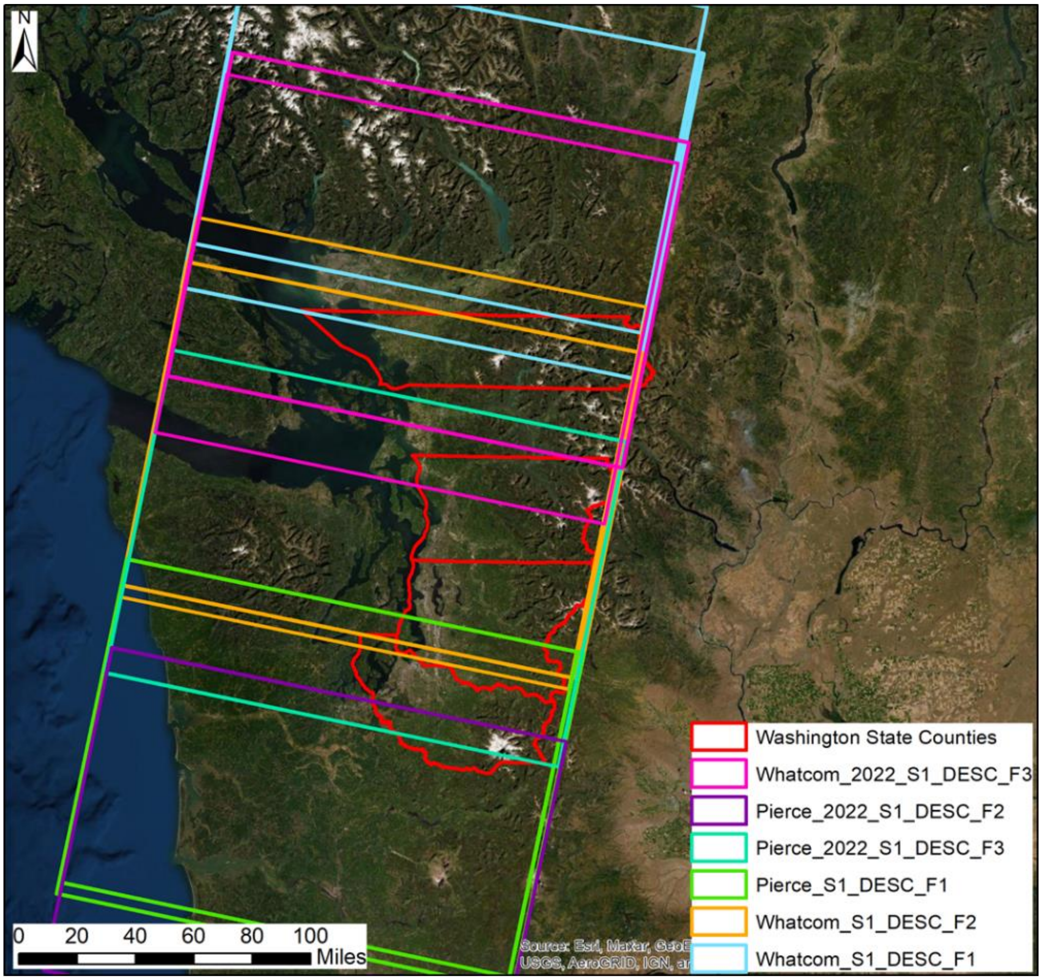


Figure A-7. Ascending Radarsat-1 spatial (top) and temporal (bottom) coverage of the study area.

A.2.4. Sentinel-1 (2014 to Present)



