

Reconstructing topographic change from historical aerial images with photogrammetry and geostatistics

Friedrich Alexander Knuth

A dissertation submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2024

Reading Committee:

David Shean, Chair

Jessica Lundquist

Amaury Dehecq

Shad O'Neel

Program Authorized to Offer Degree:

Civil & Environmental Engineering

©Copyright 2024
Friedrich Alexander Knuth

University of Washington

Abstract

Reconstructing topographic change from historical aerial images with photogrammetry and geostatistics

Friedrich Alexander Knuth

Chair of the Supervisory Committee:
David Shean
Civil & Environmental Engineering

Precisely measuring the Earth’s changing surface on decadal to centennial time scales is critical for many science and engineering applications, yet long-term records of quantitative landscape change are often temporally and geographically sparse. Archives of scanned historical aerial photographs provide an opportunity to augment these records and capture the historical state of the Earth’s surface at high resolution. However, historical images remain underutilized for quantitative analysis in Earth system science due to limitations of the input datasets and methodologies.

In the first chapter of this dissertation, I developed an automated method to photogrammetrically reconstruct high-resolution digital elevation models (DEMs) from historical aerial photographs, with a particular focus on glacierized mountain ranges in the Western United States. Processing historical photographs at scale is challenging because images can be distorted due to film degradation and scanning artifacts, camera positions are often inaccurate or unknown, and the photographs were often collected with limited stereo overlap or inadequate stereo geometry. The method developed in this chapter addresses these challenges and is accompanied by publicly-released software that facilitates automated image standardization, block detection, multi-temporal camera model optimization, and robust DEM coregistration

to high (e.g. 1 m) and low (e.g. 30 m) resolution reference terrain.

In the second chapter, I designed a temporal Gaussian Process regression framework to interpolate spatially and temporally continuous surface elevation estimates from the DEMs produced in the first chapter. DEMs generated from stereo photogrammetry often lack data in areas where there are insufficient match points between images to confidently triangulate surface elevations. Data voids are problematic for glaciological analysis because a continuous estimate of the surface elevation change across the entire glacier is required to distinguish a change in mass from a kinematic redistribution of ice. The framework leverages the per-pixel temporal surface elevation covariance to predict an elevation estimate at any time step. Furthermore, the software that executes this framework is memory-efficient, user-friendly, and open-source, which enables processing at full resolution on any machine and thereby democratizes the methodology for the community.

In my final chapter, I produced 70 years ($\sim 1950 - 2020$) of continuous topographic measurements and identified multiple periods of glacier advance, retreat, and stability. Mountain glaciers are perennial sources of freshwater that shape the natural landscape and provide important ecosystem services, such as aquatic stream habitat for keystone fish species and potential energy for hydropower generation. Over the past century, many glaciers in Western North America have lost mass and steadily retreated in response to long-term climate forcing. Some glaciers, especially those on stratovolcanoes with high-altitude accumulation areas and steep elevation gradients, present decadal climate-driven advances and kinematic movement on shorter (interannual) timescales. These changes can lead to significant sediment transport and devastating outburst floods that damage downstream infrastructure. To evaluate the method developed in the second chapter of this dissertation, I focused my analysis on three well-studied glaciers in the Pacific Northwest of the United States – South

Cascade Glacier in the Cascade Range, Nisqually Glacier at Mount Rainier, and Easton Glacier at Mount Baker. The DEMs generated by this analysis characterize multiple periods of glacier advance, retreat, and stability at these sites, which can provide useful constraints for geophysical glacier model calibration. These long-term time series of high spatial and temporal resolution estimates produced by the methods developed in this dissertation can help constrain projections of future glacier mass change under different climate forcing and mitigate impacts on downstream water resources, infrastructure, and geohazard risk.

TABLE OF CONTENTS

	Page
List of Figures	vii
List of Tables	xix
Glossary	xx
Chapter 1: Historical Structure from Motion (HSfM): Automated processing of historical aerial photographs for long-term topographic change analysis	1
1.1 Abstract	1
1.2 Introduction	2
1.3 Study sites	4
1.3.1 Mount Baker	5
1.3.2 South Cascade Glacier	5
1.4 Data	5
1.4.1 Photograph acquisition	6
1.4.2 Image scanning	6
1.4.3 Camera position metadata	8
1.4.4 Camera calibration	8
1.4.5 Reference DEM data	9
1.5 Methods	9
1.5.1 Historical image and metadata preprocessing	10
1.5.1.1 Image standardization	10
1.5.1.1.1 Fiducial marker detection	10
1.5.1.1.2 Affine transformation to match calibration data . .	13
1.5.1.1.3 Affine transformation to match mean marker positions	13
1.5.1.1.4 Pseudofiducial marker detection without affine transformation	13
1.5.1.2 Principal point determination and frame removal	14

1.5.1.3	Image enhancement	15
1.5.1.4	Camera position estimation	15
1.5.2	Structure from Motion	15
1.5.2.1	Image matching	16
1.5.2.2	Bundle adjustment	16
1.5.2.3	Dense multi-view stereo reconstruction	16
1.5.3	DEM co-registration	17
1.5.3.1	DEM gridding	17
1.5.3.2	Stable surface mask preparation	17
1.5.3.3	Iterative Closest Point (ICP) co-registration	18
1.5.3.4	Nuth and Kääb (2011) co-registration	18
1.5.4	Updating camera pose and orthomosaic generation	19
1.5.5	Single date - multiple blocks	19
1.5.6	Multiple dates - multiple blocks (4D SfM)	19
1.5.7	Accuracy assessment	20
1.5.7.1	Absolute and relative DEM accuracy	20
1.5.7.2	Spatially autocorrelated error	21
1.5.7.3	Reference DEM sensitivity testing	21
1.5.7.4	Comparison of automated HSfM method with manual GCP method	22
1.5.7.5	Camera position accuracy	22
1.5.7.6	Evaluation of image standardization approaches	22
1.6	Results	23
1.6.1	Easton Glacier, 1977	23
1.6.2	South Cascade Glacier, 1967–1997	24
1.6.2.1	Comparison with manual GCP method	28
1.6.2.2	Image standardization	30
1.6.3	Mount Baker, 1970–1992	30
1.6.3.1	Intrinsic parameter refinement with 4D SfM	31
1.6.3.2	Reference DEM sensitivity	31
1.6.4	Processing time	32
1.7	Discussion	34
1.7.1	Image matching	34

1.7.2	Availability and distribution of stable surfaces	34
1.7.3	Advantages of an automated processing approach	35
1.7.4	Toward fully automated historical image processing	35
1.7.4.1	Reference DEM preparation	35
1.7.4.2	Interior orientation preparation	36
1.7.4.3	Exterior orientation preparation	36
1.7.4.4	4D SfM for other historical archives and larger blocks	37
1.7.4.5	User-defined thresholds and parameters	39
1.7.5	Toward fully open-source software	39
1.7.6	Science applications	40
1.7.6.1	Geodetic glacier mass-balance and velocity	40
1.7.6.2	Elevation change rate precision and other applications	40
1.8	Conclusions	41
Chapter 2:	Are partial DEMs useful? A memory-efficient method to estimate long-term glacier surface elevation change from spatially and temporally sparse measurements	44
2.1	Abstract	44
2.2	Introduction	45
2.3	Study sites	47
2.4	Data	47
2.4.1	Digital Elevation Models (DEMs)	47
2.4.1.1	Historical Structure from Motion (HSfM) DEM data	49
2.4.1.2	EarthDEM data	49
2.4.1.3	USGS DEM data	50
2.4.1.4	Reference DEM data	51
2.4.2	Evaluation data	51
2.5	Methods	52
2.5.1	DEM co-registration	52
2.5.2	DEM time-series stacking	52
2.5.3	Gaussian Process regression	53
2.5.3.1	Defining a Gaussian Process kernel to estimate glacier surface elevation change	54
2.5.3.2	Outlier filtering	57

2.5.4	Evaluation analysis	58
2.5.4.1	Comparison to Nisqually glacier cross-sectional profiles . . .	58
2.5.4.2	Including vs excluding partial DEMs	59
2.5.4.3	Estimating seasonal surface elevation change	59
2.6	Results	59
2.6.1	Gaussian Process regression results	61
2.6.2	Multi-decadal surface elevation change at Nisqually glacier	62
2.6.3	Improved accuracy in the ablation zone by inclusion of partial DEMs	62
2.6.4	Seasonal bias correction	62
2.7	Discussion	64
2.7.1	Spatial vs temporal data interpolation	64
2.7.2	Seasonal bias mitigation	65
2.7.2.1	Other approaches for seasonal bias correction in glaciology .	67
2.7.3	Towards a generic GP regression glacier kernel design	67
2.7.3.1	Normalizing the dependant variable	67
2.7.3.2	Automated methods for kernel determination	67
2.7.3.3	Creating and cross-validating an adaptive GP kernel	68
2.7.3.4	Evaluation with independent measurements	68
2.7.3.5	Multi-dimensional Gaussian Process regression	69
2.7.4	Large dataset processing optimization	69
2.8	Conclusions	69
Chapter 3:	Measuring long-term geodetic glacier mass balance and kinematics at high spatiotemporal resolution	71
3.1	Abstract	71
3.2	Introduction	72
3.3	Study sites	73
3.3.1	South Cascade Glacier, Cascade Range	73
3.3.2	Easton Glacier, Mount Baker	74
3.3.3	Nisqually Glacier, Mount Rainier	74
3.4	Data	74
3.4.1	Annual void-free DEM surfaces	74
3.4.2	Auxiliary data	75

3.4.2.1	In-situ glacier mass-balance data	76
3.4.2.2	Glacier area outlines	76
3.4.2.3	Glacier center flowlines	76
3.4.2.4	Climate data	77
3.5	Methods	77
3.5.1	Delineating glacier outlines	77
3.5.2	Computing geodetic mass balance	77
3.5.2.1	Evaluation against annual in-situ glacier mass-balance measurements	78
3.5.3	Computing elevation change along glacier center flowlines	78
3.6	Results	79
3.6.1	Glacier outlines	79
3.6.2	Geodetic mass balance comparison	79
3.6.2.1	South Cascade Glacier (SCG) mass balance	80
3.6.2.2	Easton Glacier mass balance	82
3.6.2.3	Nisqually Glacier mass balance	82
3.6.3	Surface elevation change at center flowlines	82
3.7	Discussion	85
3.7.1	Temporal resolution and fidelity of surface elevation estimates	85
3.7.2	Comparison with in-situ mass-balance estimates	86
3.7.3	Converting glacier volume to mass	87
3.7.4	Kinematic waves at Nisqually Glacier	87
3.7.5	Improved center flowline estimates	87
3.7.6	Model calibration with continuous geometric time series	88
3.8	Conclusions	88
Chapter 4:	Contributions to collaborative efforts	90
4.1	An Object Storage for Distributed Acoustic Sensing (Ni et al., 2024)	90
4.1.1	Abstract	90
4.1.2	CRediT author contribution	90
4.2	Multi-decadal erosion rates from glacierized watersheds on Mount Baker, Washington, USA, reveal topographic, climatic, and lithologic controls on sediment yields. Geomorphology (Schwat et al., 2023)	91
4.2.1	Abstract	91

4.2.2	CRediT author contribution	92
4.3	icepyx: querying, obtaining, analyzing, and manipulating ICESat-2 datasets (Scheick et al., 2023)	92
4.3.1	Abstract	92
4.3.2	CRediT author contribution	92
4.4	Observing glacier elevation changes from spaceborne optical and radar sensors – an inter-comparison experiment using ASTER and TanDEM-X data (Piermattei et al., in review)	92
4.4.1	Abstract	92
4.4.2	CRediT author contribution	93
4.5	Deglaciation in the Tetons, Little Ice Age to 2021 (Case et al., in prep) . . .	94
4.5.1	Abstract	94
4.5.2	CRediT author contribution	94
4.6	Accelerating rates of glacier change and topographic controls, Glacier National Park, MT, USA: 1966-2021 (McNeil et al., in prep)	95
4.6.1	Abstract	95
4.6.2	CRediT author contribution	95
Appendix A: Supplementary Material for Chapter 1: Historical Structure from Motion (HSfM): Automated processing of historical aerial photographs for long-term topographic change analysis		
A.1	Vertical datum conventions for NAGAP altitude and elevation metadata . .	114
A.2	Tables	116
A.3	Figures	120
Appendix B: Supplementary Material for Chapter 2: Are partial DEMs useful? A memory-efficient method to estimate long-term glacier surface elevation change from spatially and temporally sparse measurements		
B.1	Functions	134
B.2	Tables	135
B.3	Figures	146
Appendix C: Supplementary Material for Chapter 3: Measuring long-term geodetic glacier mass balance and kinematics at high spatiotemporal resolution		
C.1	Figures	153

LIST OF FIGURES

Figure Number	Page
1.1 Coverage map for scanned North American Glacier Aerial Photography (NAGAP) imagery acquired between 1964 and 1997 across western North America available from the NSF Arctic Data Center. Hexagon colors show the total number of frames within each ~ 25 km bin ($\sim 1,600$ km ² area). Basemap shows surface elevation in meters above the WGS84 ellipsoid from the 3-arcsecond Copernicus DEM (European Space Agency, 2022), resampled to a 1 km grid with Albers Equal Area projection. Annotations call out hexagon cells containing our study sites, with inset maps for: A) Mount Baker site with Randolph Glacier Inventory (RGI) v6.0 outlines from 1974 source imagery (purple) and Easton Glacier highlighted in blue, and B) South Cascade Glacier site with RGI outline from 1958 source imagery.	7
1.2 Historical Structure from Motion (HSfM) automated workflow for the <i>single date - single block</i> mode.	11
1.3 Examples of fiducial and psuedofiducial markers in North American Glacier Aerial Photography (NAGAP) images. A) Sample NAGAP image acquired on 1994-09-06 over the South Cascade Glacier site (NAGAP_94V3_211) with insets showing detail of mid-side (red) and corner (green) fiducial markers. B) Sample NAGAP image acquired on 1977-09-27 over the Easton Glacier site (NAGAP_77V6_065) with insets showing detail of mid-side pseudofiducial markers (blue). Portions of the top, right, and bottom markers are missing due to problematic cropping during scanning, and left marker tip is slightly bent. See Figure A.4 for additional NAGAP fiducial and pseudofiducial templates available for marker detection.	12
1.4 Iterative camera position refinement for the 1977-09-27 North American Glacier Aerial Photography (NAGAP) images over Easton Glacier. (A) Google satellite basemap (imagery source date 2016-07-28) with initial camera positions (blue), positions after relative bundle adjustment (orange) and final positions after co-registration with the 2015 lidar reference digital surface model (green). Gray labels identify frame numbers for the first and last images in the flight line. Dashed arrows show translation vectors for image #69. (B) Corresponding camera elevation refinement in meters above the WGS84 ellipsoid.	24

1.5	Results for Historical Structure from Motion (HSfM) processing of the eight North American Glacier Aerial Photography (NAGAP) images collected on 1977-09-27 over Easton Glacier. (A) 2015-08-27 airborne lidar reference digital surface model (DSM) with 1 m posting. (B) 1977-09-27 historical NAGAP digital elevation model (DEM) with 1 m posting. (C) Mask defining stable surfaces used during co-registration. (D) Histogram of final elevation difference values over stable surfaces (reference DEM minus historical DEM). (E) Google satellite basemap (imagery source date 2016-07-28). (F) 1977-09-27 historical orthomosaic. (G) Final elevation difference map showing glacier thinning and retreat, including a portion of the adjacent Deming Glacier (RGI60-02.17738) to the northwest. (H) Same as in G, but with a stretched color ramp to bring out meter-scale elevation change, highlighting changes in forefield geomorphology. Gold outline shows extent of Figure 1.6.	25
1.6	(A) Detail of the 1977-09-27 North American Glacier Aerial Photography (NAGAP) orthomosaic over the Easton Glacier terminus and forefield. (B) Elevation difference between the 1977-09-27 NAGAP digital elevation model (DEM) and 2015-08-27 reference lidar digital surface model (DSM) (~38 years). Numbered labels show (1) moraine deposition, (2) large thinning signals at the base of the western little ice age moraine, (3) lateral moraine mass wasting, (4) debris deposition at the base of the eastern little ice age moraine, (5) stream erosion, and (6) vegetation growth.	26
1.7	(A) Google satellite basemap for the South Cascade Glacier site (imagery source date 2016-08-19). (B) Per-pixel digital elevation model (DEM) count and (C) per-pixel normalized median absolute deviation (NMAD) for all 18 historical DEMs in the 30-year time series stack (1967-09-21 to 1997-09-23). (D) Absolute accuracy metrics over stable surfaces for each historical DEM (historical DEM minus reference DEM), with box color representing stable surface area coverage. (E) Relative per-pixel accuracy metrics over stable surfaces for the full DEM time series stack, with mean standard deviation (SD) of 0.46 m and mean NMAD of 0.37 m. The NMAD box and whisker distribution summarizes of values shown in panel C. Boxes in (D) and (E) show interquartile range, with median values in orange and whiskers at 1.5 times the interquartile range.	27

1.8	(A) South Cascade Glacier elevation change between the 1994 historical digital elevation model (DEM) and the 2015 reference DEM. (B) Same as in A, but with glacier mask applied and stretched color ramp to show meter-scale change. Numbered labels show (1) glacier tributary near Post Peak, (2) 1992 glacier extent (McNeil et al., 2022a), and (3) negative elevation change attributed to talus mass wasting, with corresponding positive change over deposits. See Figure A.8 for additional detail of these features.	28
1.9	Comparison between historical digital elevation models (DEMs) generated with Historical Structure from Motion (HSfM) and the manual ground control point (GCP) methods. Top row (green) shows difference maps over stable surfaces between the 2013-2015 WorldView (WV) stereo composite reference DEM and four DEMs produced with the manual GCP method. Second row (purple) shows corresponding difference maps for HSfM output. Third row shows residual distributions and final row shows empirical variograms for each difference map. The HSfM DEMs consistently show improved accuracy and precision compared to the DEMs from the manual GCP method.	29
1.10	(A) Google satellite basemap for the Mount Baker site (imagery source date 2016-07-28). (B) Per-pixel digital elevation model (DEM) count map and (C) per-pixel normalized median absolute deviation (NMAD) for all 10 historical DEM mosaics in the time series stack (1970-09-09 to 1992-09-18). (D) Absolute accuracy metrics for each historical DEM mosaic, with box color representing available stable surface area. (E) Relative per-pixel accuracy metrics over stable surfaces for the full DEM time series stack, with mean standard deviation (SD) of 0.78 m and mean NMAD of 0.68 m. The NMAD box and whisker distribution summarizes of values shown in panel C. Boxes in (D) and (E) show interquartile ranges, with median values in orange and whiskers at 1.5 times the interquartile range.	32
1.11	Stable surface difference maps between the largest block (Figure A.10) of the 1991-09-09 historical digital elevation model (DEM) and the 2015-08-27 lidar reference DEM for the Mount Baker site processed using the (A) <i>single date - single block</i> approach, and (B) Four-dimensional Structure from Motion (4D SfM) approach. Bottom row shows corresponding empirical variograms and model results. The refined intrinsic from the 4D SfM optimization eliminate spatially correlated errors associated with "doming" artifacts present in A. .	33

1.12	Detailed examples of camera position correction during Historical Structure from Motion (HSfM) processing. (A) Images collected on 1970-09-29 over the Mount Baker site. The red dots show images with shared initial positions in the NSF Arctic Data Center (ADC) metadata. The blue dots show the final horizontal positions with color representing vertical translation magnitude. (B) Images collected on 1967-09-21 over the South Cascade Glacier site with final positions in green. A vertical translation of up to 4.3 km was required to correct the EarthExplorer (EE) archive metadata altitude of 7,500 m (24,600 ft) for these images. (C) Translation components required to correct camera positions for all images processed in this study (black), including the blocks shown in panels A (blue) and B (green).	38
2.1	Location of A. Mount Baker, B. South Cascade Glacier (SCG), and C. Mount Rainier shown at global, regional, and local scales. Grayscale basemap shows surface elevation in meters above the WGS84 ellipsoid from the 3-arcsecond Copernicus DEM (European Space Agency, 2022), resampled to a 1 km grid with Albers Equal Area projection. Satellite color imagery basemaps provided by Google and projected in Universal Transverse Mercator (UTM) zone 10N (imagery source dates: A. 2016-07-28, B. 2016-08-19, C. 2021-07-25). Randolph Glacier Inventory (RGI) v6.0. outline shown in blue and dated 1974 at Mount Baker, 1958 at SCG, and 1970 at Mount Rainier (RGI Consortium, 2017) . .	48
2.2	A. Google satellite basemap for the South Cascade Glacier (SCG) site (imagery source date 2016-08-19). B. Median surface elevation of the 71 Digital Elevation Models (DEMs) in the 63-year time series stack (1958-08-13 to 2021-08-13). C. Per-pixel DEM count. D. Per-pixel normalized median absolute deviation (NMAD) of residuals between stable ground in DEMs and reference DEM. Both C. and D. show 1958 SCG RGI glacier outline (RGI60-02.17739) in blue. E. Absolute accuracy metrics over stable ground surfaces for each DEM (DEM minus reference DEM). Boxes show interquartile range, with median values in red and whiskers at 1.5 times the interquartile range. F. Percent coverage of stable ground surface area (7.89 km ²) in (20.20 km ²) scene over which statistics shown in E are computed. G. Percent coverage of SCG RGI glacier extent (2.89 km ²) seen in C.	50

2.3	Workflow diagram for Geospatial Time Series Analysis (GTSA) raster time series stacking and regression procedure. The Geospatial Data Abstraction Library (GDAL) reprojects rasters on to a common reference grid. The xarray package acts as a high-level handler to stack and rechunk the data on disk using Zarr, then perform memory-efficient time-series regression analysis on each time-series chunk using dask. Final model predictions can be output in Zarr, NetCDF, or GeoTIFF format.	54
2.4	Historical (pre-2000) Digital Elevation Models (DEMs) at South Cascade Glacier (SCG). DEMs with partial ($< 65\%$) coverage of the SCG Randolph Glacier Inventory (RGI) outline highlighted in green. Glacier outline shown in blue. Voids in the DEM are generally seen at higher elevations.	60
2.5	Elevation change relative to mean elevation at four points (P1-4) sampled along South Cascade Glacier centerline with Gaussian Process (GP) estimation shown with orange line and 95% confidence interval. Linear regression for comparison show with green line. Column A. shows the full time series at each location. Column B. shows seasonal variability in a zoomed in temporal window from 2015 to 2020. C. Per-pixel DEM count and sample points. C. Per-pixel linear elevation change trend (dh/dt) from 1958 to 2021 and sample points.	61
2.6	Cross-sectional elevation averages along historic profiles at Nisqually Glacier. Panels A. B. C. correspond to Profile 1 ($r^2=0.84$, RMSE= 9.13 m), Profile 2 ($r^2=0.79$, RMSE=8.56 m), and Profile 3 ($r^2=0.04$, RMSE=10.31 m). Annual mean elevations along the profiles extracted from the GP generated surfaces shown in color with GP standard deviation (STD). Annual mean field measurements show in black. RMSE, r^2 , and $\% \pm \sigma$ values were computed between available field measurements and GP elevation estimate corresponding in space and time. D. Mean subtracted elevation profiles extracted from GP generated surfaces. E. Profile locations plotted over RGI Nisqually glacier outline (RGI60-02.14336, 1970 extent).	63
2.7	Partial DEMs with $<65\%$ glacier outline coverage subtracted from surfaces generated with the Gaussian Process (GP) regression. A. Elevation difference maps for surfaces generated without the inclusion of the partial DEMs. B. Elevation difference maps for surfaces generated with the inclusion of the partial DEMs. Including the partial DEMs in the GP regression reduces residual error. 1958 South Cascade Glacier outline from Randolph Glacier Inventory shown in black.	64

2.8	Effect of using a periodic kernel to estimate seasonal variability. Panels A and B show difference between GP estimated surfaces and the May, June, and October 2015 DEMs within 2015 USGS South Cascade Glacier outline. A. Difference maps between GP surfaces estimated without including the periodic kernel component. B. Difference maps between GP surfaces estimated including the periodic kernel component.	65
2.9	Median and NMAD of residuals within 2015 glacier extent for seasonal elevations estimated with and without the periodic Gaussian Process kernel. Residuals are computed from difference values between the estimated surfaces and the photogrammetrically derived DEMs.	66
3.1	Study sites A. South Cascade Glacier, B. Easton Glacier, and C. Nisqually Glacier. Each panel shows Google satellite basemap with Randolph Glacier Inventory (RGI) outlines in light blue and center glacier flowlines computed by the Open Global Glacier Model (OGGM) shown in dark blue (Maussion et al., 2019; RGI Consortium, 2017). A. 1958 South Cascade Glacier RGI glacier extent (basemap 2016-08-19). B. 1874 Easton Glacier RGI glacier extent (basemap 2016-07-28). C. 1970-1994 Nisqually Glacier RGI glacier (basemap 2021-07-25).	75
3.2	Glacier area change at A. South Cascade Glacier (SCG, 1958–2021, 1.125 km ² area loss), B. Easton Glacier (1947–2020, 0.096 km ² area loss), and C. Nisqually Glacier (1951–2020, 0.514 km ² area loss). The area change time series show continuous glacier area retreat at SCG, a period of advance followed by retreat at Easton Glacier, and multiple periods of advance and retreat at Nisqually Glacier (Section 3.6.1)	80
3.3	A. Annual in-situ mass balance time series at South Cascade Glacier (SCG, McNeil et al., 2022b). B. Five-year point-centered rolling mean of A. C. Annual geodetic mass balance from DEM surfaces interpolated with Gaussian Process regression. Decadal mean mass balance of B and C. D. Pacific Decadal Oscillation (PDO). F. Decadal PDO mean. G. Percent coverage of RGI SCG glacier extent (RGI60-02.18778, 2.92 km ² , dated 1958).	81
3.4	A. Annual in-situ mass balance time series at Easton Glacier (Pelto and Brown, 2012; WGMS, 2021). B. Five-year point-centered rolling mean of A. C. Annual geodetic mass balance from DEM surfaces interpolated with Gaussian Process regression. Decadal mean mass balance of B and C. D. Pacific Decadal Oscillation (PDO). F. Decadal PDO mean. G. Percent coverage of RGI Easton glacier extent (RGI60-02.17739, 2.88 km ² , dated 1974).	83

3.5	A. Annual in-situ mass balance time series at Nisqually Glacier (Riedel and Larrabee, 2015; WGMS, 2021). B. Five-year point-centered rolling mean of A. C. Annual geodetic mass balance from DEM surfaces interpolated with Gaussian Process regression. Decadal mean mass balance of B and C. D. Pacific Decadal Oscillation (PDO). F. Decadal PDO mean. G. Percent coverage of RGI Nisqually glacier extent (RGI60-02.14336, 4.44 km ² , dated 1970).	84
3.6	Glacier kinematics and terminus elevation change at A. South Cascade Glacier, B. Easton Glacier, and C. Nisqually Glacier. Maps show RGI outlines (A, RGI60-02.18778; B, RGI60-02.17739; C, RGI60-02.14336) and center flowlines computed with the Open Global Glacier Model (OGGM). Colors highlight mean elevation along 100 m distance bins start 1 km up from the terminus. Time periods with low opacity at all elevations and distance bins indicate periods of equilibrium, except when the mean elevation levels off, which indicates bare ground is sampled and the terminus has receded from this distance bin.	85
A.1	Flight paths, camera positions with frame numbers and non-overlapping image blocks (unique colors) for North America Glacier Aerial Photography (NAGAP) images over the Mount Baker site.	121
A.2	Flight paths and camera positions with frame numbers for North America Glacier Aerial Photography (NAGAP) images over the South Cascade Glacier site.	122

A.3	Results of reference digital elevation model (DEM) sensitivity tests for the Mount Baker site. (A) Reference digital surface model (DSM) prepared from 3DEP airborne lidar data collected August 27, 2015, posted at 1 m. (B) Reference DEM prepared from the global 30 m Copernicus DEM, with variable acquisition dates between 2010 and 2015. (C) Elevation difference map (A minus B). Note artifacts over steep terrain (e.g., southwest and east flanks) in the Copernicus DEM, likely due to phase unwrapping errors. Residual differences over glaciers and vegetation can be attributed to glacier thinning and variable penetration of the lidar and radar sources. (D) Histogram of elevation difference values over stable surfaces showing acceptable agreement between the two datasets. (E) Per-pixel normalized median absolute deviation (NMAD) map for the historical DEM stack processed using the 1 m lidar reference DEM. See Figure 10 for additional details. (F) Same as in E, for the historical DEM stack processed using the 30 m Copernicus reference DEM. (G) Per-pixel NMAD difference map (E minus F). (H) Relative accuracy metrics over stable surfaces for the two historical DEM stacks. Boxes show interquartile ranges, with median values in blue and whiskers at 1.5 times the interquartile range. The mean NMAD is 0.68 m for the historical DEM stack processed using the 1 m lidar reference DEM and 1.26 m for the stack processed with the 30 m Copernicus reference DEM.	123
A.4	Fiducial and pseudofiducial marker templates for the North America. Glacier Aerial Photography (NAGAP) Arctic Data Center (ADC) images used during automated image standardization. Count represents the total number of scanned images in the ADC archive containing each type of marker. One roll identifier (77V6) includes frames that display multiple marker types, suggesting that the same film roll was used in multiple cameras.	124
A.5	Orthoimage footprint count maps for all blocks over the South Cascade Glacier site.	125
A.6	Elevation difference maps for the South Cascade Glacier site (2015 reference digital elevation model (DEM) minus historical DEM), with color ramp stretch to bring out detail over the stable surfaces.	126

A.7	Comparison of digital elevation models (DEMs) generated using the manual ground control point (GCP) method and Historical Structure from Motion (HSfM) for the same input images over South Cascade Glacier. Per-pixel elevation difference maps (manual GCP method minus HSfM) are clipped to the glacier outlines for 1970, 1979, 1986, and 1992 provided by the USGS (McNeil et al., 2022a; O’Neel et al., 2019). Red indicates that manual GCP method DEM is lower than the HSfM DEM, while blue indicates the opposite. Mean differences over the glacier surface range from -1.61 to -0.22 m.	127
A.8	(A) The 1994-09-06 North American Glacier Aerial Photography (NAGAP) orthomosaic over the South Cascade Glacier terminus. (B) Elevation difference between 1994-09-06 NAGAP digital elevation model (DEM) and the 2015 reference DEM, showing (B1) mass wasting and erosion of talus and (B2) associated deposits on the valley floor.	128
A.9	Empirical variogram and model for each digital elevation model (DEM) at the South Cascade Glacier site. The 1970-09-29, 1974-08-10, 1984-08-14, 1986-09-05, and 1987-08-21 DEMs have higher spatially correlated error, as can be seen in the corresponding difference maps (Figure A.6) and Figure 7).	129
A.10	Orthoimage footprint count maps for all blocks over the Mount Baker site. Non-overlapping blocks for a single date are numbered and outlined with a white border.	130
A.11	Elevation difference maps for the Mount Baker site (2015 reference digital elevation model (DEM) minus historical DEM).	131
A.12	Empirical variogram and model for each digital elevation model (DEM) at the Mount Baker site. The 1970-09-29, 1974-08-10, 1984-08-14, 1986-09-05, and 1987-08-21 DEMs have higher spatially correlated error, as can be seen in the corresponding difference maps (Figure A.6 and Figure 7). The large 1979-10-06 DEM has the largest errors with highest spatial autocorrelation.	132
B.1	A. Google satellite basemap for the Mount Baker site (imagery source date 2019-07-26). B. Median surface elevation of the 55 Digital Elevation Models (DEMs) in the 73-year time series stack (1947-09-14 to 2020-12-12). C. Per-pixel DEM count. D. Per-pixel normalized median absolute deviation (NMAD) of residuals between stable ground in DEMs and reference DEM. Both C. and D. show 1974 RGI glacier outlines in blue. E. Absolute accuracy metrics over stable ground surfaces for each DEM (DEM minus reference DEM). Boxes show interquartile range, with median values in red and whiskers at 1.5 times the interquartile range. F. Percent coverage of stable ground surface area (34.67 km ²) in (129.31 km ²) scene over which statistics shown in E are computed. G. Percent coverage of the 1974 RGI glacierized extent (39.75 km ²) seen in C.	146

B.2	A. Google satellite basemap for the Mount Rainier site (imagery source date 2021-07-26). B. Median surface elevation of the 94 Digital Elevation Models (DEMs) in the 69-year time series stack (1951-08-16 to 2020-09-01). C. Per-pixel DEM count. D. Per-pixel normalized median absolute deviation (NMAD) of residuals between stable ground in DEMs and reference DEM. Both C. and D. show 1970 RGI glacier outlines in blue. E. Absolute accuracy metrics over stable ground surfaces for each DEM (DEM minus reference DEM). Boxes show interquartile range, with median values in red and whiskers at 1.5 times the interquartile range. F. Percent coverage of stable ground surface area (134.42 km ²) in (311.57 km ²) scene over which statistics shown in E are computed. G. Percent coverage of the 1970 RGI glacierized extent (79.89 km ²) seen in C. .	147
B.3	Digital Elevation Model (DEM) count binned by month. Historical (pre year 2000) DEM bins in blue. Modern (year 2000 or after) DEM bins in orange. Total count per month listed at the top of each bin.	148
B.4	Monthly DEM coverage by year.	149
B.5	A. Elevation change relative to mean elevation for ten points (P1-10) sampled along South Cascade glacier centerline with Gaussian Process (GP) prediction without periodic kernel shown with orange line and 95% confidence interval. Filtered outliers outside 3σ threshold shown in black. The σ value is the standard deviation for each estimate returned by the GP regression. C. Per-pixel DEM count and sample points. C. Per-pixel linear elevation change trend (1958-2021) and sample points.	150
B.6	Elevations at four points (P1-4) sampled along South Cascade Glacier centerline with Gaussian Process (GP) estimation shown with orange line and 95% confidence interval. Here, the dependant values (elevation) are not normalized by the <i>GaussianProcessRegressor</i> prior to GP regression, which results in a smaller confidence interval (Section 2.7.3.1). Column A. shows the full time series at each location. Column B. shows seasonal variability in a zoomed in temporal window from 2015 to 2020. C. Per-pixel DEM count and sample points. C. Per-pixel linear elevation change trend (dh/dt) from 1958 to 2021 and sample points.	151

C.1	Squared Pearson correlation coefficient (r^2), root mean squared error (RMSE), and p-values for 3, 5, and 10 year in-situ mass balance averages compared with geodetic mass balance derived from subtracting surfaces interpolated with Gaussian Process (GP) regression. Columns A, B, and C plot the time averaged in-situ mass balance on the y-axis and geodetic mass balance on the x-axis. The red line represents the least-squares regression line. South Cascade Glacier shows the highest r^2 (0.43) for the the 5-year averaging window. Easton Glacier and Nisqually Glacier show the highest r^2 (0.18 and 0.41, respectively) for the 3-year averaging window.	153
C.2	Example glacier area outlines (7 of 63) for the South Cascade Glacier time series (1958–2021). Outlines were delineated from DEM difference maps created by subtracting the DEM with minimum glacier extent (2021). Top row shows DEM difference maps and glacier outline in light blue for first year in each decade (1960–2020). Bottom row shows glacier outline in blue.	154
C.3	Example glacier area outlines (8 of 73) for the Easton Glacier time series 1947–2020. Outlines were delineated from DEM difference maps created by subtracting a DEM with minimum glacier extent (2021). To obtain a synthetic DEM and compute the 2020 DEM difference map and outline, we used the Gaussian Process regression to estimate a synthetic surface for 2021, which is beyond the temporal bounds of the input DEM time series. Top row shows DEM difference maps and glacier outline in light blue for first year in each decade (1950–2020). Bottom row shows glacier outline in blue.	155
C.4	Example glacier area outlines (8 of 69) for the Nisqually Glacier, time series 1947–2020. Outlines were delineated from DEM difference maps created by subtracting DEM with minimum glacier extent (2021). To obtain a synthetic DEM and compute the 2020 DEM difference map and outline, we used the Gaussian Process regression to estimate a synthetic surface for 2021, which is beyond the temporal bounds of the input DEM time series. Top row shows DEM difference maps and glacier outline in light blue for first year in each decade (1950–2020). Bottom row shows glacier outline in blue.	156

C.5	Enhanced temporal resolution of geodetic mass balance. A. Annual in-situ mass balance time series at South Cascade Glacier (SCG, McNeil et al., 2022b). B. Five-year point-centered rolling mean of A. C. Annual geodetic mass balance from DEM surfaces interpolated with Gaussian Process regression. D. Geodetic mass balance from USGS geodetic data release (McNeil et al., 2022a). E. Percent coverage of RGI SCG glacier extent (RGI60-02.18778, 2.92 km ² , dated 1958). The geodetic mass balance in D is computed from the USGS DEMs with full glacier coverage shown in E. Panel C. shows the enhanced temporal resolution of geodetic mass balance computed from the augmented and interpolated DEM time series.	157
C.6	Annual geodetic mass balance from DEM surfaces interpolated with Gaussian Process regression at A. South Cascade Glacier, B. Easton Glacier, and C. Nisqually Glacier. Panels A', B', and C' show the respective input DEM coverage of RGI outlines (RGI60-02.18778, RGI60-02.17739, RGI60-02.14336). D. Pacific Decadal Oscillation (PDO).	158

LIST OF TABLES

Table Number		Page
A.1	Metashape v.1.6.0 processing parameters for the <i>single date - single block</i> mode.	116
A.2	Results for 243 images comprising 18 total blocks at South Cascade Glacier (SCG) using the <i>multiple dates - multiple blocks</i> processing mode. Each date has a single block for the SCG site. Area is computed from the valid pixel count of each output digital elevation model (DEM), excluding "no data" values. The RMS reprojection error for each block is reported in pixels and converted to meters using the block median ground sample distance (GSD). The normalized median absolute deviation (NMAD) is computed from per-pixel elevation difference values with respect to the reference DEM over stable surfaces. . . .	117
A.3	Image standardization evaluation results. Columns include the focal length error, principal point error, and RMS reprojection error computed by Metashape, as well as the normalized median absolute deviation (NMAD) of per-pixel elevation difference values over stable surfaces. Baseline: (TR0) Image standardization without affine transformation. Experiments: (TR1) Image standardization with affine transformation to match calibrated values; (TR2) Image standardization with affine transformation to match mean fiducial marker positions; (TR3) Image standardization without affine transformation, using pseudofiducial markers to compute principal point and remove frame. . .	118
A.4	Results for 261 images comprising 21 total blocks at Mount Baker using the <i>multiple dates - multiple blocks</i> processing mode. See Table A.2 caption for details. Unlike the South Cascade Glacier site, some dates include multiple spatially distinct blocks.	119
B.1	South Cascade Glacier. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs. . .	135
B.2	Mount Baker. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs.	138
B.3	Mount Rainier. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs.	141

GLOSSARY

ACD: Arctic Data Center

API: Application Programming Interface

ASP: Ames Stereo Pipeline

CLAHE: Contrast Limited Histogram Equalization

CONUS: Ames Stereo Pipeline

DEM: Digital Elevation Model

DGTM: Digital Glacier Time Machine

EE: EarthExplorer

GCP: Ground Control Point

GDAL: Geospatial Data Abstraction Library

GTSA: Geospatial Time Series Analysis

GP: Gaussian Process

IDW: Inverse Distance Weighting

ICP: Iterative Closest Point

HIPP: Historical Image Pre-Processing

HSFM: Historical Structure from Motion

IPCC: Intergovernmental Panel on Climate Change

NAGAP: North American Glacier Aerial Photography

NASA: National Aeronautics and Space Administration

NED: National Elevation Dataset

NETCDF: Network Common Data Form

NLCD: National Land Cover Dataset

NMAD: Normalized Median Absolute Deviation

NSF: National Science Foundation

OGGM: Open Global Glacier Model

PGC: Polar Geospatial Center

PREEVENTS: Prediction of and Re- silience against Extreme Events

RGI: Randolph Glacier Inventory

SETSM: Surface Extraction from TIN based Search-space Minimization

SCG: South Cascade Glacier

SFM: Structure from Motion

USGS: United Stated Geological Survey

UW: University of Washington

WV: WorldView

ACKNOWLEDGMENTS

This work was supported by a University of Washington Innovation Award to study long-term glacier mass balance and dynamics in response to climate forcing. Additional funding was provided by the United States Geological Survey (USGS) Ecosystem Mission Area, Land Change (Climate R&D) Program cooperative agreement (#G19AC00433) and the National Science Foundation (NSF) Prediction of and Resilience against Extreme Events (PREEVENTS) program award (ICER 1663859).

I thank my advisor David Shean for the opportunity to pursue a PhD at the University of Washington. I am grateful for the time, keen insight, and attention to detail he has dedicated to this work. I thank the late Austin Post and the USGS Glaciology program for acquiring the North American Glacier Aerial Photography (NAGAP) photographs over the years. I also thank Matt Nolan and the team at the University of Alaska Fairbanks for scanning and archiving the NAGAP photographs.

I am deeply grateful to all my committee members (David Shean, Jessica Lundquist, Amaury Dehecq, Shad O’Neel, and David Perkel) for their guidance throughout this process and feedback in this work. Romain Hugonnet was an honorary committee member and I thank him for his enthusiasm, sharing his expertise, and our many inspiring conversations. I would also like to thank my colleagues Michelle Hu, Shashank Bhushan, Eric Gagliano, Quinn Brencher, Seth Vanderwilt, Eli Schwat, Joachim Meyer, Gregoire Guillet, Oleg Alexandrov, Chris McNeil, and Caitlyn Florentine for their constructive insights and support over the years. Finally, I thank John Delaney, Timothy Crone, and Anthony Arendt for providing their mentorship, compassion, and perspective.

Michelle Hu and Shashank Bhushan are dear friends and colleagues. We started this program together and I couldn’t have finished it without them. I have been fortunate to be a part of the UW Civil and Environmental Engineering community and extend a warm and heartfelt thank you to all its members, both past and present.

I dedicate this work to my family and friends, as well as all people that cherish

this land we study.

Chapter 1

HISTORICAL STRUCTURE FROM MOTION (HSFM): AUTOMATED PROCESSING OF HISTORICAL AERIAL PHOTOGRAPHS FOR LONG-TERM TOPOGRAPHIC CHANGE ANALYSIS

The chapter is published as: **F. Knuth**, D. Shean, S. Bhushan, E. Schwat, O. Alexandrov, C. McNeil, A. Dehecq, C. Florentine, S. O’Neel (2023). *”Historical Structure from Motion (HSfM): Automated processing of historical aerial photographs for long-term topographic change analysis”* in Remote Sensing of Environment. <https://doi.org/10.1016/j.rse.2022.113379>

1.1 Abstract

Precisely measuring the Earth’s changing surface on decadal to centennial time scales is critical for many science and engineering applications, yet long-term records of quantitative landscape change are often temporally and geographically sparse. Archives of scanned historical aerial photographs provide an opportunity to augment these records with accurate elevation measurements that capture the historical state of the Earth surface. Structure from Motion (SfM) photogrammetry workflows produce high-quality digital elevation models (DEMs) and orthoimage mosaics from these historical images, but time-intensive tasks like manual image preprocessing (e.g., fiducial marker identification) and ground control point (GCP) selection impede processing at scale. We developed an automated method to process historical images and generate self-consistent time series of high-resolution (0.5-2 m) DEMs and orthomosaics, without manual GCP selection. The method relies on SfM to correct camera interior and exterior orientation and a robust multi-stage co-registration approach using modern reference terrain datasets for geolocation refinement. We demonstrate the method using scanned images from the North American Glacier Aerial Photography (NAGAP) archive collected between 1967 and 1997. We present results for two sites with variable photo acquisition geometry and overlap — Mount Baker and South Cascade Glacier in Washington

State, USA. The automated method corrects initial camera position errors of several kilometers and produces accurately georeferenced, high-resolution DEMs and orthoimages, regardless of camera configuration, acquisition geometry, terrain characteristics, and reference DEM properties. The average RMS reprojection error following bundle adjustment optimization was 0.67 px (0.15 m) for the 261 images contributing to 10 final DEM mosaics between 1970 and 1992 at Mount Baker, and 0.65 px (0.13 m) for the 243 images contributing to 18 individual DEMs between 1967 and 1997 at South Cascade Glacier. The relative accuracy of elevation values in the historical time series stacks was 0.68 m at Mount Baker and 0.37 m at South Cascade Glacier. Our products have reduced systematic error and improved accuracy compared to DEM products generated using SfM with manual GCP selection. Final elevation change measurement precision was $\sim 0.7\text{--}1.0$ m over a 30-year period, enabling the study of processes with rates as low as $\sim 1\text{--}3$ cm/yr. Our results demonstrate the potential of this scalable method to rapidly process archives of historical imagery and deliver new quantitative insights on long-term geodetic change and Earth surface processes.