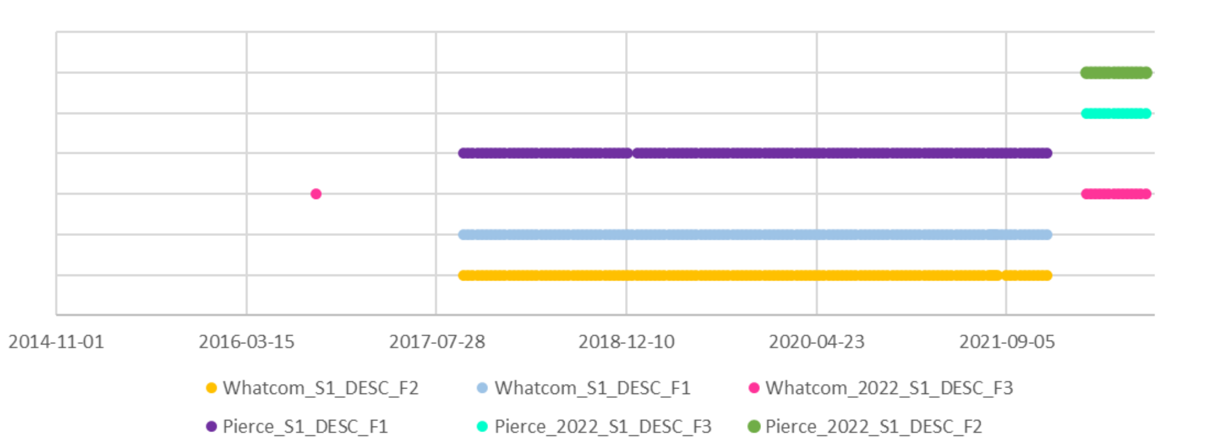


Figure A-8. Descending Sentinel-1 spatial (top) and temporal (bottom) coverages over the study area.

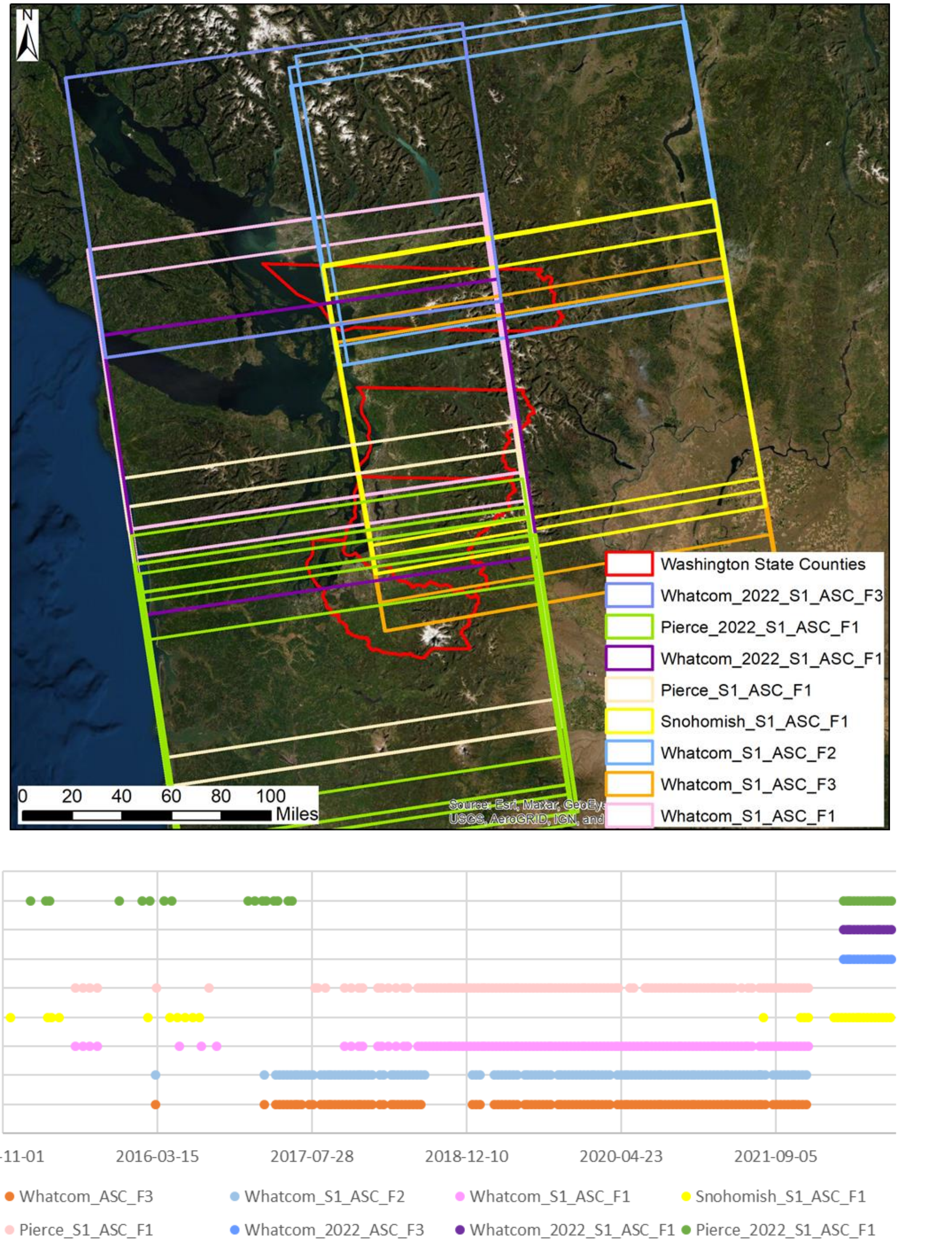
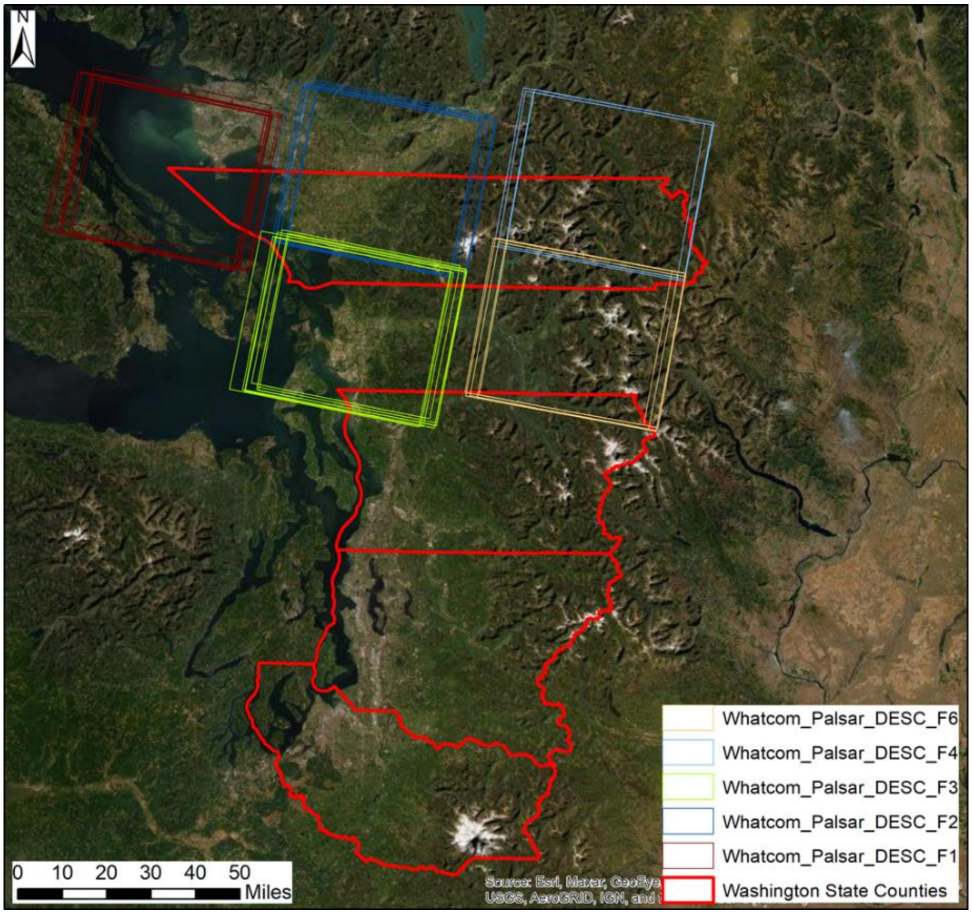


Figure A-9. Ascending Sentinel-1 spatial (top) and temporal (bottom) coverage over the study area.

A.3 L-BAND COVERAGES

A.3.1. ALOS-1 (2006 to 2011)



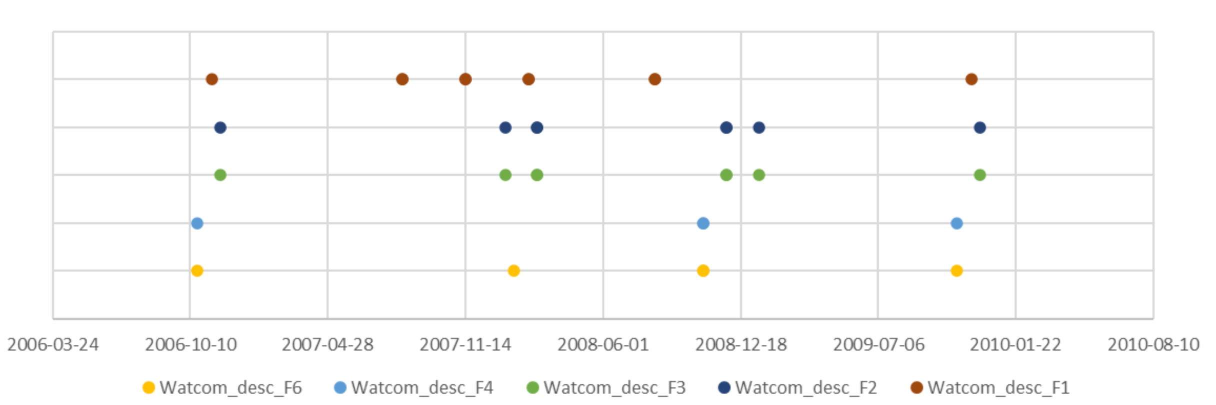


Figure A-10. Descending ALOS-1 spatial (top) and temporal (bottom) coverage over Whatcom County.