1.2 Introduction

Millions of analog photographs documenting land surface change between the 1910s and 2000s sit isolated in vaults. A small fraction of these photographs has been digitally scanned, but remains underutilized for quantitative analysis in Earth system science due to limited metadata and poor geolocation accuracy. Measuring surface elevation change is fundamental to many Earth science disciplines, including hydrology, glaciology, geomorphology, and volcanology (e.g., Eaton and Murata, 1960; Østrem, 1975; Schumm, 1956). Observations of surface elevation change through time help quantify the nature of many geophysical processes, such as glacier mass balance (e.g., Hugonnet et al., 2021; Shean et al., 2020), ice dynamics in response to climate forcing (e.g., Dehecq et al., 2019; Kehrl et al., 2017), sediment transport (e.g., Anderson and Pitlick, 2014), and volcanically induced deformation (e.g., Henderson et al., 2019). Scanned historical aerial image archives provide an opportunity to “go back in time” and derive accurate historical digital elevation models (DEMs) and orthoimages for long-term measurements of surface change with many applications, including Earth system modeling, climate adaptation, urban planning, and land management (Bauer et al., 2021).

Photogrammetry is the science of making precise measurements in photographs (e.g., Albertz, 2002; Karara, 1967; LaChapelle, 1962; Meydenbauer, 1867). Traditional stereo photogrammetry methods used overlapping photographs and stereoplotters to manually

delineate contour lines (e.g., Ray, 1960; Van Wijk, 1967) and interpolate elevations to prepare continuous DEM grids (e.g., Chandler and Cooper, 1989; Gesch et al., 2014). These approaches have offered valuable information over the past century, yet associated errors remain high and careful manual calibration and correction of these products is required for use in modern applications (e.g., geodetic glacier-mass-balance calculations) (Fischer et al., 2015).

The Structure from Motion (SfM) photogrammetric technique (e.g., Snavely et al., 2008) draws on both traditional photogrammetry and modern computer vision theory (Eltner and Sofia, 2020; Westoby et al., 2012) to provide improved automated stereo reconstruction. Traditional photogrammetric approaches require rigorously calibrated camera systems with precisely known interior orientation parameters (e.g. Brown, 1971; Tayman, 1984) and/or manually defined tie points between images to reconstruct the relative camera exterior orientation (position and attitude) (e.g., Westoby et al., 2012). Modern SfM approaches, by comparison, rely almost entirely on information in the images and simple camera models to iteratively solve for camera interior orientation and relative camera exterior orientation using thousands of automatically detected feature matches between overlapping images (e.g., Lowe, 1999; Martin-Brualla et al., 2015; Snavely et al., 2008). This advancement provides an essential foundation toward automated processing of historical archive imagery with poorly constrained camera information.

Due to the nature of historical imagery, several labor- and time-intensive tasks often hinder processing large datasets (e.g., Bjørk et al., 2012; Child et al., 2020; Geyman et al., 2022; Girod et al., 2018; Mölg and Bolch, 2017; O’Neel et al., 2019; Roberti et al., 2021; Walstra et al., 2007). To begin, the film must be scanned by a trained operator with professional equipment. Historical aerial images were typically collected on nitrate and acetate film, which can degrade and warp with age. The film may be further stretched and distorted during scanning, especially if a non-photogrammetric scanner is used (e.g., Gruber and Leberl, 2001; Nielsen, 2017; Salach, 2017; Sevara, 2016). In some cases, the scanning process can introduce additional sources of error, such as over-exposure, irregular film rotation on the scanner, and omission of entire portions of the photo frame. Perhaps more importantly, inaccurate or unknown camera pose (extrinsic position and orientation) significantly reduces the accuracy of the resulting products in a geographic coordinate system. The current solution to this issue usually involves manually selecting features in the images with known three-dimensional (3D) world coordinates to serve as ground control points (GCPs) (e.g., Feurer and Vinatier, 2018; Mölg and Bolch, 2017; Warrick et al., 2017), which provide absolute constraints during

joint optimization (bundle adjustment) of camera interior and exterior orientation (e.g., Mikhail et al., 2001; Tarolli and Mudd, 2019; Westoby et al., 2012). For historical aerial photographs taken over remote areas, these GCPs are typically persistent natural features that are identifiable in both modern and historical datasets and assumed to be static over time, such as prominent rock outcrops and large boulders. Confident image feature identification requires at least three pixels, and the error of natural GCP coordinates scales with the modern and historical image resolution. The time-intensive GCP picking process is further limited by the resolution and accuracy of the modern reference data. Finally, the lack of accurate camera pose information for historical images prohibits predetermination of overlapping image blocks needed for efficient feature matching. Here, we define a block as three or more overlapping images collected on the same acquisition date with the same camera. This limitation can be overcome with brute-force matching of all potential image pairs, which is computationally expensive and potentially error-prone for surfaces with repetitive texture.

To solve these issues, we developed an automated method that includes image preprocessing and block detection, photogrammetric surface reconstruction, and DEM co-registration to efficiently generate accurate historical DEMs and orthomosaics without manual intervention. Our goal was to develop a robust and generic approach that is scalable and applicable to any collection of historical vertical aerial photography, even when metadata records are incomplete. To that end, we focused our efforts on the challenging U.S. Geological Survey (USGS) North American Glacier Aerial Photography (NAGAP) archive. We evaluated this method for two sites in the Pacific Northwest region of the contiguous United States with mountain glacier and geomorphic change signals. Our methodology addresses several common limitations of historical aerial image processing to generate accurate DEMs, which reduces uncertainty for future studies of long-term glacier mass change.

1.3 Study sites

We focus our study on Mount Baker (261 NAGAP images covering $\sim 143 \text{ km}^2$ area) and South Cascade Glacier (243 NAGAP images covering $\sim 32 \text{ km}^2$ area), which are both located in Washington State, USA (Figure 1.1). The sites differ in terms of terrain and land cover characteristics (Figures 1.1A and B), with variable NAGAP image acquisition geometries (Figures A.1 and A.2). Glacier outlines for each site were extracted from the Randolph Glacier Inventory (RGI) v6.0 (RGI Consortium, 2017).

1.3.1 *Mount Baker*

Mount Baker is a stratovolcano in northern Washington State. It holds the record for highest seasonal snowfall in the USA (Leffler et al., 2001) and is the source of considerable sediment transported by the Skagit and Nooksack Rivers (Czuba et al., 2011). Easton Glacier (*RGI60-02.17739*) covers an area of 2.89 km² (1974 extent) on the southern flank of Mount Baker (Figure 1.1A) and has been monitored annually by the North Cascade Glacier Climate Project since 1984 (Pelto and Brown, 2012; WGMS, 2021). The lower glacier is flanked by Little Ice Age lateral moraines to the east and west (Osborn et al., 2012), and encroaching conifer vegetation to the south, but otherwise surrounded by exposed and unvegetated bedrock and periglacial deposits.

1.3.2 *South Cascade Glacier*

South Cascade Glacier (*RGI60-02.18778*) covers an area of 2.92 km² (1958 extent) in the northern Cascade Range. It is one of five benchmark glaciers monitored by the USGS to capture long-term glacier mass change for western North America and Alaska (RGI regions 1 and 2, respectively) (Meier and Tangborn, 1965; O’Neel et al., 2019). South Cascade Glacier has the longest continuous record of annual mass-balance measurements in the contiguous United States, from 1958 to present (McNeil et al., 2022b).

1.4 *Data*

The current method supports historical image and metadata retrieval from multiple archives, including the National Science Foundation (NSF) Arctic Data Center (ADC) and the USGS Earth Resources Observation and Science (EROS) Aerial Photo Single Frames archive available via the USGS EarthExplorer (EE) portal. For this study, we used historical images collected by the USGS NAGAP program, primarily hosted in digitized format by the NSF ADC (Nolan, 2012; Nolan et al., 2017), with subsets of data hosted by USGS EE.

The NAGAP program collected ~100,000 aerial photographs of glaciers in western North America and Alaska between the 1960s and 1990s (Figure 1.1) (Post, 1995; Post et al., 1971). The main objective of the NAGAP program was to document regional glacier change to complement the long-term USGS Benchmark Glacier field monitoring program (Berkner, 1954; Crandell et al., 1965; Florentine and Mckeen, 2022; Nace, 1969; UNESCO, 1970). Due to the remote location and inaccessibility of many North American glaciers, aerial photography

provided an effective approach to conduct regional glacier surveys and provide context for the benchmark glaciers with traditional stake mass-balance measurements (e.g., O’Neel et al., 2019; Zemp et al., 2013). Some of the NAGAP photographs were initially used to derive contour maps using traditional photogrammetric methods (Harper, 1993; LaChapelle, 1962).

1.4.1 Photograph acquisition

Many of the NAGAP photographs were acquired with near vertical (nadir) orientation, often with $\sim 60\%$ forelap to provide stereo coverage. Photographs were captured on 9×9 inch (22.86×22.86 cm) panchromatic film, using metric cameras with ~ 6 inch (151.283–151.674 mm) focal length. Cameras were mounted inside the fuselage of a fixed-wing aircraft with viewing port and manually triggered by an operator (Austin Post, personal communication, October 2011). The NAGAP photo collection flight lines typically followed the glacier centerline, starting over proglacial terrain and ending near or above the glacier Equilibrium-Line Altitude (ELA) (Figures A.1, A.2). The photographs generally offer continuous spatial coverage over the entire glacier for smaller, lower elevation sites (e.g., South Cascade Glacier), while larger, high-elevation sites, such as Mount Baker or Mount Rainier, have some gaps in photo coverage over the summit.

1.4.2 Image scanning

Between 2014 and 2017, (Nolan et al., 2017) scanned $\sim 20,000$ of the total $\sim 100,000$ NAGAP film negatives, giving priority to nadir panchromatic photographs. Each film was scanned at 20-micron resolution using two Vexcel Ultrascan 5000 Model US5000 flatbed scanners with a precision of $\pm 2\text{ }\mu\text{m}$ (Gruber and Leberl, 2001). Scanned images were stored as 8-bit grayscale TIF files with dimensions of approximately $12,000\times 12,000$ pixels. The ground sample distance (GSD) of the 20-micron scans ranges from approximately 0.1 to 1.0 m for typical flight altitudes of 500 to 3,000 m above ground level. In August 2017, the $\sim 20,000$ scanned images and metadata were publicly released through the NSF Arctic Data Center (Nolan et al., 2017). Some of these same images are also available via the EE archive at 25-micron resolution. The USGS offers on-demand scanning services at 7- or 14-micron resolution, which may provide additional detail depending on the original film quality and resolving power. In practice, limitations associated with film grain, motion blur, and the film development process may limit resolving power, especially for older images (1940s-1960s), and the available 20-micron scans may already oversample the true image resolution. The

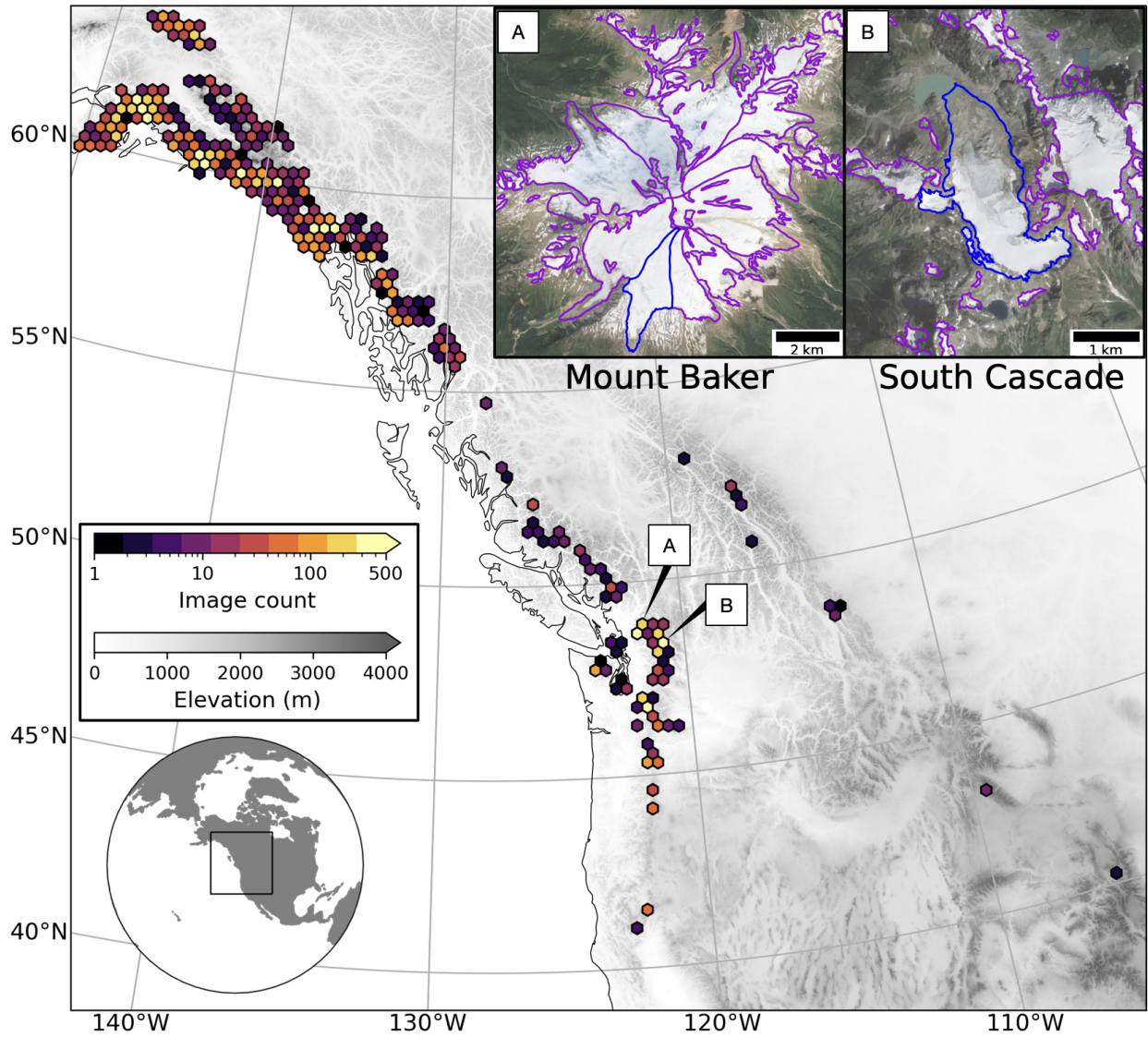


Figure 1.1: Coverage map for scanned North American Glacier Aerial Photography (NAGAP) imagery acquired between 1964 and 1997 across western North America available from the NSF Arctic Data Center. Hexagon colors show the total number of frames within each ~ 25 km bin ($\sim 1,600$ km² area). Basemap shows surface elevation in meters above the WGS84 ellipsoid from the 3-arcsecond Copernicus DEM (European Space Agency, 2022), resampled to a 1 km grid with Albers Equal Area projection. Annotations call out hexagon cells containing our study sites, with inset maps for: A) Mount Baker site with Randolph Glacier Inventory (RGI) v6.0 outlines from 1974 source imagery (purple) and Easton Glacier highlighted in blue, and B) South Cascade Glacier site with RGI outline from 1958 source imagery.

remaining $\sim 80,000$ NAGAP photographs, including some oblique and color photographs, are currently archived at the University of Alaska Fairbanks.

1.4.3 *Camera position metadata*

Camera longitude and latitude positions for the scanned NAGAP images were manually estimated using basemaps in Google Earth (Nolan et al., 2017). Altitude information (assumed to be feet above home airport elevation or mean sea level), when available, was read from the photo frame and recorded in the NAGAP metadata files. The ADC archive includes metadata files in comma-separated value (csv) format containing acquisition date, longitude, latitude, and in some cases, altitude. Additional metadata files in keyhole markup language (kml) format are available for a subset of photographs from the 1970s, 1980s and 1990s, with fields for image file name, longitude, latitude, and altitude as orthometric height above the EGM96 geoid (Nolan et al., 2017). We use the positions in the kml files where available, and supplement with the csv files or EE metadata if necessary. The EE archive metadata typically includes fields for the camera center longitude, latitude, and altitude, along with estimated image footprint corner longitude and latitude coordinates. We convert all vertical altitude or elevation values to height above the WGS84 ellipsoid before processing, and evaluate the accuracy of available camera position metadata in Section 1.5.7.5.

1.4.4 *Camera calibration*

Camera calibration reports contain information that can be used to recover the interior orientation, including focal length, distances between fiducial markers, lens distortion, and the location of the optical center on the film (principal point of autocollimation) (Gruber and Leberl, 2001; Tayman, 1984). The cameras used for the NAGAP program were regularly calibrated (Tayman, 1984), with some calibration reports available via EE or the U.S. Department of Agriculture Remote Sensing Applications Center (USDA RSAC) database (USDA Forest Service, 2018). Calibration reports for a given film roll can be retrieved from the USDA RSAC database using the lens serial number, focal length, and acquisition date, all of which can usually be manually extracted from the analog metadata available on photo frame border. Alternatively, we implemented support for automated EE API queries to retrieve the corresponding camera calibration report under the same object identifier as the NAGAP image, if available.

1.4.5 Reference DEM data

We prepared high-quality reference DEM data for processing and evaluation of output products at both study sites. For the Mount Baker site, we generated a high-resolution 1 m reference digital surface model (DSM) from airborne lidar data collected for the USGS 3DEP program by Quantum Spatial on August 27, 2015, using a Leica ALS80 scanner (Ramsey, 2016) (Figure A.3). The lidar point cloud data were obtained from the Washington Department of Natural Resources (WADNR) lidar portal. The reported vertical accuracy (RMSE) of the lidar point cloud is 0.04 m (Ramsey, 2016).

For the South Cascade Glacier site, we prepared a high-resolution (2 m) composite reference DEM to use for co-registration and accuracy assessment. The composite DEM was generated from five summer Maxar WorldView (WV) stereo images acquired between 2013 and 2015 using an automated processing workflow (Shean et al., 2016). The five DEMs were co-registered and a weighted average composite was created, which offers superior absolute accuracy and improved coverage over steep slopes compared to any individual WV DEM. For analysis of change over glacier surfaces, we use a single "snapshot" WV reference DEM from October 14, 2015 (McNeil et al., 2022a) and glacier outlines for 1970, 1979, 1986, and 1992 provided by the USGS (McNeil et al., 2022a; O'Neel et al., 2019).

In addition to these high-resolution reference DEM products, we also evaluated the Copernicus DEM (Section 1.5.7.3), a 30 m DEM product ("GLO-30") with global coverage (European Space Agency, 2022). The Copernicus DEM has a reported absolute horizontal accuracy of < 6 m (CE90) and absolute vertical accuracy of < 4 m (LE90) (European Space Agency, 2020; NSDDA, 1998).

All reference DEMs were reprojected to UTM Zone 10N (EPSG:32610) and adjusted to provide elevation values in meters above the WGS84 ellipsoid.

1.5 Methods

We developed an automated pipeline — Historical Structure from Motion (HSfM) — which enables rapid generation of DEMs and orthomosaics from archives of aerial imagery. The core workflow in the HSfM method involves the following steps: 1) image preprocessing, 2) SfM reconstruction, 3) co-registration with modern reference DEM data, and 4) orthomosaic generation using refined camera extrinsics (Figure 1.2). Image preprocessing is performed with OpenCV v4.4 (Bradski and Kaehler, 2008), SfM reconstruction and orthomosaic generation

with Agisoft Metashape v1.6.0 (Metashape, 2021), and co-registration with the NASA Ames Stereo Pipeline (ASP) v2.6.1 (Beyer et al., 2019, 2018; Shean et al., 2016) followed by Nuth and Kääb (2011) co-registration implemented in the *demcoreg* Python package (Shean et al., 2021). The HSfM package includes Python function libraries, scripts, and notebooks that provide a high-level interface for the full processing workflow. All code is open-source and publicly available (Knuth et al., 2021a), with the exception of Agisoft Metashape.

1.5.1 Historical image and metadata preprocessing

We developed the Historical Image Pre-Processing (HIPP) library (Knuth et al., 2021b) for scanned historical image retrieval and standardization. The HIPP package includes utilities to search the ADC and EE archives using spatial bounds, temporal bounds and keywords. The returned images are grouped into "image sets" by camera and acquisition date, then automatically downloaded and standardized in parallel. An image set is defined as all images that were acquired with the same camera on the same date. Image data can be loaded from disk or directly from image servers (e.g., ADC arcticdata.io or EE earthexplorer.usgs.gov) for remote data retrieval and in-memory processing.

1.5.1.1 Image standardization

After retrieval, the scanned historical images must be standardized to 1) remove any distortion introduced during film storage, handling, and/or scanning, 2) enhance contrast, and 3) remove the photo frame. The HIPP package offers three approaches to standardize images, depending on the availability of camera calibration reports and visibility of fiducial markers in the scanned images: 1) affine transformation to match calibration data, 2) affine transformation to match mean marker positions, and 3) pseudofiducial marker detection without affine transformation.

1.5.1.1.1 Fiducial marker detection

Fiducial markers are used to define the interior geometry of a film camera. Generally, four *mid-side* fiducial markers are located at the center of each photo frame side, along with four *corner* fiducial markers in the photo frame corners (Figure 1.3). By precisely measuring the position of each marker in the scanned images, the apparent dimensions of the scanned image (pixels) can be adjusted to match the known interior dimensions of the calibrated camera (mm).

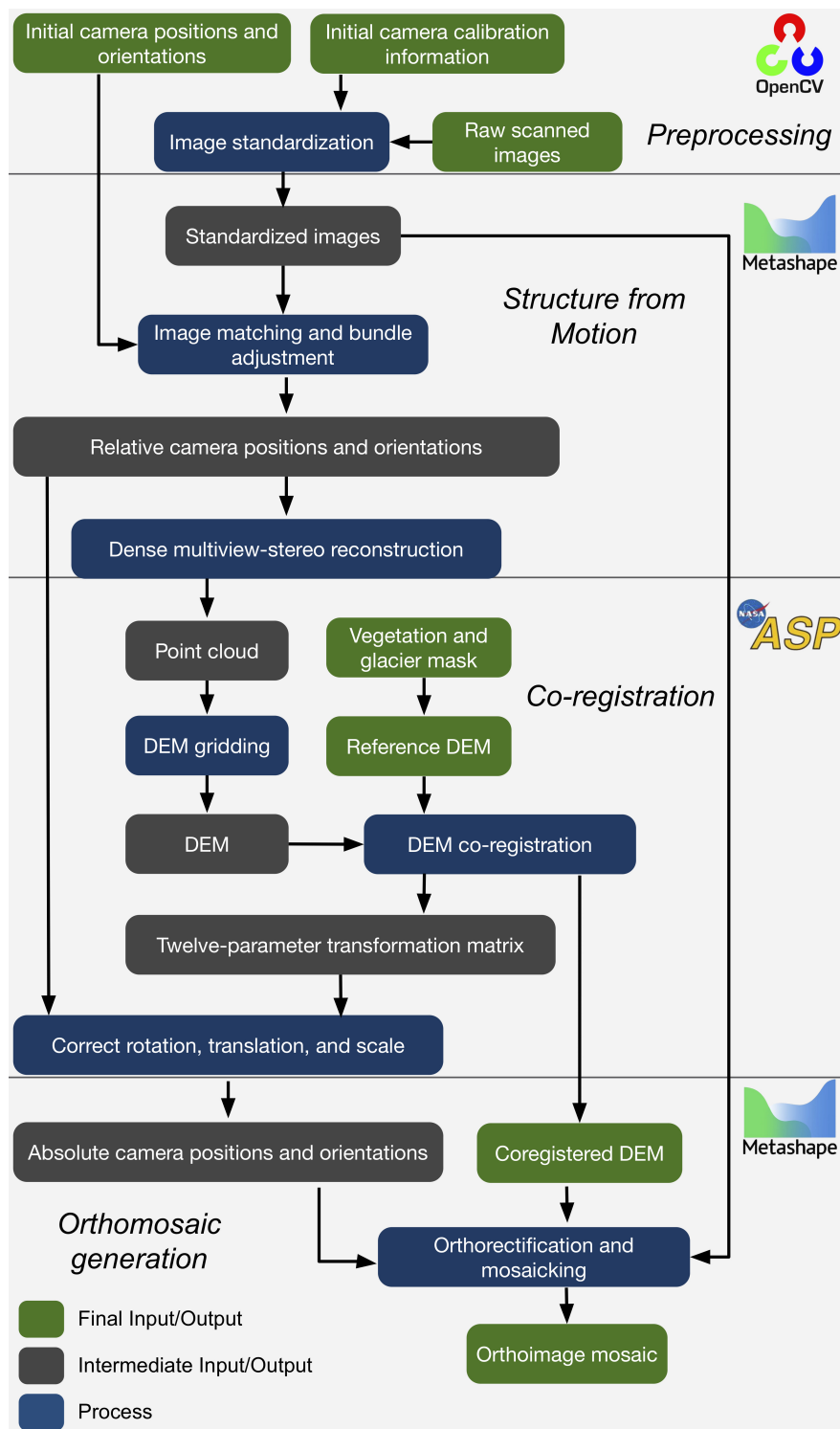


Figure 1.2: Historical Structure from Motion (HSfM) automated workflow for the *single date - single block* mode.

HIPP uses fiducial marker templates to automate fiducial marker detection for all images in a set. The software includes a number of predefined fiducial marker templates for the NAGAP archive (Figure A.4), and interactive tools that can be used to generate representative templates for scanned images from other sources (e.g., EE archive). When processing images from other sources, templates for one corner and one mid-side marker need to be created for each camera/lens combination. These templates are created from a user-selected sample image that is 1) representative of all other images from the same camera/lens combination and 2) does not suffer from overexposure, dust, scratches, or other issues that obscure the marker. The user selects the center position of representative fiducial markers in the sample image and HIPP generates standardized templates at both the native resolution of the scanned image and an upsampled resolution ($8\times$) for improved subpixel precision during subsequent template matching.

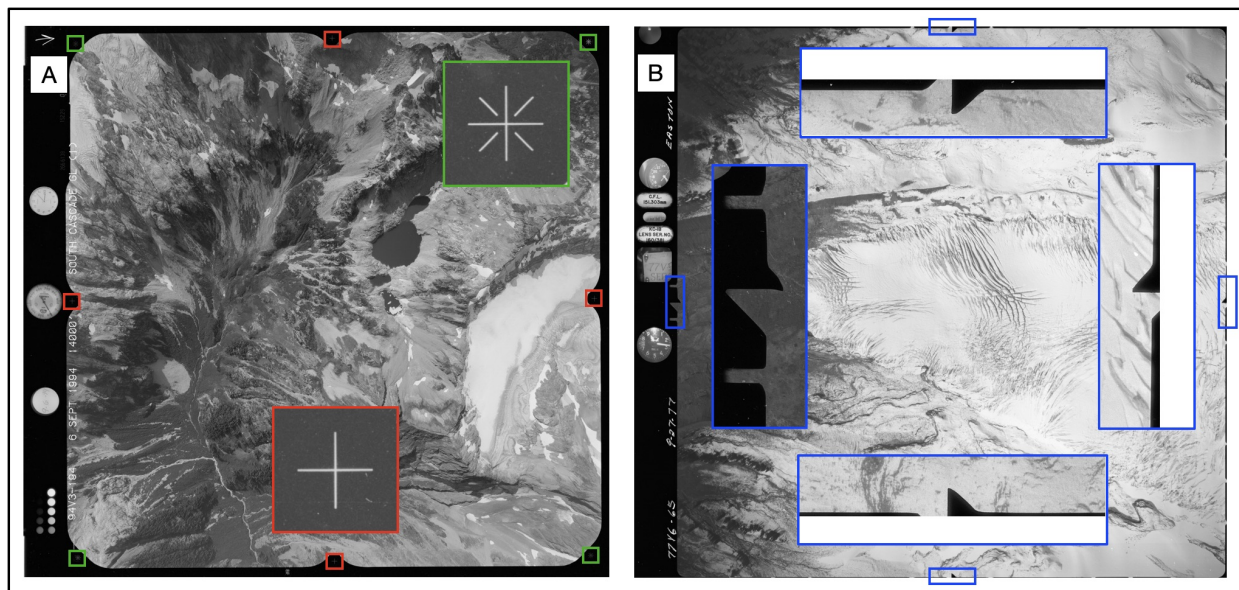


Figure 1.3: Examples of fiducial and pseudofiducial markers in North American Glacier Aerial Photography (NAGAP) images. **A)** Sample NAGAP image acquired on 1994-09-06 over the South Cascade Glacier site (NAGAP_94V3_211) with insets showing detail of mid-side (red) and corner (green) fiducial markers. **B)** Sample NAGAP image acquired on 1977-09-27 over the Easton Glacier site (NAGAP_77V6_065) with insets showing detail of mid-side pseudofiducial markers (blue). Portions of the top, right, and bottom markers are missing due to problematic cropping during scanning, and left marker tip is slightly bent. See Figure A.4 for additional NAGAP fiducial and pseudofiducial templates available for marker detection.

Once fiducial marker templates are created, HIPP determines the sub-pixel fiducial marker coordinates for all images in the set using the OpenCV *matchTemplate* algorithm with search windows defined for the corresponding fiducial marker locations in each image. To ensure match quality, the *matchTemplate* score (range 0–1) for each fiducial marker must be within a predefined threshold of the mean score for all matches at the same fiducial marker location across all images in the set, otherwise the detected position is discarded. A default threshold of 0.01 was used in this study as it robustly excluded spurious matches for a large sample of the NAGAP images. HIPP produces quality control plots showing the subpixel position of each template match, the distance between fiducial markers, and orthogonality metrics for opposing fiducial markers. These plots can be used to evaluate the quality of fiducial marker detection and adjust the threshold if necessary.

1.5.1.1.2 Affine transformation to match calibration data

When camera calibration reports are available, HIPP computes a 2D affine transformation between the observed fiducial marker positions for each scanned image and the known fiducial marker positions from the camera calibration report. For this study, the marker positions were manually extracted from the available calibration reports, but the HIPP package includes experimental utilities for optical character recognition (OCR) to facilitate bulk extraction. The affine transformation is used to warp each scanned image to restore a uniform calibrated interior geometry for the image set, as well as compute an updated pixel pitch.

1.5.1.1.3 Affine transformation to match mean marker positions

For cases with high-quality fiducial marker matches but no available calibration information, we compute the average position of each fiducial marker (relative to the inferred principal point) across the full image set, and use these average positions to define the affine transform needed to standardize each image.

1.5.1.1.4 Pseudofiducial marker detection without affine transformation

The most common case for the NAGAP archive involves no available calibration information and imprecise, unusable, and/or missing fiducial markers in the scanned images (Figure A.4). In these cases, we use distinct shapes (e.g., notch patterns) on the photo frame as "pseudofiducial markers." The pseudofiducial markers are centered on the four sides of the photo frame for the NAGAP cameras. Their locations can be used to define the precise frame

midpoint positions, which are then used to estimate the principal point location (Figure 1.3). The HIP software includes predefined pseudofiducial marker templates for all images in the NAGAP ADC collection (Figure A.4), and utilities to define custom pseudofiducial templates when processing images without fiducial markers from other collections.

The pseudofiducial marker workflow uses the same template matching approach described above for the fiducial markers, only without subpixel refinement due to the inferior match precision. In addition, the frame appears physically damaged in some image sets and improperly cropped during scanning in others (e.g., Figure 1.3B), which can introduce errors in the resulting pseudofiducial matches. To accommodate partially visible pseudofiducials, we pad the scanned image with a black border (DN value of 0, default width of 250 px) which provides a larger search window for template matching. To ensure match quality, the matched position of each pseudofiducial marker must be within a threshold of 50 pixels of the mean position for all matches at the same marker location across all images in the set, or it is discarded. The default value was determined by examining quality control plots produced by HIP and identifying an appropriate threshold to exclude spurious matches for a large sample of NAGAP images.

1.5.1.2 *Principal point determination and frame removal*

The principal point is computed as the center point between all detected markers that passed quality control checks. A minimum of two markers is necessary to estimate the principal point, while including additional markers provides redundancy that will improve accuracy. If the principal point cannot be determined automatically from the marker template matching, the HIP *pick_fiducials* utility can be used to manually select mid-side or corner points to determine the principal point.

After the principal point position is determined, each image is cropped to a fixed square area around the principal point to remove the photo frame. The output image dimensions are set based on the minimum distance between the fiducial or pseudofiducial markers and the principal point minus an offset that removes the image frame from all images in the set. At this stage, we consider the image set to be standardized with common interior orientation, and ready for photogrammetric processing.

1.5.1.3 Image enhancement

HIPP includes several options to improve cropped image contrast as a final preprocessing step. In this study we used the Contrast Limited Histogram Equalization (CLAHE) algorithm implemented in OpenCV (*createCLAHE* with a *clipLimit*=2 and *tileGridSize*=(8,8)), followed by a linear histogram stretch with minimum and maximum values set to the 0.1 and 99.9th percentile of cropped image values. This image enhancement improved feature matching for under- or over- exposed surfaces (e.g., shadows, snow) and provided more consistent orthoimage mosaics.

1.5.1.4 Camera position estimation

As described in Section 1.4.3, we extract camera longitude, latitude, and altitude (converted to geodetic height) from available metadata whenever possible. For photographs with horizontal position data but no altitude or elevation information, HIPP samples the approximate surface elevation beneath each initial horizontal camera position using the USGS elevation data API, which queries the $\frac{1}{3}$ arc-second National Elevation Dataset (NED) (USGS, 2019). HIPP then converts the NED orthometric heights (above the NAVD88 vertical datum) to geodetic height above the WGS84 ellipsoid. Finally, we assume a flight altitude of 1,000 m above this surface elevation and determine the corresponding camera position elevation above the ellipsoid. The estimated flight altitude of 1,000 m above ground level was determined by iteratively examining the true positions for a large sample of NAGAP images processed with HSfM. Since the NAGAP photos were generally acquired at a constant elevation (above vertical datum) for each site rather than a constant altitude above ground, HIPP determines the maximum estimated camera elevation for the image set and assign this value to any cameras in the set lacking elevation information.

1.5.2 Structure from Motion

The HSfM method supports three processing modes for a range of potential input image configurations: (1) *single date - single block*, (2) *single date - multiple blocks*, (3) *multiple dates - multiple blocks*. Each mode builds upon the functionality provided by the previous mode. As mentioned in Section 1.2, we define a block as three or more overlapping images acquired on the same acquisition date with the same camera. Multiple separate blocks may exist for the same image set (e.g., blocks for non-overlapping flightlines covering adjacent glaciers).

When individual blocks from multiple acquisition dates (and potentially multiple cameras) overlap at the same site, these form a single "multi-temporal block" which we processed with the *multiple dates - multiple blocks* mode. These multi-temporal blocks are used to improve intrinsic and extrinsic parameters for all cameras prior to processing each block with the *single date - single block* mode. We now briefly describe the critical processing steps in the *single date - single block* workflow (Figure 1.2), which forms the core of all processing modes.

1.5.2.1 Image matching

The HSfM workflow begins by identifying sparse feature matches (tie points) between all possible standardized image combinations in the block using the Metashape *matchPhotos* function with *high* matching accuracy (native image resolution). See Table A.1 for additional details on feature matching settings.

1.5.2.2 Bundle adjustment

Bundle adjustment optimization relies on the fundamental collinearity equations to optimize interior and/or exterior camera orientation parameters using these feature matches (e.g., Ackermann, 1981; Fraser, 1997). The HSfM workflow performs a bundle adjustment optimization (Metashape *alignCameras* function) using the sparse feature matches and known values for focal length, pixel pitch, and initial camera position. We assume an initial accuracy of 1,000 m for the camera position estimates described in Sections 1.4.3 and 1.5.1.4. While estimates for flightline heading are available for some photos, we assume an initial nadir orientation and north heading for all cameras (pitch, roll, and yaw of 0°) and assign estimated accuracy of 10° for pitch and roll, and 180° for yaw. We use the Metashape default Brown-Conrady lens distortion model (Brown, 1971), and solve for a subset of intrinsic parameters during bundle adjustment, including focal length (F), principal point coordinates (Cx, Cy), as well as radial (K1, K2, K3) and tangential (P1, P2) lens distortion coefficients.

1.5.2.3 Dense multi-view stereo reconstruction

Once interior and exterior camera parameters are refined, HSfM performs dense multi-view stereo reconstruction. This process begins with dense image correlation for pairs of overlapping images using the Metashape *buildDepthMaps* function with *high* quality (downscale factor = 2) and *AggressiveFiltering* to remove outliers (Table A.1). Finally, HSfM

uses the *buildDenseCloud* Metashape multi-view triangulation function to generate a dense point cloud, which is exported in LAZ format.

1.5.3 DEM co-registration

The output historical DEM will have absolute position, rotation, and potentially scaling error, due to inaccurate initial camera positions and bundle adjustment without GCPs. To correct these issues, HSfM includes a multi-stage co-registration process to align the initial DEM to a modern reference DEM.

1.5.3.1 DEM gridding

The HSfM workflow generates a DEM from the dense point cloud using the ASP *point2dem* utility, which uses an Inverse Distance Weighting (IDW) algorithm with 1-grid-cell search radius to improve prediction of true elevation values for a given cell, while avoiding interpolation artifacts over large data gaps. We conservatively set the output DEM grid cell size using a multiplicative factor of 2–3 times the native image GSD to reduce noise/artifacts and data volume, while preserving sufficient detail for geodetic analysis. The native GSD values for the NAGAP images generally range from 0.1–0.3 m, and we use a standard posting of 1 m for all DEMs for our study sites.

1.5.3.2 Stable surface mask preparation

Successful co-registration of historical DEMs with evolving surfaces (e.g., glaciers) requires careful identification of nearby control surfaces that are stable and static over time. Fortunately, most of the NAGAP datasets were acquired over high alpine sites above the treeline with a good distribution of stable, exposed surfaces to use for co-registration. We assumed that all non-forested and non-glacierized surfaces in our study areas were stable for the time period between the historical photo acquisition and the modern reference DEM acquisition. While irrelevant for local relative elevation change analysis following co-registration, this assumption is supported by estimated regional erosion (< 0.3 mm/yr) (Reiners et al., 2003) and vertical deformation (< 2 mm/yr) (Lau et al., 2020) rates for Washington State, which will offset each other, and are negligible compared to our DEM elevation uncertainty and elevation change rate uncertainty.

We use the *dem_mask.py* utility implemented in the *demcoreg* Python package (Shean et al.,

2021) to mask the reference DEM over glacier polygons from the RGI v6.0 (RGI Consortium, 2017) and forest landcover classes (41–43) from the 30-m National Land Cover Dataset (NLCD) (Dewitz, 2016). The user can also manually define polygons over stable control surfaces and apply the inverse to mask the reference DEM for use during co-registration.

1.5.3.3 Iterative Closest Point (ICP) co-registration

The first stage of our multi-stage co-registration procedure uses a three-step Iterative Closest Point (ICP) alignment routine implemented in the HSfM Python function *pc_align_p2p_sp2p*, which wraps the ASP *pc_align* command-line tool (Beyer et al., 2018; Shean et al., 2016). The *pc_align* tool provides various implementations of the ICP algorithm (Pomerleau et al., 2013) along with robust outlier filtering and other configurable parameters, including the maximum expected offset between the two input point clouds. The first ICP co-registration step uses the *pc_align point-to-plane* ICP method to compute a rigid body translation and rotation needed that minimizes the large initial offset between the historical and reference DEM. The second step refines the resulting transform by correcting for scale, along with residual translation and rotation offsets, using the *similarity-point-to-point* ICP method. The final step further improves this transform, again using the *similarity-point-to-point* method, but with a masked version of the reference DEM and tighter constraints to refine the final transformation over a subset of exposed, stable surfaces. The maximum expected three dimensional displacement decreases for each of the three steps in the HSfM co-registration process as alignment improves. These values are configurable, with default values set to 2,000, 1,000, and 100 m, respectively, based on observed offsets for a large sample of NAGAP DEMs.

1.5.3.4 Nuth and Kääb (2011) co-registration

The second stage of our multi-stage co-registration uses the aspect- and slope-dependent method developed by Nuth and Kääb (2011) and implemented in the *demcoreg dem_align.py* utility. In addition to the reference DEM masking described above, *dem_align.py* applies a filter to mask surfaces in the reference DEM that have a slope less than 0.1° or greater than 40° , an absolute elevation offset greater than 100 m, or elevation offset that exceeds a robust 3-sigma outlier threshold ($\text{median} \pm 3 \times \text{NMAD}$). Generally, this second stage does not significantly change results following successful ICP co-registration, but it can provide sub-pixel co-registration accuracy in mountainous terrain and remove residual systematic offsets for non-optimal ICP runs.

1.5.4 Updating camera pose and orthomosaic generation

After successful co-registration, the final 12-parameter ICP transform and the 3D translation computed by *dem_align.py* are applied to the self-consistent camera positions from the previous bundle adjustment, which improves their absolute geolocation accuracy. These updated camera positions are imported into Metashape with tight constraints on geolocation accuracy (0.01 m) and the global *chunk.updateTransform* function is run to update camera orientations for the block. The updated camera models and the co-registered historical DEM are then used to orthorectify each input image. Finally, a seamless, blended orthomosaic is produced at the median native GSD of the input images, with geolocation accuracy similar to the co-registered DEM.

1.5.5 Single date - multiple blocks

The second mode supported by HSfM is *single date - multiple blocks*, which is used if there are multiple, non-overlapping blocks in the input image set. The first step in this mode attempts to identify all blocks by passing the standardized images and initial extrinsic/intrinsic metadata to the bundle adjustment and dense cloud reconstruction functions, as described in the *single date - single block* approach. Here, *matchPhotos* and *buildDenseCloud* are run with *medium* matching accuracy and quality parameters to expedite processing (Table A.1). The resulting list of overlapping images with shared feature matches ("aligned images") is then parsed by HSfM to identify separate blocks. The block detection algorithm iterates on unaligned images until no additional blocks with 3 or more images can be identified. Each block is then processed using the *single date - single block* mode outlined above, and all co-registered DEMs and orthomosaics are mosaicked using the ASP *dem_mosaic* utility. The refined camera model for each block will be slightly different in this mode. While this was acceptable for our test cases, a better approach is to solve for a single set of intrinsic parameters shared by all blocks acquired with the same camera on a single date, as described in the *multiple dates - multiple blocks* mode below.

1.5.6 Multiple dates - multiple blocks (4D SfM)

The most sophisticated *multiple dates - multiple blocks (4D SfM)* mode supported by HSfM performs a large joint optimization ("multi-temporal bundle adjustment") using all available images across all acquisition dates for a given site. Previous studies refer to this general

concept as *multi-epoch* or *multi-temporal* reconstruction (e.g., Feurer and Vinatier, 2018; Korpela, 2006; Vargo et al., 2017; Warrick et al., 2017; Zhang et al., 2021), but we prefer the shorthand *4D SfM* (four-dimensional Structure from Motion), for our approach, which includes both multi-temporal bundle adjustment and multi-temporal composite DEM co-registration. Our approach differs from previous implementations in that we: 1) do not use manually selected GCPs during optimization, 2) use a multi-stage co-registration method, and 3) perform a final optimization for each individual block via the *single date - single block* mode.

This mode begins with the block preparation routine outlined in the *single date - multiple blocks* mode, except that we include all images from all acquisition dates, with careful accounting of images that share the same camera intrinsic parameters. We use *medium* quality settings to expedite processing and produce a coarse-resolution (10 m) multi-date composite DEM that is co-registered to the reference DEM to improve initial geolocation accuracy for all optimized images. We then split the optimized images by acquisition date and run the *single date - multiple blocks* routine to process all blocks collected on the same date with the shared and optimized intrinsic parameters held fixed. Any images that were not aligned during the large joint optimization are re-introduced in the appropriate block with original pose estimates, and each block is reprocessed with *high* quality settings to further refine all poses. Though more complex, this robust approach offers improved, self-consistent results for the full time series of historical images, and we used this approach to prepare all products for our study sites.

1.5.7 Accuracy assessment

We use the following criteria to evaluate the performance of the HSfM method and quality of output products.

1.5.7.1 Absolute and relative DEM accuracy

Co-registration is deemed successful if there is no systematic error in the final elevation difference map between the co-registered historical DEM and reference DEM. Specifically, the distribution of difference values over stable surfaces should appear random with near-zero bias and limited spread, providing a measure of absolute DEM accuracy in a geodetic coordinate reference system. To make this assessment of absolute accuracy, we compute the median and Normalized Median Absolute Deviation (NMAD) of residual elevation difference values over

the masked, filtered, stable reference surfaces. These robust estimators of the residual bias and spread (Höhle and Höhle, 2009; Shean et al., 2016) are defined as:

$$m_{dz} = \text{median}(dz) \quad (1.1)$$

$$NMAD = 1.4826 \cdot \text{median}(|dz_i - m_{dz}|) \quad (1.2)$$

where dz denotes the full sample of per-pixel difference values between the historical and masked reference DEM surfaces after co-registration.