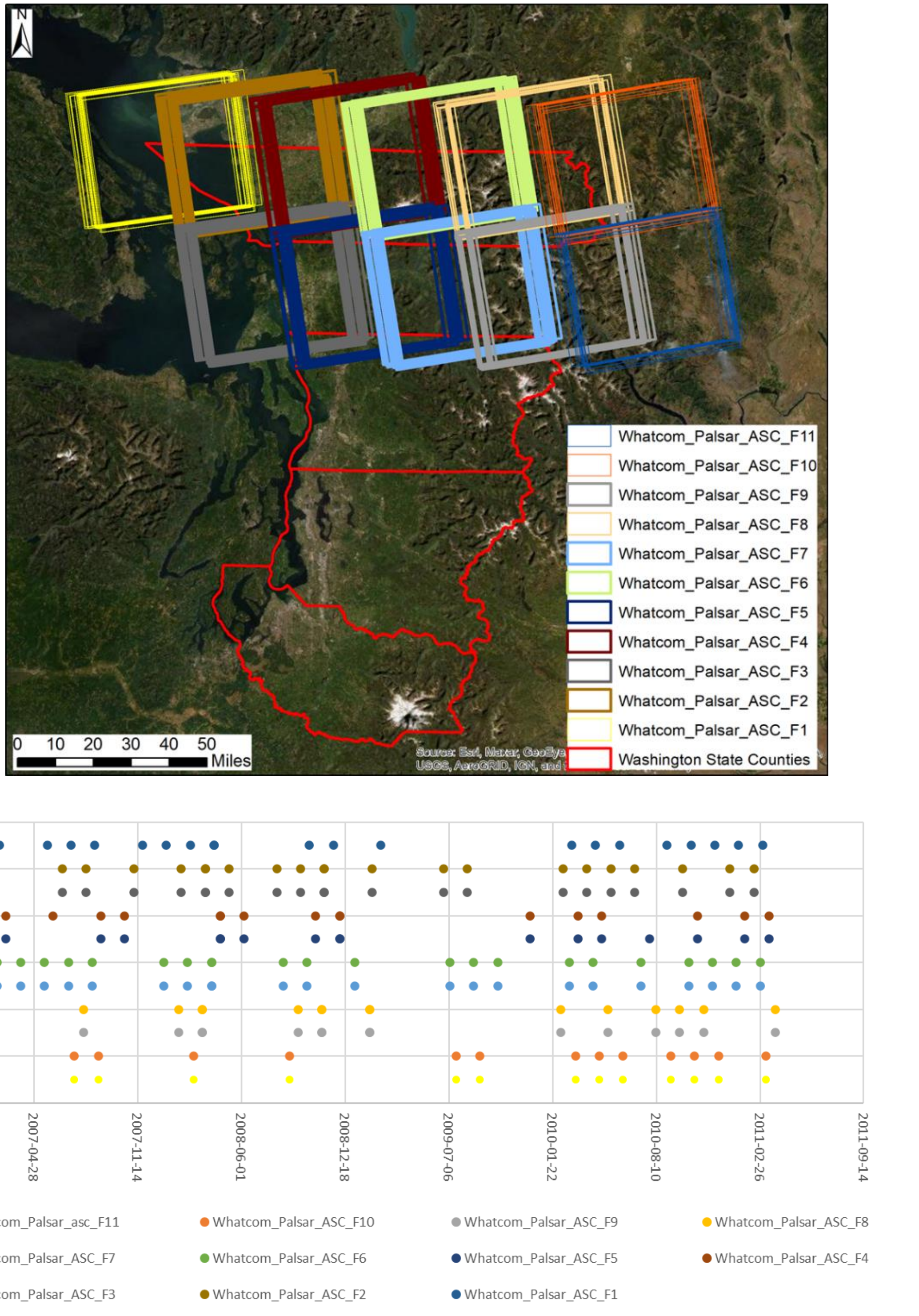
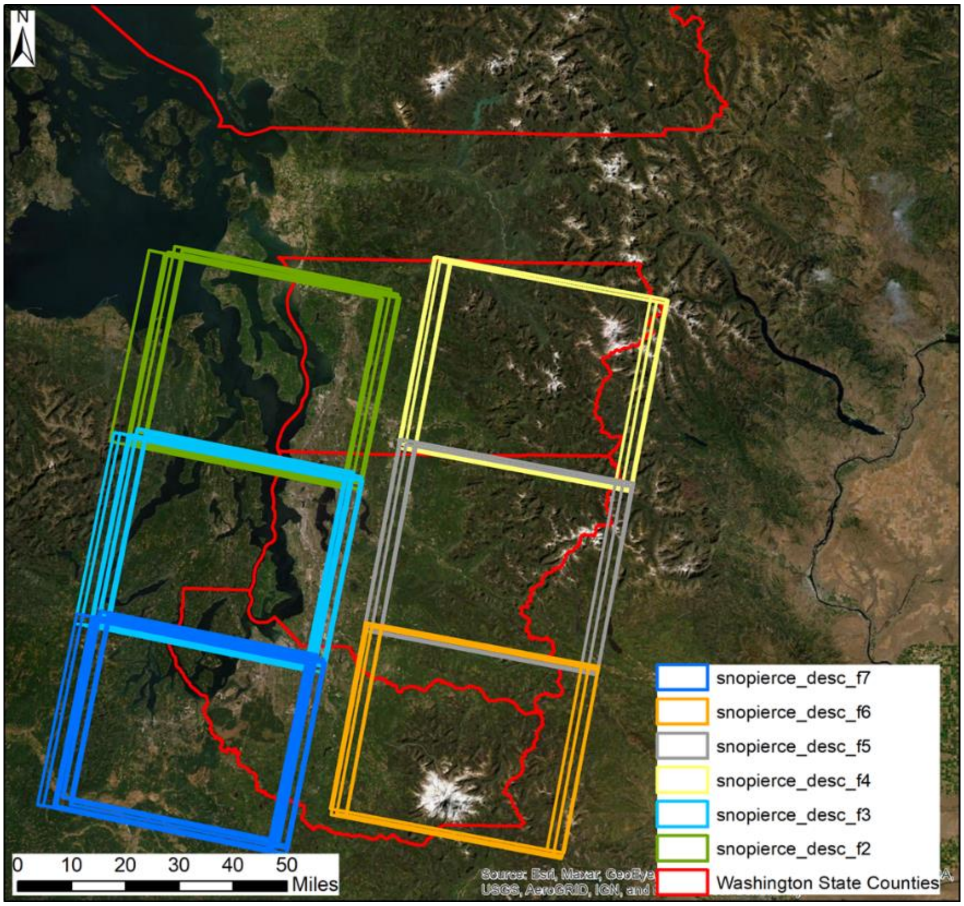


Figure A-11. Descending ALOS-1 spatial (top) and temporal (bottom) coverage over Whatcom County.

A.3.3.1 Snohomish to Pierce



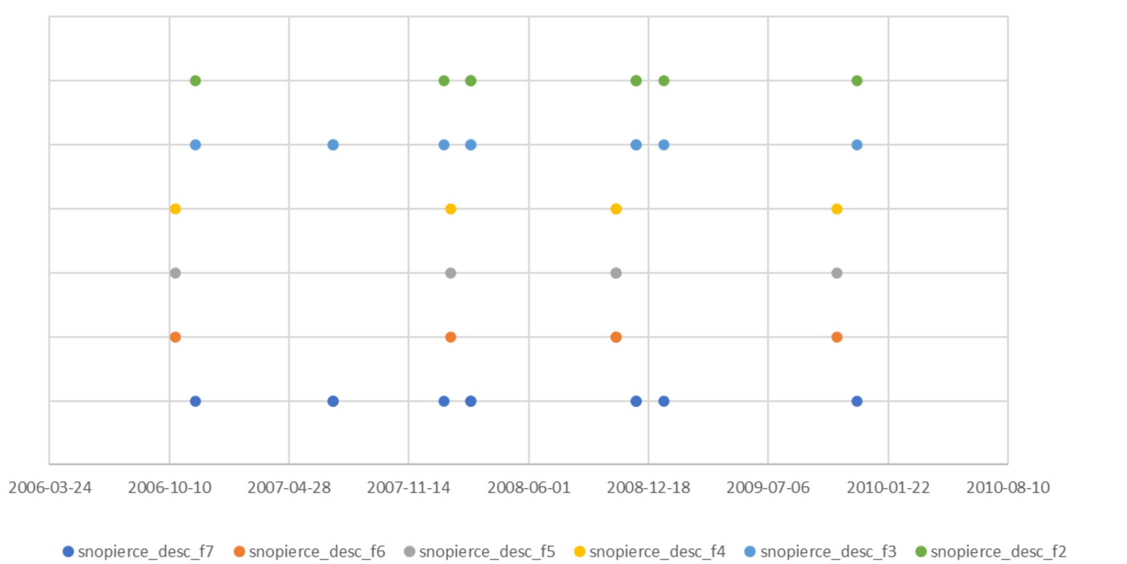