While the NMAD of these absolute difference values can be used to estimate relative accuracy (precision) of the historical DEM, it will potentially include relative errors introduced by the reference DEM. To avoid this issue, we assess the relative accuracy among the co-registered historical DEMs by computing the per-pixel standard deviation (SD) and NMAD of all elevation values in the historical DEM time-series stack. We only consider pixels over masked, filtered, stable surfaces with three or more observations in the DEM time-series stack. We then compute summary statistics for each site as the mean and median of the per-pixel SD and NMAD for all valid pixels.

1.5.7.2 Spatially autocorrelated error

To assess the spatial autocorrelation of residual error in the historical DEM products, we sampled empirical variograms for elevation difference maps between the historical and reference DEMs over stable surfaces. We used the *sample_empirical_variogram* function implemented in the xDEM package (Hugonnet et al., 2022; xdem contributors, 2021), which relies on the SciKit-GStat Python package (Mälicke et al., 2022). For each difference map, we sample and average five unique variograms with sample size of 10,000. We then use weighted least-squares to fit a double-range nested spherical variogram model to the empirical variograms, which captures both the short and long-range spatial autocorrelation of the errors (Hugonnet et al., 2022). The long-range sill is reported as additional variance above the short-range sill, and the total variance of the nested model is the sum of the short and long-range sill components.

1.5.7.3 Reference DEM sensitivity testing

As outlined in the *single date - single block* description, the HSfM method uses reference DEM data to improve the geolocation accuracy of the historical DEMs. To evaluate the sensitivity of this approach to reference DEM source and resolution, we processed the Mount Baker

historical DEMs using multiple reference DEMs, including the high resolution (1 m) product derived from airborne lidar and the medium resolution (1-arcsecond, 30 m) Copernicus DEM (Section 1.4.5). To assess the relative accuracy of time series stacks produced using each reference DEM, we computed the corresponding per-pixel standard deviation and NMAD of elevation values as described in Section 1.5.7.1.

1.5.7.4 Comparison of automated HSfM method with manual GCP method

An earlier historical image processing effort by the USGS produced historical DEMs from NAGAP images collected on 1970-09-20, 1979-10-06, 1986-09-05, and 1992-10-06 over South Cascade Glacier using Metashape with manually identified natural GCPs as control during bundle adjustment (McNeil et al., 2022a; O’Neel et al., 2019). We processed the same input images using the HSfM approach, which enabled a direct comparison of output products. We co-registered all DEMs to the same 2013-2015 composite WV reference DEM using the *dem_align.py* utility and then analyzed residuals and spatial autocorrelation over stable surfaces in the resulting elevation difference maps. We then prepared difference maps between DEMs generated using the HSfM and manual GCP method for each date, and analyzed residuals over the glacier surface.

1.5.7.5 Camera position accuracy

We use the final RMS reprojection error in pixels to evaluate the quality of the bundle adjustment optimization for each block. Where multiple blocks contribute to a final single-date DEM mosaic, we report the mean RMS reprojection error for all input blocks. We also evaluate the accuracy of the initial camera position estimates (Section 1.4.3 and 1.5.1.4) by computing the translation magnitude for refined camera position after bundle adjustment and final camera position after co-registration.

1.5.7.6 Evaluation of image standardization approaches

We evaluated the HIPPI standardization approaches for three image sets over the South Cascade Glacier site with well-defined fiducial markers and calibration reports (1994-09-06, 1996-09-10, 1997-09-23). We prepared a baseline interior orientation result for each image set using the precise fiducial marker and principal point determination approach, without subsequent affine transformation. We then examined differences between these baseline values

and values for standardization using 1) affine transformation to match calibration data, 2) affine transformation to match mean marker positions, and 3) pseudofiducial marker detection without affine transformation approaches. Specifically, we considered the estimated error (standard deviation from diagonal terms in the intrinsic parameter covariance matrix) for the optimized focal length and principal point offset computed during bundle adjustment. We also considered the total block RMS reprojection error and NMAD over stable surfaces for output DEMs generated using each approach.

1.6 Results

We highlight results for three common spatial and temporal data configurations encountered when working with historical images. These include 1) a single block of images collected on a single date (Easton Glacier, 1977), 2) single blocks collected on multiple dates for the same site (South Cascade Glacier, 1967–1997), and 3) multiple non-overlapping blocks collected on multiple dates (Mount Baker, 1970–1992).

Each of these case studies was processed using the *multiple dates - multiple blocks* mode (4D SfM), which automatically handles the respective spatial and temporal data configuration of the input images. For the Easton Glacier 1977 test case, HSfM immediately proceeded to the final *single date - single block* step, as no multi-temporal blocks could be formed for the input images from a single date. For the other two cases, the multi-temporal blocks were processed to refine shared intrinsic parameters prior to *single date - single block* processing.

1.6.1 Easton Glacier, 1977

We processed the eight available NAGAP images collected over Easton Glacier on 1977-09-27. As outlined in Section 1.5.1.4, camera altitudes were estimated at a constant 1,000 m above the highest sampled ground elevation for the image set (Figure 1.4). Camera positions were then iteratively refined, with final positions shifted by up to 600 m in the XY direction and 60 m in the Z direction following the bundle adjustment and co-registration procedures (Figure 1.4).

The RMS reprojection error for the Easton Glacier block was 0.67 px (0.15 m) and the absolute accuracy over stable surfaces in reference DEM was 0.00 m, with NMAD of 0.32 m (Figure 1.5D). The long-term elevation difference map (Figure 1.5G) reveals large glacier surface elevation change signals between 1977 and 2015, with magnitude of over 50 meters in places. The difference map also shows meter-scale geomorphic change (Figure 1.6) associated

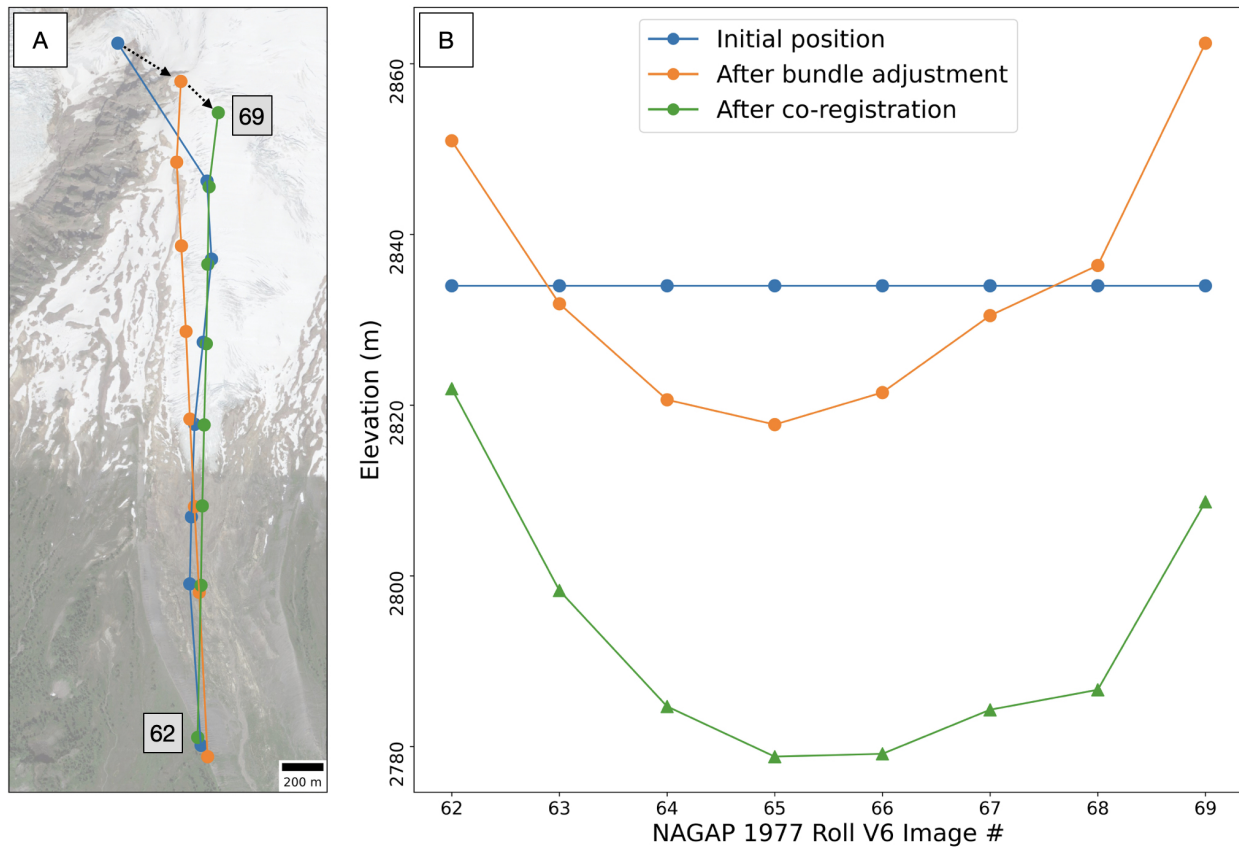


Figure 1.4: Iterative camera position refinement for the 1977-09-27 North American Glacier Aerial Photography (NAGAP) images over Easton Glacier. (A) Google satellite basemap (imagery source date 2016-07-28) with initial camera positions (blue), positions after relative bundle adjustment (orange) and final positions after co-registration with the 2015 lidar reference digital surface model (green). Gray labels identify frame numbers for the first and last images in the flight line. Dashed arrows show translation vectors for image #69. (B) Corresponding camera elevation refinement in meters above the WGS84 ellipsoid.

with lateral moraine mass wasting, stream erosion and moraine deposition following the glacier advance between 1956 and 1987 documented by Harper (1993).

1.6.2 South Cascade Glacier, 1967–1997

We successfully processed 243 images over the South Cascade Glacier site to produce 18 DEMs for 18 acquisition dates between 1967-09-21 and 1997-09-23 (Table A.2, Figure A.2). The block per-pixel image count was typically 2-3 (Figure A.5), with additional overlap

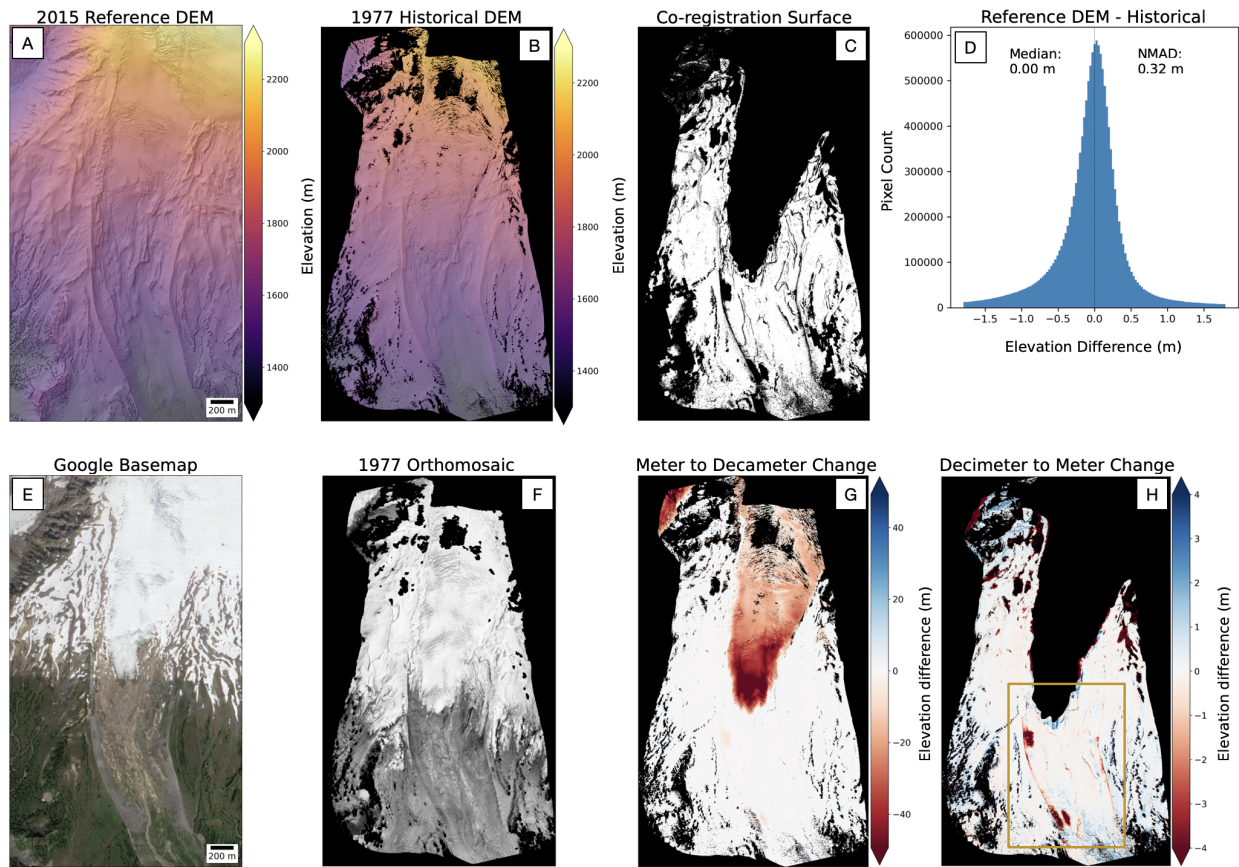


Figure 1.5: Results for Historical Structure from Motion (HSfM) processing of the eight North American Glacier Aerial Photography (NAGAP) images collected on 1977-09-27 over Easton Glacier. (A) 2015-08-27 airborne lidar reference digital surface model (DSM) with 1 m posting. (B) 1977-09-27 historical NAGAP digital elevation model (DEM) with 1 m posting. (C) Mask defining stable surfaces used during co-registration. (D) Histogram of final elevation difference values over stable surfaces (reference DEM minus historical DEM). (E) Google satellite basemap (imagery source date 2016-07-28). (F) 1977-09-27 historical orthomosaic. (G) Final elevation difference map showing glacier thinning and retreat, including a portion of the adjacent Deming Glacier (RGI60-02.17738) to the northwest. (H) Same as in G, but with a stretched color ramp to bring out meter-scale elevation change, highlighting changes in forefield geomorphology. Gold outline shows extent of Figure 1.6.

from multiple flight lines at different altitudes in some years. The mean RMS reprojection error for all blocks was 0.65 px (0.13 m) and the NMAD of difference values over stable surfaces ranged from 0.27 to 0.75 m (Table A.2), with limited spatial autocorrelation (Figure

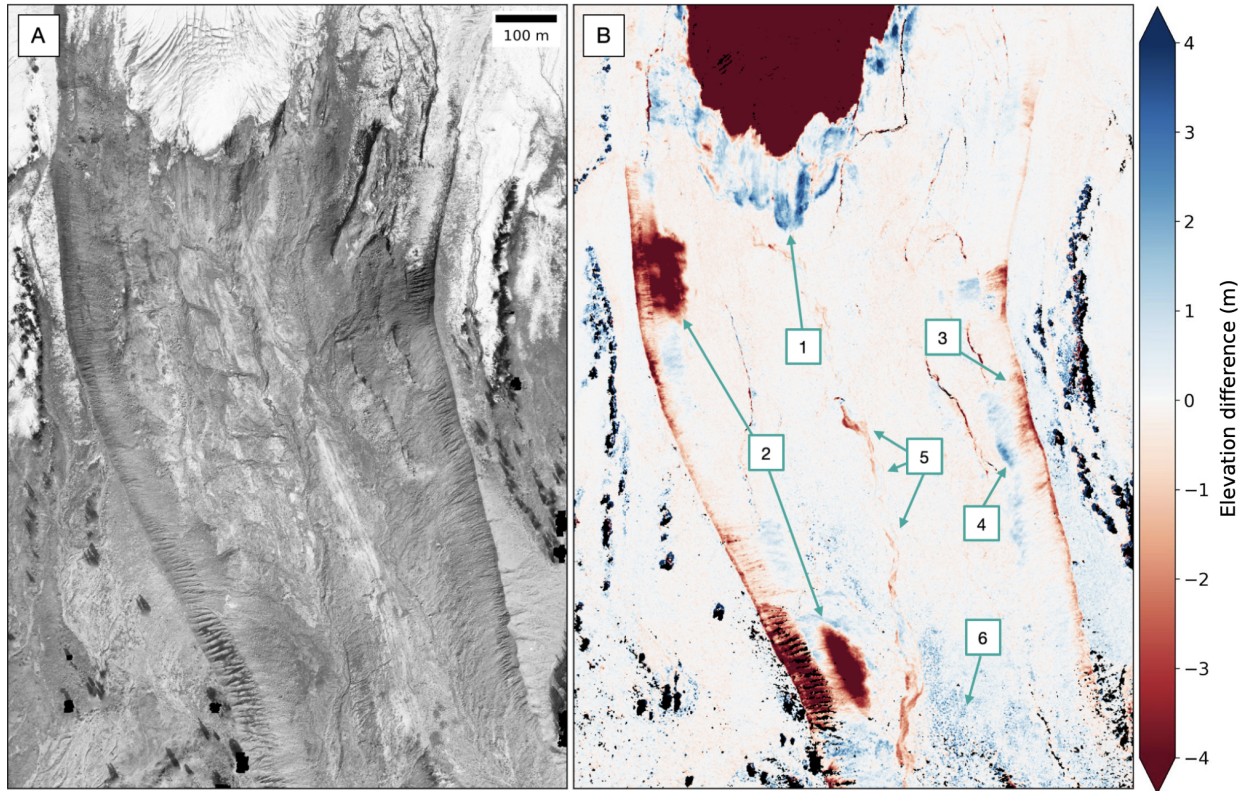


Figure 1.6: (A) Detail of the 1977-09-27 North American Glacier Aerial Photography (NAGAP) orthomosaic over the Easton Glacier terminus and forefield. (B) Elevation difference between the 1977-09-27 NAGAP digital elevation model (DEM) and 2015-08-27 reference lidar digital surface model (DSM) (~38 years). Numbered labels show (1) moraine deposition, (2) large thinning signals at the base of the western little ice age moraine, (3) lateral moraine mass wasting, (4) debris deposition at the base of the eastern little ice age moraine, (5) stream erosion, and (6) vegetation growth.

A.9). The final historical DEMs have no bias and randomly distributed residuals relative to the reference DEM (Figure 1.7D and A.6). We do not observe a relationship between the historical DEM accuracy and the stable surface area used during co-registration. The relative accuracy (NMAD) of the historical DEM time series stack was 0.37 m over stable surfaces (Figure 1.7C and E), while some portions of the thinning glacier surface with high DEM count display elevation change variability of > 25 m over the 30 year period (Figure 1.7C).

The historical DEM time series stack offers excellent temporal coverage (multiple DEMs per decade), especially over the lower glacier (Figure 1.7B). Six years (1967, 1970, 1974, 1979,

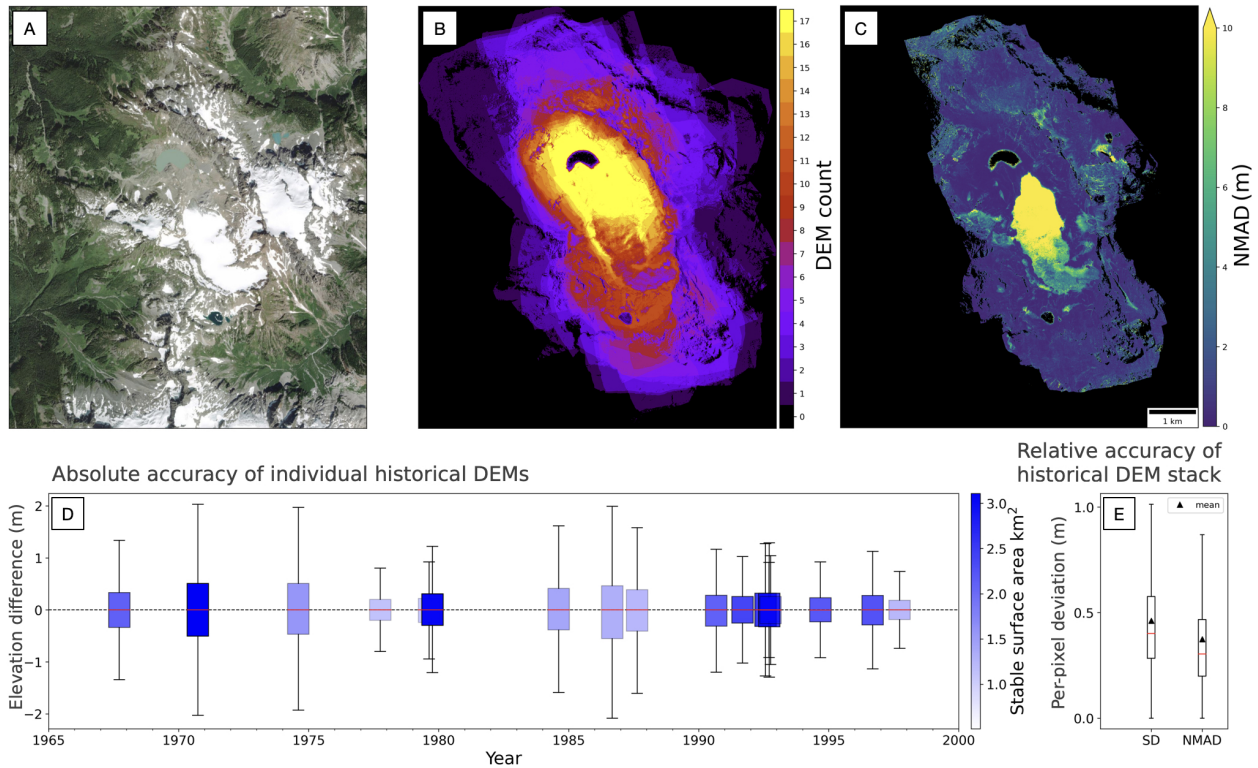


Figure 1.7: (A) Google satellite basemap for the South Cascade Glacier site (imagery source date 2016-08-19). (B) Per-pixel digital elevation model (DEM) count and (C) per-pixel normalized median absolute deviation (NMAD) for all 18 historical DEMs in the 30-year time series stack (1967-09-21 to 1997-09-23). (D) Absolute accuracy metrics over stable surfaces for each historical DEM (historical DEM minus reference DEM), with box color representing stable surface area coverage. (E) Relative per-pixel accuracy metrics over stable surfaces for the full DEM time series stack, with mean standard deviation (SD) of 0.46 m and mean NMAD of 0.37 m. The NMAD box and whisker distribution summarizes of values shown in panel C. Boxes in (D) and (E) show interquartile range, with median values in orange and whiskers at 1.5 times the interquartile range.

1994, 1996) have nearly complete coverage of the glacier, four of which (1967, 1974, 1994, 1996) were not processed for previous reanalysis efforts (e.g., McNeil et al., 2022b; O’Neel et al., 2019).

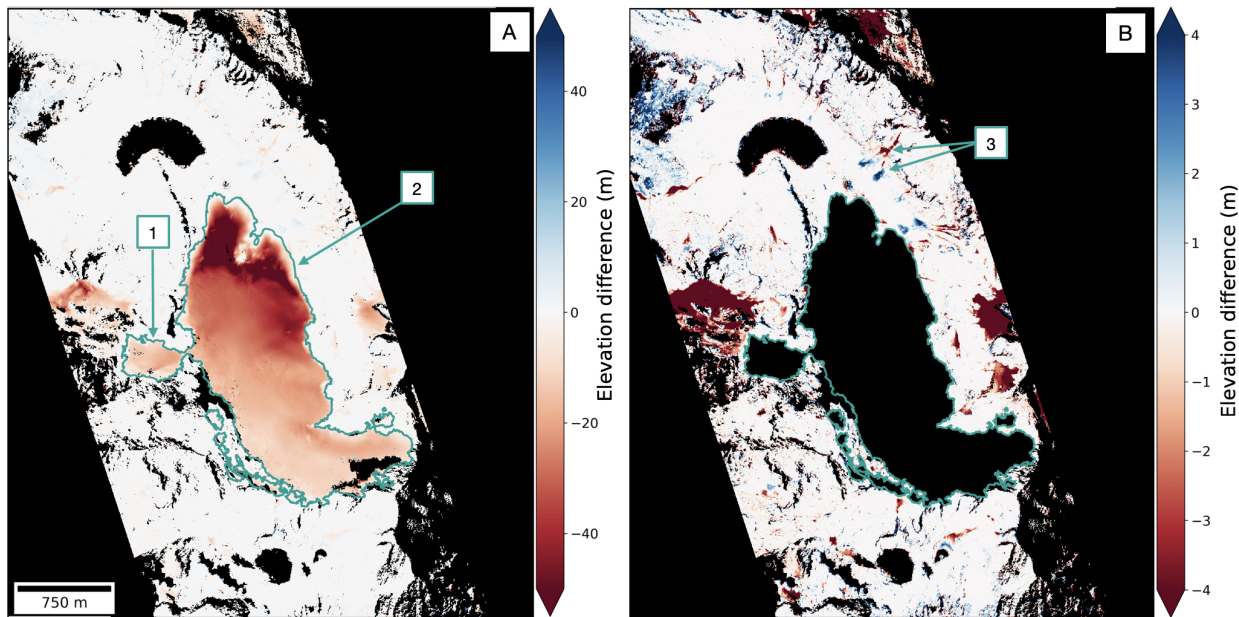


Figure 1.8: (A) South Cascade Glacier elevation change between the 1994 historical digital elevation model (DEM) and the 2015 reference DEM. (B) Same as in A, but with glacier mask applied and stretched color ramp to show meter-scale change. Numbered labels show (1) glacier tributary near Post Peak, (2) 1992 glacier extent (McNeil et al., 2022a), and (3) negative elevation change attributed to talus mass wasting, with corresponding positive change over deposits. See Figure A.8 for additional detail of these features.

1.6.2.1 Comparison with manual GCP method

The HSfM DEM products display improved absolute and relative accuracy compared to corresponding DEMs generated using the manual GCP method (Figure 1.9). The DEMs generated using the manual GCP method displayed residual horizontal and vertical offsets of 1-2 m relative to the reference DEM, likely due to natural GCP position uncertainty. After co-registering all DEMs to the same reference DEM, the HSfM residuals over stable surfaces had reduced spread compared to those from the manual GCP method (Figure 1.9). The DEMs prepared with the manual GCP method contain large spatially correlated errors (Figure 1.9) and appear biased over glacier surfaces, with mean difference ranging from -1.61 to -0.22 m compared to the HSfM DEMs (Figure A.7). These errors will bias subsequent geodetic mass balance calculations, though the actual impact for South Cascade Glacier is relatively small considering the magnitude of the mass loss signal and long time interval.

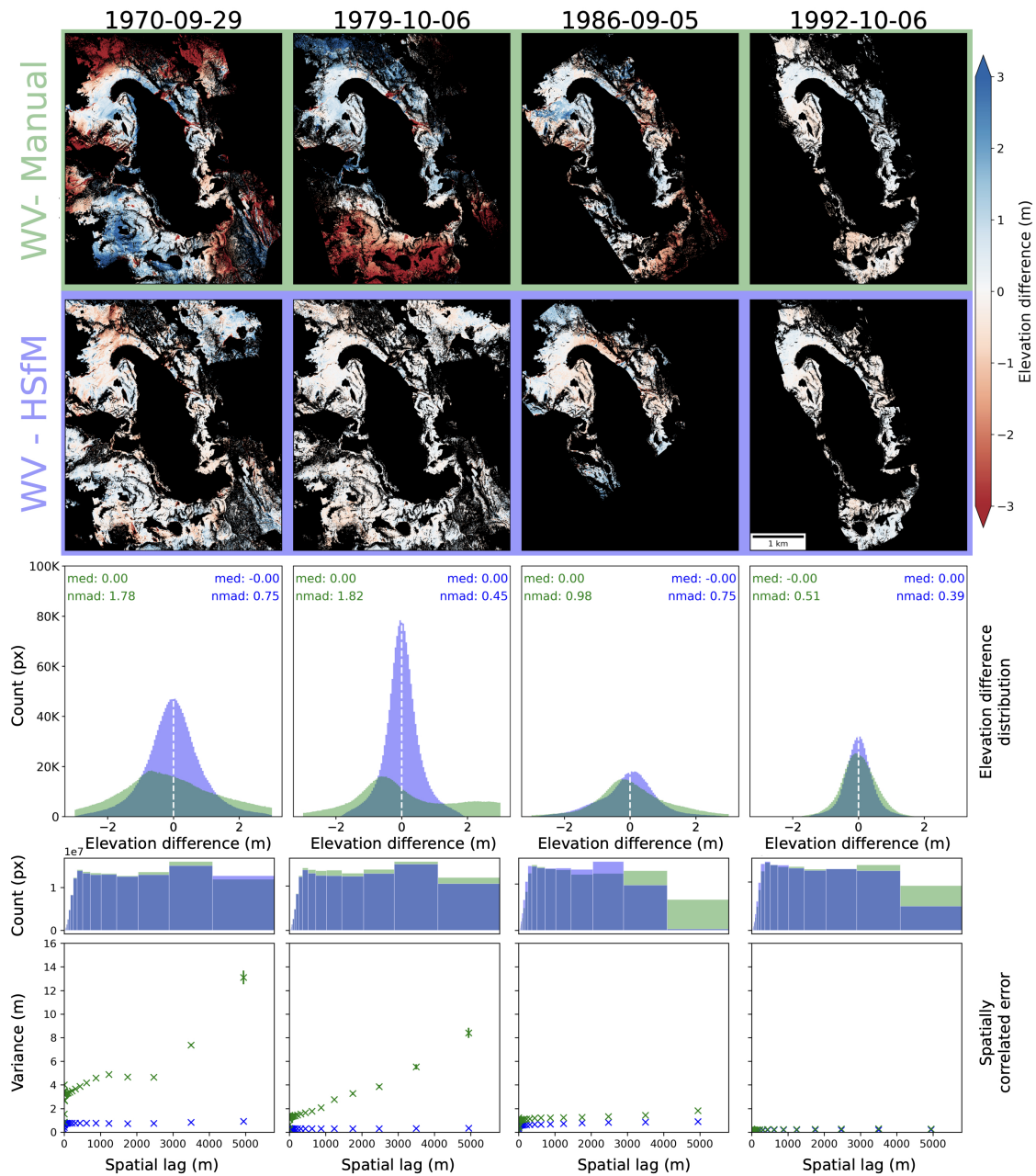


Figure 1.9: Comparison between historical digital elevation models (DEMs) generated with Historical Structure from Motion (HSfM) and the manual ground control point (GCP) methods. Top row (green) shows difference maps over stable surfaces between the 2013-2015 WorldView (WV) stereo composite reference DEM and four DEMs produced with the manual GCP method. Second row (purple) shows corresponding difference maps for HSfM output. Third row shows residual distributions and final row shows empirical variograms for each difference map. The HSfM DEMs consistently show improved accuracy and precision compared to the DEMs from the manual GCP method.

1.6.2.2 Image standardization

Three NAGAP image sets for the South Cascade Glacier site (1994-09-06, 1996-09-10, 1997-09-23) had well-defined corner and mid-side fiducial markers with corresponding calibration reports, which provided an opportunity to investigate the impact of input image standardization approach on reconstruction error and output DEM quality (Section 1.5.7.6). We observe improvement for image standardization with affine transformation to match calibrated values for these test cases (Table A.3), but overall results are similar for the three approaches. As expected, larger image sets with more overlap had the best results for all three standardization approaches. Unfortunately, because these images include true corner and mid-side fiducial markers, the photo frame does not contain the same notched pseudofiducial markers present for the majority of the NAGAP archive images (Figure A.4), and these image standardization results are not directly transferable to other pseudofiducial types. The excellent absolute and relative accuracy observed for the full historical DEM time series at our study sites (Figures 1.7 and 1.10) provides a better assessment of the generalized pseudofiducial marker standardization approach.

1.6.3 Mount Baker, 1970–1992

We successfully processed 261 images over the Mount Baker site, generating 21 DEMs for 10 dates between 1970-09-09 and 1992-09-18 (Table A.4, Figure A.2). This is the most complex case study, with multiple non-overlapping blocks for some dates (e.g., 5 DEMs on 1977-09-27, Table A.4), with DEMs that were individually co-registered prior to being combined into a final DEM mosaic for that date. During the initial multi-temporal bundle adjustment process, camera positions moved horizontally and vertically by up to 3,600 m from their originally estimated positions. Co-registration of the multi-date low-resolution composite DEM further improved the absolute camera positions for some blocks by up to 450 m. Following these initial position adjustments, the final *single date - single block* processing step required final camera position refinement of less than 100 m.

The block per-pixel image count was generally 2–3, with overlap of > 10 images for some dates and locations (Figure A.10). The mean RMS reprojection error for individual blocks was 0.67 px (0.15 m) and the NMAD of difference values with respect to stable surfaces in the reference DEM ranged from 0.52 to 1.2 m (Table A.4), with some larger DEM mosaics (e.g., 1979-10-06) displaying limited spatially correlated errors at longer lag distances (Figure A.11 and A.12). The final historical DEMs have no bias and randomly distributed residuals relative

to the reference DEM (Figure 1.10D and A.11). We observe a relationship between the historical DEM accuracy and the stable surface area used during co-registration, with larger DEMs (e.g., 1979-10-06, 143.3 km², Table A.4) displaying higher spread of residuals over stable surfaces (Figure 1.10D). The relative accuracy of elevation values in the historical time series stack was 0.68 m (NMAD) over stable surfaces (Figure 1.10C and E), while thinning glacier surfaces display elevation change variability of > 10 m (Figure 1.10C). The historical DEM time series stack shows the best temporal coverage for glaciers along the south and southeastern flank of Mount Baker with seven years of coverage over lower Easton Glacier (1970, 1974, 1977, 1979, 1990, 1991, 1992) (Figure 1.10B-C).

1.6.3.1 Intrinsic parameter refinement with 4D SfM

We observed that refining intrinsics using the *4D SfM* process (Section 1.5.6) significantly reduced systematic "doming" error due to limited image overlap and poor acquisition geometry (e.g., James and Robson, 2014). A good example of this improvement can be seen for block 1 of the 1991-09-09 image set, which spans the southeastern flank of Mount Baker (Figure A.10). The historical DEM created using intrinsic parameters independently optimized for a single block shows systematic elevation-dependent error, with significant spatial autocorrelation at ~ 2 -4 km lag distances (Figure 1.11A). By comparison, the historical DEM created with the refined intrinsic parameters from *4D SfM* processing has near-zero difference over stable surfaces at all elevations and no significant long-range spatial autocorrelation error (Figure 1.11B). This improvement stems from the additional constraints provided by overlapping image sets, even when large portions of the scene (e.g., glaciers) are changing over time.

1.6.3.2 Reference DEM sensitivity

The reference DEM sensitivity tests for the Mount Baker site showed that the HSfM method can produce accurate results using a global, low-resolution reference DEM. The relative per-pixel accuracy over stable surfaces for the full Mount Baker DEM time series stack was 0.68 m after co-registration with the 1 m lidar reference DEM and 1.26 m after co-registration with the 30 m Copernicus reference DEM (Figure A.3). The Copernicus DEM for the Mount Baker site contains apparent phase unwrapping artifacts over a portion of the southwestern flank (Figure A.3C), which increased errors during co-registration of smaller DEMs over these areas and led to higher, but still acceptable, errors in the DEM time-series stack.

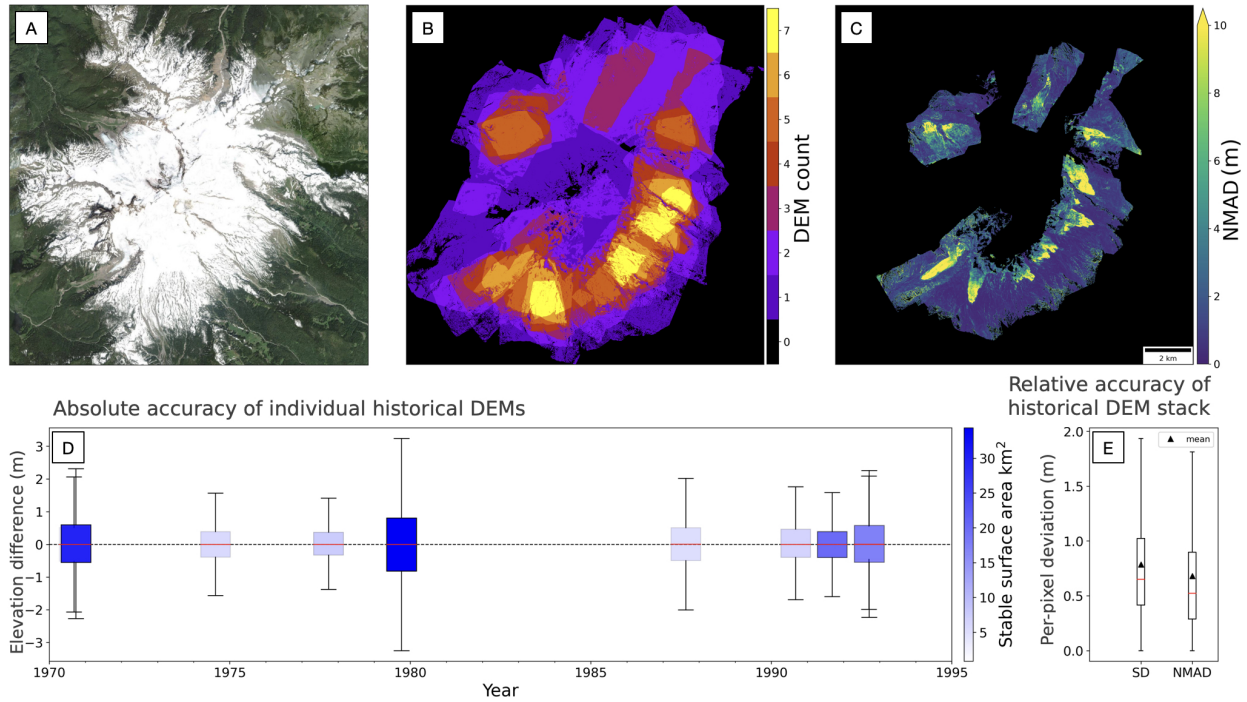


Figure 1.10: (A) Google satellite basemap for the Mount Baker site (imagery source date 2016-07-28). (B) Per-pixel digital elevation model (DEM) count map and (C) per-pixel normalized median absolute deviation (NMAD) for all 10 historical DEM mosaics in the time series stack (1970-09-09 to 1992-09-18). (D) Absolute accuracy metrics for each historical DEM mosaic, with box color representing available stable surface area. (E) Relative per-pixel accuracy metrics over stable surfaces for the full DEM time series stack, with mean standard deviation (SD) of 0.78 m and mean NMAD of 0.68 m. The NMAD box and whisker distribution summarizes values shown in panel C. Boxes in (D) and (E) show interquartile ranges, with median values in orange and whiskers at 1.5 times the interquartile range.

1.6.4 Processing time

We ran preliminary benchmarking tests with the NAGAP images ($\sim 12,000 \times 12,000$ px) to provide a general sense of processing time for the full HIPP/HSfM workflow. These tests show that processing time scales linearly with the number of input images and co-registration area. Images were downloaded with a 1 Gigabit internet connection to a dedicated desktop workstation running Ubuntu Linux 18.04 with a 3.3 GHz 10-core processor, 64GB RAM, and a 11GB graphics processing unit with 3584 CUDA cores. The total processing time for all images and DEMs for the Mount Baker site was approximately 15 hours. The total processing

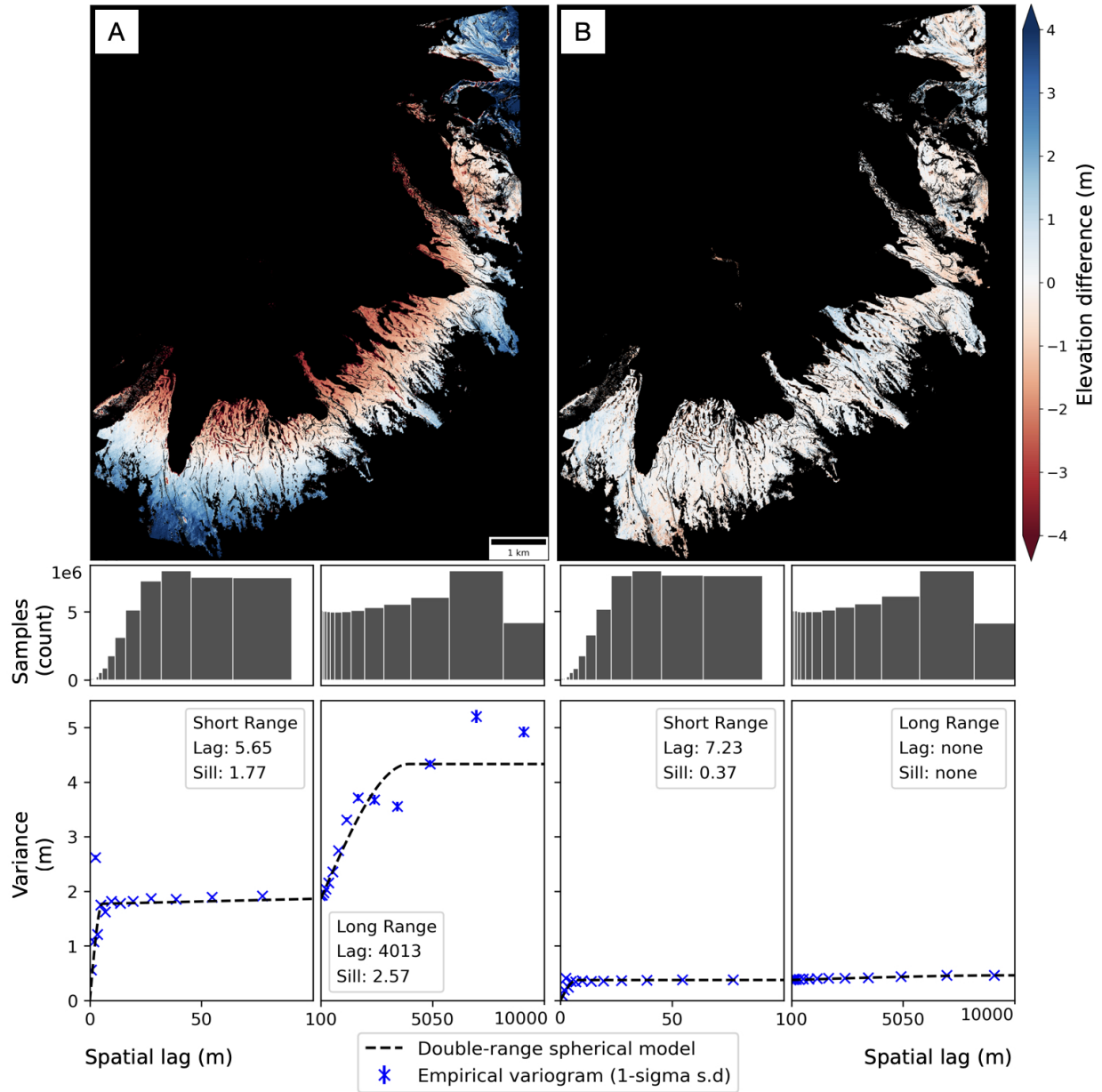


Figure 1.11: Stable surface difference maps between the largest block (Figure A.10) of the 1991-09-09 historical digital elevation model (DEM) and the 2015-08-27 lidar reference DEM for the Mount Baker site processed using the (A) *single date - single block* approach, and (B) Four-dimensional Structure from Motion (4D SfM) approach. Bottom row shows corresponding empirical variograms and model results. The refined intrinsics from the 4D SfM optimization eliminate spatially correlated errors associated with "doming" artifacts present in A.

time for all images and DEMs for the South Cascade Glacier site was approximately 8 hours. We observed average wall times of 5 seconds per image during preprocessing, 30 seconds per image during SfM reconstruction, and 12 seconds per km² during co-registration with a 1-m reference DEM.

1.7 Discussion

Our results show that the HSfM method produces accurate DEMs from scanned historical aerial photographs with limited metadata. Here we discuss some limitations of the input datasets and methodology, as well as broader implications and future directions for this work.

1.7.1 Image matching

Of the 597 total images processed over Mount Baker and South Cascade Glacier, 93 were excluded during initial block preparation (Section 1.5.6). There are many possible causes for this exclusion, including incorrect archive metadata (i.e., the images were not actually collected at Mount Baker or South Cascade), presence of clouds in images, or uncaught errors during image preprocessing and fiducial marker detection. Additionally, some images contain over- and under-exposed areas (e.g., snow and shadows), which is problematic for feature detection and brute-force matching. Future efforts to improve histogram equalization and noise reduction may help improve match point detection to overcome these issues. More sophisticated image overlap determination could eliminate the need for brute-force matching, including distance thresholds for image sets with sufficient initial camera position accuracy.

1.7.2 Availability and distribution of stable surfaces

In some cases, a historical image block is located over changing surfaces with limited or no stable surfaces (e.g., snow-covered mountain summits, glacier ice, or dense forest canopy). This is problematic for the co-registration steps, which require stable surfaces with adequate spatial distribution across the block. One potential workaround involves the traditional workflow with manual GCP selection for a limited subset of exposed stable point locations to constrain the bundle adjustment (e.g., Westoby et al., 2012). Alternatively, an initial co-registration with the unmasked reference DEM can remove gross geolocation errors, followed by a constrained ICP co-registration (e.g., a simple translation, without rotation or scaling parameters) using the small sample of stable surfaces. For cases with no stable surfaces, but

accurate "before" and "after" DEMs, one can interpolate to prepare a "dynamic reference DEM" or "dynamic GCPs" for the historical image acquisition date based on observed elevation change (e.g., Shean et al., 2019).

1.7.3 Advantages of an automated processing approach

For some limited historical image sets over smaller sites, a trained operator can manually preprocess images and select GCPs for SfM processing to obtain results with sufficient accuracy for their application in a matter of hours to days. This approach, however, does not scale for larger processing efforts, and our results show that the automated HSfM method rapidly produced (Section 1.6.4) more DEMs with higher accuracy and less systematic error than the manual GCP approach (Section 1.6.2.1). Some of the observed systematic error in the DEMs from the manual GCP approach may be a result of different operators and evolving processing strategies. An automated and standardized processing approach like HSfM can eliminate most human error, with improved data provenance and reproducibility.

1.7.4 Toward fully automated historical image processing

While most of the HSfM method is automated, processing some historical datasets may require one-time manual preparation steps. In the following sections, we summarize these steps, suggest options for automation, and offer additional guidance for new HSfM users.

1.7.4.1 Reference DEM preparation

The HSfM method requires a reference DEM with sufficient coverage over stable surfaces within the footprint of the historical image block. While a high-resolution DEM from airborne lidar or satellite/airborne stereo is preferred, a global DEM with medium resolution (e.g., Copernicus 30 m DEM) can also be used. The results presented in Section 1.6.3.2 show that the historical DEM stack prepared using the 30 m Copernicus reference DEM can be used for analysis of many long-term geodetic change signals, even though overall relative accuracy is less than the stack prepared using the 1 m lidar reference DEM. Regardless of the reference DEM used, the HSfM method offers a notable improvement over workflows involving manual GCPs selected from a low-resolution reference DEM, which can introduce horizontal and vertical error. Future enhancements to the HSfM pipeline will provide automated reference DEM preparation (e.g., OpenTopography Global DEM API) when a reference DEM is not

provided by the user.

1.7.4.2 Interior orientation preparation

The HIP software can automatically extract essential intrinsic parameters for focal length and pixel pitch (scanning resolution) from the EE archive metadata. For the NAGAP images in the ADC archive, HIP maps relevant intrinsic parameters to all image file names using metadata tables bundled with the software. For other archives or scanned historical image sets, the user can provide these parameters to the high-level processing routines.

The HIP software requires fiducial or pseudofiducial marker templates to define interior orientation, standardize, and crop the scanned images. We prepared these templates for most NAGAP images in the ADC archive (Figure A.4) and included them in the HIP software, along with metadata tables that map input image file names to the corresponding templates. Additional databases of marker templates and metadata mapping can be prepared for other historical image archives (e.g., EE) to enable fully automated preprocessing. As described in Section 1.5.1.1, the interactive HIP utilities can be used to create a new representative set of templates for historical images from an unknown source. Future approaches using convolutional neural networks trained on large samples of fiducial markers from many historical image sources may eliminate the need for manual template preparation (e.g., Nielsen, 2017).

The image standardization results confirm that the scanned NAGAP ADC images do not have systematic issues (e.g., rotation or stretching) requiring more complex standardization. This result is a testament to the quality of NAGAP film preservation and scanning efforts (Gruber and Leberl, 2001; Nolan et al., 2017; Sevara, 2016). While the best possible accuracy was obtained using precise fiducial marker matching and an affine transformation to match calibrated interior orientation (Section 1.6.2.2), the alternative standardization approaches involving affine transformation to mean marker positions and pseudofiducial markers without affine transformation also provided high-quality results. The latter approaches enable fully-automated preprocessing of NAGAP images from the full ADC archive, as the pseudofiducial marker approach is the only option for a majority of these images.

1.7.4.3 Exterior orientation preparation

The HSfM method requires initial camera position estimates in a geodetic coordinate system. Fortunately, historical image archives that support spatial queries (e.g., EE) inherently contain these initial position estimates. For other image sources, initial camera position estimates

can be manually extracted from photo flight line index maps sometimes archived with the images or by analyzing features in the images and manually estimating camera positions using a reference basemap, as was done for the ADC NAGAP metadata (Nolan et al., 2017).

The accuracy of the camera positions is critical, as this ultimately determines the accuracy of the triangulated points and resulting DEM. Unfortunately, estimates for historical image positions can contain horizontal and vertical errors of several kilometers. We used a large set of NAGAP and EE test cases with variable initial position accuracy to develop the HSfM workflow with appropriate weights and tolerances. Our results show that the HSfM routines can correct initial camera position error up to 5 km (Figure 1.12). The HSfM approach was even able to process image sets with a single shared horizontal position and no altitude information in the archive metadata, such as 1970-09-29 images collected over Mount Baker (Figure 1.12). This suggests that for smaller sites and image sets with adequate overlap, the user may only need to provide a single approximate estimate of latitude and longitude to effectively seed the bundle adjustment and co-registration steps. This approach can potentially eliminate the tedious process of manually estimating accurate position metadata during bulk scanning efforts.

An alternative approach to determine accurate camera pose during preprocessing involves feature matching between historical images and modern basemaps; then solving for the required homography or projective transform using known intrinsic parameters. Recent implementations of this approach (e.g., Heisig and Simmen, 2021; Maiwald and Maas, 2021; Zhang et al., 2021) using neural networks (e.g., DeTone et al., 2018; Sarlin et al., 2020) are promising, though challenges remain for small image footprints in rugged mountain terrain with limited stable surfaces.

1.7.4.4 4D SfM for other historical archives and larger blocks

While the NAGAP camera equipment and acquisition geometry evolved over the decades, the NAGAP images in the ADC archive were systematically scanned and the block sizes are relatively small. Other historical aerial photography archives contain heterogeneous image sets acquired using a range of camera and lens combinations (different focal length, film size, lens distortion) at different altitudes, with different overlap, different spatial coverage (including large blocks spanning 10s to 100s of km), and different scanning resolution (e.g., Section 1.4.2). Though it increases complexity, we recommend the multi-temporal bundle adjustment approach (Section 1.5.6) for most sites with overlapping image sets, either from a

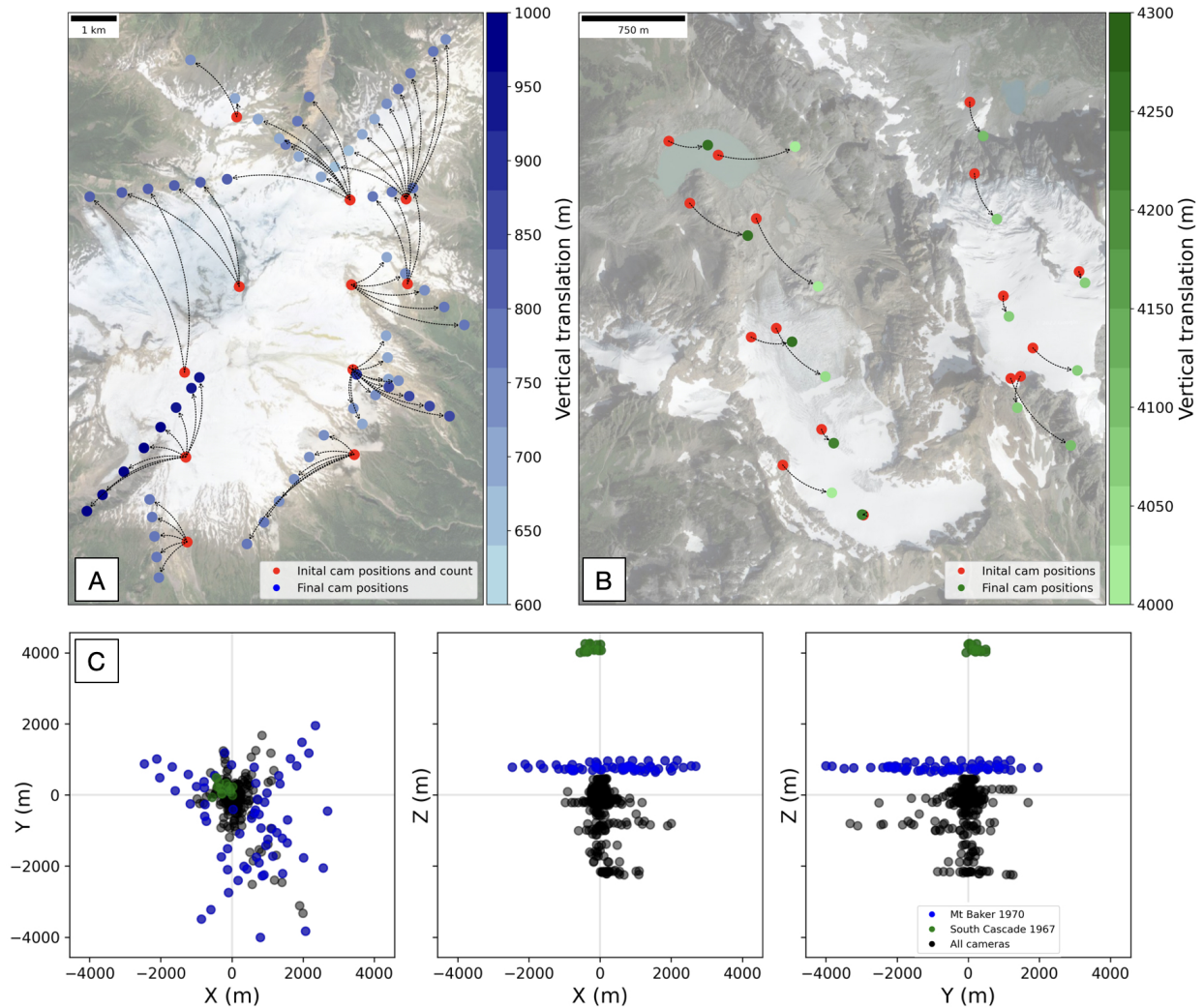


Figure 1.12: Detailed examples of camera position correction during Historical Structure from Motion (HSfM) processing. **(A)** Images collected on 1970-09-29 over the Mount Baker site. The red dots show images with shared initial positions in the NSF Arctic Data Center (ADC) metadata. The blue dots show the final horizontal positions with color representing vertical translation magnitude. **(B)** Images collected on 1967-09-21 over the South Cascade Glacier site with final positions in green. A vertical translation of up to 4.3 km was required to correct the EarthExplorer (EE) archive metadata altitude of 7,500 m (24,600 ft) for these images. **(C)** Translation components required to correct camera positions for all images processed in this study (black), including the blocks shown in panels A (blue) and B (green).

single archive or multiple heterogeneous archives. Metashape will jointly refine shared intrinsic

parameters using feature matches across all overlapping images, which should eliminate or reduce systematic error (e.g., "doming") in the final DEM products (Figure 1.11). The user can specify image sets acquired by each unique camera, or supervise the automated parsing done by Metashape based on unique input image dimensions. Preliminary tests using 4D SfM to process historical images from cameras with different focal lengths (132 and 152 mm) in the EE archive scanned at 25-micron resolution with NAGAP ADC images scanned at 20-micron resolution show promising results. Future work involving 4D SfM using images from other archives with larger spatial coverage will provide an opportunity to refine HSfM processing approaches and evaluate long-range spatial autocorrelation of errors.

1.7.4.5 *User-defined thresholds and parameters*

As described throughout the text, we set various thresholds, weights and tuning parameters for HIPPI/HSfM using a suite of test datasets from the NAGAP and EE archives. These parameters should work well for automated processing of the NAGAP archive, but may require tuning for other historical image datasets. The HIPPI and HSfM packages generate quality control metrics and plots that can help guide parameter adjustment as needed.

1.7.5 *Toward fully open-source software*

While the HIPPI and HSfM repositories are open source, the current HSfM method relies on the commercial Agisoft Metashape software. Metashape provides robust SfM reconstruction for poorly constrained historical image inputs, with excellent documentation, an intuitive Python API, and an active user community. While short-term trials offer the functionality needed to run HSfM, continued use requires the purchase of a license, and the closed source prevents detailed examination of the underlying algorithms.

We developed an experimental HSfM workflow using the open-source NASA Ames Stereo Pipeline (ASP) command-line utilities (Knuth et al., 2021a) for the *single date - single block* processing mode. Preliminary tests showed promising results for the 1977-09-27 blocks at Mount Baker (Figure A.10), but slightly larger errors than the Metashape products (NMAD increase of 0.05 m over stable surfaces compared to the reference DEM). However, the ASP workflow failed for more complex NAGAP image sets with inaccurate initial position estimates (e.g., Figure 1.12A), as the current ASP bundle adjustment routines are more sensitive to initial camera pose estimates and uncertainty.

The code for the experimental ASP workflow is included in the HSfM repository, but we

did not pursue further development and testing for the ongoing NAGAP archive processing or this manuscript. We are hopeful that planned improvements in the ASP bundle adjustment routines and/or support for other open-source photogrammetry packages (e.g., COLMAP (Schönberger and Frahm, 2016; Schönberger et al., 2016)) will enable development of a robust, fully open-source HSfM workflow in the future.

1.7.6 Science applications

Here we consider some of the broader implications of this work and highlight several new science applications enabled by the HSfM workflow and data products.

1.7.6.1 Geodetic glacier mass-balance and velocity

Processing the NAGAP and EE archives will enable the study of long-term geodetic mass balance for glaciers in western North America with unprecedented accuracy. The increased temporal resolution and accuracy will help calibrate glacier mass-balance records from field measurements (O’Neel et al., 2019; Zemp et al., 2013) and improve estimates of historic contributions to sea level rise (e.g., Arendt et al., 2002). On interannual to decadal time scales, glaciers show both temporally and spatially heterogeneous response patterns, as a function of their local geometry and regional climate forcing (e.g., Christian et al., 2022; Menounos et al., 2019). Uncertainty associated with decadal glacier mass change remains high for western North America, compared to other regions in the world (e.g., Zemp et al., 2019). These historical DEMs can be combined with modern satellite and airborne DEM time series to better constrain regional glacier change and understand connections to climate forcing for a range of timescales (seasonal to centennial) (e.g., Dehecq et al., 2020; Geyman et al., 2022; Hugonnet et al., 2021; Mannerfelt et al., 2022).

Beyond mass balance observations, the historical orthomosaics from the same year or adjacent years can be used to prepare maps of historical glacier surface velocity using feature tracking (e.g., Dehecq et al., 2022; Li et al., 2017; Wang et al., 2016). These observations can be combined with modern glacier velocity observations to assess long-term relationships with mass balance trends (e.g., Dehecq et al., 2019).

1.7.6.2 Elevation change rate precision and other applications

The historical DEM accuracy was ~ 0.5 m for our study sites, with a total time period of ~ 30

years between the first and last historical DEM, and a total time period of ~ 50 years between the first historical DEM and the reference DEM. Depending on error correlation, these products allow for elevation change measurements with precision of $\sim 0.7\text{--}1.0$ m, enabling analysis of elevation change rates as small as $\sim 1\text{--}3$ cm/yr, with spatial resolution of <1 m. This precision is remarkable considering the data origin — degrading film rolls from aerial observation programs never intended for these applications. This elevation change precision enables analysis of many other processes beyond the relatively large glacier change signals considered here. For example, the HSfM products can be used for regional analysis of proglacial erosion and deposition (e.g., Anderson and Shean, 2022), with implications for sediment transport and downstream flood hazards.

1.8 Conclusions

Automated processing of scanned historical aerial photographs has remained a technically challenging, yet scientifically valuable objective across many disciplines. We developed an automated method to produce accurately georeferenced historical digital elevation models (DEMs) for science and engineering applications. The method overcomes current bottlenecks for historical Structure from Motion (SfM) processing at scale by automating image preprocessing, block detection, and DEM co-registration. Image preprocessing and standardization approaches provide accurate interior orientation for a range of fiducial marker types and detection strategies. The multi-temporal *4D SfM* approach significantly improves both intrinsic and extrinsic camera model parameters, which mitigates systematic DEM error (Figure 1.11). Finally, a robust multi-stage DEM co-registration approach, instead of manual ground control point (GCP) selection, refines absolute geolocation accuracy using a modern reference DEM.

We tested the Historical Structure from Motion (HSfM) method for two study sites with variable image overlap, acquisition geometry, and reference terrain characteristics. We produced 39 DEMs from 504 historical images acquired between 1967 and 1997. While the HSfM method performed best with an accurate, high-resolution reference DEM (e.g., airborne lidar), we show that using a relatively coarse global reference DEM (30 m Copernicus DEM, (European Space Agency, 2022)) also offered precise relative elevation change measurements for historical DEM time series stacks. This implies that HSfM can be used to process historical aerial photos anywhere on Earth. The automated HSfM multi-temporal bundle adjustment and co-registration approach outperformed traditional workflows involving a limited number

of manually defined GCPs (Section 1.6.2.1), while also improving data provenance and reproducibility. The resulting historical DEM stacks have relative accuracy of 0.37-0.68 m and an elevation change rate precision of $\sim 1\text{-}3$ cm/yr, which is negligible compared to the magnitude of observed long-term glacier and geomorphic change signals.

The HSfM method enables systematic processing of historical image archives at scale and precise surface elevation change measurements over a broad range of spatial and temporal scales. These measurements offer new insights into the underlying processes driving the observed changes. We are continuing to process the remainder of the scanned North American Glacier Aerial Photography (NAGAP) archive and suitable collections from the EarthExplorer (EE) archive with the goal of improving our understanding of regional mass balance and the climate sensitivity of North American glaciers.

Data and software availability

All scanned images and initial metadata used in this study are publicly available from the Arctic Data Center and Earth Explorer archives. The reference DEM data are publicly available as described in Section 1.4.5. The HSfM DEMs and orthoimage mosaics are publicly available at doi:10.5281/zenodo.7297154. Both the Historical Image Pre-Processing (HIPP, doi:10.5281/zenodo.5510876) and Historical Structure from Motion (HSfM, doi:10.5281/zenodo.5510870) repositories are publicly available on Github with MIT license, documentation, and Jupyter notebook examples.

Funding

This work was funded in part by a University of Washington Innovation Award to D.S., USGS Ecosystem Mission Area, Land Change (Climate R&D) Program cooperative agreement #G19AC00433, and NSF PREEVENTS program award: ICER 1663859.

CRedit author contributions

Friedrich Knuth: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review and Editing, Visualization. **David Shean:** Conceptualization, Methodology, Resources, Writing - Original Draft, Writing - Reviewing and Editing, Supervision, Project administration, Funding acquisition. **Shashank Bhushan:** Investigation, Visualization, Writing - Reviewing and Editing. **Eli**

Schwat: Software, Validation, Formal analysis, Data Curation, Writing - Reviewing and Editing. **Oleg Alexandrov:** Software, Writing - Reviewing and Editing. **Chris McNeil:** Validation, Writing - Reviewing and Editing. **Amaury Dehecq:** Investigation, Writing - Reviewing and Editing. **Caitlyn Florentine:** Writing - Reviewing and Editing, Funding acquisition. **Shad O’Neel:** Writing - Reviewing and Editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We thank the late Austin Post and the USGS Glaciology program for acquiring the NAGAP photographs over the years. We also thank Matt Nolan and the team at the University of Alaska Fairbanks for scanning and archiving the NAGAP photographs. Scott McMichael provided additional support and guidance on using the Ames Stereo Pipeline software. Knut Christianson, Michelle Koutnik and Erin Whorton contributed to the UW Innovation Award proposal. Erin Whorton and Scott Anderson participated in early discussions on SfM workflows for historical images using GCPs. We appreciate the detailed and constructive comments from Louis Sass and anonymous reviewers, which improved this manuscript. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

Chapter 2

ARE PARTIAL DEMS USEFUL? A MEMORY-EFFICIENT METHOD TO ESTIMATE LONG-TERM GLACIER SURFACE ELEVATION CHANGE FROM SPATIALLY AND TEMPORALLY SPARSE MEASUREMENTS

2.1 *Abstract*

Digital Elevation Models (DEMs) derived from overlapping images often lack data in saturated areas, such as snow-covered surfaces or shadows. This can result in large data voids, for example in the accumulation zone of glaciers. In severe instances, these DEMs may be discarded from geodetic glacier mass-balance analysis because the spatial coverage is too sparse to compute a complete volume change estimate over the entire glacier surface. Additionally, high-resolution and long-term geospatial raster datasets are often resampled to a lower resolution for processing and in order to fit into memory on a local machine. This resampling sacrifices detail and precludes measuring high-resolution glacier surface elevation changes and feature movement (e.g. crevasses).

Here we present a framework that enables memory-efficient computations to interpolate raster time-series data and fill voids in larger-than-memory datasets. We leveraged a temporal Gaussian Process (GP) regression technique to reconstruct approximately 70 years (~1950–2020) of spatially and temporally continuous glacier surfaces at three sites – South Cascade Glacier, Mount Baker, and Mount Rainier in Washington State, USA. We conditioned the GP regression with historical (pre-2000) DEMs generated from the North American Glacier Aerial Photography dataset and other images in the EarthExplorer archive, as well as modern (post-2000) EarthDEM "strips" generated from WorldView optical stereo satellite imagery.

By comparing our results to historical cross-sectional profiles at Nisqually glacier on Mount Rainier we found that the GP regression reconstructed surface elevation anomalies moving through the glacier. Furthermore, we demonstrate that partial DEMs improve the overall estimate of surface elevation change when using GP regression, despite potentially being of limited use to standard spatial interpolation techniques. Finally, we demonstrate that the GP regression can provide a seasonal bias correction by fitting a periodic kernel to

the seasonal glacierized surface elevation change captured by the modern EarthDEM time series. These results inspire confidence in applying this method to other sites and producing long-term estimates of regional glacier surface elevation change.

The analysis is accompanied by the open-source, user-friendly, and memory-efficient Geospatial Time Series Analysis (GTSA) software package, which enables individuals with limited computational resources to reproduce these results and participate in studies involving the processing of larger-than-memory datasets. This contribution will facilitate standardization and collective refinement of data-driven approaches that precisely measure glacier surface elevation change at high spatiotemporal resolution.

2.2 Introduction

Digital elevation models (DEMs) generated from stereo photogrammetry often lack data in areas where there is insufficient texture to confidently triangulate match points in overlapping images and estimate surface elevations. These issues can occur, for example, in saturated shadows or in snow covered areas. Data voids are problematic for glaciological analysis because a continuous estimate of the surface elevation change across the entire glacier is required to distinguish a change in glacier mass from a kinematic redistribution of ice. A common strategy to mitigate data voids is to employ spatial interpolation techniques, such as hypsometric interpolation (e.g., Arendt et al., 2006; Berthier et al., 2010; Furbish and Andrews, 1984; McNabb et al., 2019).

Hypsometric interpolation relies on the relationship between glacier surface elevation change and elevation. This technique computes the median elevation change for a given elevation bin, then fits a polynomial function to all bins with sufficient surface elevation change measurements and interpolates bin-averaged values for pixels missing data. A major challenge with this method is when there are limited or no surface elevation change measurements available for a significant and contiguous part of the glacier surface (McNabb et al., 2019; Seehaus et al., 2020). As a result, when spatial coverage across elevation bins is too sparse, digital elevation models with partial glacier coverage are often discarded from geodetic glacier mass-balance analysis, despite having the potential to provide valuable information for areas with valid data, such as the ablation area.

Another issue encountered when comparing surface elevation change measurements between different glaciers across a larger geographic region is that the images used to generate the DEMs were likely acquired at different times of year. For example, a DEM at a hypothet-

ical glacier A might exist only for June 1st in 1950, 1970, and 1990, while DEMs at glacier B might exist only for October 1st in 1940, 1980 and 1990. As a result, it is difficult to compare elevation change estimates between glaciers A and B, without estimating the state of change at corresponding time stamps, due to both seasonal and inter-annual surface elevation change variability.

Temporal interpolation methods such as Gaussian Process regression are suitable to robustly estimate non-linear elevation change at any time stamp and location, based on the expected temporal covariance structure in a given per-pixel elevation time series (Hugonnet et al., 2021). Estimating the covariance structure provides an opportunity to compare exact dates and time periods more precisely than existing methods that interpolate per-pixel linear trends to approximate inter-annual change (e.g., Brun et al., 2017; Dussailant et al., 2019; Shean et al., 2020; Wang and Kääb, 2015; Willis et al., 2012) and leverage climate data or in-situ measurements to make a seasonal adjustments (e.g., Belart et al., 2019; Cogley, 2009; Cox and March, 2004; Geyman et al., 2022; Krimmel, 1999; O’Neel et al., 2019; Reeh, 1991; Zemp and Welty, 2023).

In this study, we leveraged Gaussian Process (GP) regression to model the per-pixel covariance between surface elevations in DEM time series and provide an uncertainty estimate for each interpolated measurement (Hugonnet et al., 2021; Williams and Rasmussen, 2006). We derived a covariance function that consists of two Matérn kernels to interpolate decadal and interannual change, as well as a periodic kernel to provide a seasonal bias correction. The first Matérn kernel (Matérn, 1960; Stein, 1999) is parameterized to capture long-term climate driven trends that occur on length scales of 20-30 years. The second Matérn kernel is parameterized to capture shorter term dynamic changes due to ice moving through the system on length scales of 5-10 years. The periodic kernel is parameterized to capture seasonal variations in per-pixel surface elevation change due to snow accumulation and ablation.

The implication of this temporal interpolation approach is that GP regression can estimate surface elevation change not only for voided areas in the partial DEMs, but the complete surface area at any timestamp in between the input DEMs. This approach provides the community with a method to robustly estimate continuous elevation change in historical DEM datasets and make regional long-term comparisons of glacier mass change at high spatiotemporal resolution. The software to stack and process the DEMs is open source, memory efficient, and user-friendly, which further democratizes the methodology for members of the community that do not have access to high-performance computing environments.

2.3 Study sites

Our analysis focuses on Digital Elevation Models (DEMs) produced over South Cascade Glacier (SCG), Mount Baker, and Mount Rainier (Figure 2.1). Heterogeneous surface elevation change across elevation bands at SCG inspired us to develop an approach that is robust to spatial variability and is therefore easily transferable to glaciers with more homogeneous change along elevation bands (O’Neel et al. (2019)). Spatial void interpolation techniques may over or underestimate the glacier surface elevation change at SCG when interpolating along a given elevation band (McNabb et al., 2019). Our approach is potentially more robust because spatial heterogeneity in elevation change for a given elevation band does not influence the predictions for an individual per-pixel elevation time series. To further evaluate the GP regression performance we scaled the analysis to Mount Baker and Mount Rainier, which are geographically larger sites with sparser temporal data density.

2.4 Data

In this analysis we used stereo-photogrammetric DEMs derived from historical (pre-2000) aerial images (Knuth et al., 2023; McNeil et al., 2022a) and modern (post-2000) WorldView (WV) satellite images (Porter et al., 2022). Reference DEM data used for DEM co-registration include lidar-derived Digital Surface Models (DSMs) at Mount Baker and Mount Rainier (Ramsey, 2016; Sciences, 2009), as well as a custom 2013-2015 WV composite DSM at South Cascade (Knuth et al., 2023; Shean et al., 2016). For the statistics and analysis computed over glacierized surfaces we used glacier outlines extracted from the Randolph Glacier Inventory (RGI) v6.0 (RGI Consortium, 2017), as well as a 2015 glacier outline provided by the USGS Glacier Benchmark Project (McNeil et al., 2022a). For time-series evaluation purposes we used points extracted along the glacier centerlines, estimated by the Open Global Glacier Model (OGGM) software (Maussion et al., 2019), as well as a compilation of historical cross-sectional profile measurements at Nisqually Glacier on Mount Rainier (Stevens et al., 2016).

2.4.1 Digital Elevation Models (DEMs)

Below we describe the 51 historical and 169 modern DEMs used in this study and illustrate their spatial coverage over the RGI outlines with panels C and G in Figure 2.2 at SCG, Figure B.1 at Mount Baker, and Figure B.2 at Mount Rainier. We consider a DEM to provide full

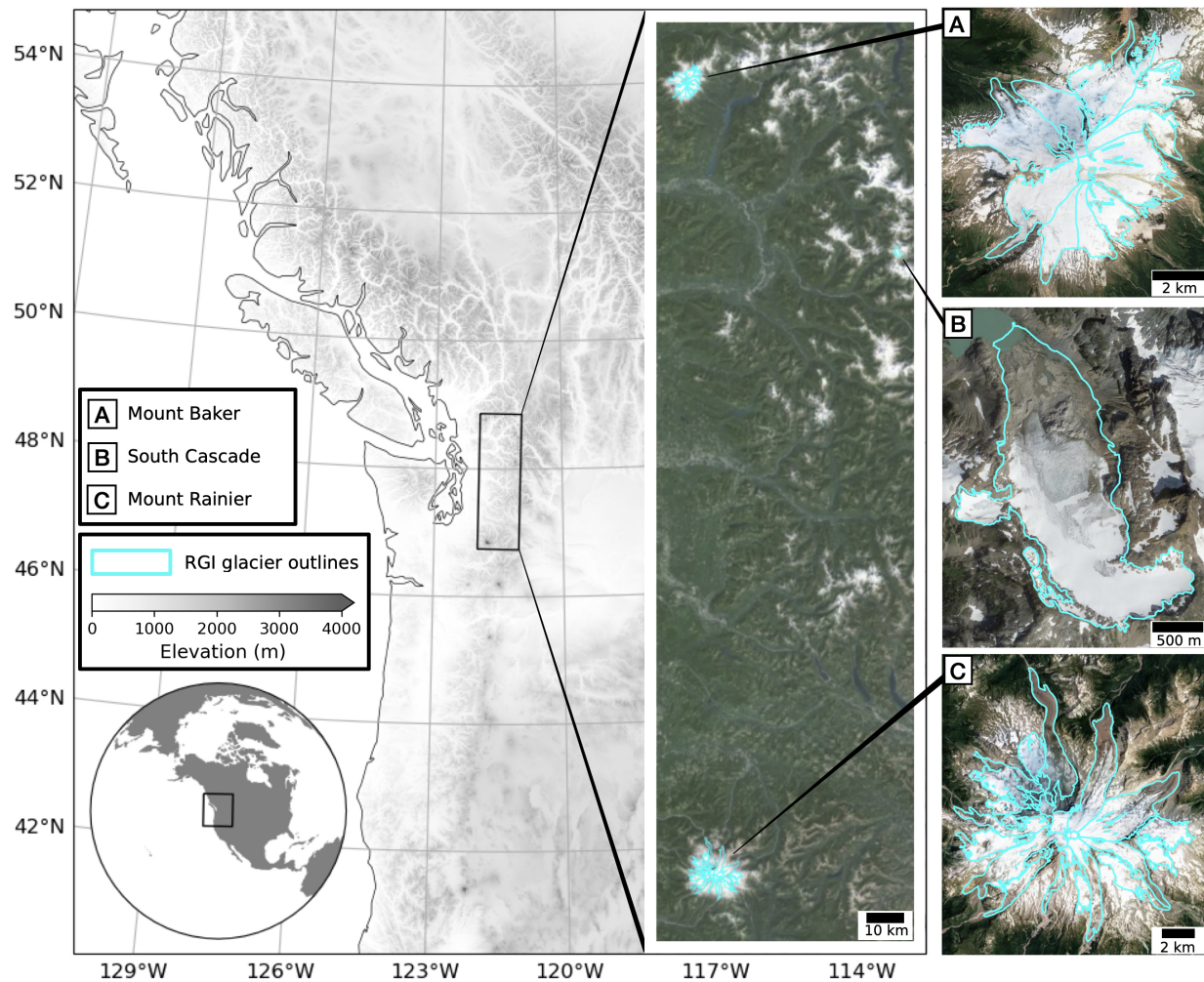


Figure 2.1: Location of A. Mount Baker, B. South Cascade Glacier (SCG), and C. Mount Rainier shown at global, regional, and local scales. Grayscale basemap shows surface elevation in meters above the WGS84 ellipsoid from the 3-arcsecond Copernicus DEM (European Space Agency, 2022), resampled to a 1 km grid with Albers Equal Area projection. Satellite color imagery basemaps provided by Google and projected in Universal Transverse Mercator (UTM) zone 10N (imagery source dates: A. 2016-07-28, B. 2016-08-19, C. 2021-07-25). Randolph Glacier Inventory (RGI) v6.0. outline shown in blue and dated 1974 at Mount Baker, 1958 at SCG, and 1970 at Mount Rainier (RGI Consortium, 2017)

glacier coverage when it covers 65% or more of the glacierized area, and partially covering the glacier when it covers less than that. On average the DEMs cover 67% of the RGI glacier outlines.

All historical DEMs were captured at or near the end of the seasonal melt cycle during the months of July, August, September, and October (Figure B.3). Of the 52 modern DEMs collected at SCG, 25 were captured at the end of the seasonal melt cycle and the remaining 27 DEMs at various times throughout the year (Figure B.4). The mean historical DEM posting is ~ 2 m with six DEMs posted at ~ 4 m and one DEM (1958-08-13) at SCG posted at 9.83 m. The modern DEMs are posted at ~ 2 m, with the exception of the 2004-09-26 SCG DEM, which is posted at 5 m. The normalized median absolute deviations (NMADs) (Höhle and Höhle, 2009) of DEM difference values computed over stable ground during DEM co-registration averages to 1.55m for the historical DEMs and 1.83 m for the modern DEMs. The NMAD is a robust metric to estimate residual bias and spread and is computed from the per-pixel difference values between a given DEM and reference DEM over non-glacierized, non-forested areas, which we consider to be stable surfaces. Tables B.1, B.2, and B.3 provide a full list of DEMs at all three sites and include the acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and processing source.

2.4.1.1 Historical Structure from Motion (HSfM) DEM data

We produced 23 DEMs for this analysis using the Historical Structure from Motion (HSfM) software at Mount Baker and Mount Rainier from images in the North American Glacier Aerial Photography (NAGAP) and EarthExplorer (EE) archives (Knuth et al., 2021a, 2023; Nolan et al., 2017). In addition we used 28 (1967–1997) historical DEMs previously generated at SCG and Mount Baker (Knuth and Shean, 2022; Knuth et al., 2023).

2.4.1.2 EarthDEM data

We used 162 DEM strips from the EarthDEM catalog (Porter et al., 2022). These (2008–2020) modern DEMs are provided by the Polar Geospatial Center (PGC) and were derived from stereo-satellite imagery using the Surface Extraction from TIN-based Search-space Minimization (SETSM) photogrammetric software (Noh and Howat, 2015). The DEMs were generated from stereo satellite images collected at various acquisition dates throughout the year (Tables B.1, B.2, and B.3) and are posted at 2 m.

The PGC provides bitmask files which were used as a preliminary filter for problematic regions with unrealistic elevation estimates (e.g. due to clouds) in the DEMs. The bitmask raster files corresponding to each DEM contain integer values defined as 0=good data, 1=edge, 2=water, and 4=cloud (Porter et al., 2022). We preserved DEM pixels with bitmask raster

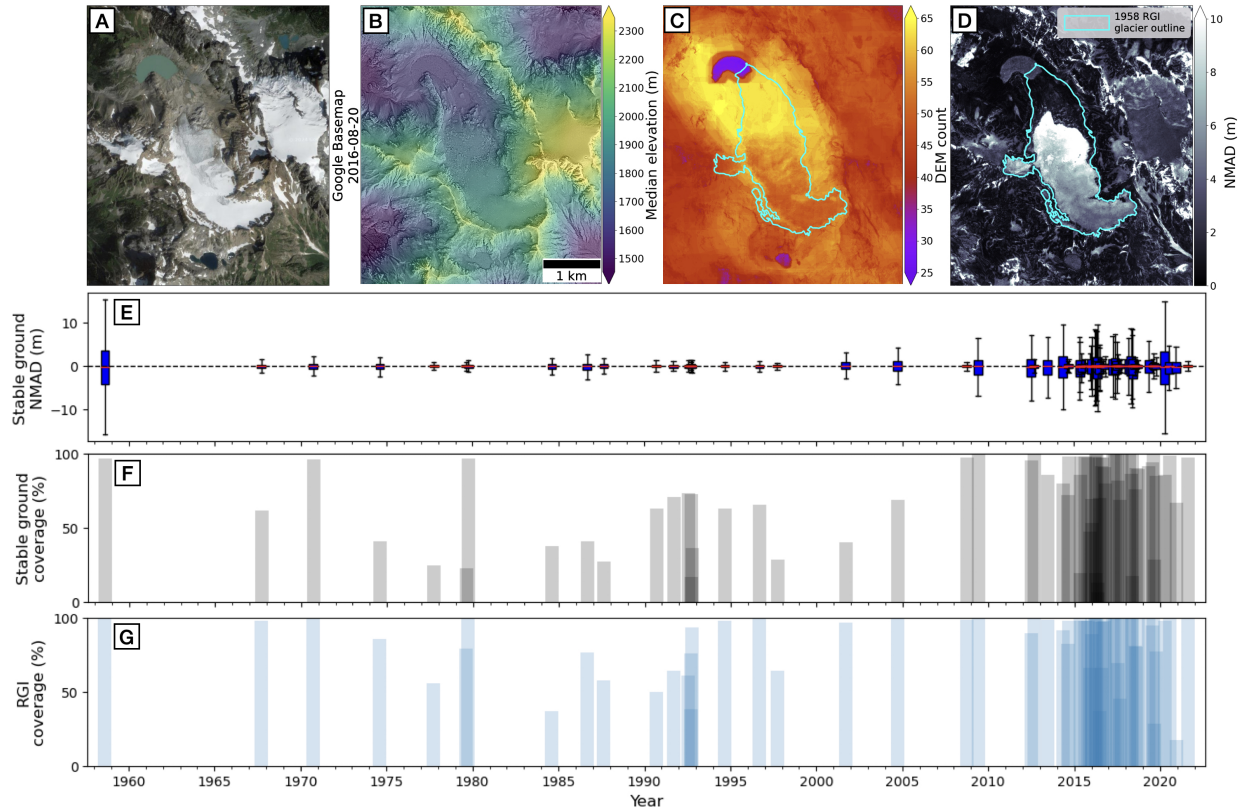


Figure 2.2: A. Google satellite basemap for the South Cascade Glacier (SCG) site (imagery source date 2016-08-19). B. Median surface elevation of the 71 Digital Elevation Models (DEMs) in the 63-year time series stack (1958-08-13 to 2021-08-13). C. Per-pixel DEM count. D. Per-pixel normalized median absolute deviation (NMAD) of residuals between stable ground in DEMs and reference DEM. Both C. and D. show 1958 SCG RGI glacier outline (RGI60-02.17739) in blue. E. Absolute accuracy metrics over stable ground surfaces for each DEM (DEM minus reference DEM). Boxes show interquartile range, with median values in red and whiskers at 1.5 times the interquartile range. F. Percent coverage of stable ground surface area (7.89 km^2) in (20.20 km^2) scene over which statistics shown in E are computed. G. Percent coverage of SCG RGI glacier extent (2.89 km^2) seen in C.

values 0 “good” and 2 “water”.

2.4.1.3 USGS DEM data

In addition to the HSfM and EarthDEM data products, for SCG we used a 2015-10-14 hand-digitized glacier outline and 10 publicly available DEMs from the USGS geodetic data

release (McNeil et al., 2022a). The USGS DEMs include 5 historical and 5 modern DEMs that together range from 1958-08-13 to 2021-08-13, which provides the minimum and maximum temporal bounds at SCG for the DEM time series combined from all sources. In some cases, the DEMs were produced from the same images that were used to produce HSfM or EarthDEM products. There are six DEMs that exist in both the USGS and HSfM or EarthDEM time series. For these instances we choose the product that has the highest RGI glacier outline coverage, followed by lowest NMAD of stable ground residuals between the DEMs and respective reference DEM as the secondary selection criteria.

2.4.1.4 Reference DEM data

DEMs at SCG were co-registered with a custom high-resolution (2 m) 2013-2015 composite DEM derived from end-of-summer WV imagery that is snow free over stable ground (Knuth et al., 2023; Shean et al., 2016). This composite provides a better estimate of the stable ground reference surface during the co-registration procedure. DEMs at Mount Baker were co-registered with a 1 m reference digital surface model (DSM) generated from airborne lidar data collected for the USGS 3DEP program by Quantum Spatial on August 27, 2015 (Knuth et al., 2023; Ramsey, 2016). For DEM co-registration at Mount Rainier we generated a 2 m reference DSM from airborne lidar data collected for the Mount Rainier National Park Service by Watershed Sciences in three stages (September 2007, September 2008, and October 2008) (Sciences, 2009). We treat this DSM as a single timestamp dated 2008-10-01. For both Mount Baker and Mount Rainier, the lidar point cloud data were obtained from the Washington Department of Natural Resources (WADNR) lidar portal. All reference DEMs were reprojected to UTM Zone 10N (EPSG:32610), vertically adjusted to the height above the WGS84 ellipsoid, and included in the final raster time series stacks.

2.4.2 Evaluation data

We used the Open Global Glacier Model (OGGM) glacier centerline estimates (Maussion et al., 2019) to systematically extract elevation time series samples from the DEM raster stack and evaluate our temporal interpolation method. These samples were used to visualize the time series at a given spatial point and evaluate the GP regression during testing. The cross-sectional profiles and estimated sampling locations at Nisqually Glacier on Mount Rainier were compiled and provided by Stevens et al. (2016) and are further described in Section 2.5.4.1.

2.5 Methods

We developed the open-source Geospatial Time Series Analysis (GTSA) software package to execute the workflow described in this manuscript in a reproducible and user-friendly manner. The workflow includes DEM co-registration, DEM stacking, chunking the DEM stack on disk for memory-efficient processing, and finally performing a statistical estimation of per-pixel elevation change through time. Additional community software packages used include *demcoreg* for co-registration (Shean et al., 2021) and OGGM for the programmatic extraction of glacier centerlines and visualization of the modeled output (MauSSION et al., 2019).

2.5.1 DEM co-registration

Co-registration is necessary to mitigate systematic bias between the DEMs (e.g., Nuth and Kääb, 2011). It is recommended to always perform a co-registration for DEMs obtained from various sources, as they can have incorrectly described vertical datum definitions in their metadata, in addition to residual vertical and horizontal offsets. Here we used the Nuth and Kääb (2011) co-registration method to minimize offsets over stable ground between the input DEMs and the reference DEMs. To execute the Nuth and Kääb (2011) co-registration we used the *dem_align.py* tool provided by the *demcoreg* Python package (Shean et al., 2021). This tool facilitates isolating the stable surfaces prior to co-registration by masking the reference DEM with programmatically downloaded glacier polygons from the Randolph Glacier Inventory (RGI) v6.0 (RGI Consortium, 2017), as well as forest landcover classes (41–43) from the 30-m National Land Cover Dataset (NLCD) (Dewitz, 2016). To assess residual error after co-registration, we computed the NMAD of stable surface difference values (Höhle and Höhle, 2009). These NMAD values are assigned as the initial uncertainty for input elevation measurements at a given spatial and temporal coordinate during the time-series regression procedure described in Section 2.5.3.

2.5.2 DEM time-series stacking

Once all DEMs are co-registered, we use the Geospatial Time Series Analysis (GTSA) library to reproject all DEMs to a common grid and stack them along the time dimension (Knuth, 2023). The raster stack is stored in *Zarr* format and chunked on disk for memory-efficient data retrieval during computations performed along the time axis (Figure 2.3). This is an

important step that enables the parallelized processing architecture provided by the *Dask* python library to efficiently retrieve and process data chunks. Data are written to disk as spatial chunks that include all values along the time dimension. Each chunk is one MB in size and has a spatial dimension that is programatically determined by *Dask* to achieve the specified chunk size. Optimal chunk sizes for parallelized processing are then programmatically determined by the *GTSA* software, depending on the memory size of per-pixel time series and can range from 2 to 200 MB. Chunk sizes did not exceed 2 MB for the time series used in this analysis using <100 time stamps. Small chunks require less memory for individual processing units (e.g. Dask workers, CPU cores, virtual CPU threads), while larger chunks require more memory. This Zarr storage architecture is critical for memory-efficient processing because data chunks can be retrieved individually and processed in parallel, rather than loading the full data cube in to memory at once.