Figure A-12. Descending ALOS-1 spatial (top) and temporal (bottom) coverage over Snohomish, King and Pierce Counties.

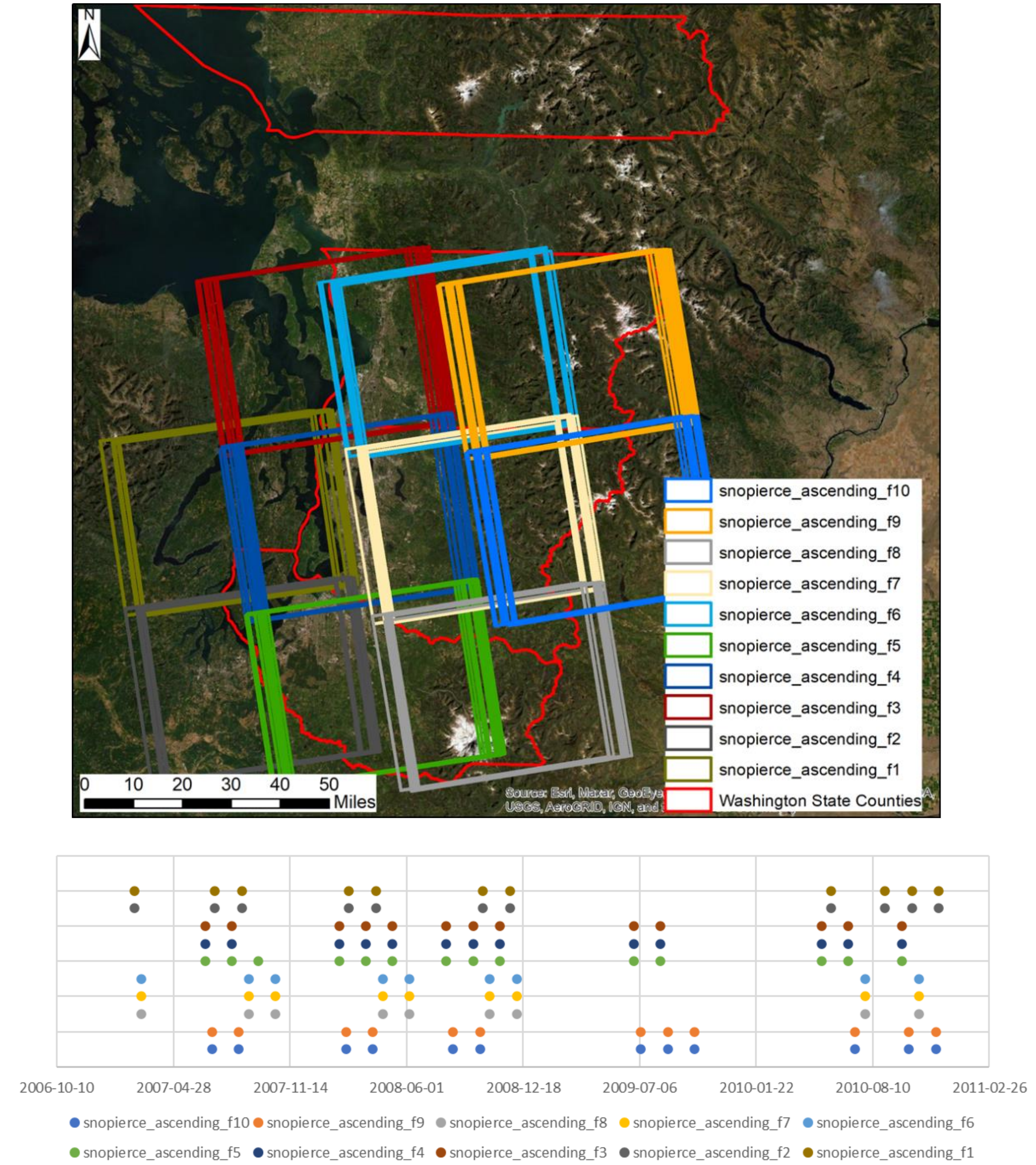
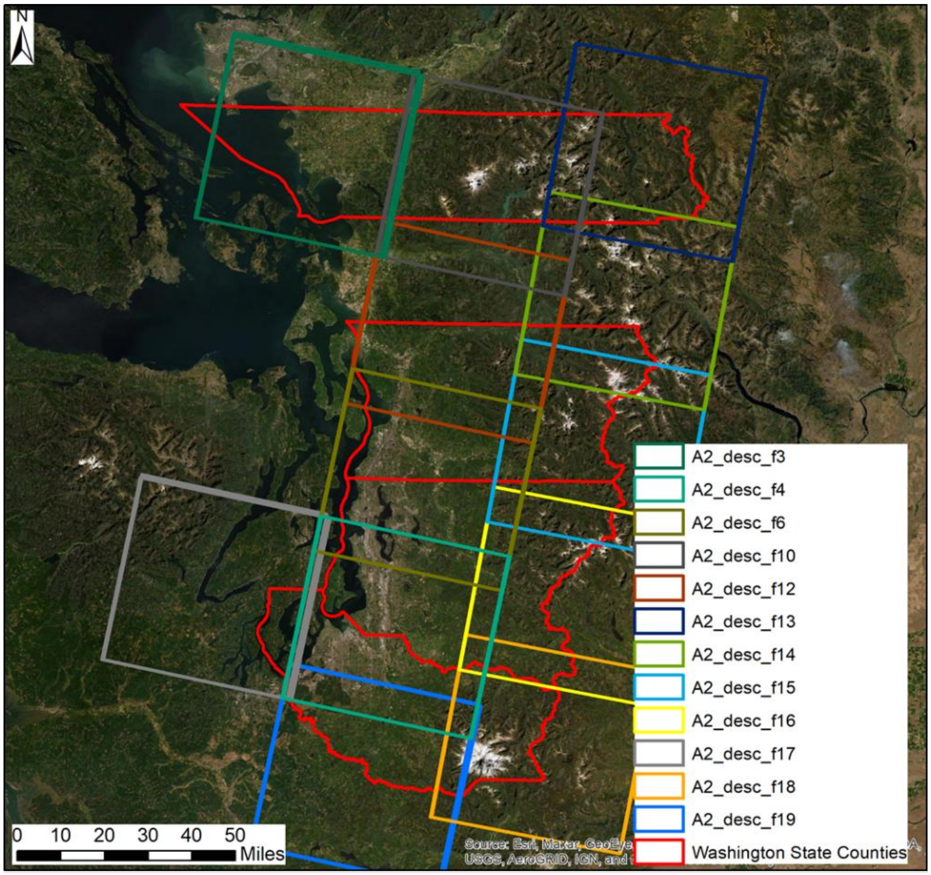