2.5.3 Gaussian Process regression

Gaussian Process (GP) regression is a Bayesian non-parametric technique commonly used in the fields of machine learning (Williams and Rasmussen, 2006). It is fully specified by a mean function (e.g. 0 in a mean subtracted time series) as well as the covariance functions that model the variance about the mean. GP regression builds upon established techniques in the geostatistical literature such as "kriging", which perform spatial interpolation based on the covariance structure of data (Cressie, 2015). This approach extends the domain beyond the spatial dimension and can model expected variance along any number of dimensions. In our case, we leverage GP regression to model the temporal structure of per-pixel elevation change in the DEM time series stacks and estimate temporally continuous values for each pixel in the spatial grid. GP regression is powerful because it can not only interpolate data based on the covariance structure of proximal and distance data points used to condition the regression, but also fit covariance functions that model and project recurring (e.g. seasonal) signals learned from sparse measurements. For example, given a periodic covariance function (or "kernel"), GP regression can perfectly reconstruct a recurring sinusoidal signal if the input data frequency is without noise and sufficient to express the structure of the signal (e.g. $2 \times$ the signal bandwidth, i.e. the Nyquist frequency (Nyquist, 1928)). Temporal GP regression has been successfully applied in the Earth Sciences for DEM time series analysis, for example, by Hugonnet et al. (2021) to reconstruct two decades of glacier mass balance estimates from stereo optical ASTER image derived DEMs at 30 m resolution between 2000 and 2019. Our

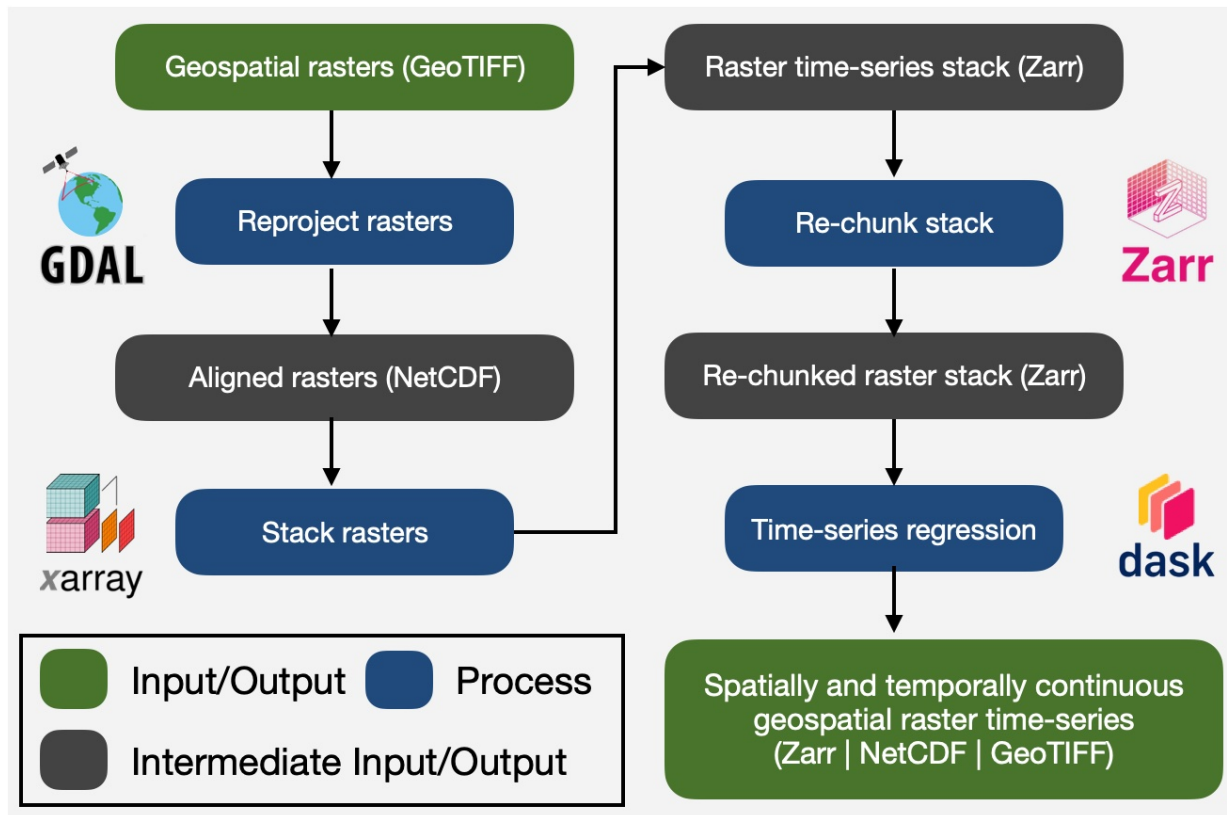


Figure 2.3: Workflow diagram for Geospatial Time Series Analysis (GTSA) raster time series stacking and regression procedure. The Geospatial Data Abstraction Library (GDAL) reprojects rasters on to a common reference grid. The xarray package acts as a high-level handler to stack and rechunk the data on disk using Zarr, then perform memory-efficient time-series regression analysis on each time-series chunk using dask. Final model predictions can be output in Zarr, NetCDF, or GeoTIFF format.

method builds upon this approach by providing memory-efficient and user-friendly software to apply the GP technique to temporally sparse, high-resolution (1-2 m), and long-term (~ 70 year) DEM time series.

2.5.3.1 Defining a Gaussian Process kernel to estimate glacier surface elevation change

Glaciers advance and retreat over multiple decades in response to periodic and long-term climate forcing. The kinematic response of a glacier to imbalances of mass across the ice surface is variable on sub-decadal time scales and on seasonal time scales, the surface elevation rises

and falls due to snowfall and ablation. A GP kernel can be comprised of multiple components (separate covariance functions) operating on different temporal length scales to model the respective variance. By investigating the data structure and referencing published estimates for characteristic length scales or glacier surface elevation variance (Hugonnet et al., 2021), we determined a GP kernel comprised of three main components (Equation 2.1) that are suitable to capture the long-term, short-term, and seasonal surface elevation variability expected for mountain glaciers in the Pacific Northwest. Note that we did not define a special mean function, used a constant value of 0 to estimate the mean for the mean subtracted time series, and designed this kernel to maintain realistic long term trajectories despite temporal data gaps or missing data at the edge of time series.

First, we observed a seasonal sinusoidal trend that is representative of snow accumulation and ablation patterns. To capture this trend we used a periodic kernel (Equation B.3) that repeats a high-frequency signal with annual periodicity across the entire predicted time series. It is similar to the periodic kernel used in Hugonnet et al. (2021), but with an estimated variability (σ_{seas}) of 17 meters, instead of the globally estimated of 5 meter variability. The 17 m variability is an upper bound estimate for our region of interest and is determined by the average seasonal snowfall depth (640 inches) recorded by the National Park Service at Paradise Station on Mount Rainier (Leffler et al., 2001; NPS, 2024). Another difference between the periodic kernel used in this analysis and the kernel used by Hugonnet et al. (2021) is the choice of length scale (l_{seas}) that determines the average annual periodicity. We provided a length scale of 5 years, instead of 1 year, to the kernel, which effectively enables it to determine the average annual periodicity from a 5 year covariance window of dense observations, instead of an annual covariance window. This makes the prediction less sensitive to outliers that can cause an unrealistic shape for the annually repeated signal. The 5-year length scale was chosen based on the 2015-2020 time period of dense observations with seasonal coverage in the modern DEM input time series (Figure B.4). After determining the average seasonal structure, the kernel projects this periodic signal (high in winter, low in summer) across every year in the long-term (~ 70 year) predicted time series.

Next, we implemented two Matérn kernels (Equation B.1) with different length scales to capture long-term change due to climate forcing and short-term change due to the kinematic movement of ice (Matérn, 1960; Stein, 1999). The Matérn kernel is a more general form of the commonly used Radial Basis Function (RBF), which is employed in many machine learning frameworks (Williams and Rasmussen, 2006). Note that as $\nu \rightarrow \infty$ in Equation B.1,

the Matérn kernel becomes identical to the RBF. An advantage of the Matérn kernel is that when ν is small, it will not over-smooth a signal, unlike the RBF kernel, which is prone to "over-" or "under-shooting" the time series trend, and is therefore more suitable to modelling geophysical processes (Stein, 1999). Upon testing various values between 0.1 and 10 for ν , (higher values performed the same as the RBF) we chose a value of 1.5 for both Matérn kernels. This value is a special case for ν , as Equation B.1 becomes once differentiable, and provided the right balance between sensitivity to variability in the data, while maintaining long and short term trajectories despite temporal data sparsity (e.g. >10 year gaps in the time series).

The first Matérn kernel we defined captures long-term change due to climate forcing, such as the Pacific Decadal Oscillation (PDO) climatology index, which has a 20-30 year periodicity (Mantua et al., 1997). We chose a 30-year length scale (l_{long}) for this kernel, based on the upper bound for the periodicity of the PDO index. The expected variability (σ_{long}) was set to 30 m and determined by the maximum observed per-pixel NMAD (29 m) of elevation values over the glacierized area within the 1958 RGI glacier polygon at South Cascade Glacier (Figure 2.2D). While the maximum observed variability over glacierized areas at Mount Baker is 43 m (Figure B.1D), and 86 m at Mount Rainier (Figure B.2D), choosing a higher value for σ_{long} did not make a difference as the 30 m variability estimate provided sufficient freedom to deviate from the mean and maintain the long term trajectory.

Next, we implemented another Matérn kernel to capture short-term changes in elevation that can be a result of ice instabilities and kinematic waves moving through the glacier. The variogram analysis conducted by Hugonnet et al. (2021) to determine characteristic variability over respective length scales found that "inter-annual glacier elevations are on average within 5 m of each other within a year, within 9 m within 1.5 year and within 11 m within 3 years". These length scales and expected variances used were established with thousands of variograms sampled globally to describe the average characteristics of short-term glacier movement (Supplementary Information, Page 9, Hugonnet et al., 2021). We leveraged this information and set the length scale (l_{short}) for the short term Matérn kernel used in this analysis to 10 years with an estimated variability (σ_{short}) of 30 m.

In our raster time series stacks, glacier surface elevations h have coordinates in time t and space x, y . We fit the GP regression only along the time dimension. Thus, the glacier surface elevation h becomes a function of time $h(t)$ and is independent of other points in space. The GP regression that estimates temporal surface elevation variance σ_h^2 at a given

pixel (x, y) is conditioned by the temporal lag Δt between time series measurements, the expected uncertainty (σ_{stable}^2) of those measurements, and the expected elevation variance and temporal length scales assigned to the long ($\sigma_{long}^2, l_{long}$), short ($\sigma_{short}^2, l_{short}$), and seasonal ($\sigma_{seas}^2, l_{seas}$) kernel components, as described above. For σ_{stable}^2 we use the NMAD², where the NMAD is computed from the residual differences over stable ground between elevation values in the input DEMs and the respective reference DEMs. This provides an uncertainty metric that approximates the standard deviation, is robust to outliers, and estimates the uncertainty of elevation values used to condition the GP regression. The temporal variance at a given pixel location x, y is thus defined as:

$$\begin{aligned} \sigma_h^2(x, y, \Delta t) = & Periodic(\sigma_{seas}^2, l_{seas}, \Delta t) + \\ & Matérn(\sigma_{long}^2, l_{long}, \Delta t) + \\ & Matérn(\sigma_{short}^2, l_{short}, \Delta t) + \\ & \sigma_{stable}^2 \end{aligned} \tag{2.1}$$

For any given time series at an (x, y) pixel location, we set a threshold that ensures a minimum of 3 observations spread over at least 10 years, else no estimate is made for the time series at this location. To execute the GP regression we used the *GaussianProcessRegressor* module implemented in the *scikit-learn v1.3.0* Python software (Pedregosa et al., 2011). By default, this module subtracts the mean from the dependant variable (elevation) and divides by the standard deviation to normalize the data from 0–1. We tested running the GP regression with and without normalizing the dependant variable, which is controlled by setting the *normalize_y* flag. The impact of this normalization is further discussed in Section 2.7.3.1.

2.5.3.2 Outlier filtering

Prior to fitting a final GP regression we filter outliers to avoid introducing bias to the final GP regression estimate. Elevation outliers are values that are unrealistically high or low and do not represent the Earth’s surface. These can arise from clouds or other blunders and artifacts that might occur during photogrammetric processing. Examination of the DEMs revealed that outliers are primarily present in the EarthDEM time series. These are first filtered by applying the spatial bitmasks that are supplied along with the EarthDEM data products and described in Section 2.4.1.2. After stacking (Section 2.5.2), we then applied the

GP regression along the time axis without the periodic kernel component to filter additional outliers that were not captured by the EarthDEM bitmasks. We leveraged the uncertainty metric provided by the GP regression to filter points that are greater than two times the standard deviation. Once the outliers are removed we apply the complete GP regression kernel with its periodic component (Equation 2.1) to make a final surface elevation estimate.

2.5.4 Evaluation analysis

We performed three evaluations to determine how well the GP regression performed at estimating the evolution of glacier surfaces. First we compared the residuals and correlation between the generated surfaces and historical cross-sectional elevation profiles at Nisqually Glacier. Second, we examined if the surface elevation estimates improved by inclusion of partial ($< 65\%$ glacier coverage) DEMs. Third, we investigated if the periodic component in the GP kernel captures seasonal variability over the glacierized surface and thus provides a seasonal bias correction.

2.5.4.1 Comparison to Nisqually glacier cross-sectional profiles

Measurements along three cross-sectional profiles at Nisqually glacier were routinely commissioned by the Tacoma City Light starting in 1931 (Heliker et al., 1984) and continue to present day under the direction of the National Park Service (Stevens et al., 2016). Early measurements were made with a transit and stadia rod up until the 1960's, after which a theodolite was used up until 1984 (Heliker et al., 1984). The exact measurement techniques used between 1984 and 2013 are currently unknown (Stevens et al., 2016). The mean cross-sectional profile elevations and estimated sampling positions used in this study range from 1950 to 2015 and were compiled by Stevens et al. (2016). These averaged elevations were computed from variable sample counts at poorly known locations, so it is hard to compare exact elevation measurements to the corresponding points in the surfaces generated from the GP regression. Nevertheless, we sampled the surfaces generated by the GP regression using corresponding positions and computed root mean squared error (RMSE) and r^2 correlation metrics between elevations at the sampled locations and corresponding historic elevation estimates at the same locations. The historic profile elevation estimates were recorded above an unknown vertical datum so we subtracted the mean offset prior to computing the error statistics. In addition, for each year, we sampled all unique positions across the profile and computed the average profile elevation.

2.5.4.2 *Including vs excluding partial DEMs*

To evaluate if partial DEMs are useful for precisely measuring glacier surface elevation change, we ran the GP regression once conditioned with all DEMs, and once conditioned without the partial DEMs. We qualitatively designated a $< 65\%$ threshold of coverage within the RGI glacier outline to determine if a DEM is considered a "partial DEM" or not. All eight partial DEMs at SCG identified with this threshold (see Figure 2.4) have limited, and sometimes contiguously sparse, coverage. These areas without valid data are primarily at higher elevations in the glacier accumulation zone, which are often overexposed in the image due to snow cover (Figure 2.2A). The reconstructed surfaces at time stamps corresponding to the original partial DEM observation were then subtracted from the partial input DEM to compare residual error in the estimate.

2.5.4.3 *Estimating seasonal surface elevation change*

The seasonal temporal coverage at SCG from ~ 2015 onwards (Figure B.4) enables estimating mean seasonal elevation change variability over the glacierized surface. Because seasonal DEMs with snow coverage were co-registered to the snow-free reference DEM at SCG, we expect some negative bias for snow-on DEMs. Nevertheless, seasonal elevation change due to snow accumulation is proportionally higher over the glacierized surface than over stable ground at lower elevations, even when snow-covered stable surfaces have been co-registered to snow-free stable reference surfaces (Hugonnet et al., 2021). To examine if the modern DEMs provide information that can be leveraged to compute a seasonal bias correction over the glacierized surface, we ran the GP regression once with the periodic kernel, and once without the periodic kernel. We then binned the residual error between the estimated surfaces and the seasonal input DEMs by month and within the 2015 glacierized area.

2.6 *Results*

Here we highlight preliminary results for the GP regression that aim to evaluate if 1) the GP regression reconstructed an evolution of surface elevation that is comparable to the historic cross-sectional profiles at the Nisqually glacier, 2) if the partial DEMs improved the overall surface elevation estimation, and 3) if the periodic GP regression kernel component provided a seasonal surface elevation bias correction.

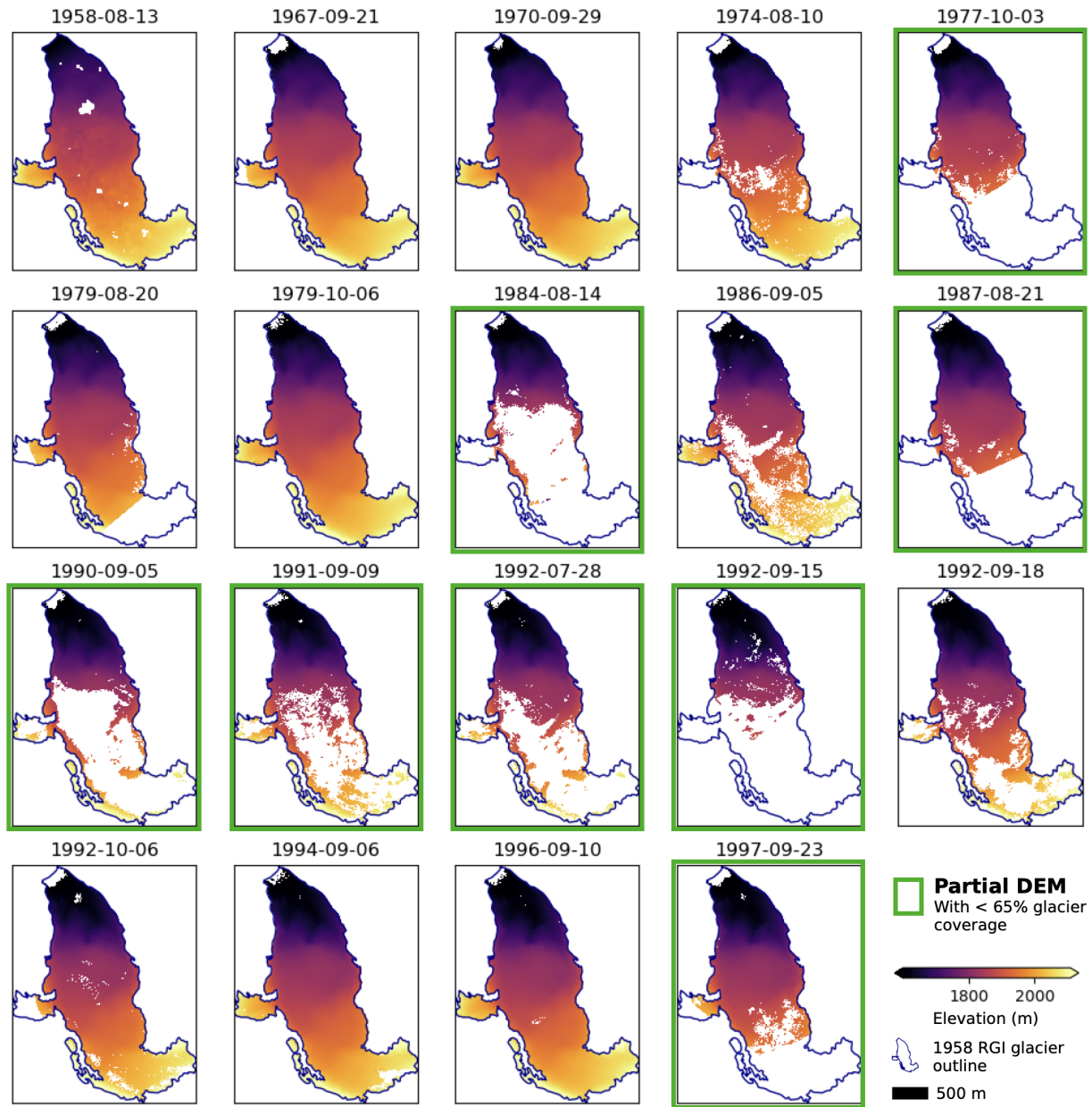


Figure 2.4: Historical (pre-2000) Digital Elevation Models (DEMs) at South Cascade Glacier (SCG). DEMs with partial (< 65%) coverage of the SCG Randolph Glacier Inventory (RGI) outline highlighted in green. Glacier outline shown in blue. Voids in the DEM are generally seen at higher elevations.

2.6.1 Gaussian Process regression results

We generated 2,678 DEM surfaces at monthly intervals between the start and end date in the DEM input time series at all three sites, as well as at the same dates as the input DEMs. The input DEM dates range from 1958-08-13 to 2021-08-13 at SCG (756 + 71 DEMs), from 1947-09-14 to 2020-12-12 at Mount Baker (874 + 55 DEMs), and from 1951-08-16 to 2020-09-01 at Mount Rainier (828 + 94 DEMs). During testing, we examined hundreds of point-sampled time series along the glacier centerlines at SCG, Easton Glacier on Mount Baker, and Nisqually Glacier on Mount Rainier to qualitatively determine if the GP regression reconstructs the surface elevations. In Figure 2.5 we show the temporal regression fits at four locations along the glacier centerline at SCG. In some cases, the filtering process removed outliers in the EarthDEM time series, as is seen in Figure B.5.

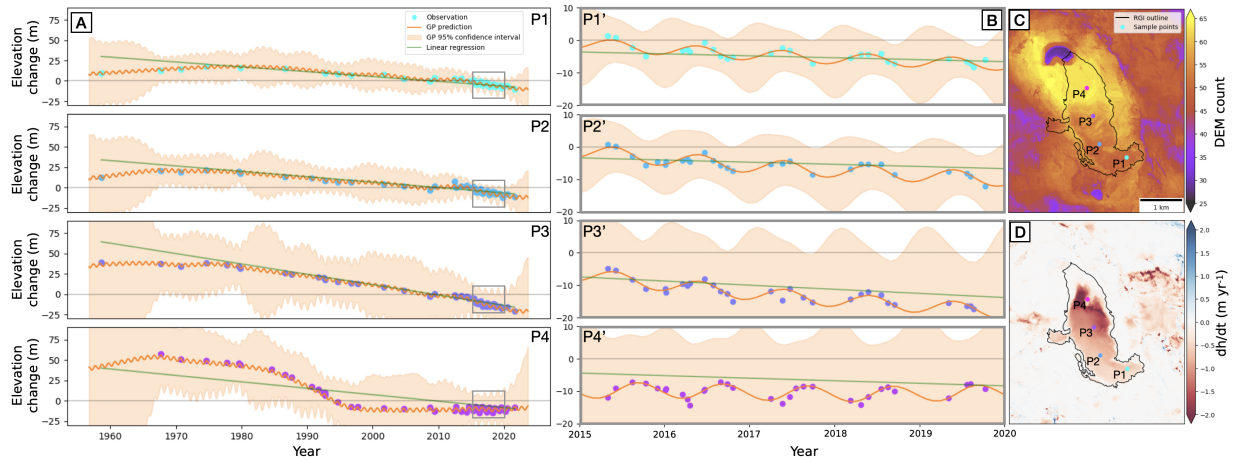


Figure 2.5: Elevation change relative to mean elevation at four points (P1-4) sampled along South Cascade Glacier centerline with Gaussian Process (GP) estimation shown with orange line and 95% confidence interval. Linear regression for comparison show with green line. Column A. shows the full time series at each location. Column B. shows seasonal variability in a zoomed in temporal window from 2015 to 2020. C. Per-pixel DEM count and sample points. C. Per-pixel linear elevation change trend (dh/dt) from 1958 to 2021 and sample points.

2.6.2 Multi-decadal surface elevation change at Nisqually glacier

After subtracting the mean elevation offset (~ 60 m) to correct for the vertical datum offset, surface elevation estimates generated by the GP regression and historical elevation measurements at the same locations along the historic profiles at Nisqually glacier showed a strong correlation at Profile 1 ($r^2=0.84$) and Profile 2 ($r^2=0.79$) (Figure 2.6). At Profile 1 all historical measurements fell within one standard deviation of the uncertainty estimated by the GP regression. At Profile 2, 87% of the historical measurements fell within one standard deviation of the uncertainty estimated by the GP regression. The comparison of measurements at Profile 3 did not reveal a strong correlation ($r^2=0.04$), while 77% of the measurements fell within one standard deviation of the GP regression estimate. The RMSE values are around ~ 10 m for all three cross-sectional profiles and all measurements fell within the 95% confidence interval of the elevation estimates generated by the GP regression.

2.6.3 Improved accuracy in the ablation zone by inclusion of partial DEMs

There were a total of eight DEMs that were classified as partial DEMs ($< 65\%$ 1958 RGI glacier outline coverage) at SCG. We ran a GP regression without and with the partial DEMs as input (Figure 2.7A,B). Visual inspection of the residuals seen in Figure 2.7 shows a clear improvement in the accuracy of the estimates when including the partial DEMs. Residual error, even after including the partial DEMs, is due to the uncertainty associated with input measurements σ_{stable}^2 provided to the GP regression (Equation 2.1). It is intuitive that including more data will always improve the GP regression, however this comparison provides a qualitative measure of how much of an improvement is gained by including these partial DEMs. These results demonstrate that temporal GP regression can leverage information in the partial DEMs to improve the surface elevation estimation in the ablation area, which is the most dynamic and variable region of the glacier.

2.6.4 Seasonal bias correction

The periodic component of the GP regression kernel captured the mean seasonal surface elevation change during the 2015–2020 period in which there were sufficient DEMs to capture seasonal variability (Figure B.4). This recurring high-frequency seasonal surface elevation change signal was then estimated by the GP regression for the entire time series at each pixel (e.g. four pixels shown in Figure 2.5A). By examining the time series at sampled points in the

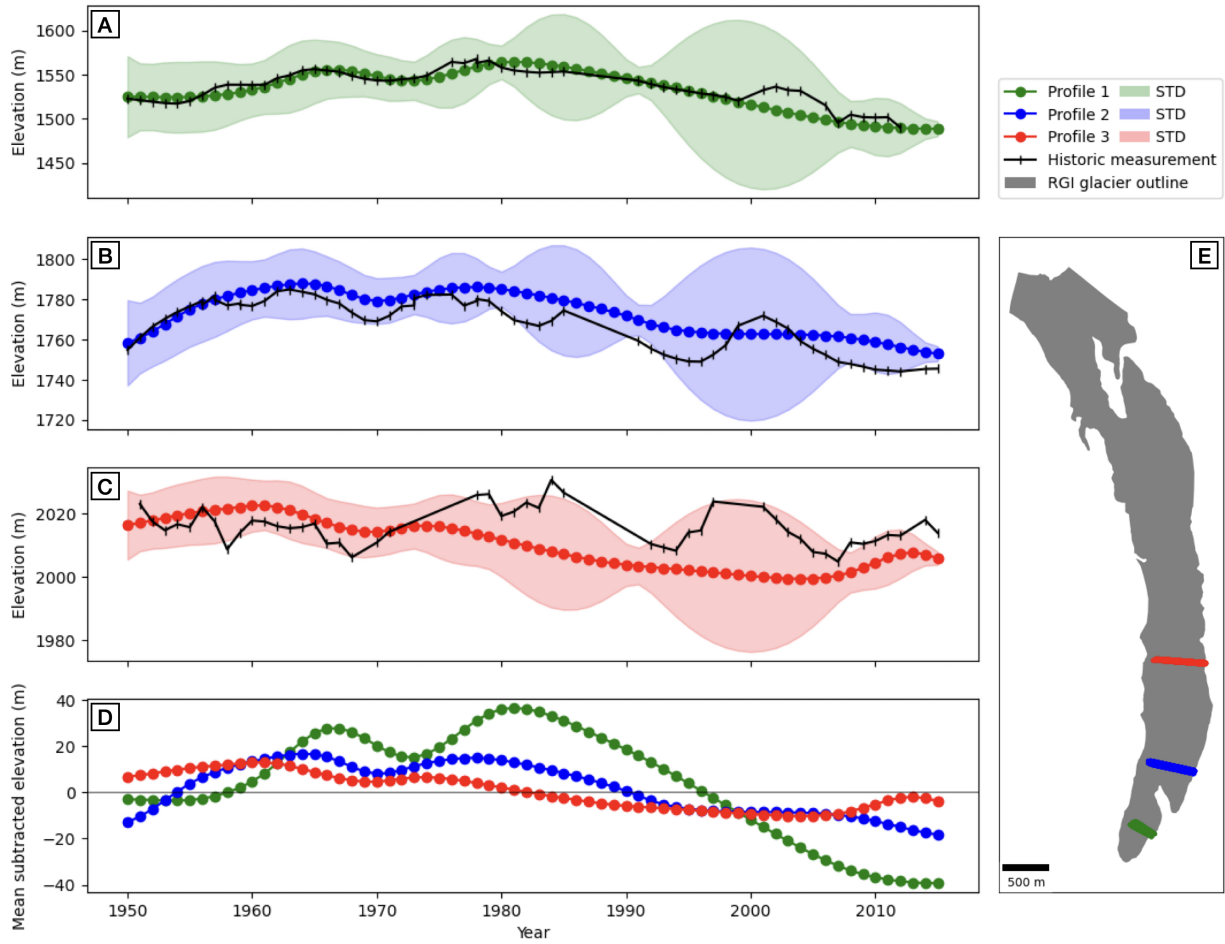


Figure 2.6: Cross-sectional elevation averages along historic profiles at Nisqually Glacier. Panels A. B. C. correspond to Profile 1 ($r^2=0.84$, $RMSE=9.13$ m), Profile 2 ($r^2=0.79$, $RMSE=8.56$ m), and Profile 3 ($r^2=0.04$, $RMSE=10.31$ m). Annual mean elevations along the profiles extracted from the GP generated surfaces shown in color with GP standard deviation (STD). Annual mean field measurements show in black. $RMSE$, r^2 , and $\% \pm \sigma$ values were computed between available field measurements and GP elevation estimate corresponding in space and time. D. Mean subtracted elevation profiles extracted from GP generated surfaces. E. Profile locations plotted over RGI Nisqually glacier outline (RGI60-02.14336, 1970 extent).

2015–2020 period, we see that the GP regression captures seasonal surface elevation variability (Figure 2.5B). The residual error maps demonstrate that the GP surface elevation estimate without the periodic kernel component has higher systematic seasonal bias when subtracted from the corresponding input DEMs (Figure 2.8A) than the GP regression estimate with the

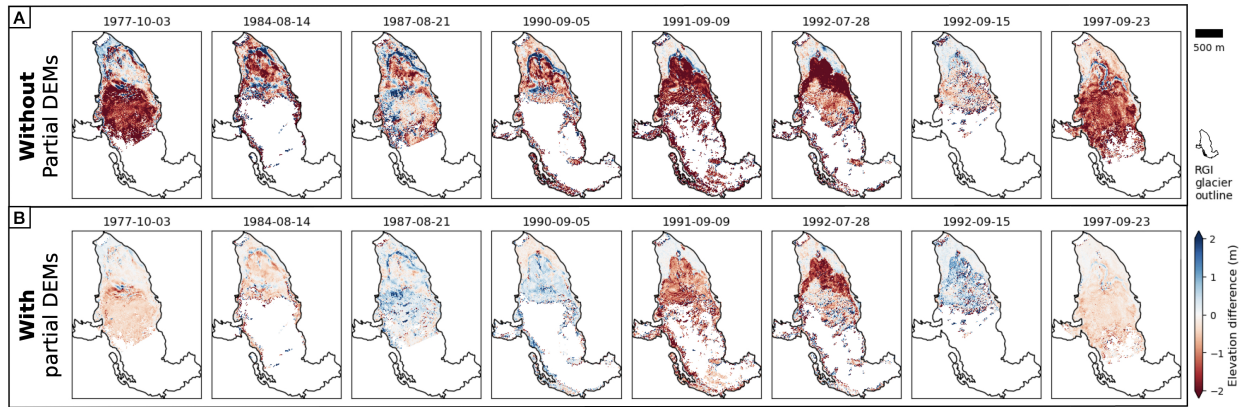


Figure 2.7: Partial DEMs with $<65\%$ glacier outline coverage subtracted from surfaces generated with the Gaussian Process (GP) regression. A. Elevation difference maps for surfaces generated without the inclusion of the partial DEMs. B. Elevation difference maps for surfaces generated with the inclusion of the partial DEMs. Including the partial DEMs in the GP regression reduces residual error. 1958 South Cascade Glacier outline from Randolph Glacier Inventory shown in black.

periodic kernel component (Figure 2.8B). Generally, the seasonal bias correction was greater for DEMs in all months, except January and December months (Figure 2.9).

2.7 Discussion

We demonstrated that Gaussian Process regression can estimate the evolution of glacier surface elevation change from temporally and geographically sparse measurements. Here we discuss limitations of the input datasets, methodology, and evaluation performed, which motivate our ongoing research and development efforts.

2.7.1 Spatial vs temporal data interpolation

The temporal interpolation technique may outperform spatial interpolation techniques, such as hypsometric interpolation, when contiguous elevation bands are missing over large regions of glacierized surfaces. However, when there are sufficiently representative measurements along elevation bands, a spatial interpolation may outperform the temporal interpolation performed with the GP regression technique. Thus, under these conditions, it may be recommended to use the hypsometric interpolation technique first to fill spatial data voids in the input DEMs,

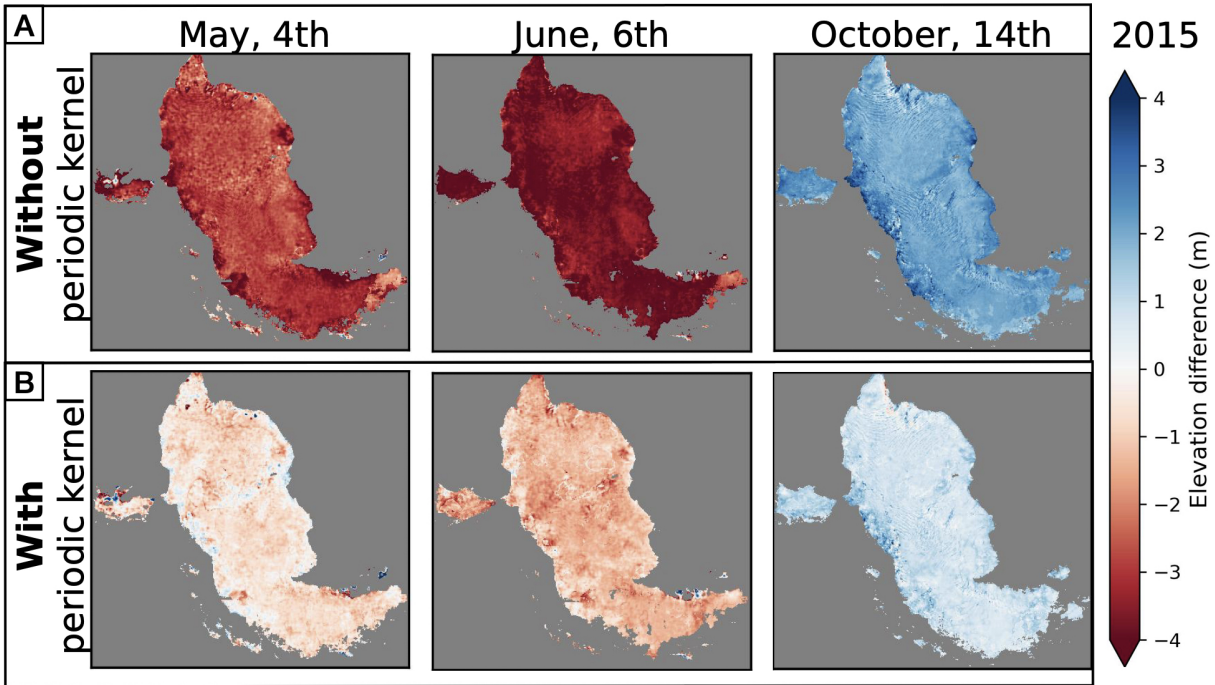


Figure 2.8: Effect of using a periodic kernel to estimate seasonal variability. Panels A and B show difference between GP estimated surfaces and the May, June, and October 2015 DEMs within 2015 USGS South Cascade Glacier outline. A. Difference maps between GP surfaces estimated without including the periodic kernel component. B. Difference maps between GP surfaces estimated including the periodic kernel component.

before running a temporal GP regression. An edge case we did not encounter in our dataset, but that can likely occur, is when no data are available at any time step at a given pixel location. This can result in voids, even after the temporal GP regression. For these instances it is advisable to run a hypsometric interpolation at the very end to fill any remaining data voids (Hugonnet et al., 2021). Future work aims at systematically validating these assumptions through rigorous comparisons of spatial and temporal interpolation methods applied to commonly encountered sparsity conditions over glacierized surfaces in DEMs.

2.7.2 Seasonal bias mitigation

In this analysis we did not attempt to identify snow-free surfaces in the snow-on DEMs (such as plowed roads or permanently exposed rock) and apply a final vertical shift during DEM

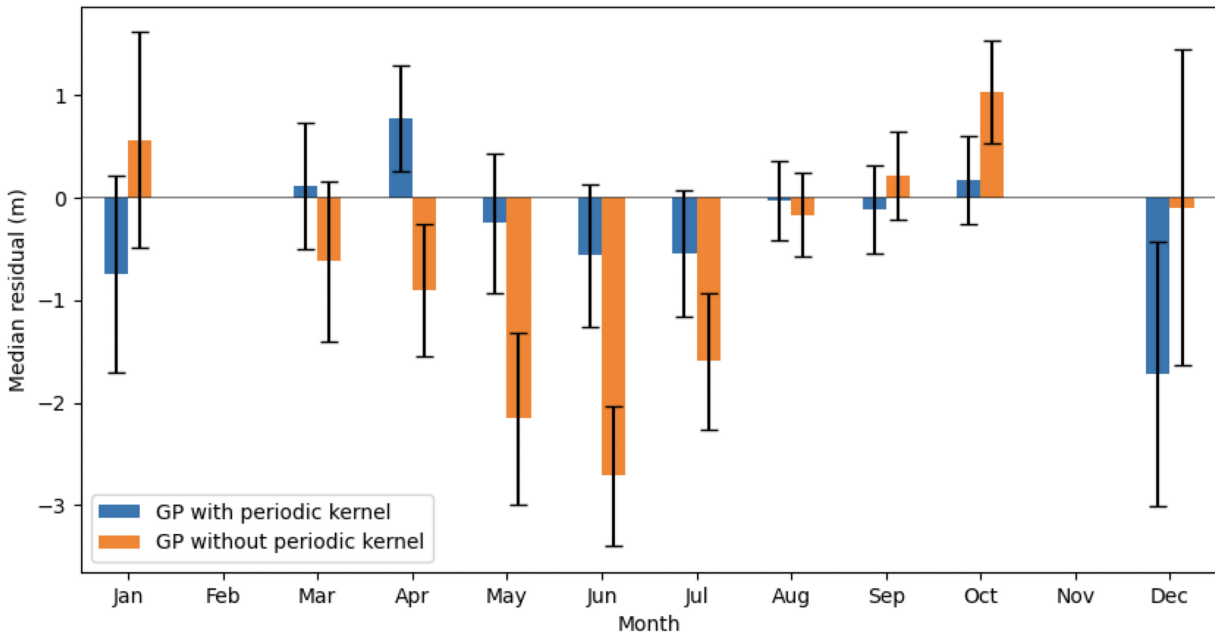


Figure 2.9: Median and NMAD of residuals within 2015 glacier extent for seasonal elevations estimated with and without the periodic Gaussian Process kernel. Residuals are computed from difference values between the estimated surfaces and the photogrammetrically derived DEMs.

co-registration (e.g., Hu et al., 2023). This is a critical next step to obtain a true estimate of spatially distributed snow depths. While SCG sits deep in the Cascade Mountain Range and insufficient exposed surfaces may be available to perform this approach, it is feasible at Mount Rainier and Mount Baker, which have multiple road networks leading up to the volcanoes. Not all roads are plowed in the winter so this process must be done carefully and is a topic for future work and investigation.

At this stage, there remains an unmitigated elevation bias after co-registering the snow-on to snow-off surfaces identified by the programmatic masking using only the RGI glacier outlines and NLCD vegetation land cover classes as masks. However, despite snow-on stable ground surfaces being co-registered to snow-off stable reference terrain, snow is expected to be proportionally deeper over the glacierized surface than over stable ground at lower elevation (Hugonnet et al., 2021). Our results show that this seasonal elevation change signal over the glacierized area can be detected (Section 2.6.4). The periodic kernel component generally provided a seasonal bias mitigation over the glacierized area in 2015 (Figure 2.9)

that propagated to all time stamps (Figure 2.5A).

2.7.2.1 Other approaches for seasonal bias correction in glaciology

There are other methods to provide a seasonal bias mitigation in glaciologic research, which do not require elaborate and sensitive DEM co-registration. Instead, they leverage climate data or auxiliary in-situ point measurements to make a seasonal adjustment (e.g., Belart et al., 2019; Cogley, 2009; Cox and March, 2004; Krimmel, 1999; O’Neel et al., 2019; Reeh, 1991; Zemp and Welty, 2023). While these techniques are easily applied and improve the overall seasonal glacier mass balance estimate, an experiment and methods comparison exercise would provide valuable insight on the best approach.

2.7.3 Towards a generic GP regression glacier kernel design

We took a parsimonious approach and leveraged a priori knowledge about glacier behaviour to design a GP regression kernel that is interpretable and can estimate long-term glacier surface elevation change, even when input data are temporally sparse. Here we discuss a few strategies to improve the GP kernel design.

2.7.3.1 Normalizing the dependant variable

As described at the end of Section 2.5.3.1, by default, the *GaussianProcessRegressor* module normalizes the dependant variable (elevation) to range from 0-1. Normalizing the data in this manner is a common practice in GP regression to ensure numerical stability during optimization and to adjust the sensitivity of the regression to the scale of the input data. By testing the GP regression with (Figure 2.5) and without (Figure B.6), we observed that the uncertainty returned from the GP regression significantly increases when the data are normalized. In both cases, the uncertainty estimates appear either unrealistically high (with normalization) or unrealistically low (without normalization). Further investigation is required to determine when it is appropriate to normalize the data and obtain a trustworthy confidence interval from the GP regression.

2.7.3.2 Automated methods for kernel determination

In the GP literature and software implementations there are embedded cross-validation procedures to ”learn” the appropriate kernel structure (Williams and Rasmussen, 2006).

These optimization routines can be complex, opaque, and are intended for *n-dimensional* machine learning problems, rather than more intuitive and interpretable spatiotemporal analyses. Variogram analysis is an alternative approach to quantitatively and programmatically determine the appropriate temporal length scales and variance supplied to the GP kernel (Hugonnet et al., 2021). This approach is easily interpretable and common in the kriging literature and field of geospatial statistics (Cressie, 2015). However, it remains poorly adapted and not often applied in GP regression frameworks because these commonly operate along multiple non-spatiotemporal dimensions for which covariance length scales are less interpretable. Future work aims to leverage temporal variogram analysis to validate our assumptions about appropriate kernel length scales and variance.

2.7.3.3 Creating and cross-validating an adaptive GP kernel

To create a GP kernel that can optimally estimate variance for all regions of the glacier surface, it may be advised to pursue an adaptive (or "treed") kernel structure (e.g., Gramacy and Lee, 2008) that modulates the kernel parameterization depending on the region of the glacier over which it is operating. Furthermore, it is possible that different regions of the glacier would benefit from different combinations of covariance functions in the GP kernel. Given the accuracy of historical and modern DEMs (e.g., Knuth et al., 2023; Shean et al., 2016), establishing a systematic and quantitative Leave One Out Cross Validation (LOOCV) procedure is a promising next step in optimizing the GP kernel design to perform robustly across any glacierized surface on Earth.

2.7.3.4 Evaluation with independent measurements

The evaluation with mean cross-sectional profile at Nisqually glacier informed us that the surface elevation trends can be captured and that the estimates are within uncertainty bounds provided by the GP regression. Given the dearth of precise and independent historical measurements, rigorously revisiting the estimated exact positions of each measurement that contributed to the historic mean profile elevations is a valuable endeavor. Future work could further leverage independent surface elevation measurements, such as NASA's Ice, Cloud, and land Elevation Satellite (ICESat) laser altimetry to validate the modern elevation estimates.

2.7.3.5 *Multi-dimensional Gaussian Process regression*

An advanced approach to estimating the evolution of the glacier surface elevation is mapping the covariance of surface elevation change in multiple dimensions. The current approach leverages only the per-pixel surface elevation covariance, however, as indicated by the hypsometric spatial interpolation technique, it is evident that there is a spatial covariance signal of surface elevation change that can inform the GP estimation. Additional parameters, such as slope, aspect, and ice velocity may be informative parameters and could be transformed into a coordinate system that a multi-dimensional GP framework can leverage. However, it is important to note that computations will scale exponentially with the number of dimensions, which will require carefully optimized and memory-efficient processing strategies.

2.7.4 *Large dataset processing optimization*

There are existing approaches to optimize the re-chunking of data such as the temporally dimensions DEM raster stacks described in this manuscript (e.g., kerchunk contributors, 2024). The programmatic determination of chunk sizes implemented in *GTSA* and process of writing the re-chunked Zarr file to disk outperformed the attempt to first re-chunk the data with the *kerchunk* library in-memory, then write the re-chunked object to disk. Future work is needed to perform a more in-depth comparison to libraries such as *kerchunk* that aim to streamline this critical process. This process is critical for reduced memory requirements and democratizing the method for the broader community, which may not have access to high performance computing environments.

2.8 *Conclusions*

Long-term glacier surface elevation time series provide valuable insight into how glaciers respond to climate forcing and kinematic instabilities. These measurements remain hidden in the vast archives of historical photographs, which can be used to generate high-resolution DEMs (e.g., Knuth et al., 2023). Despite augmenting the record with these historical DEMs, the data often contain voids over shadowed and snow-covered regions across the glacier surface.

We show that per-pixel Gaussian Process (GP) time-series regression can fill spatial and temporal voids in long-term DEM time series and provide continuous estimates of glacier surface elevation change. The key findings of this research are that 1) GP regression can

estimate the evolution of glacier surface elevation, as demonstrated by the evaluation against independently collected surface elevation measurements at Nisqually glacier. 2) Partial DEMs can provide useful information, especially in dynamic regions of the glacier, such as the ablation area. 3) Including a periodic component in the GP kernel can estimate seasonal surface elevation change and improves results by providing a seasonal bias correction to the surface elevation estimates.

The capacity to estimate surface elevation change using GP regression is limited by the temporal density and accuracy of the input DEM time series. A lack of DEM measurements during time intervals when the glacier was rapidly changing will lead to inaccurate estimates during that dynamic period. Furthermore, co-registering snow-on DEMs to snow-free reference terrain can introduce unmitigated bias, unless snow-free surfaces are identified in the snow-on DEMs and used to compute a vertical adjustment.

The broader implications of this work are that historical DEM time series can be augmented with GP regression to provide spatially and temporally continuous estimates for the evolution of glacier surfaces. This may provide new insight into the mass balance and dynamic response of glaciers to climate forcing at unprecedented temporal and spatial resolution. Future work will aim to refine the GP kernel structure, expand processing to additional sites, and derive regionally representative insights about the evolving sensitivity of glaciers to climate forcing.

Data and software availability

All EarthDEM, USGS, and reference DEM data are publicly available as described in Sections 2.4.1.2, 2.4.1.3, and 2.4.1.4. The Geospatial Time Series Analysis (GTSA, doi:10.5281/zenodo.8188085) repository is publicly available on Github with MIT license, documentation, and Jupyter notebook examples.

Chapter 3

MEASURING LONG-TERM GEODETIC GLACIER MASS BALANCE AND KINEMATICS AT HIGH SPATIOTEMPORAL RESOLUTION

3.1 Abstract

Mountain glaciers are perennial sources of freshwater that shape the natural landscape and provide important ecosystem services, such as aquatic stream habitat for keystone fish species, hydropower, and freshwater supply for recreation. Over the past century, many glaciers in Western North America have lost mass and steadily retreated in response to long-term climate forcing. Some glaciers, especially those on stratovolcanoes with high-altitude accumulation areas and steep elevation gradients, present climate-driven advances on decadal timescales and intermittent kinematic movement on shorter (interannual) timescales. This kinematic movement can destabilize hillslopes and lead to devastating outburst floods and landslides.

In this study, we leveraged annual Digital Elevation Model (DEM) surfaces interpolated with Gaussian Process regression between ~ 1950 – 2020 to compute continuous estimates for glacier mass balance, as well as surface elevation change along center flowlines. To evaluate our approach, we examined three well-studied glaciers in the Pacific Northwest of the United States – South Cascade Glacier in the Cascade Range, Nisqually Glacier at Mount Rainier, and Easton Glacier at Mount Baker. We hand-delineated ~ 70 years of annual glacier outlines from DEM difference maps and computed geodetic glacier mass balance estimates for comparison against in-situ mass-balance measurements. We found an average $\overline{RMSE}$ of 0.77 m w.e. and average $\overline{r^2}$ of 0.34 between our geodetic mass-balance estimates and available in-situ glacier mass balance measurements averaged over 3–5 years. We also computed elevation change along the glacier center flowlines and examined the frequency of kinematic waves moving through the glacier systems.

Our results show that South Cascade Glacier retreated during the entire ~ 1950 – 2020 period time period, while Easton Glacier advanced between 1950–1985, then retreated again between 1985–2020. In ~ 2017 Easton Glacier reached the same size as it was in 1950. Nisqually Glacier advanced and retreated multiple times during the ~ 70 -year time period.

These results suggest that the long-term interpolated DEM surfaces can capture short term area, mass-balance, and kinematic movement at high spatio-temporal resolution derived from geodetic measurement. Furthermore, the void-free and temporally continuous glacier surface elevation grids may provide new and useful information to the modeling community, including estimated periods of stability. Accurately projecting future glacier change requires long-term observation of glacier response to changing climate conditions. These measurements can help improve our understanding of how glaciers responded to climate conditions in the past and how their sensitivity evolved through time. Calibrating physical models with this information will improve projections of future climate driven mass change and kinematic behaviour of mountain glaciers.

3.2 Introduction

Glacier mass balance is a fundamental measurement in glaciology that provides insight into the glacier’s water budget as well as its sensitivity to climate forcing. The glacier’s mass balance is traditionally recorded in-situ with mass-balance stakes placed at various locations on the glacier surface (Meier and Tangborn, 1965; Ostrem et al., 1966). Stakes are installed primarily along the glacier center flowline, then periodically measured throughout seasonal accumulation and ablation cycles to extrapolate glacier mass change estimates across the glacier surface (Fountain et al., 2009; Krimmel, 2001; O’Neel et al., 2019; Rasmussen and Conway, 2001; Zemp et al., 2019).

To augment and calibrate the annual record of in-situ stake mass-balance measurements, geodetic methods have been employed since the 1980, by which time-stamped Digital Elevation Models (DEMs), derived e.g. from satellite imagery, lidar, or aerial photography, are subtracted to obtain surface elevation change across a continuous grid across the glacier surface (e.g., Bolch et al., 2008; Krimmel, 1989, 1999; O’Neel et al., 2019). This precisely measured elevation change at high spatial resolution can provide a spatially resolved volume change estimate with lower uncertainty compared to mass change measurements extrapolated from sparse mass-balance stake observations (Florentine et al., 2023; McNabb et al., 2019; O’Neel et al., 2019; Zemp et al., 2013).

In this study we leveraged spatially and temporally continuous glacier surface elevation estimates, derived from DEM time series and per-pixel Gaussian Process regression, to compute continuous glacier mass and surface elevation change. We then delineated glacier area outlines to derive area-averaged mass-balance estimates and compared these with in-situ

glacier mass balance records. Finally, we examined the long-term surface elevation change along the glacier center flowlines to measure periods of glacier advance and retreat. Our results show that we can derive glacier mass balance at interannual resolution from the interpolated historical DEM time series which is comparable to the mass-balance estimates derived from in-situ measurement. This is significant because it indicates that DEM time series can be used to infer not only long-term trends and calibrate in-situ derived mass balance, but also short-term variability in response to climate forcing.

3.3 Study sites

To validate our approach, we focused our study on three well-studied alpine glaciers in the Pacific Northwest region of the United States – South Cascade Glacier in the northern Cascade Range, Easton Glacier at Mount Baker, and Nisqually Glacier at Mount Rainier. These glaciers are small ($<5 \text{ km}^2$) – compared to glaciers in Alaska and High-mountain Asia – and are governed by their local geometry and temperate maritime climate. Mount Baker (3,286 m) and Mount Rainier (4,392 m) are the two highest stratovolcanoes in the region and receive considerable precipitation, due to rapid orographic uplift of humid air streaming in from the Pacific Ocean (Hu and Nolin, 2019; Menounos et al., 2019; Neiman et al., 2008). Geometric characteristics (e.g. aspect, slope, length, elevation range) for each glacier are obtained from the Randolph Glacier Inventory v6.0 (RGI Consortium, 2017)

3.3.1 South Cascade Glacier, Cascade Range

South Cascade Glacier (SCG) is a northwest facing valley glacier (aspect 350°) and is one of the five primary benchmark glaciers routinely monitored by the United States Geological Survey (USGS, O’Neel et al., 2019). The SCG mass-balance record begins in 1958 and has significantly contributed to estimating long-term glacier mass change for all glaciers in Western North America and Canada (RGI region 2, Meier and Tangborn, 1965; RGI Consortium, 2017; Zemp et al., 2013). SCG has a shallow mean slope (12.8°) and sits in a valley that is flanked by steep cliffs and talus debris on either side, which provide protection from wind and solar radiation. This shallow profile and valley geometry results in a particular accumulation area that spans across elevation bands along the south-western flank of the glacier. The low elevation of the accumulation zone and microclimate created by the valley influenced steady glacier retreat and thinning since 1958 (O’Neel et al., 2019). The SCG

area of the 1958 RGI outline (RGI60-02.18778) is 2.92 km^2 and the elevation ranges from $\sim 1600\text{--}2200 \text{ m}$ over a distance of $\sim 3300 \text{ m}$ (RGI Consortium, 2017).

3.3.2 *Easton Glacier, Mount Baker*

Easton Glacier is a south-west facing glacier (aspect 200°) located on the southern flank of the Mount Baker stratovolcano, which receives the highest seasonal snowfall in the United States (Leffler et al., 2001). The glacier mass balance at Easton Glacier has been routinely measured by the North Cascade Glacier Climate Project since 1989 and contributes freshwater to the Skagit River watershed (Pelto and Brown, 2012; WGMS, 2021). The accumulation area of the glacier is fully exposed to wind and solar radiation at high elevation on the stratovolcano. At lower elevation, Little Ice Age lateral moraines form the glacier valley and are comprised of unvegetated bedrock and periglacial deposits (Osborn et al., 2012). The Easton Glacier area of the 1974 RGI outline (RGI60-02.17739) is 2.88 km^2 and the elevation ranges from $\sim 1600\text{--}3000 \text{ m}$ over a distance of $\sim 4300 \text{ m}$ with a mean slope of 18.6° (RGI Consortium, 2017).

3.3.3 *Nisqually Glacier, Mount Rainier*

Nisqually Glacier is a south-east facing, long, and steep glacier (aspect 165°) located in the southern flank of the Mount Rainier stratovolcano. The glacier mass balance has been routinely measured by the National Park Service since 2002 and contributes freshwater to the Nisqually River watershed (Riedel and Larrabee, 2015; WGMS, 2021). Nisqually Glacier has notoriously caused frequent outburst floods and debris flows over the years, along with the Kautz and South Tahoma Glaciers, which have caused significant damage to downstream infrastructure and remain difficult to predict (Allstadt et al., 2015; Anderson and Shean, 2022; Driedger and Fountain, 1989). The Nisqually Glacier area of the 1970-1994 RGI outline (RGI60-02.14336) is 4.44 km^2 and the elevation ranges from $\sim 1400\text{--}4300 \text{ m}$ over a distance of $\sim 6200 \text{ m}$ with a mean slope of 24.5° (RGI Consortium, 2017).

3.4 **Data**

3.4.1 *Annual void-free DEM surfaces*

In this study, we leveraged annual void-free DEM surfaces to make continuous geometric measurements of the glaciers. These DEMs were generated by interpolating spatially and

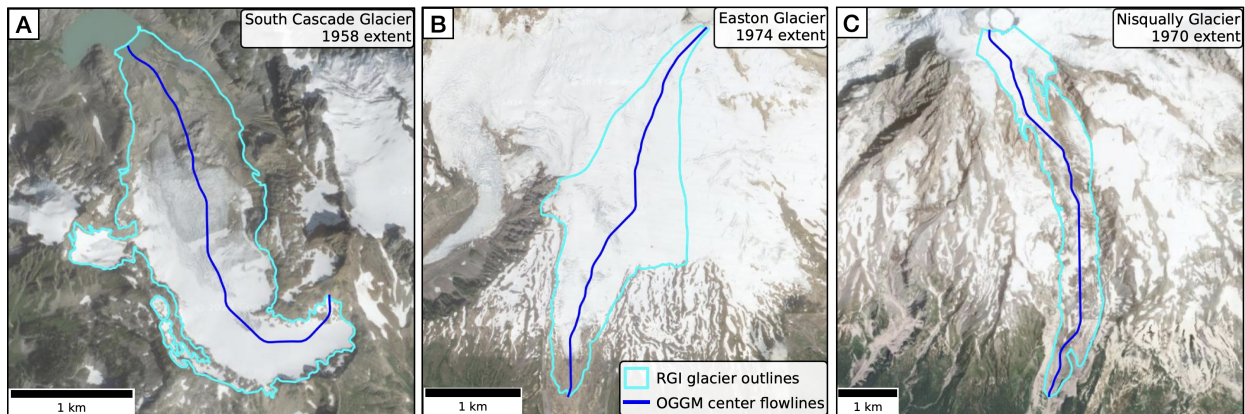


Figure 3.1: Study sites A. South Cascade Glacier, B. Easton Glacier, and C. Nisqually Glacier. Each panel shows Google satellite basemap with Randolph Glacier Inventory (RGI) outlines in light blue and center glacier flowlines computed by the Open Global Glacier Model (OGGM) shown in dark blue (Maussion et al., 2019; RGI Consortium, 2017). A. 1958 South Cascade Glacier RGI glacier extent (basemap 2016-08-19). B. 1874 Easton Glacier RGI glacier extent (basemap 2016-07-28). C. 1970-1994 Nisqually Glacier RGI glacier (basemap 2021-07-25).

temporally sparse DEM time series derived from historical aerial photographs, lidar, and modern satellite images at all three sites (Knuth, 2024). We used the Geospatial Time Series Analysis (GTSA) software (Knuth, 2023) to stack the input DEMs and interpolated each per-pixel time series using a temporal Gaussian Process regression, as described in Knuth (2024). These interpolated surfaces provide continuous elevation estimates for September 30th of each year during the time range of input DEMs, along with a per-pixel uncertainty estimate provided by the GP regression. The annual and spatially continuous DEM surface time series ranges from 1958–2021 at SCG (63 DEMs), from 1947–2020 at Easton Glacier (73 DEMs), and from 1951–2020 at Nisqually Glacier (69 DEMs).

3.4.2 Auxiliary data

We used in-situ glacier mass-balance measurements, glacier outlines delineated from optical images, and modeled glacier center flowlines to evaluate our geodetic area-averaged glacier mass-balance and investigate surface elevation change estimates.

3.4.2.1 *In-situ glacier mass-balance data*

To evaluate the accuracy of geodetic mass balance estimates produced in this study we downloaded available annual net mass-balance derived from in-situ stake measurements at all three sites. At SCG these data were collected by the USGS Glacier Benchmark program and range from 1958–2021 (McNeil et al., 2022b). At Easton Glacier mass balance data were collected by the North Cascade Glacier Climate Project and range from 1984–2021 (Pelto and Brown, 2012; WGMS, 2021). At Nisqually Glacier measurements were collected by the National Park Service and range from 2003–2015 (Riedel and Larrabee, 2015; WGMS, 2021).

3.4.2.2 *Glacier area outlines*

We leveraged independently generated glacier area outlines at each site as checkpoints for glacier outlines created in this study. These independently derived outlines were created by delineating the estimated glacier boundary in georeferenced optical images (e.g. Bayr et al., 1994; Berthier et al., 2023; Hall et al., 1987; Paul et al., 2013). At SCG we used the 1958 RGI outline, as well as 10 outlines provided with the USGS geodetic data release for the years 1958, 1970, 1979, 1986, 1992, 2001, 2004, 2008, 2015, and 2021 (McNeil et al., 2022a; RGI Consortium, 2017). At Easton Glacier, we used the single 1974 RGI outline (RGI Consortium, 2017). At Nisqually Glacier, we used three outlines: the 1970-1994 composite RGI outline, as well as the 2015 and 2021 outlines provided by the National Park Service (Beason et al., 2023; RGI Consortium, 2017). These outlines provided us with initial estimated extents for manual glacier outline delineation from the DEM difference maps, as described in Section 3.5.1.

3.4.2.3 *Glacier center flowlines*

The central line that estimates the dominant flow of ice through the glacier system (i.e. the center flowline) was computed using the Open Global Glacier Model (OGGM, Maussion et al., 2019). This estimated flowline is computed by OGGM from the 30 m NASADEM surface elevation product, which is derived from the 2000 Shuttle Radar Topography Mission (SRTM) global DEM (Maussion et al., 2019). We used this center flowline estimate to bin elevation change by distance bin along the flowline and observe changes in the glacier surface elevation through time, as further described in Section 3.5.3.

3.4.2.4 *Climate data*

We used the Pacific Decadal Oscillation (PDO) index as a proxy for regional climate forcing. The PDO is characterized by shifts in the mean Pacific Ocean sea surface temperature (SST) (Mantua et al., 1997) and provides a regional estimate of the climatology in the Pacific Northwest. In North America and Alaska, weather patterns generally display above average temperature and precipitation values during the positive phase of the PDO and below average temperature and precipitation values during the negative phase. The glaciers mass budget is governed by these climate forcings (specifically the amount of winter precipitation and mean annual temperature) and responds immediately, while the kinematic response occurs at a time lag after forcing and varies based on factors such as the size of the glacier and its geometry (e.g. Jóhannesson et al., 1989). The characteristic response time of small ($< 10 \text{ km}^2$) glaciers in the Pacific Northwest is 10-60 years (Christian et al., 2022).

3.5 *Methods*

3.5.1 *Delineating glacier outlines*

To compute specific glacier mass balance (Cogley et al., 2010) we delineated glacier outlines from long-term DEM difference maps. We computed DEM difference maps by subtracting each DEM from the DEM surface where the glacier is at its minimum extent, which reveals the glacier extent at a given time step (e.g. Maurer et al., 2019). We then evaluated all existing glacier outlines as initial references (Section 3.4.2.2) and manually adjusted the outline nearest in time to match the glacier extent revealed in a given difference map. Finally, we computed the 5-year centered rolling mean of the glacier area time series and derived the rate of area change. The final glacier outlines were used to estimate time-varying area and compute the specific geodetic glacier mass balance at each time step (Florentine et al., 2023).

3.5.2 *Computing geodetic mass balance*

To compute annual glacier mass balance we subtracted the September 30th DEM surface estimate from one year (t_1) with the September 30th DEM surface estimate from another year (t_2). September 30th is considered the end the summer ablation season ($\sim$ May–September, O’Neel et al., 2019), before snow begins to accumulate again in October (Lundquist et al., 2023). Thus, the difference between September 30th surface elevations ($t_2 - t_1$) provides a reasonable estimate of net mass balance from one year to another (Belart et al., 2019).

After subtracting the DEM pair, we computed the volume change by summing all elevation difference values within the union of the glacierized area between t_1 and t_2 . We then divided this volume by the mean glacierized area between t_1 and t_2 , applied the density conversion factor to estimate the mass of the volume, and finally divided by the elapsed time in years between observations to obtain an estimated mass-balance rate in meters water equivalent ($m\ w.e.$) per year. See Equation 3.1):

$$\dot{B} = \frac{\Delta V}{\bar{A}} \frac{\rho_{ice}}{\rho_{water}} \frac{1}{\Delta t} \quad (3.1)$$

where $\dot{B}$ is the glacier-wide specific mass balance, ΔV is the volume change over the mean glacierized area $\bar{A}$, $\frac{\rho_{ice}}{\rho_{water}}$ is the density conversion factor and Δt is the time difference in years between t_1 and t_2 . Here we used a density conversion factor of $850 \pm 60\ kg\ m^3$ to estimate the water mass per unit volume when the Δt is greater than 5 years, and twice the uncertainty $\pm 120\ kg\ m^3$ when the time delta is shorter than 5 years (Belart et al., 2019; Huss, 2013).

3.5.2.1 Evaluation against annual in-situ glacier mass-balance measurements

To evaluate geodetic mass balance against in-situ glacier mass balance measurements, we extracted available net annual mass balance from the WGMS and USGS glacier mass balance data releases (Section 3.4.2.1, McNeil et al., 2022b; WGMS, 2021). We then computed a 3, 5, and 10-year centered rolling mean of these annual net mass balance measurements to compare these averages with the geodetic mass balances obtained from subtracting DEMs interpolated with GP regression. The 3, 5, and 10-year averaging windows were chosen to investigate the temporal resolution of the geodetic mass balance time series. We computed the root mean squared error (RMSE) between the geodetic and averaged in-situ annual mass balance time series to assess the magnitude of error in our estimates. To determine the fidelity of the estimated geodetic mass balance we computed the Pearson rank correlation coefficient (r^2) between the cumulative geodetic and averaged in-situ annual mass balance time series.

3.5.3 Computing elevation change along glacier center flowlines

We used the OGGM software to estimate the main glacier center flowlines for each glacier (Section 3.4.2.3). Starting 1 km up from the terminus along the center flowline, we then extracted surface elevations from the DEM time series at 1 m intervals along the glacier

center flowline and computed the mean elevation for each year within 100 m distance bins (Krimmel and Vaughn, 1987).

3.6 Results

3.6.1 Glacier outlines

We produced a combined total of 205 glacier area outlines from the DEM difference maps at all three sites, as described in Section 3.5.1 and shown in Figures C.2, C.3, and C.4. At SCG, we delineated 63 glacier outlines for the 1958–2021 period and included the 10 outlines obtained from the USGS geodetic data release with minor adjustments. We used the more detailed 1958 USGS outline, instead of the 1958 RGI outline as reference for that year. SCG continuously decreased in area between 1958–2021. The rate of area change was highest during the ~1985–1995 period (Figure 3.2A). SCG was at a maximum extent in 1958 and minimum extent in 2021 and lost a total of 1.125 km² in area during this time period. At Easton Glacier we delineated 73 outlines for the 1947–2020 period. We found that the 1974 RGI outline was closest to the 1985 extent seen in the difference maps and adjusted to the extent of elevation change in 1985. Easton Glacier increased in area from 1947–1988, then decreased from 1988–2020. The rates of area change were highest during the ~1970–1980 and ~2015–2020 periods (Figure 3.2B). Easton glacier was at a maximum extent in 1988 and minimum extent in 2020 and lost a total of 0.096 km² in area during this time period. Notably, the area in 1947 was approximately the same as in 2017. At Nisqually glacier we delineated 67 outlines for the 1951–2020 period, including the 2 outlines from NPS data release with minor adjustments. We found that the 1970–1994 RGI outline was closest to the 1974 and 1990 extents seen in the difference maps and adjusted to the extent of elevation change at these dates. Nisqually decreased in area from 1951–1962, increased from 1962–1968, decreased from 1968–1973, increased from 1973–1980, and finally decreased from 1980–2020. Nisqually was at a maximum extent in 1951 and minimum extent in 2020 and lost a total of 0.514 km² in area during this time period.

3.6.2 Geodetic mass balance comparison

Here we present results for each site that compare the geodetic mass balance with in-situ mass balance measurements.

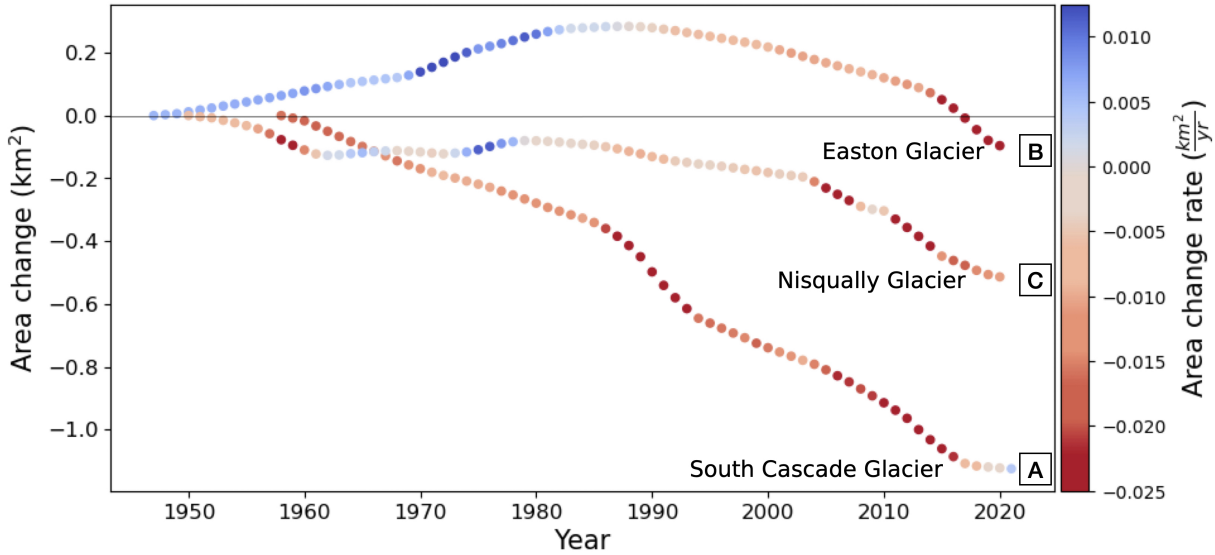


Figure 3.2: Glacier area change at A. South Cascade Glacier (SCG, 1958–2021, 1.125 km² area loss), B. Easton Glacier (1947–2020, 0.096 km² area loss), and C. Nisqually Glacier (1951–2020, 0.514 km² area loss). The area change time series show continuous glacier area retreat at SCG, a period of advance followed by retreat at Easton Glacier, and multiple periods of advance and retreat at Nisqually Glacier (Section 3.6.1)

3.6.2.1 South Cascade Glacier (SCG) mass balance

At SCG, we found the highest correlation ($r^2 = 0.43$) between the 5-year rolling mean of in-situ glacier mass balance measurements and the geodetic mass balance derived from surfaces interpolated with GP regression (Figure C.1). The RMSE between the 5-year averaged in-situ mass balance and geodetic mass balance was 0.55 m w.e.. It is noteworthy that the negative peak in geodetic mass balance around the year 2015 (Figure 3.3 C) appears more similar to the raw in-situ mass balance seen in Figure 3.3 A, than the 5-year averaged product in Figure 3.3 B for that time frame. This indicates that for this time frame ~2015–2020 the geodetic mass balance may provide a temporal resolution that is finer than 5-years.

When averaging the time series in Figure 3.3 B and C for each decade, we obtain the decadal rates of change expressed in Figure 3.3 D, which qualitatively indicate agreement for the averages computed over these decadal time frames. Figure 3.3 E shows the PDO index, which is averaged for each decade in Figure 3.3 F. By qualitatively comparing the average decadal mass balance estimates in Figure 3.3 D with the average decadal PDO in

Figure 3.3 F, it appears that as the PDO index goes down, the glacier mass balance goes up, and vice versa. Panel G in Figure 3.3 shows the percent of the glacier covered by each of the input DEMs, prior to interpolation with the GP regression. This serves as a reference that indicates the temporal density of information used to condition the GP regression and compute the geodetic mass balance (Knuth, 2024).

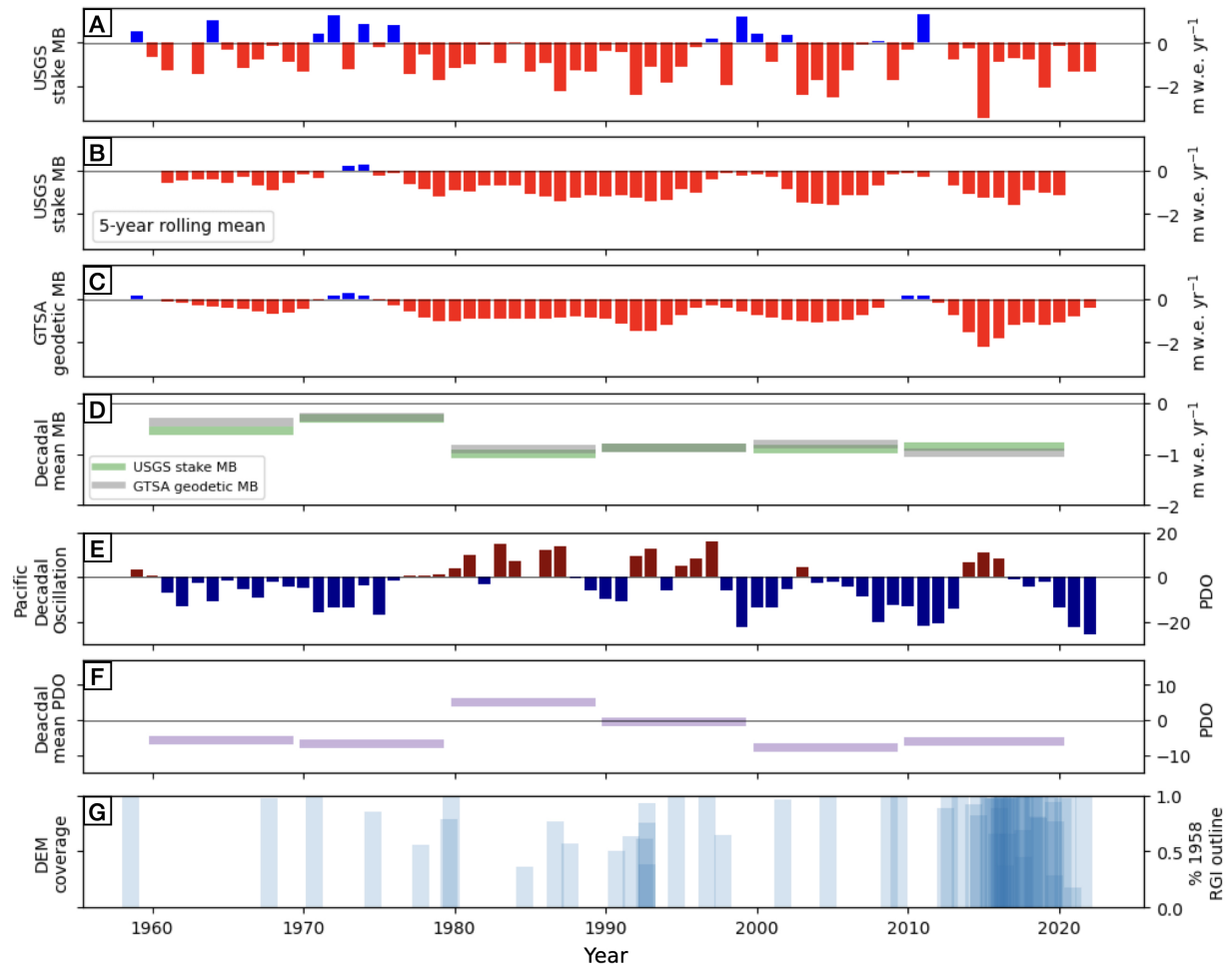


Figure 3.3: A. Annual in-situ mass balance time series at South Cascade Glacier (SCG, McNeil et al., 2022b). B. Five-year point-centered rolling mean of A. C. Annual geodetic mass balance from DEM surfaces interpolated with Gaussian Process regression. Decadal mean mass balance of B and C. D. Pacific Decadal Oscillation (PDO). F. Decadal PDO mean. G. Percent coverage of RGI SCG glacier extent (RGI60-02.18778, 2.92 km², dated 1958).

3.6.2.2 *Easton Glacier mass balance*

At Easton Glacier we found the highest correlation ($r^2 = 0.18$) between the 3-year averaged in-situ measurements and the geodetic mass balance (Figure C.1). The RMSE between these mass balance change measurements was 0.6 m w.e.. As was the case for SCG, due to the high temporal density of input DEMs (Figure 3.4 F) during the ~ 2015 –2020 period, the annual geodetic mass-balance trends are more similar to the raw in-situ mass balance seen in Figure 3.4 A, than the 3-year averaged product in Figure 3.4 B for that time frame. When averaging the time series in Figure 3.4 B and C for each decade, we obtain the rates expressed in Figure 3.4 D, which show the agreement, except for the 2000–2010 decade during which there were limited input DEMs (3.4G). Predominantly positive and negative step changes in the decadal PDO averages appear to have a relationship with predominantly negative and positive step changes seen in the long-term geodetic mass balance time series.

3.6.2.3 *Nisqually Glacier mass balance*

At Nisqually Glacier we found the highest correlation ($r^2 = 0.41$) between the 3-year averaged in-situ measurements and the geodetic mass balance (Figure C.1). The RMSE between mass balance change measurements was 1.24 m w.e. (Figure 3.5). As was the case for SCG and Easton Glacier, the high temporal density of input DEMs (Figure 3.5 G) during the ~ 2015 –2020 period may provide a geodetic mass-balance estimate with higher temporal resolution than 3-year averages. Again, there appears to be a relationship between the decadal averages of the PDO index (Figure 3.5 F) and the glacier mass balance (Figure 3.5 D).

3.6.3 *Surface elevation change at center flowlines*

By examining the surface elevation change at 100 m distance bins along glacier center flowlines we tracked the movement of ice through the glacier systems. At SCG we observed a steady lowering of all distance bins, indicating steady retreat and thinning of the glacier surface (Figure 3.6A). At Easton Glacier we observed thickening of the terminus and advance between ~ 1970 –1993 (Figure 3.6B). The period of steepest change in thickness at higher elevations (~ 1972) took approximately 8 years to propagate to the terminus. During this period of terminus advance, at higher elevations the surface began lowering and the glacier became thinner, while the elevation was rising and the glacier was becoming thicker at lower elevations. This is expected with a kinematic redistribution of ice. The velocity of the advance was

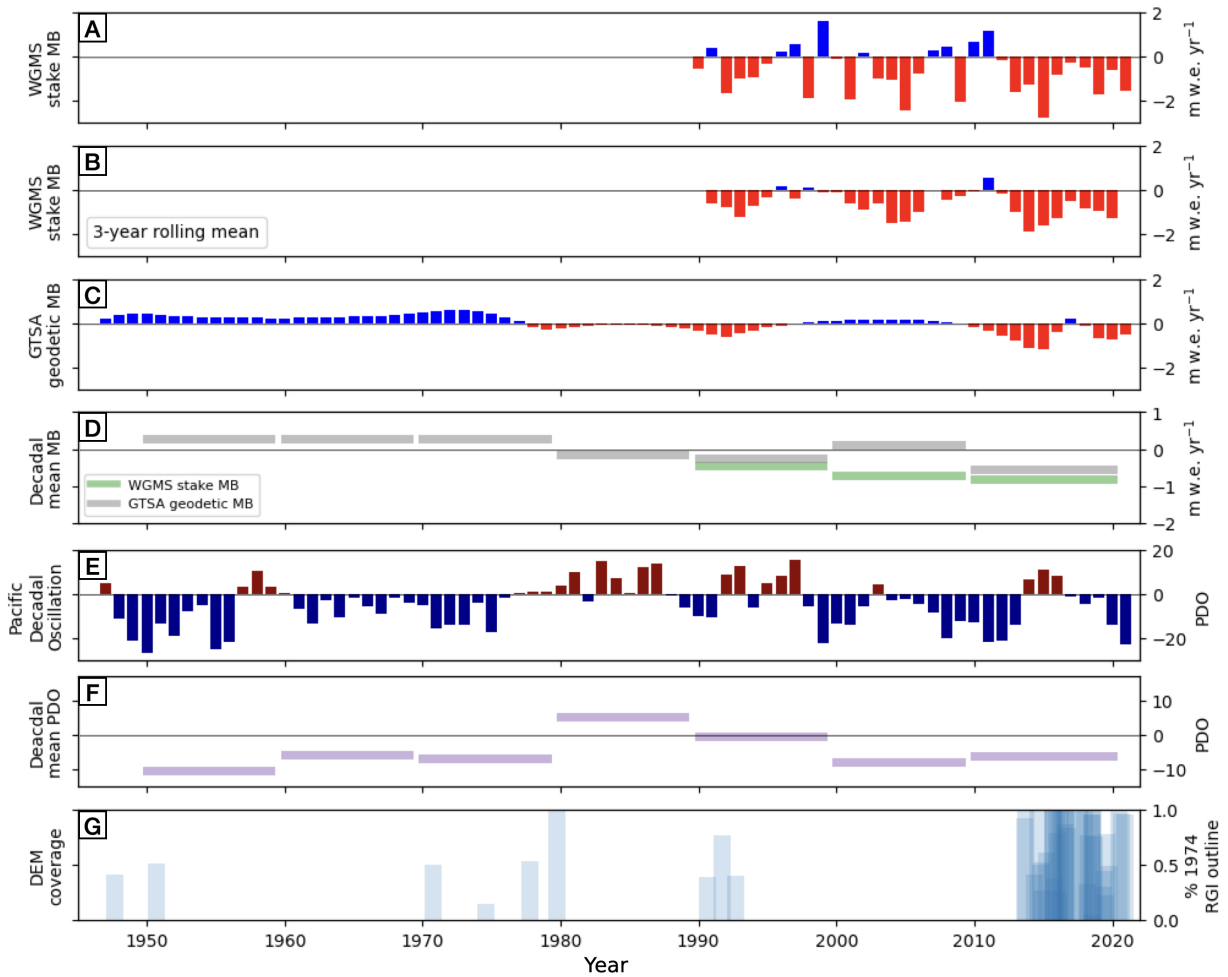


Figure 3.4: A. Annual in-situ mass balance time series at Easton Glacier (Pelto and Brown, 2012; WGMS, 2021). B. Five-year point-centered rolling mean of A. C. Annual geodetic mass balance from DEM surfaces interpolated with Gaussian Process regression. Decadal mean mass balance of B and C. D. Pacific Decadal Oscillation (PDO). F. Decadal PDO mean. G. Percent coverage of RGI Easton glacier extent (RGI60-02.17739, 2.88 km², dated 1974).

approximately $20 \frac{m}{yr}$, which is determined by the timing in onset of thickening from one distance bin near the terminus (purple colors) to the next (Figure 3.6B). At Nisqually Glacier we observed two periods of advance (~ 1950 – 1965 , ~ 1973 – 1983) and subsequent retreats (Figure 3.6C). Here, the first change in thickness at higher elevations took approximately 10 years to propagate to the terminus, while the second advance appears to have occurred more rapidly. Unlike at Easton Glacier, these two advances indicate that Nisqually Glacier may

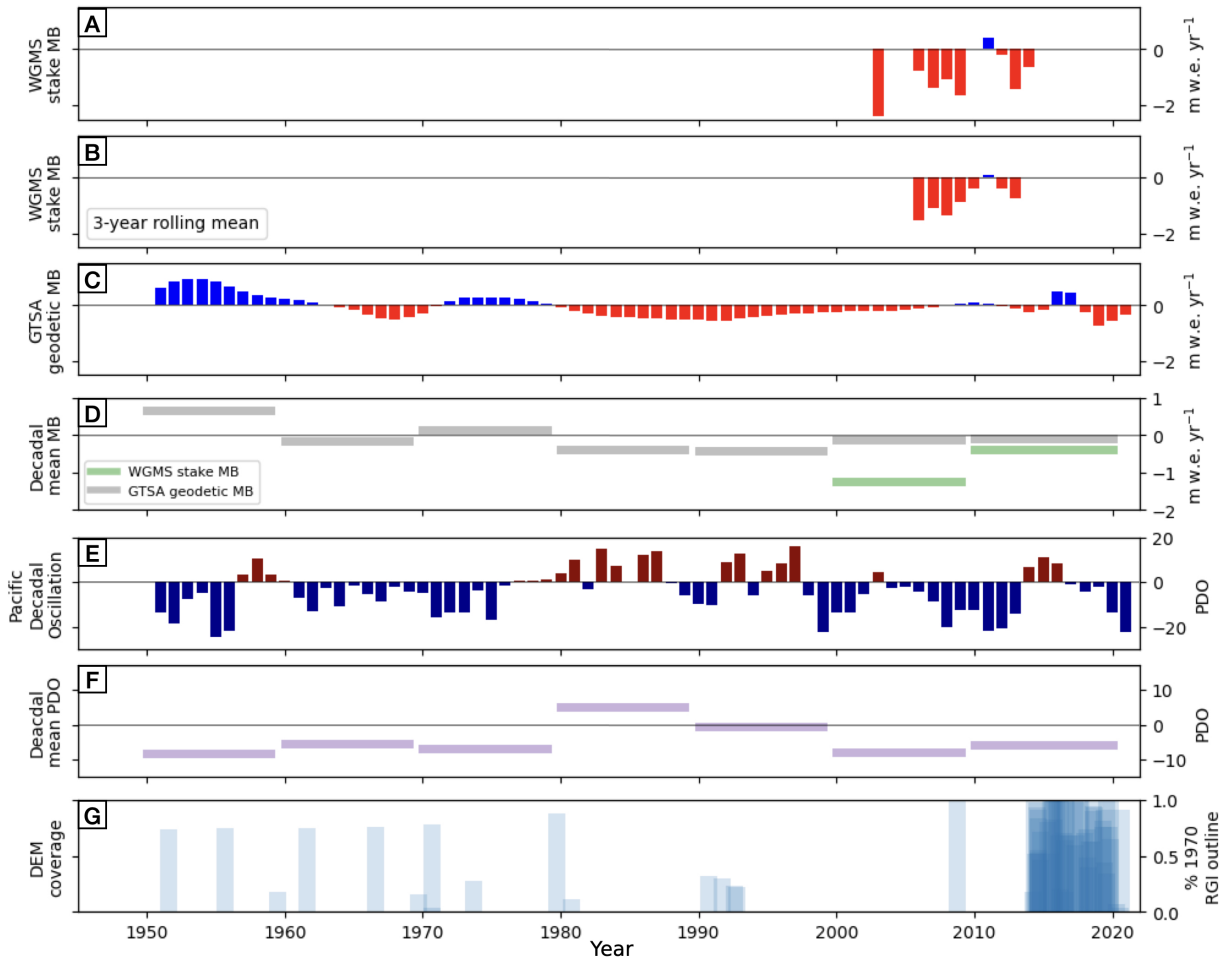


Figure 3.5: A. Annual in-situ mass balance time series at Nisqually Glacier (Riedel and Larrabee, 2015; WGMS, 2021). B. Five-year point-centered rolling mean of A. C. Annual geodetic mass balance from DEM surfaces interpolated with Gaussian Process regression. Decadal mean mass balance of B and C. D. Pacific Decadal Oscillation (PDO). F. Decadal PDO mean. G. Percent coverage of RGI Nisqually glacier extent (RGI60-02.14336, 4.44 km^2 , dated 1970).

have exceeded a threshold and entered a state in which it rapidly discharged its accumulated ice volume. The time lag between the propagation of a peak thickness anomaly from one distance bin to the next near the terminus indicates a velocity around 30 $\frac{\text{m}}{\text{yr}}$. As was the case at Easton Glacier, when the glacier terminus thickened and advanced, the glacier became thinner at higher elevations, which again indicates a kinematic redistribution of ice.