Figure A-13. Ascending ALOS-1 spatial (top) and temporal (bottom) coverage over Snohomish, King and Pierce Counties.

A.3.2 ALOS-2 (2014 to Present)



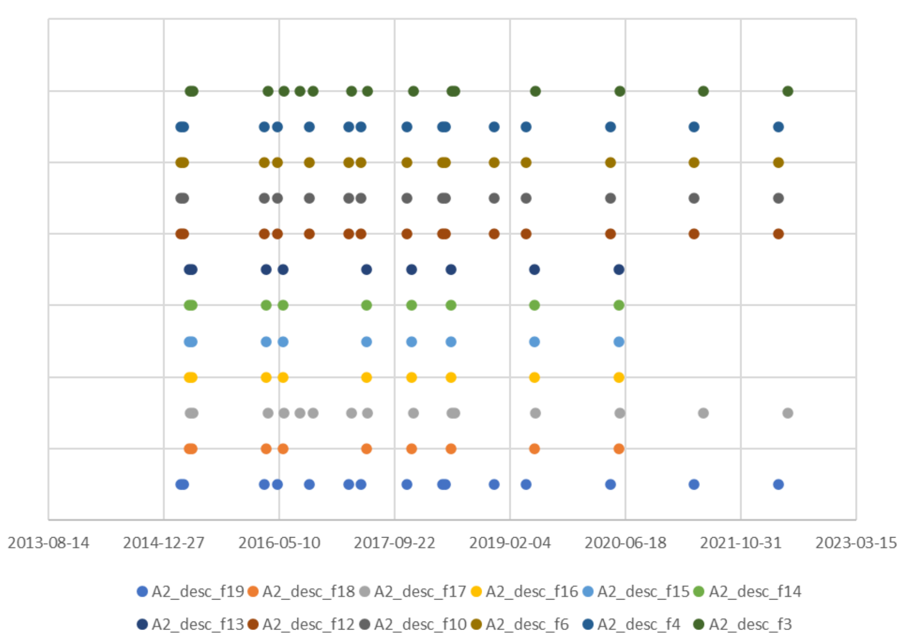


Figure A-14. Descending ALOS-2 spatial (top) and temporal (bottom) coverage over the study area.