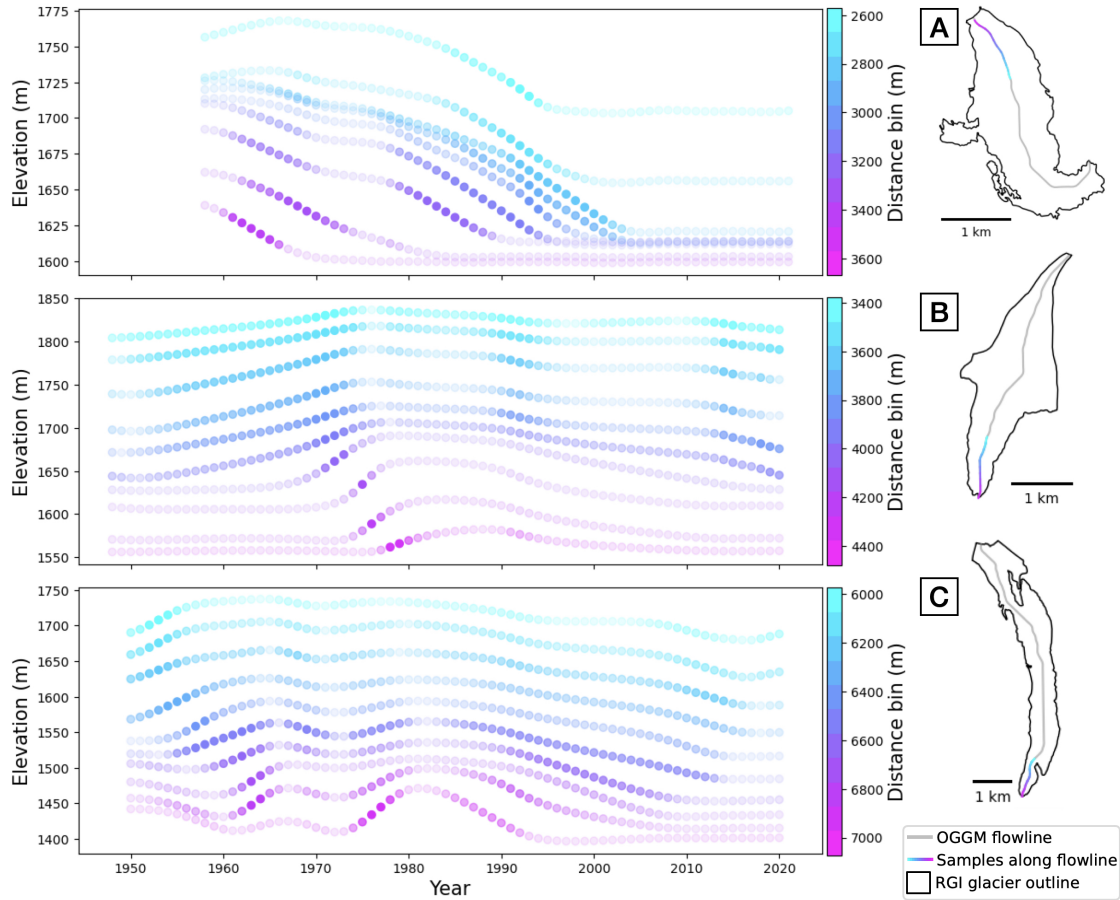


Figure 3.6: Glacier kinematics and terminus elevation change at A. South Cascade Glacier, B. Easton Glacier, and C. Nisqually Glacier. Maps show RGI outlines (A, RGI60-02.18778; B, RGI60-02.17739; C, RGI60-02.14336) and center flowlines computed with the Open Global Glacier Model (OGGM). Colors highlight mean elevation along 100 m distance bins start 1 km up from the terminus. Time periods with low opacity at all elevations and distance bins indicate periods of equilibrium, except when the mean elevation levels off, which indicates bare ground is sampled and the terminus has receded from this distance bin.

3.7 Discussion

3.7.1 Temporal resolution and fidelity of surface elevation estimates

The temporal resolution and accuracy of the mass-balance estimate depends on the temporal coverage of the DEMs and the variability that occurred during time periods with vs. without input DEM coverage. For example, surface elevation change near the terminus was variable

during the 2000–2010 period at Nisqually Glacier (Stevens et al., 2016) and there are no DEMs derived from WorldView satellites available during that time period, which means the signal was not captured by the GP regression. This underscores the need to leverage all available information during any given period to condition the GP regression. A useful dataset to that end may be the DEM data collected from the Shuttle Radar Topography Mission (SRTM), launched on February 11, 2000, and later reprocessed by NASA to provide higher accuracy. This reprocessed NASADEM product can provide valuable constraints to the GP regression, even though uncertainties due to radar penetration may be significant and limit the signal gained by adding this DEM surface during the data sparse 2000-2010 period.

At this stage, we tested 3, 5, and 10-year time windows for averaging the in-situ mass balance (Section 3.5.2.1) and compared these averages to the geodetic mass balance estimates derived from interpolated DEM time series. As expected, the results indicate that the historical time period with more temporally sparse observations appears to have a lower temporal resolution than the modern time period where temporally dense observations are available. While this preliminary approach provides some indication of the temporal resolution of the geodetic mass balance time series, a more refined evaluation is necessary. To that end, a comprehensive Leave-One-Out-Cross-Validation (LOOCV) approach may prove useful in assigning a time-varying uncertainty estimate.

3.7.2 *Comparison with in-situ mass-balance estimates*

The North Cascades Climate Project routinely collected mass-balance measurements at Easton Glacier (Pelto and Brown, 2012), yet their measurement technique differs from that used by the USGS at South Cascade Glacier (McNeil et al., 2022b) and the National Park Service at Nisqually Glacier (Riedel and Larrabee, 2015). Future work must carefully examine the differences and assess the uncertainty associated with each technique. This is a critical next step towards establishing greater confidence in the validation of geodetic mass balance computed from interpolated DEM time series with in-situ mass balance estimates.

Comparing the mass balance products requires propagating uncertainty estimates for both the geodetic and in-situ mass balance estimates. A more comprehensive uncertainty evaluation is needed for the geodetic estimates that takes multiple sources of uncertainty (e.g. per-pixel stereo reconstruction error, NMAD over stable ground, Gaussian Process regression, spatially correlated error, density conversion, area estimation, etc.) into account, before reporting a final uncertainty and propagating these to the mass balance estimates.

3.7.3 *Converting glacier volume to mass*

Improvements and spatially variable estimates for the standard density conversion of $850 \pm 60 \text{ kg m}^3$ will provide more accurate mass balance change estimates. For example, volume change near the terminus has a density closer to the density of ice, while volume change near the accumulation area has a density closer to the density of firn. Thus, a standard assumption of $850 \pm 60 \text{ kg m}^3$ for the entire glacierized area is not necessarily representative. It will be particularly interesting to consider a more refined density estimate during periods of minimal change in geodetic glacier mass balance, as these periods can have very large uncertainty associated with the standard density assumption of $850 \pm 60 \text{ kg m}^3$ (Huss, 2013).

3.7.4 *Kinematic waves at Nisqually Glacier*

Kinematic waves observed in this study may be due to the glacier geometry which has a steep slope and follows a long and narrow channel down the flank of the stratovolcano. Other causes for kinematic instabilities may be basal sliding from heat flux at the base of the glacier, as well as bedrock lithology that reduces friction (Cuffey and Paterson, 2010). Future work will further examine the nature of kinematic waves observed at Nisqually Glacier, the timing of thickness anomalies at higher elevations than 1 km above the terminus, and contribution of ice originating from Wilson Glacier to the west of Nisqually Glacier.

3.7.5 *Improved center flowline estimates*

In this analysis we used a static estimate of the glacier center flowline. This estimated flowline was computed by OGGM from a coarse 30 m NASADEM surface elevation product (Maussion et al., 2019). As the glacier changes its shape and topographic profile over time, the glacier center flowline changes as well. In Figure 3.6 we see that distance bins at higher elevations ($\sim 1750 \text{ m}$) level off earlier than some of the bins at lower elevations ($\sim 1625 \text{ m}$). This is a result of bare ground having been reached at higher elevation, while the glacier is still retreating at lower elevation alongside the flowline estimated by OGGM. In other words, the true center flowline curves around the location where samples were taken at higher elevation, and which has already reached bare ground. A way to mitigate this would be to compute updated flowline estimates from each DEM in the time series.

3.7.6 *Model calibration with continuous geometric time series*

South Cascade Glacier appears to have reached a period of stability in the 1970s, which is indicated by the small positive mass balance and minimal elevation change rate near the terminus. Easton Glacier may have reached a similar state of stability a decade later in the 1980s, during what appears to have been a period of minimal negative mass balance and terminus elevation change. Nisqually Glacier shows more variable mass balance and terminus elevation change than both South Cascade Glacier and Easton Glacier, especially during the 1960–1980 period.

Time series of geometric constraints (e.g. annual area, length, slope, mean elevation (ELA), terminus elevation, volume, mass balance, and equilibrium state estimates) can be computed from the DEM time series provided in this analysis and be leveraged by future work to calibrate glacier models (e.g., Christian et al., 2022). These continuous estimates, with uncertainty, may provide a significant aid in model parameter tuning that exceed the current information gained from static or limited time series in public archives (e.g., RGI Consortium, 2017; WGMS, 2021).

3.8 *Conclusions*

Digital elevation models derived from scanned historical aerial photographs are underutilized in measuring long-term patterns of glacier surface elevation change. This is primarily due to the challenges involved in photogrammetric processing of these images, including image standardization and estimating the relative and absolute historical camera geometry. Recent advances in overcoming these challenges through automated processing methods are accelerating the processing of entire archives of historical images, which reveal patterns of long-term topographic change (e.g. Knuth et al., 2023). When combining these historical DEMs with DEMs derived from modern sources, we are presented with unprecedented and long-term records of surface elevation change. Even so, compared to the spatial and temporal density of modern records collected over the past decades, these DEM time series remain both spatially and temporally sparse.

Interpolation techniques, such as Gaussian Process regression gleaned from the geostatistics community (e.g. "kriging"), enable us to make informed estimates and interpolate surface elevation change to produce spatially and temporally continuous surface elevation maps. Combining these void-free grids with established techniques, such as computing geodetic

glacier mass balance from DEM difference maps, gives a data driven perspective to estimating the continuous elevation change of glacier surfaces. This is valuable, not only as a first-order estimate of change, but also as checkpoints for the modeling community that can leverage time series of derivative geometric products, as well as fully resolved and continuous surfaces with per-pixel uncertainty to calibrate both simple and more complex physics-based models.

Measuring glacier mass balance with traditional stake measurements on the glacier requires substantial effort and is often hindered by weather and logistical challenges. By leveraging these interpolated long-term DEM surfaces, we increase our capacity to extract meaningful information about glacier mass balance and kinematic movement of ice. Finding the rhythm, timing, and explanatory conditions of outburst floods at glaciers such as Nisqually, for example, remains a challenge for future investigation.

The main findings of this research are that DEM surfaces, augmented with Gaussian process interpolation, can reconstruct geodetic mass balance at enhanced temporal resolution and reveal patterns of mass change that are otherwise only obtainable through in-situ measurement. Furthermore, we find that the mean surface elevations measured along the glacier center flowlines revealed a steady retreat at South Cascade Glacier, a prolonged advance at Easton Glacier, and multiple kinematic waves moving through the system at Nisqually Glacier. These findings validate that the interpolated surfaces can estimate patterns of change with confidence and may aid in projecting future advances and the timing of outburst floods. Finally, we provide new and continuous estimates for geometric glacier characteristics that can be leveraged for model calibration during periods of glacier equilibrium and validation at any state of perturbation.

Our results, validated against glaciers with known mass balance and kinematic behaviour, demonstrate that this method can be applied to other sites with entirely unknown long-term behaviour, to ultimately obtain regionally representative insight to glacier change and improve the projection of these water resources.

Chapter 4

CONTRIBUTIONS TO COLLABORATIVE EFFORTS

This chapter provides a brief overview of collaborations I contributed to during my time as a Ph.D. student.

4.1 *An Object Storage for Distributed Acoustic Sensing (Ni et al., 2024)*

4.1.1 Abstract

Large-scale processing and dissemination of distributed acoustic sensing (DAS) data are among the greatest computational challenges and opportunities of seismological research today. Current data formats and computing infrastructure are not welladapted or user-friendly for large-scale processing. We propose an innovative, cloud-native solution for DAS seismology using the MinIO open-source object storage framework. We develop data schema for cloud-optimized data formats—Zarr and TileDB, which we deploy on a local object storage service compatible with the Amazon Web Services (AWS) storage system. We benchmark reading and writing performance for various data schema using canonical use cases in seismology. We test our framework on a local server and AWS. We find much-improved performance in compute time and memory throughout when using TileDB and Zarr compared to the conventional HDF5 data format. We demonstrate the platform with a computing heavy use case in seismology: ambient noise seismology of DAS data. We process one month of data, pairing all 2089 channels within 24 hr using AWS Batch autoscaling.

4.1.2 CRediT author contribution

Conceptualization, Methodology, Writing - Review and Editing

FK proposed the MinIO open-source object storage solution to manage the dissemination of the Distributed Acoustic Sensing (DAS) data and seamless integration with cloud native frameworks, such as Amazon Web Services (AWS) Simple Storage Service (S3). FK advised

on the chunking strategy for larger-than-memory data stored in the Zarr cloud-optimized data format (Miles et al., 2020), based on the work done in Chapter 2 of this dissertation.

4.2 Multi-decadal erosion rates from glacierized watersheds on Mount Baker, Washington, USA, reveal topographic, climatic, and lithologic controls on sediment yields. *Geomorphology (Schwat et al., 2023)*

4.2.1 Abstract

Understanding land surface change in and sediment export out of proglacial landscapes is critical for understanding geohazard and flood risks over engineering timescales and characterizing landscape evolution over geomorphic timescales. We used automated Structure from Motion software to process historical aerial photographs and, with modern lidar data, generated a high-resolution DEM time series with coverage over 10 glacierized watersheds on Mount Baker, Washington, USA for the time period between 1947 and 2015. We measured basin-wide sediment yields and sediment redistribution on hillslopes and in stream channels. Slopes within most measured erosion sites are above theoretical and observed debris-flow thresholds. We observed significant erosion of hillslopes and limited deposition on hillslopes and in stream channels. Sediment delivery ratios during time periods with net erosion averaged 0.73. We determined, consistent with previous field observations, that debris flows originating from moraines are a primary erosion mechanism in proglacial zones on Mount Baker. Time series measurements indicate that temporal variability in erosion rates is associated with climate oscillations, with higher erosion rates during cooler-wetter periods. Basin-wide sediment yield is positively correlated with lithology ($r^2 = 0.54$), hillslope angle ($r^2 = 0.52$), drainage area ($r^2 = 0.82$), and negatively correlated with stream channel slope ($r^2 = 0.67$). Topographic differences between high and low yielding basins indicate that spatial variability in erosion on Mount Baker is sensitive to Pleistocene and Holocene glacial and volcanic activity. Specific sediment yields in six basins averaged 4600 ton/km²/yr, consistent with global measurements in glacierized catchments. Specific sediment yield decreased with increasing basin area, with total loads in the downstream main stem Nooksack River estimated between 480 and 820 ton/km²/yr. Proglacial sediment yields account for between 18 and 32 % of total sediment load in the main stem Nooksack River and exceed contributions by bluff and terrace erosion, which account for between 8 and 13 % of total load. Our findings indicate that erosion in glacierized basins is sensitive to decadal climate oscillations and that high proglacial sediment yields provide an important contribution to river systems downstream,

particularly in catchments where upland topography and lithology is favorable.

4.2.2 CRediT author contribution

Methodology, Software, Data Curation, Formal Analysis, Writing - Review and Editing

FK developed the Historical Image Pre-Processing (HIPPP) and Historical Structure from Motion (HSfM) software used to generate the Digital Elevation Models and orthoimages used for this study and described in Chapter 1 of this dissertation. FK provided guidance on the DEM time series analysis and processing for change detection.

4.3 *icepyx: querying, obtaining, analyzing, and manipulating ICESat-2 datasets (Scheick et al., 2023)*

4.3.1 Abstract

icepyx is both a software library and a community composed of ICESat-2 (NASA satellite) data users, developers, maintainers, and the scientific community. We are working together to develop a shared library of resources - including existing resources, new code, tutorials, and use-cases/examples - that simplify the process of querying, obtaining, analyzing, and manipulating ICESat-2 datasets to enable scientific discovery.

4.3.2 CRediT author contribution

Methodology, Software, Data Curation, Visualization

FK contributed to the early development of icepyx in the form of enhancements to authentication, parallelized data retrieval from the openaltimetry.org API, and visualization modules.

4.4 *Observing glacier elevation changes from spaceborne optical and radar sensors – an inter-comparison experiment using ASTER and TanDEM-X data (Piermattei et al., in review)*

4.4.1 Abstract

Observations of glacier mass changes are key to understanding the response of glaciers to climate change and related impacts, such as regional runoff, ecosystem changes, and global sea-

level rise. Spaceborne optical and radar sensors make it possible to quantify glacier elevation changes, and thus multi-annual mass changes, on a regional and global scale. However, estimates from a growing number of studies show a wide range of results with differences often beyond uncertainty bounds. Here, we present the outcome of a community-based inter-comparison experiment using spaceborne optical stereo (ASTER) and synthetic aperture radar interferometry (TanDEM-X) data to estimate elevation changes for defined glaciers and target periods that pose different assessment challenges. Using provided or self-processed digital elevation models (DEMs) for five test sites, 12 research groups provided a total of 97 spaceborne elevation-change datasets using various processing strategies. Validation with airborne data showed that using an ensemble estimate is promising to reduce random errors from different instruments and processing methods, but still requires a more comprehensive investigation and correction of systematic errors. We found that scene selection, DEM processing, and co-registration have the biggest impact on the results. Other processing steps, such as treating spatial data voids, differences in survey periods, or radar penetration, can still be important for individual cases. Future research should focus on testing different implementations of individual processing steps (e.g. co-registration) and addressing issues related to temporal corrections, radar penetration, glacier area changes, and density conversion. Finally, there is a clear need for our community to develop best practices, use open, reproducible software, and assess overall uncertainty in order to enhance inter-comparison and empower physical process insights across glacier elevation-change studies.

4.4.2 CRediT author contribution

Methodology, Software, Formal Analysis, Visualization, Writing - Review and Editing

FK contributed to the experiment as part of the Université Grenoble Alpes (UGA) group. FK helped conceptualize, design, and develop reproducible code to execute the experiments and visualize the results. This exercise helped lay the foundation for the work presented in Chapter 2 of this dissertation.

4.5 *Deglaciation in the Tetons, Little Ice Age to 2021 (Case et al., in prep)*

4.5.1 *Abstract*

The Tetons are a mountain range in northwest Wyoming, USA. Its glaciers are responsible for some of the range's most iconic features, and remain integral to the alpine ecosystem and the recreational visitor experience. Like other alpine glaciers, ice area and volume in the Tetons peaked during the Little Ice Age (LIA) and has since declined. Much work remains to be done to document glacial change in the Teton Range over the course of the last 150 years, from the end of the LIA (maximum glaciation in 1850-1870) to the present day. Here we present a database of LIA moraines in the Teton Range, an updated remote sensing analysis of glacier area and volume change from 1954-2022, *in situ* observations of surface elevation change and velocity of Middle Teton Glacier, and a slab model estimating ice thickness and volume across the range. We describe three additional glaciers within the Grand Teton National Park boundary, one near Ice Floe lake and two in the north of the park, and present maps of the Teton's relic ice and rock glaciers. All Teton glaciers experienced significant change since the LIA, losing 12-96% (mean=65%) of their visible glaciated area and a cumulative 0.015 km³ of ice loss since the mid-20th century. Petersen, Ice Floe, and Teepee glaciers fragmented into discontinuous ice patches and only four of the GRTE's 14 glaciers have modern surface areas greater than 0.1 km². These observations will help inform efforts to understand the future rates of change in ice volume in the Tetons, with implications for alpine ecosystem management and natural hazard mitigation.

4.5.2 *CRedit author contribution*

Methodology, Software, Data Curation, Formal Analysis, Writing - Review and Editing

FK developed the Historical Image Pre-Processing (HIPP) and Historical Structure from Motion (HSfM) software used to generate the Digital Elevation Models and orthoimages used for this study and described in Chapter 1 of this dissertation. FK provided guidance on the DEM time series analysis and processing for change detection.

4.6 Accelerating rates of glacier change and topographic controls, Glacier National Park, MT, USA: 1966-2021 (McNeil et al., in prep)

4.6.1 Abstract

Changing mountain glaciers impact downstream hydrology and alpine ecosystems and provide tangible evidence of climate change to the broader public. Recent advances in photogrammetry and remote sensing data availability allow these changes to be quantified at regional spatial scales. In turn, explaining glacier-to-glacier variability over multi-decadal time scales has only recently become possible due to advances in data availability and technology. In this study, we use historical aerial photographs, modern satellite stereo imagery, and LiDAR data to quantify area, volume, and mass change at 35 glaciers within Glacier National Park, MT, USA from 1966-2021. All 35 glaciers lost area and volume over the 55-year study interval. Collectively, regional glacier mass loss was -0.21 ± 0.07 Gt representing a 46% decrease in the region's total previously estimated ice volume. Glacier mass loss rates were faster over the period 2008-2021 than 1966-2008. Variability in glacier mass loss rates is likely explained by topographic controls, such as elevation distribution, glacier aspect, clear sky radiation, snow avalanches, and wind redistribution of snow. The greatest rates of glacier volume change in the region are observed at Grinnell Glacier where lake calving processes influence glacier mass balance. The USGS Benchmark Glacier (Sperry Glacier) in the region shows rates of mass loss that are 160-170% higher than the average mass loss rate of the region, suggesting a need for caution when regionalizing in situ glaciological records of glacier change.

4.6.2 CRediT author contribution

Methodology, Software, Data Curation, Formal Analysis, Writing - Review and Editing

FK developed the Historical Image Pre-Processing (HIPPP) and Historical Structure from Motion (HSfM) software used to generate the Digital Elevation Models and orthoimages used for this study and described in Chapter 1 of this dissertation. FK provided guidance on the DEM time series analysis and processing for change detection.

BIBLIOGRAPHY

- Ackermann, F. (1981). Block adjustment with additional parameters. *Photogrammetria* 36, 217–227. doi:10.1016/0031-8663(81)90040-5
- Albertz, J. (2002). Albrecht meydenbauer-pioneer of photogrammetric documentation of the cultural heritage. *International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences* 34, 19–25
- Allstadt, K., Shean, D., Campbell, A., Fahnestock, M., and Malone, S. (2015). Observations of seasonal and diurnal glacier velocities at mount rainier, washington, using terrestrial radar interferometry. *The Cryosphere* 9, 2219–2235. doi:https://doi.org/10.5194/tc-9-2219-2015
- Anderson, S. and Pitlick, J. (2014). Using repeat lidar to estimate sediment transport in a steep stream. *Journal of Geophysical Research: Earth Surface* 119, 621–643. doi:10.1002/2013JF002933
- Anderson, S. W. and Shean, D. (2022). Spatial and temporal controls on proglacial erosion rates: A comparison of four basins on mount rainier, 1960 to 2017. *Earth Surface Processes and Landforms* 47, 596–617. doi:10.1002/esp.5274
- Arendt, A., Echelmeyer, K., Harrison, W., Lingle, C., Zirnheld, S., Valentine, V., et al. (2006). Updated estimates of glacier volume changes in the western chugach mountains, alaska, and a comparison of regional extrapolation methods. *Journal of Geophysical Research: Earth Surface* 111. doi:https://doi.org/10.1029/2005JF000436
- Arendt, A. A., Echelmeyer, K. A., Harrison, W. D., Lingle, C. S., and Valentine, V. B. (2002). Rapid wastage of alaska glaciers and their contribution to rising sea level. *Science* 297, 382–386. doi:10.1126/science.1072497
- Bauer, P., Stevens, B., and Hazeleger, W. (2021). A digital twin of earth for the green transition. *Nature Climate Change* 11, 80–83. doi:10.1038/s41558-021-00986-y

- Bayr, K. J., Hall, D. K., and Kovalick, W. M. (1994). Observations on glaciers in the eastern austrian alps using satellite data. *International Journal of Remote Sensing* 15, 1733–1742. doi:<https://doi.org/10.1080/01431169408954205>
- Beason, S., Kenyon, T., Jost, R., and Walker, L. (2023). Changes in glacier extents and estimated changes in glacial volume at mount rainier national park, washington, usa from 1896 to 2021: Natural resource report NPS/MORA/NRR—2023/2524. doi:<https://doi.org/10.36967/2299328>
- Belart, J. M., Magnússon, E., Berthier, E., Pálsson, F., Aðalgeirsdóttir, G., and Jóhannesson, T. (2019). The geodetic mass balance of eyjafjallajökull ice cap for 1945–2014: processing guidelines and relation to climate. *Journal of Glaciology* 65, 395–409. doi:<https://doi.org/10.1017/jog.2019.16>
- Berkner, L. V. (1954). International scientific action: The international geophysical year 1957–58. *Science* 119, 569–575. doi:[10.1126/science.119.3096.569](https://doi.org/10.1126/science.119.3096.569)
- Berthier, E., Floriciou, D., Gardner, A. S., Gourmelen, N., Jakob, L., Paul, F., et al. (2023). Measuring glacier mass changes from space—a review. *Reports on Progress in Physics* 86, 036801. doi:<https://doi.org/10.1088/1361-6633/acaf8e>
- Berthier, E., Schiefer, E., Clarke, G. K., Menounos, B., and Rémy, F. (2010). Contribution of alaskan glaciers to sea-level rise derived from satellite imagery. *Nature Geoscience* 3, 92–95. doi:<https://doi.org/10.1038/ngeo737>
- [Dataset] Beyer, R., Alexandrov, O., and ScottMcMichael (2019). NeoGeography-Toolkit/StereoPipeline: ASP 2.6.2. doi:[10.5281/zenodo.3247734](https://doi.org/10.5281/zenodo.3247734)
- Beyer, R. A., Alexandrov, O., and McMichael, S. (2018). The Ames Stereo Pipeline: NASA’s Open Source Software for Deriving and Processing Terrain Data. *Earth and Space Science* 5, 537–548. doi:[10.1029/2018EA000409](https://doi.org/10.1029/2018EA000409)
- Bjørk, A. A., Kjær, K. H., Korsgaard, N. J., Khan, S. A., Kjeldsen, K. K., Andresen, C. S., et al. (2012). An aerial view of 80 years of climate-related glacier fluctuations in southeast Greenland. *Nature Geoscience* 5, 427–432. doi:[10.1038/ngeo1481](https://doi.org/10.1038/ngeo1481)

- Bolch, T., Buchroithner, M., Pieczonka, T., and Kunert, A. (2008). Planimetric and volumetric glacier changes in the khumbu himal, nepal, since 1962 using corona, landsat tm and aster data. *Journal of Glaciology* 54, 592–600. doi:10.3189/002214308786570782
- Bradski, G. and Kaehler, A. (2008). *Learning OpenCV: Computer Vision with the OpenCV Library* (O'Reilly Media, Inc.)
- Brown, D. (1971). Close-range camera calibration, Photogrammetric Engineering. *Engineering and Remote Sensing* E 37.8, 855–866
- Brun, F., Berthier, E., Wagnon, P., Kääb, A., and Treichler, D. (2017). A spatially resolved estimate of high mountain asia glacier mass balances from 2000 to 2016. *Nature geoscience* 10, 668–673. doi:https://doi.org/10.1038/ngeo2999
- Case, E., Knuth, F., McGrath, D., Gore, J., Caskey, S., and Kingslake, J. (in prep). Deglaciation in the tetons, little ice age to 2021. *The Cryosphere*
- Chandler, J. and Cooper, M. (1989). The extraction of positional data from historical photographs and their application to geomorphology. *The Photogrammetric Record* 13, 69–78. doi:10.1111/j.1477-9730.1989.tb00647.x
- Child, S. F., Stearns, L. A., Girod, L., and Brecher, H. H. (2020). Structure-from-motion photogrammetry of antarctic historical aerial photographs in conjunction with ground control derived from satellite data. *Remote Sensing* 13, 21. doi:10.3390/rs13010021
- Christian, J. E., Whorton, E., Carnahan, E., Koutnik, M., and Roe, G. (2022). Differences in the transient responses of individual glaciers: a case study of the cascade mountains of washington state, usa. *Journal of Glaciology* , 1–13doi:10.1017/jog.2021.133
- Cogley, J., Arendt, A., Bauder, A., Braithwaite, R., Hock, R., Jansson, P., et al. (2010). *Glossary of glacier mass balance and related terms*, vol. 86 of *IHP-VII Technical Documents in Hydrology* (France: International Hydrological Programme)
- Cogley, J. G. (2009). Geodetic and direct mass-balance measurements: comparison and joint analysis. *Annals of Glaciology* 50, 96–100

- Cox, L. H. and March, R. S. (2004). Comparison of geodetic and glaciological mass-balance techniques, gulkana glacier, alaska, usa. *Journal of Glaciology* 50, 363–370
- Crandell, D., Wright, H. E., and Frey, D. G. (1965). The glacial history of western Washington and Oregon. In *The Quaternary of the United States* (Princeton University Press). 341–354
- Cressie, N. (2015). *Statistics for spatial data* (John Wiley & Sons)
- Cuffey, K. M. and Paterson, W. S. B. (2010). *The physics of glaciers* (Academic Press)
- Czuba, J. A., Magirl, C. S., Czuba, C. R., Grossman, E. E., Curran, C. A., Gendaszek, A. S., et al. (2011). *Sediment load from major rivers into Puget Sound and its adjacent waters* (U.S. Department of the Interior, U.S. Geological Survey)
- Dehecq, A., Altena, B., Gardner, A. S., Trouvé, E., and Leinss, S. (2022). Remote sensing of glacier motion. *Surface Displacement Measurement from Remote Sensing Images* , 339–372doi:10.1002/9781119986843.ch11
- Dehecq, A., Gardner, A. S., Alexandrov, O., McMichael, S., Hugonnet, R., Shean, D., et al. (2020). Automated processing of declassified kh-9 hexagon satellite images for global elevation change analysis since the 1970s. *Frontiers in Earth Science* 8, 566802. doi:10.3389/feart.2020.566802
- Dehecq, A., Gourmelen, N., Gardner, A. S., Brun, F., Goldberg, D., Nienow, P. W., et al. (2019). Twenty-first century glacier slowdown driven by mass loss in High Mountain Asia. *Nature Geoscience* 12, 22–27. doi:10.1038/s41561-018-0271-9
- DeTone, D., Malisiewicz, T., and Rabinovich, A. (2018). Superpoint: Self-supervised interest point detection and description. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*. 224–236
- [Dataset] Dewitz, J. (2016). National Land Cover Dataset (NLCD) 2016 Products. doi:10.5066/P96HHBIE
- Driedger, C. L. and Fountain, A. G. (1989). Glacier outburst floods at mount rainier, washington state, usa. *Annals of Glaciology* 13, 51–55. doi:https://doi.org/10.3189/S0260305500007631

- Dussaillant, I., Berthier, E., Brun, F., Masiokas, M., Hugonnet, R., Favier, V., et al. (2019). Two decades of glacier mass loss along the andes. *Nature Geoscience* 12, 802–808. doi: <https://doi.org/10.1038/s41561-019-0432-5>
- Eaton, J. P. and Murata, K. (1960). How Volcanoes Grow: Geology, geochemistry, and geophysics disclose the constitution and eruption mechanism of Hawaiian volcanoes. *Science* 132, 925–938. doi:10.1126/science.132.3432.925
- Eltner, A. and Sofia, G. (2020). Structure from motion photogrammetric technique. In *Developments in Earth surface processes* (Elsevier), vol. 23. 1–24. doi:10.1016/B978-0-444-64177-9.00001-1
- [Dataset] European Space Agency (2020). Copernicus DEM Product Handbook (v3.0)
- [Dataset] European Space Agency (2022). Copernicus Digital Elevation Model
- Feurer, D. and Vinatier, F. (2018). Joining multi-epoch archival aerial images in a single sfm block allows 3-d change detection with almost exclusively image information. *ISPRS journal of photogrammetry and remote sensing* 146, 495–506. doi:10.1016/j.isprsjprs.2018.10.016
- Fischer, M., Huss, M., and Hoelzle, M. (2015). Surface elevation and mass changes of all swiss glaciers 1980–2010. *The Cryosphere* 9, 525–540. doi:10.5194/tc-9-525-2015
- Florentine, C. and Mckeen, L. L. (2022). *US Geological Survey Benchmark Glacier Project*. Tech. rep., US Geological Survey. doi:10.3133/fs20223050
- Florentine, C., Sass, L., McNeil, C., Baker, E., and O’Neel, S. (2023). How to handle glacier area change in geodetic mass balance. *Journal of Glaciology* , 1–7doi:<https://doi.org/10.1017/jog.2023.86>
- Fountain, A. G., Hoffman, M. J., Granshaw, F., and Riedel, J. (2009). The ‘benchmark glacier’ concept – does it work? lessons from the north cascade range, usa. *Annals of Glaciology* 50, 163–168. doi:10.3189/172756409787769690
- Fraser, C. S. (1997). Digital camera self-calibration. *ISPRS Journal of Photogrammetry and Remote sensing* 52, 149–159. doi:10.1016/S0924-2716(97)00005-1

- Furbish, D. and Andrews, J. (1984). The use of hypsometry to indicate long-term stability and response of valley glaciers to changes in mass transfer. *Journal of glaciology* 30, 199–211. doi:<https://doi.org/10.3189/S0022143000005931>
- Gesch, D. B., Oimoen, M. J., Evans, G. A., et al. (2014). *Accuracy assessment of the US Geological Survey National Elevation Dataset, and comparison with other large-area elevation datasets: SRTM and ASTER*, vol. 1008 (US Department of the Interior, US Geological Survey Sioux Falls, SD, USA). doi:[10.3133/ofr20141008](https://doi.org/10.3133/ofr20141008)
- Geyman, E. C., JJ van Pelt, W., Maloof, A. C., Aas, H. F., and Kohler, J. (2022). Historical glacier change on svalbard predicts doubling of mass loss by 2100. *Nature* 601, 374–379. doi:[10.1038/s41586-021-04314-4](https://doi.org/10.1038/s41586-021-04314-4)
- Girod, L., Nielsen, N. I., Couderette, F., Nuth, C., and Kääb, A. (2018). Precise DEM extraction from Svalbard using 1936 high oblique imagery. *Geoscientific Instrumentation, Methods and Data Systems* 7, 277–288. doi:[10.5194/gi-7-277-2018](https://doi.org/10.5194/gi-7-277-2018)
- Gramacy, R. B. and Lee, H. K. H. (2008). Bayesian treed gaussian process models with an application to computer modeling. *Journal of the American Statistical Association* 103, 1119–1130. doi:<https://doi.org/10.1198/016214508000000689>
- Gruber, M. and Leberl, F. (2001). Description and evaluation of the high quality photogrammetric scanner ultrascan 5000. *ISPRS journal of photogrammetry and remote sensing* 55, 313–329. doi:[10.1016/S0924-2716\(01\)00024-7](https://doi.org/10.1016/S0924-2716(01)00024-7)
- Hall, D. K., Ormsby, J., Bindschadler, R. A., and Siddalingaiah, H. (1987). Characterization of snow and ice reflectance zones on glaciers using landsat thematic mapper data. *Annals of Glaciology* 9, 104–108. doi:<https://doi.org/10.3189/S0260305500000471>
- Harper, J. T. (1993). Glacier Terminus Fluctuations on Mount Baker, Washington, U.S.A., 1940–1990, and Climatic Variations. *Arctic and Alpine Research* 25, 332–340. doi:[10.1080/00040851.1993.12003019](https://doi.org/10.1080/00040851.1993.12003019)
- Heisig, H. and Simmen, J.-L. (2021). Re-engineering the past: Countrywide geo-referencing of archival aerial imagery. *PFG–Journal of Photogrammetry, Remote Sensing and Geoinformation Science* 89, 487–503. doi:[10.1007/s41064-021-00162-z](https://doi.org/10.1007/s41064-021-00162-z)

- Heliker, C., Johnson, A. H., and Hodge, S. (1984). *The Nisqually Glacier, Mount Rainier, Washington, 1857-1979: A summary of the long-term observations and a comprehensive bibliography*. Tech. rep., US Geological Survey. doi:<https://doi.org/10.3133/ofr83541>
- Henderson, S. T., Pritchard, M. E., Cooper, J. R., and Aoki, Y. (2019). Remotely sensed deformation and thermal anomalies at Mount Pagan, Mariana Islands. *Frontiers in Earth Science* , 238doi:10.3389/feart.2019.00238
- Hu, J. M. and Nolin, A. W. (2019). Snowpack contributions and temperature characterization of landfalling atmospheric rivers in the western cordillera of the united states. *Geophysical Research Letters* 46, 6663–6672. doi:<https://doi.org/10.1029/2019GL083564>
- Hu, J. M., Shean, D., and Bhushan, S. (2023). Six consecutive seasons of high-resolution mountain snow depth maps from satellite stereo imagery. *Geophysical Research Letters* 50, e2023GL104871. doi:<https://doi.org/10.1029/2023GL104871>
- Hugonnet, R., Brun, F., Berthier, E., Dehecq, A., Mannerfelt, E. S., Eckert, N., et al. (2022). Uncertainty analysis of digital elevation models by spatial inference from stable terrain. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 15, 6456–6472. doi:10.1109/JSTARS.2022.3188922
- Hugonnet, R., McNabb, R., Berthier, E., Menounos, B., Nuth, C., Girod, L., et al. (2021). Accelerated global glacier mass loss in the early twenty-first century. *Nature* 592, 726–731. doi:10.1038/s41586-021-03436-z
- Huss, M. (2013). Density assumptions for converting geodetic glacier volume change to mass change. *The Cryosphere* 7, 877–887. doi:10.5194/tc-7-877-2013
- Höhle, J. and Höhle, M. (2009). Accuracy assessment of digital elevation models by means of robust statistical methods. *ISPRS Journal of Photogrammetry and Remote Sensing* 64, 398–406. doi:10.1016/j.isprsjprs.2009.02.003
- James, M. R. and Robson, S. (2014). Mitigating systematic error in topographic models derived from UAV and ground-based image networks. *Earth Surface Processes and Landforms* 39, 1413–1420. doi:10.1002/esp.3609

- Jóhannesson, T., Raymond, C., and Waddington, E. (1989). Time-scale for adjustment of glaciers to changes in mass balance. *Journal of Glaciology* 35, 355–369
- Karara, H. (1967). Mono versus stereo analytical photogrammetry—theoretical considerations and experimental results. *Photogrammetria* 22, 99–113. doi:10.1016/0031-8663(67)90029-4
- Kehrl, L. M., Joughin, I., Shean, D. E., Floricioiu, D., and Krieger, L. (2017). Seasonal and interannual variabilities in terminus position, glacier velocity, and surface elevation at Helheim and Kangerlussuaq Glaciers from 2008 to 2016. *Journal of Geophysical Research: Earth Surface* 122, 1635–1652. doi:10.1002/2016JF004133
- [Dataset] kerchunk contributors (2024). kerchunk
- [Dataset] Knuth, F. (2023). Geospatial Time Series Analysis (GTSA): Methods to stack geospatial rasters and run memory-efficient computations. doi:10.5281/zenodo.8188086
- Knuth, F. (2024). Are partial Dems useful? a memory-efficient method to estimate long-term glacier surface elevation change from spatially and temporally sparse measurements. In *Building a Digital Glacier Time Machine with photogrammetry and Gaussian Process regression to study long-term glacier surface elevation change in Western North America* (University of Washington), Department of Civil and Environmental Engineering, chap. 3. PhD dissertation
- [Dataset] Knuth, F., Schwat, E., Shean, D., Bhushan, S., and Alexandrov, O. (2021a). Historical Structure from Motion (HSfM) pre- release v0.1. doi:10.5281/zenodo.5510870
- [Dataset] Knuth, F., Schwat, E., Shean, D., and McNeil, C. (2021b). Historical Image Pre-Processing (HIPPP) pre-release v0.1. doi:10.5281/zenodo.5510876
- [Dataset] Knuth, F. and Shean, D. (2022). Historical digital elevation models (DEMs) and orthoimage mosaics for North American Glacier Aerial Photography (NAGAP) program, version 1.0. doi:10.5281/zenodo.7297154
- Knuth, F., Shean, D., Bhushan, S., Schwat, E., Alexandrov, O., McNeil, C., et al. (2023). Historical structure from motion (hsfm): Automated processing of historical aerial pho-

- tographs for long-term topographic change analysis. *Remote Sensing of Environment* 285, 113379. doi:<https://doi.org/10.1016/j.rse.2022.113379>
- Korpela, I. (2006). Geometrically accurate time series of archived aerial images and airborne lidar data in a forest environment. *Silva Fennica* 40. doi:10.14214/sf.355
- Krimmel, R. M. (1989). Mass balance and volume of south cascade glacier, washington 1958–1985. In *Glacier Fluctuations and Climatic Change*, ed. J. Oerlemans (Dordrecht: Springer Netherlands), 193–206. doi:https://doi.org/10.1007/978-94-015-7823-3_13
- Krimmel, R. M. (1999). Analysis of difference between direct and geodetic mass balance measurements at south cascade glacier, washington. *Geografiska Annaler: Series A, Physical Geography* 81, 653–658. doi:<https://doi.org/10.1111/1468-0459.00093>
- Krimmel, R. M. (2001). *Water, ice, meteorological, and speed measurements at South Cascade Glacier, Washington, 1999 balance year*. 4265 (US Department of the Interior, US Geological Survey)
- Krimmel, R. M. and Vaughn, B. H. (1987). Columbia glacier, alaska: changes in velocity 1977–1986. *Journal of Geophysical Research: Solid Earth* 92, 8961–8968. doi:<https://doi.org/10.1029/JB092iB09p08961>
- LaChapelle, E. (1962). Assessing glacier mass budgets by reconnaissance aerial photography. *Journal of Glaciology* 4, 290–297. doi:10.3189/S0022143000027593
- Lau, N., Borsa, A. A., and Becker, T. W. (2020). Present-day crustal vertical velocity field for the contiguous united states. *Journal of Geophysical Research: Solid Earth* 125, e2020JB020066. doi:10.1029/2020JB020066
- Leffler, R. J., Horvitz, A., Downs, R., Changery, M., Redmond, K. T., and Taylor, G. (2001). Evaluation of a National Seasonal Snowfall Record at the Mount Baker, Washington, Ski Area. *National Weather Digest* 25
- Li, R., Ye, W., Qiao, G., Tong, X., Liu, S., Kong, F., et al. (2017). A new analytical method for estimating antarctic ice flow in the 1960s from historical optical satellite

- imagery. *IEEE Transactions on Geoscience and Remote Sensing* 55, 2771–2785. doi:10.1109/TGRS.2017.2654484
- Lowe, D. G. (1999). Object recognition from local scale-invariant features. In *Proceedings of the seventh IEEE international conference on computer vision* (Ieee), vol. 2, 1150–1157. doi:10.1109/ICCV.1999.790410
- Lundquist, J. D., Kim, R. S., Durand, M., and Prugh, L. R. (2023). Seasonal peak snow predictability derived from early-season snow in north america. *Geophysical Research Letters* 50, e2023GL103802. doi:https://doi.org/10.1029/2023GL103802
- Maiwald, F. and Maas, H.-G. (2021). An automatic workflow for orientation of historical images with large radiometric and geometric differences. *The Photogrammetric Record* 36, 77–103. doi:10.1111/phor.12363
- [Dataset] Mälicke, M., Möller, E., Schneider, H. D., and Müller, S. (2022). mmaelicke/scikit-gstat: A scipy flavoured geostatistical variogram analysis toolbox. doi:10.5281/zenodo.5970098
- Mannerfelt, E. S., Dehecq, A., Hugonnet, R., Hodel, E., Huss, M., Bauder, A., et al. (2022). Halving of swiss glacier volume since 1931 observed from terrestrial image photogrammetry. *The Cryosphere Discussions* , 1–32
- Mantua, N. J., Hare, S. R., Zhang, Y., Wallace, J. M., and Francis, R. C. (1997). A pacific inter-decadal climate oscillation with impacts on salmon production. *Bulletin of the american Meteorological Society* 78, 1069–1080. doi:https://doi.org/10.1175/1520-0477(1997)078<1069:APICOW>2.0.CO;2
- Martin-Brualla, R., Gallup, D., and Seitz, S. M. (2015). Time-lapse mining from internet photos. *ACM Transactions on Graphics (TOG)* 34, 1–8. doi:10.1145/2766903
- Matérn, B. (1960). Spatial variation. stochastic models and their application to some problems in forest surveys and other sampling investigations. *Meddelanden från Statens Skogsforskningsinstitut*

- Maurer, J. M., Schaefer, J., Rupper, S., and Corley, A. (2019). Acceleration of ice loss across the Himalayas over the past 40 years. *Science advances* 5, eaav7266. doi:10.1126/sciadv.aav7266
- Maussion, F., Butenko, A., Champollion, N., Dusch, M., Eis, J., Fourteau, K., et al. (2019). The open global glacier model (oggm) v1.1. *Geoscientific Model Development* 2019, 909–931. doi:10.5194/gmd-12-909-2019
- McNabb, R., Nuth, C., Kääb, A., and Girod, L. (2019). Sensitivity of glacier volume change estimation to dem void interpolation. *The Cryosphere* 13, 895–910. doi:10.5194/tc-13-895-2019
- McNeil, C., Knuth, F., Martin-Mikle, C., Florentine, C., Menounos, B., Sass, L., et al. (in prep). Accelerating rates of glacier change and topographic controls, glacier national park, mt, usa: 1966-2021
- McNeil, C. J., Florentine, C. E., Bright, V. A., Fahey, M. J., Evan, E. M. C. F. L., Thoms, E., et al. (2022a). Geodetic data for usgs benchmark glaciers: Orthophotos, digital elevation models, glacier boundaries and surveyed positions doi:10.5066/P9R8BP3K
- [Dataset] McNeil, C. J., Sass, L., Florentine, C., Baker, E. H., Peitzsch, E. H., Whorton, E. N., et al. (2022b). Glacier-Wide Mass Balance and Compiled Data Inputs: USGS Benchmark Glaciers. doi:10.5066/F7HD7SRF
- Meier, M. F. and Tangborn, W. V. (1965). Net Budget and Flow of South Cascade Glacier, Washington. *Journal of Glaciology* 5, 547–566. doi:10.3189/S0022143000018608
- Menounos, B., Hugonnet, R., Shean, D., Gardner, A., Howat, I., Berthier, E., et al. (2019). Heterogeneous changes in western north american glaciers linked to decadal variability in zonal wind strength. *Geophysical Research Letters* 46, 200–209. doi:10.1029/2018GL080942
- [Dataset] Metashape, A. (2021). 1.6.5 Professional Edition
- Meydenbauer, A. (1867). Die Photometrographie. *Wochenblatt des Architektenvereins zu Berlin*