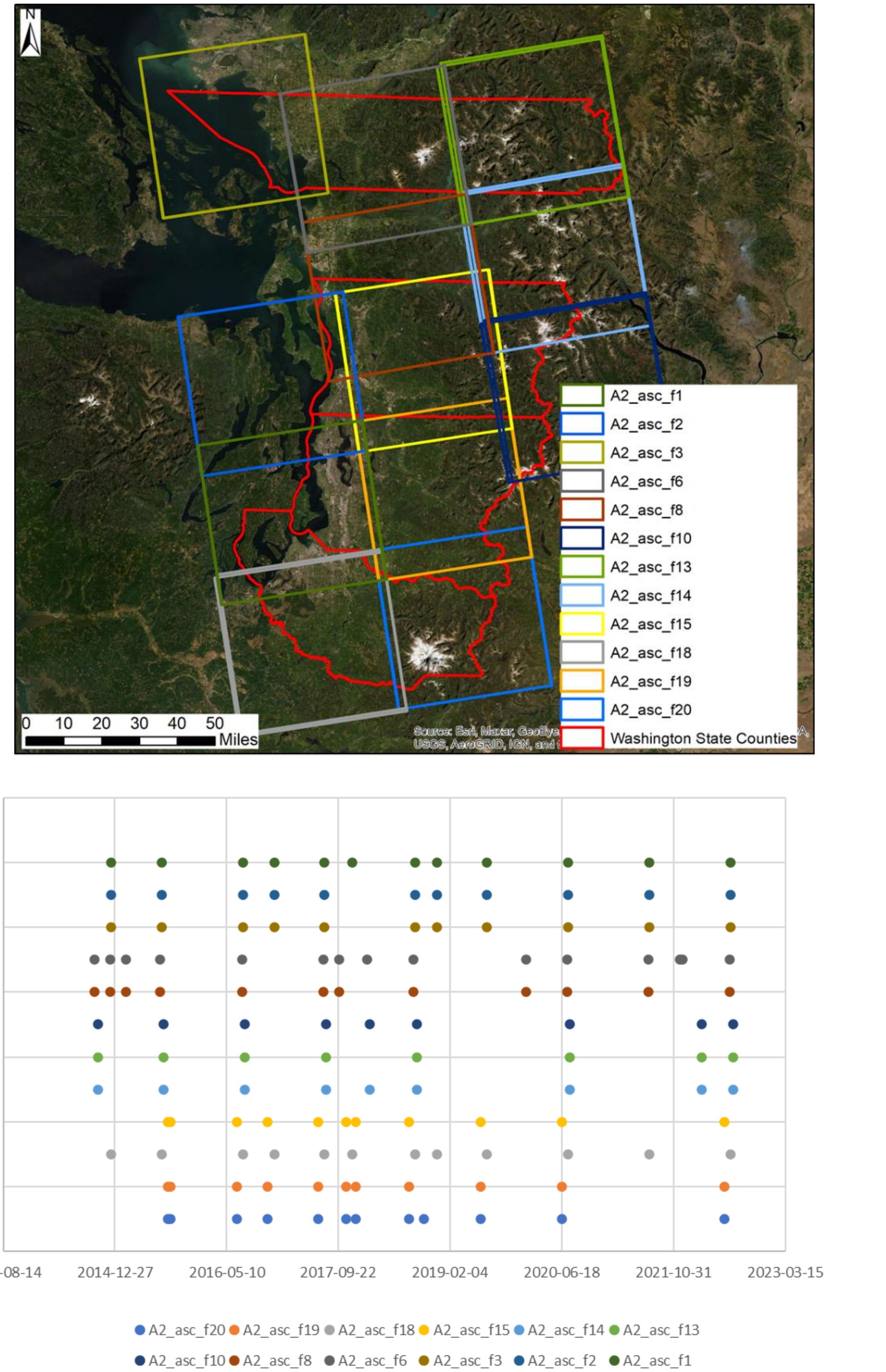


Figure A-15. Ascending ALOS-2 spatial (top) and temporal (bottom) coverage over the study area.