- Mikhail, E. M., Bethel, J. S., and McGlone, J. C. (2001). *Introduction to modern photogrammetry*, vol. 19
- [Dataset] Miles, A., Kirkham, J., Durant, M., Bourbeau, J., Onalan, T., Hamman, J., et al. (2020). zarr-developers/zarr-python: v2.4.0. doi:10.5281/zenodo.3773450
- Mölg, N. and Bolch, T. (2017). Structure-from-motion using historical aerial images to analyse changes in glacier surface elevation. *Remote Sensing* 9, 1021. doi:10.3390/rs9101021
- Nace, R. L. (1969). *Water and man: a world view: the International Hydrological Decade* (UNESCO, IHD)
- Neiman, P. J., Ralph, F. M., Wick, G. A., Lundquist, J. D., and Dettinger, M. D. (2008). Meteorological characteristics and overland precipitation impacts of atmospheric rivers affecting the west coast of north america based on eight years of ssm/i satellite observations. *Journal of Hydrometeorology* 9, 22–47. doi:https://doi.org/10.1175/2007JHM855.1
- Ni, Y., Denolle, M. A., Fatland, R., Alterman, N., Lipovsky, B. P., and Knuth, F. (2024). An object storage for distributed acoustic sensing. *Seismological Research Letters* 95, 499–511. doi:https://doi.org/10.1785/0220230172
- Nielsen, N. I. (2017). *Recovering Data with Digital Photogrammetry and Image Analysis Using Open Source Software*. Master’s thesis, University of Oslo
- Noh, M.-J. and Howat, I. M. (2015). Automated stereo-photogrammetric dem generation at high latitudes: Surface extraction with tin-based search-space minimization (setsm) validation and demonstration over glaciated regions. *GIScience & Remote Sensing* 52, 198–217. doi:10.1080/15481603.2015.1008621
- [Dataset] Nolan, M. (2012). Phase one data rescue of the Austin Post air photo collection and new repeat aerial photography of Alaskan valley glaciers. NSF Award #1107737
- [Dataset] Nolan, M., Post, A. S., Hauer, W., Zinck, A., and O’Neel, S. (2017). Photogrammetric scans of aerial photographs of North American glaciers. doi:10.18739/A2KC07

- [Dataset] NPS, N. P. S. (2024). Annual Snowfall Totals - Mount Rainier National Park (U.S. National Park Service) — nps.gov. <https://www.nps.gov/mora/planyourvisit/annual-snowfall-totals.htm>. [Accessed 03-06-2024]
- NSDDA, F. (1998). Geospatial positioning accuracy standards part 3: National standard for spatial data accuracy (no. fgdc-std-007.3-1998)
- Nuth, C. and Kääb, A. (2011). Co-registration and bias corrections of satellite elevation data sets for quantifying glacier thickness change. *The Cryosphere* 5, 271–290. doi:10.5194/tc-5-271-2011
- Nyquist, H. (1928). Certain topics in telegraph transmission theory. *Transactions of the American Institute of Electrical Engineers* 47, 617–644
- O’Neel, S., McNeil, C., Sass, L. C., Florentine, C., Baker, E. H., Peitzsch, E., et al. (2019). Reanalysis of the US Geological Survey Benchmark Glaciers: long-term insight into climate forcing of glacier mass balance. *Journal of Glaciology* 65, 850–866. doi:10.1017/jog.2019.66
- Osborn, G., Menounos, B., Ryane, C., Riedel, J., Clague, J. J., Koch, J., et al. (2012). Latest Pleistocene and Holocene glacier fluctuations on Mount Baker, Washington. *Quaternary Science Reviews* 49, 33–51. doi:10.1016/j.quascirev.2012.06.004
- Østrem, G. (1975). ERTS data in glaciology—an effort to monitor glacier mass balance from satellite imagery. *Journal of Glaciology* 15, 403–415. doi:10.3189/S0022143000034511
- Ostrem, G., Stanley, A., et al. (1966). Glacier mass balance measurements: a manual for field and office work
- Paul, F., Barrand, N. E., Baumann, S., Berthier, E., Bolch, T., Casey, K., et al. (2013). On the accuracy of glacier outlines derived from remote-sensing data. *Annals of Glaciology* 54, 171–182. doi:<https://doi.org/10.3189/2013AoG63A296>
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., et al. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research* 12, 2825–2830

- Pelto, M. and Brown, C. (2012). Mass balance loss of Mount Baker, Washington glaciers 1990–2010. *Hydrological Processes* 26, 2601–2607. doi:10.1002/hyp.9453
- Piermattei, L., Zemp, M., Sommer, C., Brun, F., Braun, M. H., Andreassen, L. M., et al. (in review). Observing glacier elevation changes from spaceborne optical and radar sensors – an inter-comparison experiment using ASTER and TanDEM-x data. *The Cryosphere* doi:10.5194/egusphere-2023-2309
- Pomerleau, F., Colas, F., Siegwart, R., and Magnenat, S. (2013). Comparing ICP variants on real-world data sets. *Autonomous Robots* 34, 133–148. doi:10.1007/s10514-013-9327-2
- Porter, C., Howat, I., Husby, E., Noh, M.-J., Khuvis, S., Danish, E., et al. (2022). EarthDEM - Strips, Version 1 doi:10.7910/DVN/LHE9O7
- Post, A. (1995). Annual aerial photography of glaciers in northwest North America: How it all began and its golden age. *Physical Geography* doi:10.1080/02723646.1995.10642540
- [Dataset] Post, A., Richardson, D., Tangborn, W., and Rosselot, F. (1971). Inventory of glaciers in the North Cascades, Washington. doi:10.3133/pp705A
- [Dataset] Ramsey, D. (2016). USGS Mt. Baker LiDAR Technical Report
- Rasmussen, L. and Conway, H. (2001). Estimating south cascade glacier (Washington, USA) mass balance from a distant radiosonde and comparison with blue glacier. *Journal of Glaciology* 47, 579–588. doi:https://doi.org/10.3189/172756501781831873
- Ray, R. G. (1960). *Aerial photographs in geologic interpretation and mapping*. 373–375 (US Government Printing Office). doi:10.3133/pp373
- Reeh, N. (1991). Parameterization of melt rate and surface temperature in the Greenland ice sheet. *Polarforschung* 59, 113–128
- Reiners, P. W., Ehlers, T. A., Mitchell, S. G., and Montgomery, D. R. (2003). Coupled spatial variations in precipitation and long-term erosion rates across the Washington Cascades. *Nature* 426, 645–647. doi:10.1038/nature02111

- [Dataset] RGI Consortium (2017). Randolph Glacier Inventory 6.0. doi:10.7265/N5-RGI-60
- Riedel, J. L. and Larrabee, M. A. (2015). Mount rainier national park glacier mass balance monitoring annual report, water year 2011: North coast and cascades network. natural resource data Series NPS/NCCN/NRDS—2015/752
- Roberti, G., Ward, B. C., van Wyk deVries, B., Perotti, L., Giardino, M., Friele, P. A., et al. (2021). Structure from motion used to revive archived aerial photographs for geomorphological analysis: an example from Mount Meager volcano, British Columbia, Canada. *Canadian Journal of Earth Sciences* 58, 1253–1267. doi:10.1139/cjes-2020-0140
- Salach, A. (2017). Sapc—application for adapting scanned analogue photographs to use them in structure from motion technology. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences* 42, 197
- Sarlin, P.-E., DeTone, D., Malisiewicz, T., and Rabinovich, A. (2020). SuperGlue: Learning feature matching with graph neural networks. In *CVPR*
- Scheick, J., Leong, W. J., Bisson, K., Arendt, A., Bhushan, S., Fair, Z., et al. (2023). icepyx: Querying, obtaining, analyzing, and manipulating icesat-2 datasets. *Journal of Open Source Software* 8, 4912. doi:https://doi.org/10.21105/joss.04912
- Schönberger, J. L. and Frahm, J.-M. (2016). Structure-from-motion revisited. In *Conference on Computer Vision and Pattern Recognition (CVPR)*
- Schönberger, J. L., Zheng, E., Pollefeys, M., and Frahm, J.-M. (2016). Pixelwise view selection for unstructured multi-view stereo. In *European Conference on Computer Vision (ECCV)*
- Schumm, S. A. (1956). Evolution of drainage systems and slopes in badlands at Perth Amboy, New Jersey. *Geological society of America bulletin* 67, 597–646. doi:10.1130/0016-7606(1956)67[597:EODSAS]2.0.CO;2
- Schwat, E., Istanbuluoglu, E., Horner-Devine, A., Anderson, S., Knuth, F., and Shean, D. (2023). Multi-decadal erosion rates from glacierized watersheds on mount baker, washington, USA, reveal topographic, climatic, and lithologic controls on sediment yields. *Geomorphology* 438. doi:https://doi.org/10.1016/j.geomorph.2023.108805

- [Dataset] Sciences, W. (2009). Lidar remote sensing data collection: Mount rainier, wa
- Seehaus, T., Morgenshtern, V. I., Hübner, F., Bänsch, E., and Braun, M. H. (2020). Novel techniques for void filling in glacier elevation change data sets. *Remote Sensing* 12, 3917. doi:<https://doi.org/10.3390/rs12233917>
- Sevara, C. (2016). Capturing the Past for the Future: an Evaluation of the Effect of Geometric Scan Deformities on the Performance of Aerial Archival Media in Image-based Modelling Environments. *Archaeological Prospection* 23, 325–334. doi:10.1002/arp.1539
- [Dataset] Shean, D., Bhushan, S., Lilien, D., Knuth, F., Schwat, E., Meyer, J., et al. (2021). demcoreg: v1.1.0. doi:10.5281/zenodo.5733347
- Shean, D. E., Alexandrov, O., Moratto, Z. M., Smith, B. E., Joughin, I. R., Porter, C., et al. (2016). An automated, open-source pipeline for mass production of digital elevation models (DEMs) from very-high-resolution commercial stereo satellite imagery. *ISPRS Journal of Photogrammetry and Remote Sensing* 116, 101–117. doi:10.1016/j.isprsjprs.2016.03.012
- Shean, D. E., Bhushan, S., Montesano, P., Rounce, D. R., Arendt, A., and Osmanoglu, B. (2020). A systematic, regional assessment of high mountain Asia glacier mass balance. *Frontiers in Earth Science* 7, 363. doi:10.3389/feart.2019.00363
- Shean, D. E., Joughin, I. R., Dutrieux, P., Smith, B. E., and Berthier, E. (2019). Ice shelf basal melt rates from a high-resolution digital elevation model (dem) record for pine island glacier, antarctica. *The Cryosphere* 13, 2633–2656. doi:10.5194/tc-13-2633-2019
- Snavely, N., Seitz, S. M., and Szeliski, R. (2008). Modeling the world from internet photo collections. *International journal of computer vision* 80, 189–210. doi:10.1007/s11263-007-0107-3
- Stein, M. L. (1999). *Interpolation of spatial data: some theory for kriging* (Springer Science & Business Media, New York)
- [Dataset] Stevens, C., Conway, H., Kennard, P., Rasmussen, L., and Koutnik, M. (2016). Glacier retreat, outburst floods, and kinematic waves: Nisqually glacier changes related to climate

- Tarolli, P. and Mudd, S. M. (2019). *Remote Sensing of Geomorphology*, vol. 23
- Tayman, W. P. (1984). User guide for the USGS aerial camera report of calibration. *Photogrammetric Engineering and Remote Sensing* 50, 577–584
- UNESCO (1970). Combined Heat, Ice and Water Balances at Selected Glacier Basins. A Guide for Compilation and Assemblage of Data for Glacier Mass Balance Measurements. *UNESCO, International Hydrological Decade*
- [Dataset] USDA Forest Service (2018). RSAC Camera Report Database - Public Edition
- [Dataset] USGS (2019). 3D Elevation Program Digital Elevation Model
- [Dataset] USGS (2022). Aerial Photo Single Frames Data Dictionary
- Van Wijk, M. (1967). Photogrammetry applied to avalanche studies. *Journal of Glaciology* 6, 917–933. doi:10.3189/S0022143000020219
- Vargo, L. J., Anderson, B. M., Horgan, H. J., Mackintosh, A. N., Lorrey, A. M., and Thornton, M. (2017). Using structure from motion photogrammetry to measure past glacier changes from historic aerial photographs. *Journal of Glaciology* 63, 1105–1118. doi:10.1017/jog.2017.79
- Walstra, J., Dixon, N., and Chandler, J. H. (2007). Historical aerial photographs for landslide assessment: two case histories. *Quarterly Journal of Engineering Geology and Hydrogeology* 40, 315–332. doi:10.1144/1470-9236/07-011
- Wang, D. and Kääb, A. (2015). Modeling glacier elevation change from dem time series. *Remote Sensing* 7, 10117–10142. doi:https://doi.org/10.3390/rs70810117
- Wang, S., Liu, H., Yu, B., Zhou, G., and Cheng, X. (2016). Revealing the early ice flow patterns with historical declassified intelligence satellite photographs back to 1960s. *Geophysical Research Letters* 43, 5758–5767. doi:10.1002/2016GL068990
- Warrick, J. A., Ritchie, A. C., Adelman, G., Adelman, K., and Limber, P. W. (2017). New techniques to measure cliff change from historical oblique aerial photographs and

- structure-from-motion photogrammetry. *Journal of Coastal Research* 33, 39–55. doi:10.2112/JCOASTRES-D-16-00095.1
- Westoby, M. J., Brasington, J., Glasser, N. F., Hambrey, M. J., and Reynolds, J. M. (2012). ‘structure-from-motion’ photogrammetry: A low-cost, effective tool for geoscience applications. *Geomorphology* 179, 300–314. doi:10.1016/j.geomorph.2012.08.021
- [Dataset] WGMS (2021). World Glacier Monitoring Service. doi:10.5904/wgms-fog-2021-05
- Williams, C. K. and Rasmussen, C. E. (2006). *Gaussian processes for machine learning*, vol. 2 (MIT press Cambridge, MA)
- Willis, M. J., Melkonian, A. K., Pritchard, M. E., and Rivera, A. (2012). Ice loss from the southern patagonian ice field, south america, between 2000 and 2012. *Geophysical research letters* 39. doi:https://doi.org/10.1029/2012GL053136
- [Dataset] xdem contributors (2021). xdem. doi:10.5281/zenodo.4809698
- Zemp, M., Huss, M., Thibert, E., Eckert, N., McNabb, R., Huber, J., et al. (2019). Global glacier mass changes and their contributions to sea-level rise from 1961 to 2016. *Nature* 568, 382–386. doi:10.1038/s41586-019-1071-0
- Zemp, M., Thibert, E., Huss, M., Stumm, D., Rolstad Denby, C., Nuth, C., et al. (2013). Reanalysing glacier mass balance measurement series. *The Cryosphere* 7, 1227–1245. doi:10.5194/tc-7-1227-2013
- Zemp, M. and Welty, E. (2023). Temporal downscaling of glaciological mass balance using seasonal observations. *Journal of Glaciology* , 1–6doi:https://doi.org/10.1017/jog.2023.66
- Zhang, L., Rupnik, E., and Pierrot-Deseilligny, M. (2021). Feature matching for multi-epoch historical aerial images. *ISPRS Journal of Photogrammetry and Remote Sensing* 182, 176–189. doi:10.1016/j.isprsjprs.2021.10.008

Appendix A

SUPPLEMENTARY MATERIAL FOR CHAPTER 1: HISTORICAL STRUCTURE FROM MOTION (HSFM): AUTOMATED PROCESSING OF HISTORICAL AERIAL PHOTOGRAPHS FOR LONG-TERM TOPOGRAPHIC CHANGE ANALYSIS

A.1 Vertical datum conventions for NAGAP altitude and elevation metadata

Here we provide a brief summary of altitude and elevation metadata for the North American Glacier Aerial Photography (NAGAP) archive:

- Altitude values printed or hand-written on the photo frames are assumed to be relative to mean sea level.
- Altitude values listed in the Arctic Data Center (ADC) metadata comma-separated value (csv) files were transcribed from the analog altimeter values in the photo frames in scanned images by Nolan et al. (2017).
- Elevation values for positions in the ADC metadata keyhole markup language (kml) are provided as height above the EGM96 geoid in meters.
- Altitude values provided in the EarthExplorer (EE) metadata are specified as "flying height above ground level" (USGS, 2022).

For the images collected on 1967-09-21 at South Cascade Glacier we used the raw images provided by the NAGAP ADC collection and camera position metadata provided by the EE archive, since no position information is available from the ADC records. The flight altitude is listed as 24,601 feet (7,498 m) for all images in the EE metadata, while 11,000 feet (3,352 m) is hand written on the image frames. The final mean camera elevation after HSfM

processing was 11,086 feet (3,379 m) above the WGS84 ellipsoid. This shows that the EE metadata is incorrect for this image set, and the 11,000 value written on the frame is closer to the true elevation. This example illustrates the importance of checking metadata and properly defining vertical datum definitions when processing historical aerial photographs.

A.2 Tables

Table A.1: Metashape v.1.6.0 processing parameters for the *single date - single block* mode.

Function	Parameters	Description
<i>matchPhotos</i>	<i>downscale=1</i>	Image downscaling factor 1 = high accuracy 2 = medium accuracy
	<i>generic_preselection=True</i>	Use lower accuracy settings first to find matches
	<i>reference_preselection=False</i>	Try to find matches for all photos regardless of sequence and position
	<i>keypoint_limit=80,000</i>	Interest points
	<i>tiepoint_limit=8,000</i>	Match points
<i>alignCameras</i>	<i>defaults</i>	
<i>buildDepthMaps</i>	<i>downscale = 2</i>	Image downscaling factor 2 = high quality 4 = medium quality
	<i>filter_mode=AggressiveFiltering</i>	Outlier filtering mode
<i>buildDenseCloud</i>	<i>defaults</i>	

Table A.2: Results for 243 images comprising 18 total blocks at South Cascade Glacier (SCG) using the *multiple dates - multiple blocks* processing mode. Each date has a single block for the SCG site. Area is computed from the valid pixel count of each output digital elevation model (DEM), excluding "no data" values. The RMS reprojection error for each block is reported in pixels and converted to meters using the block median ground sample distance (GSD). The normalized median absolute deviation (NMAD) is computed from per-pixel elevation difference values with respect to the reference DEM over stable surfaces.

Date	Images	Blocks	Area	Reprojection error		NMAD
	—	—	(km ²)	(px)	(m)	(m)
1967-09-21	17	1	15.34	0.56	0.1	0.50
1970-09-29	18	1	32.43	0.6	0.19	0.75
1974-08-10	10	1	8.03	0.58	0.1	0.72
1977-10-03	5	1	4.47	0.53	0.09	0.30
1979-08-20	7	1	4.80	0.47	0.07	0.34
1979-10-06	19	1	24.93	0.71	0.15	0.45
1984-08-14	10	1	8.49	0.8	0.17	0.59
1986-09-05	7	1	4.75	0.83	0.13	0.75
1987-08-21	6	1	6.02	0.69	0.13	0.59
1990-09-05	7	1	13.46	0.63	0.15	0.44
1991-09-09	22	1	16.75	0.75	0.14	0.38
1992-07-28	10	1	16.75	0.88	0.22	0.47
1992-09-15	9	1	2.31	0.76	0.1	0.34
1992-09-18	15	1	20.22	0.77	0.22	0.48
1992-10-06	15	1	7.96	0.69	0.1	0.39
1994-09-06	41	1	18.48	0.59	0.07	0.34
1996-09-10	21	1	20.50	0.4	0.09	0.42
1997-09-23	4	1	4.76	0.42	0.1	0.27
Mean	—	—	—	0.65	0.13	0.47
SD	—	—	—	0.14	0.05	0.15

Table A.3: Image standardization evaluation results. Columns include the focal length error, principal point error, and RMS reprojection error computed by Metashape, as well as the normalized median absolute deviation (NMAD) of per-pixel elevation difference values over stable surfaces. Baseline: (**TR0**) Image standardization without affine transformation. Experiments: (**TR1**) Image standardization with affine transformation to match calibrated values; (**TR2**) Image standardization with affine transformation to match mean fiducial marker positions; (**TR3**) Image standardization without affine transformation, using pseudofiducial markers to compute principal point and remove frame.

Date	Images	Test Run (TR)	Focal Length error	Principal Point error		RMS Reprojection error	DEM NMAD
				Cx	Cy		
			(px)	(px)	(px)		
1994-09-06	41	0	0.45	0.29	0.24	0.581	0.46
		1	0.45	0.29	0.24	0.591	0.45
		2	0.46	0.3	0.24	0.579	0.43
		3	0.49	0.31	0.25	0.602	0.5
1996-09-10	21	0	0.48	0.67	0.44	0.397	0.66
		1	0.47	0.65	0.43	0.398	0.66
		2	0.47	0.66	0.43	0.405	0.68
		3	0.5	0.7	0.46	0.406	1.04
1997-09-23	4	0	9.5	17	23	0.462	0.66
		1	9.7	11	22	0.415	0.49
		2	9.7	13	23	0.486	0.78
		3	9.9	18	23	0.433	1.42

Table A.4: Results for 261 images comprising 21 total blocks at Mount Baker using the *multiple dates - multiple blocks* processing mode. See Table A.2 caption for details. Unlike the South Cascade Glacier site, some dates include multiple spatially distinct blocks.

Date	Images	Blocks	Area	Reprojection error		NMAD
	—	—	(km ²)	(px)	(m)	(m)
1970-09-09	4	1	5.09	0.39	0.09	0.76
1970-09-29	59	1	93.05	0.58	0.14	0.85
1974-08-10	19	4	6.48	0.7	0.09	0.58
1977-09-27	64	5	17.16	0.65	0.1	0.52
1979-10-06	48	1	143.40	0.74	0.24	1.2
1987-08-21	7	2	11.41	0.81	0.19	0.75
1990-09-05	7	2	15.83	0.66	0.18	0.64
1991-09-09	30	3	49.57	0.81	0.19	0.59
1992-09-15	4	1	1.18	0.69	0.09	0.76
1992-09-18	19	1	44.31	0.67	0.18	0.83
Mean	—	—	—	0.67	0.15	0.75
SD	—	—	—	0.12	0.05	0.19

A.3 *Figures*

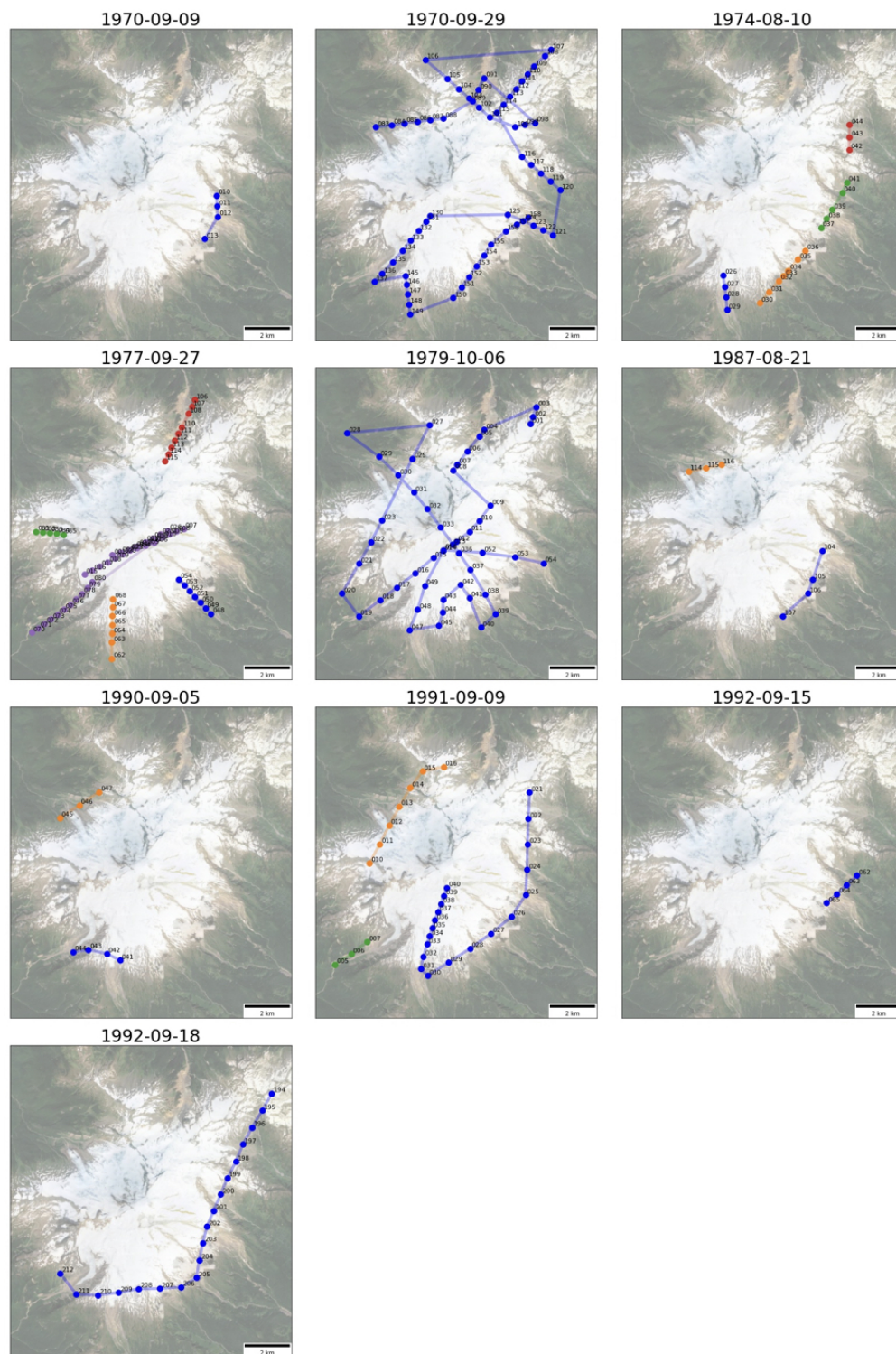


Figure A.1: Flight paths, camera positions with frame numbers and non-overlapping image blocks (unique colors) for North America Glacier Aerial Photography (NAGAP) images over the Mount Baker site.

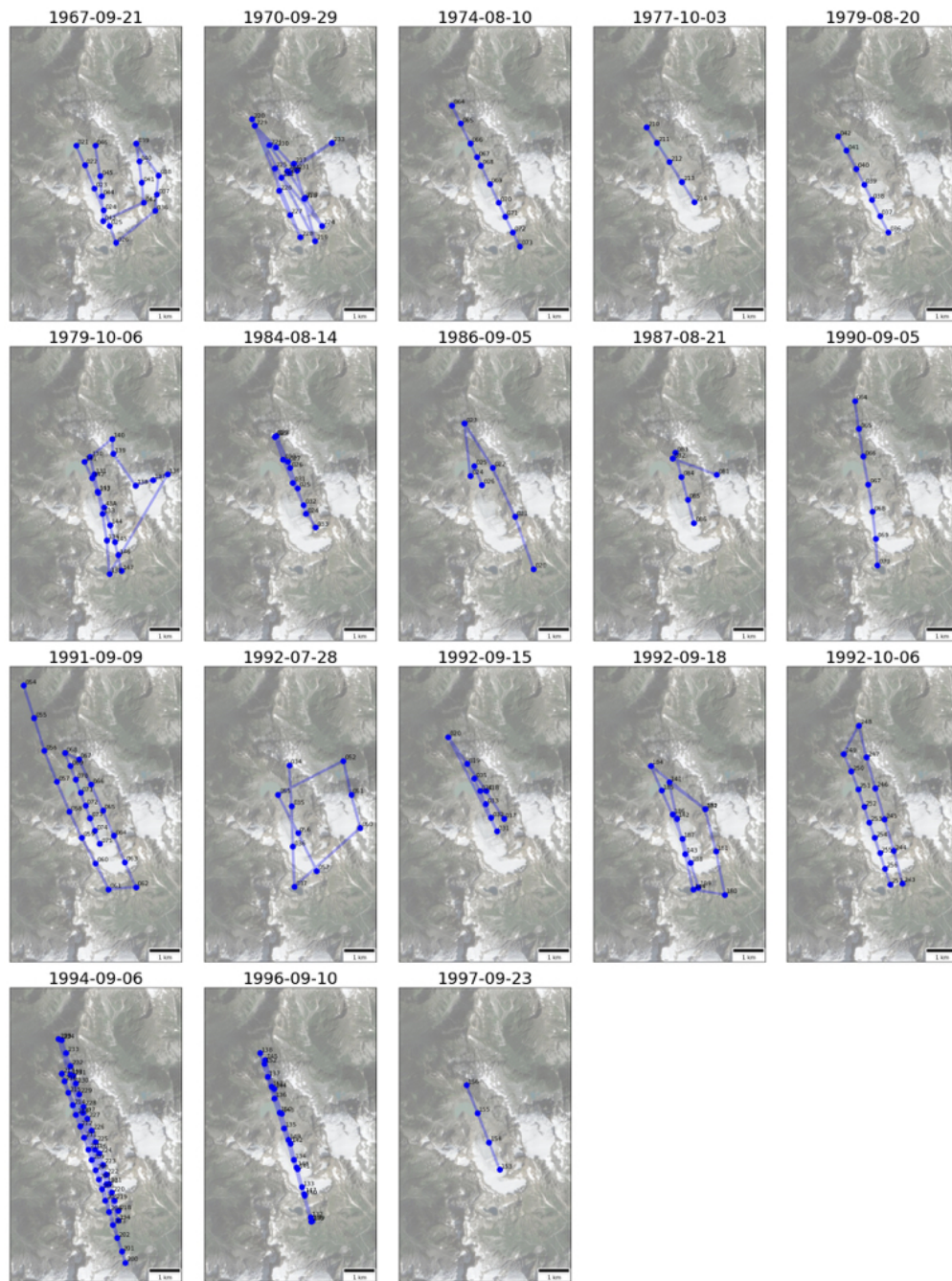


Figure A.2: Flight paths and camera positions with frame numbers for North America Glacier Aerial Photography (NAGAP) images over the South Cascade Glacier site.

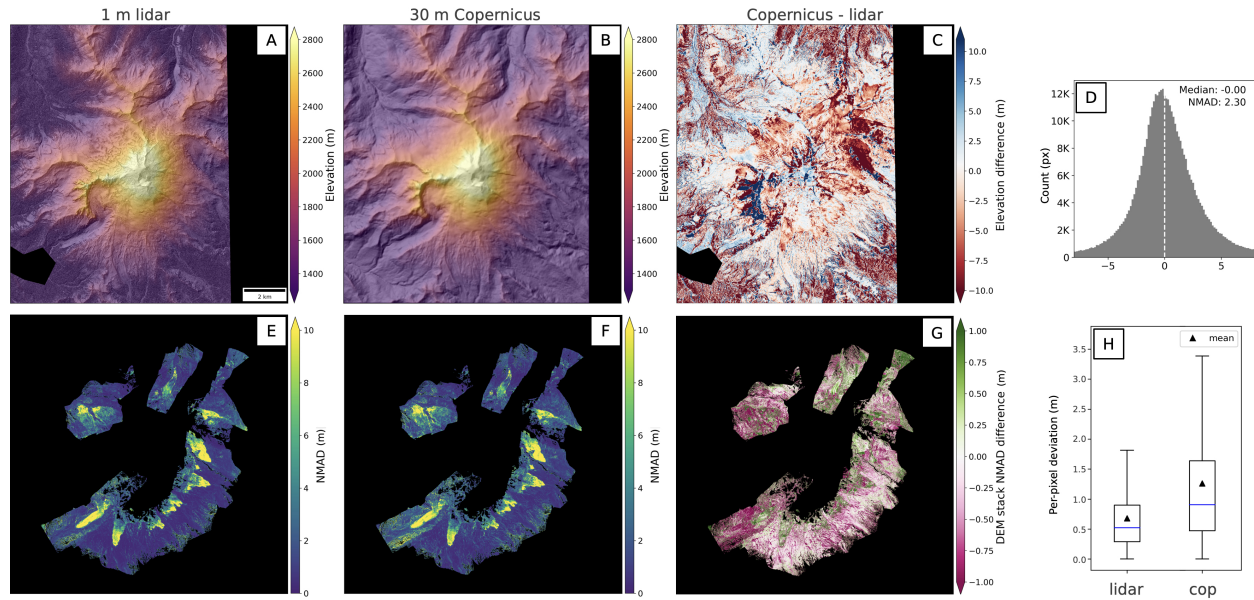


Figure A.3: Results of reference digital elevation model (DEM) sensitivity tests for the Mount Baker site. **(A)** Reference digital surface model (DSM) prepared from 3DEP airborne lidar data collected August 27, 2015, posted at 1 m. **(B)** Reference DEM prepared from the global 30 m Copernicus DEM, with variable acquisition dates between 2010 and 2015. **(C)** Elevation difference map (A minus B). Note artifacts over steep terrain (e.g., southwest and east flanks) in the Copernicus DEM, likely due to phase unwrapping errors. Residual differences over glaciers and vegetation can be attributed to glacier thinning and variable penetration of the lidar and radar sources. **(D)** Histogram of elevation difference values over stable surfaces showing acceptable agreement between the two datasets. **(E)** Per-pixel normalized median absolute deviation (NMAD) map for the historical DEM stack processed using the 1 m lidar reference DEM. See Figure 10 for additional details. **(F)** Same as in E, for the historical DEM stack processed using the 30 m Copernicus reference DEM. **(G)** Per-pixel NMAD difference map (E minus F). **(H)** Relative accuracy metrics over stable surfaces for the two historical DEM stacks. Boxes show interquartile ranges, with median values in blue and whiskers at 1.5 times the interquartile range. The mean NMAD is 0.68 m for the historical DEM stack processed using the 1 m lidar reference DEM and 1.26 m for the stack processed with the 30 m Copernicus reference DEM.

Fiducial marker templates

Corner	Midside	Rolls	Count
		91V4, 92V1, 92V2, 92V4, 93V1, 93V2, 93V3, 93V4, 94V1, 94V2, 94V3, 94V4, 94V5, 94V6, 95V1, 95V2, 95V3, 96V1, 97V1, 97V2	4046

Pseudofiducial templates

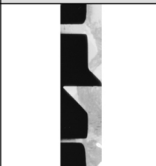
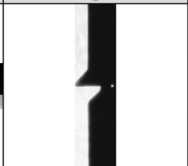
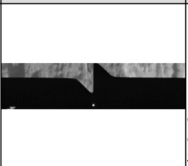
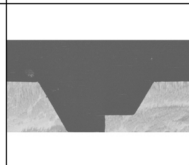
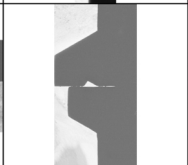
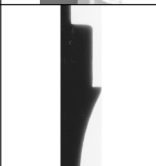
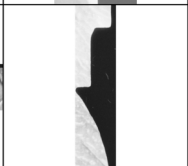
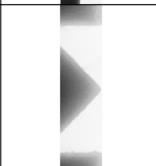
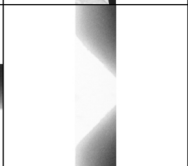
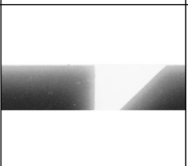
Name	Left	Top	Right	Bottom	Rolls	Count
Notch					74V1, 74V2, 74V3, 74V4, 75V1, 75V2, 75V3, 75V4, 76V1, 76V2, 77V1, 77V2, 77V3, 77V4, 77V5, *77V6, 78V1, 78V2, 78V3, 78V4, 78V5, 79V1, 79V2, 79V3, 79V4, 79V5, 79V6, 80V1, 80V2, 80V3, 81V1, 81V2, 81V3, 81V4, 84V1, 86V1, 87V1, 87V2, 88V1, 90V1, 90V2, 90V3, 91V1, 91V2, 91V3, 92V3, 92V5	11012
Block					72V1, 72V2, 72V4, 74V5, 75V5	2036
Curve					67V4, 70V1, 70V2, 71V1, 71V3, 73V1, 73V2, 73V3	548
Triangle					*77V6	43

Figure A.4: Fiducial and pseudofiducial marker templates for the North America. Glacier Aerial Photography (NAGAP) Arctic Data Center (ADC) images used during automated image standardization. Count represents the total number of scanned images in the ADC archive containing each type of marker. One roll identifier (77V6) includes frames that display multiple marker types, suggesting that the same film roll was used in multiple cameras.

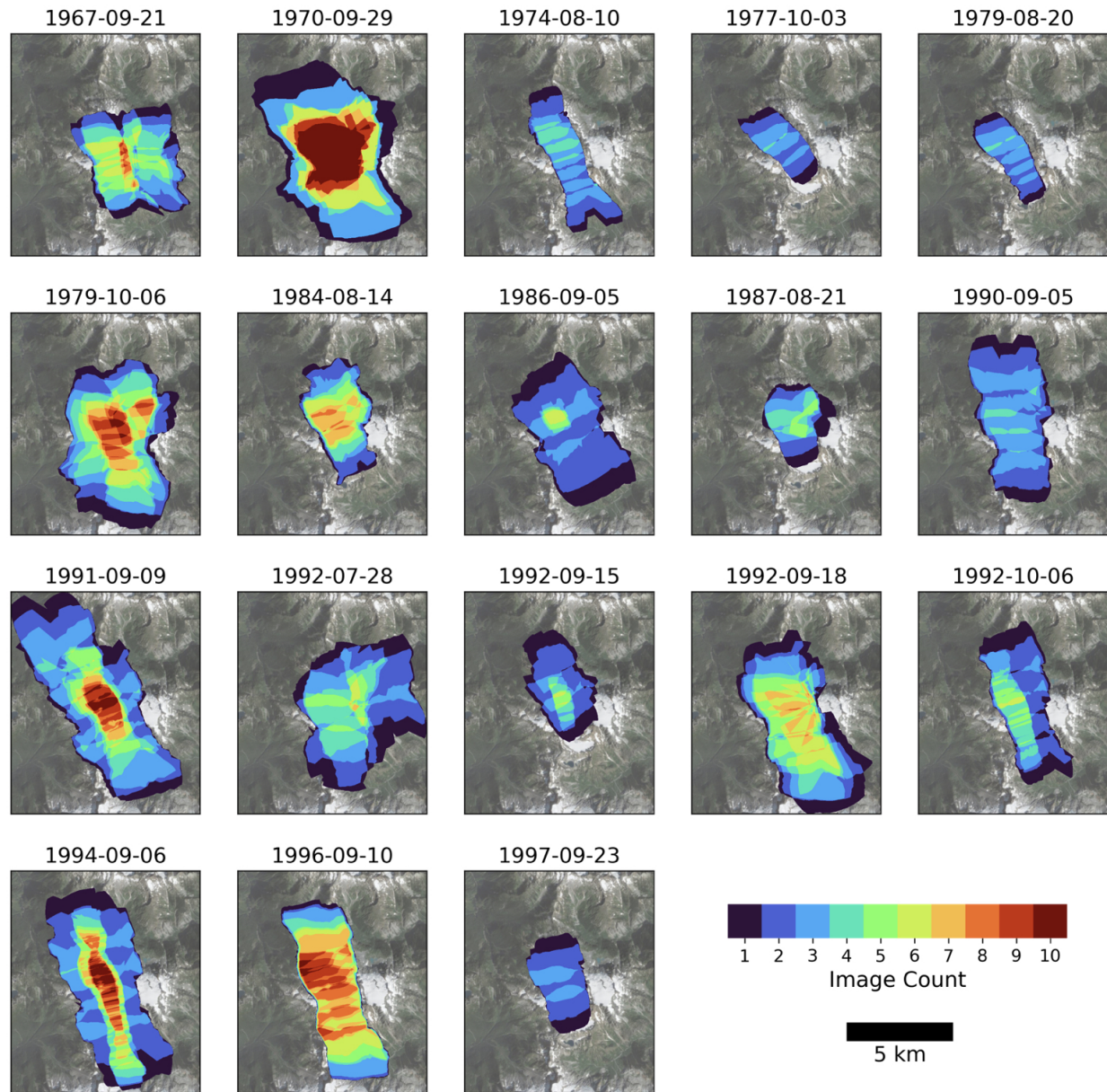


Figure A.5: Orthoimage footprint count maps for all blocks over the South Cascade Glacier site.

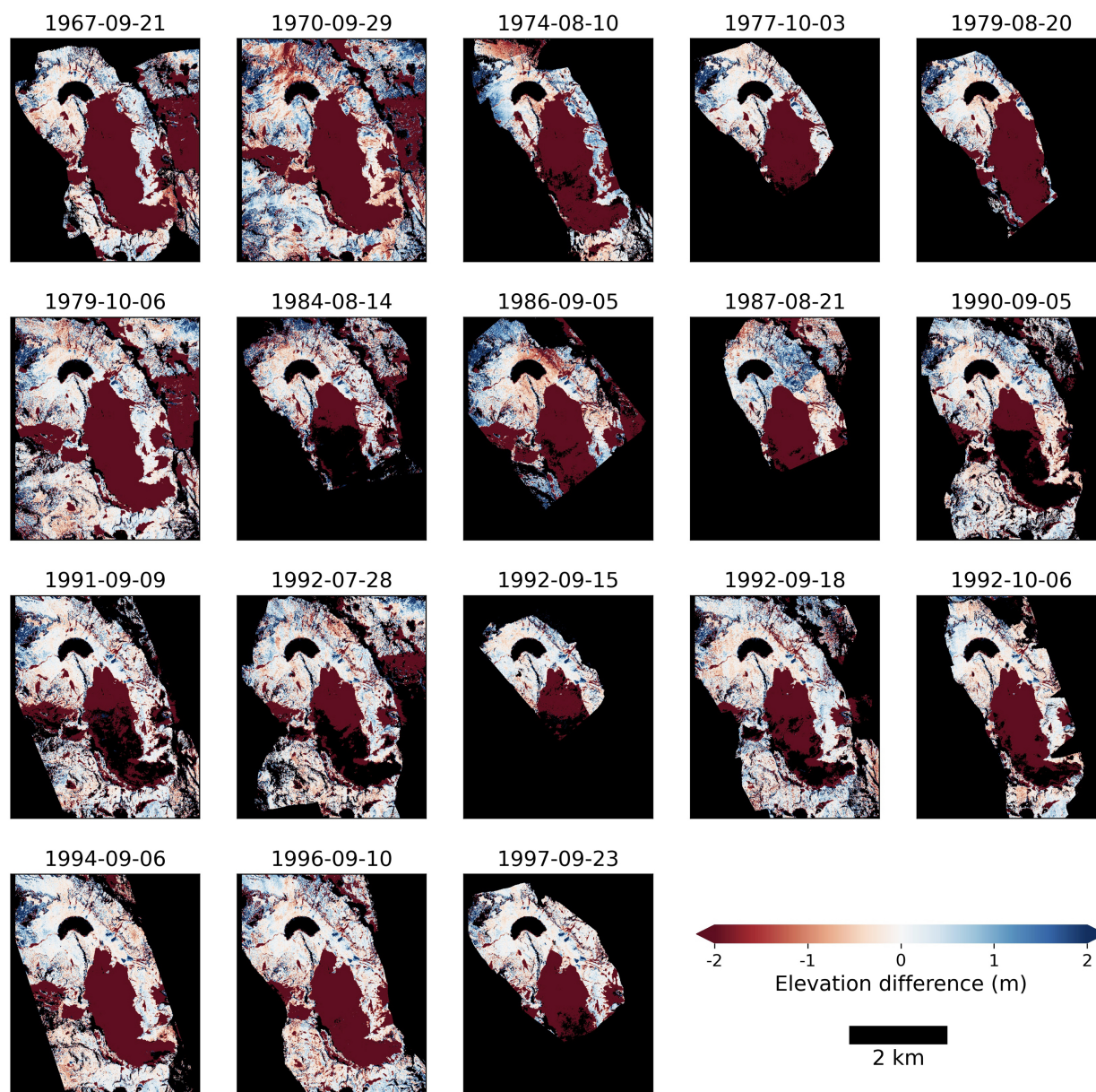


Figure A.6: Elevation difference maps for the South Cascade Glacier site (2015 reference digital elevation model (DEM) minus historical DEM), with color ramp stretch to bring out detail over the stable surfaces.

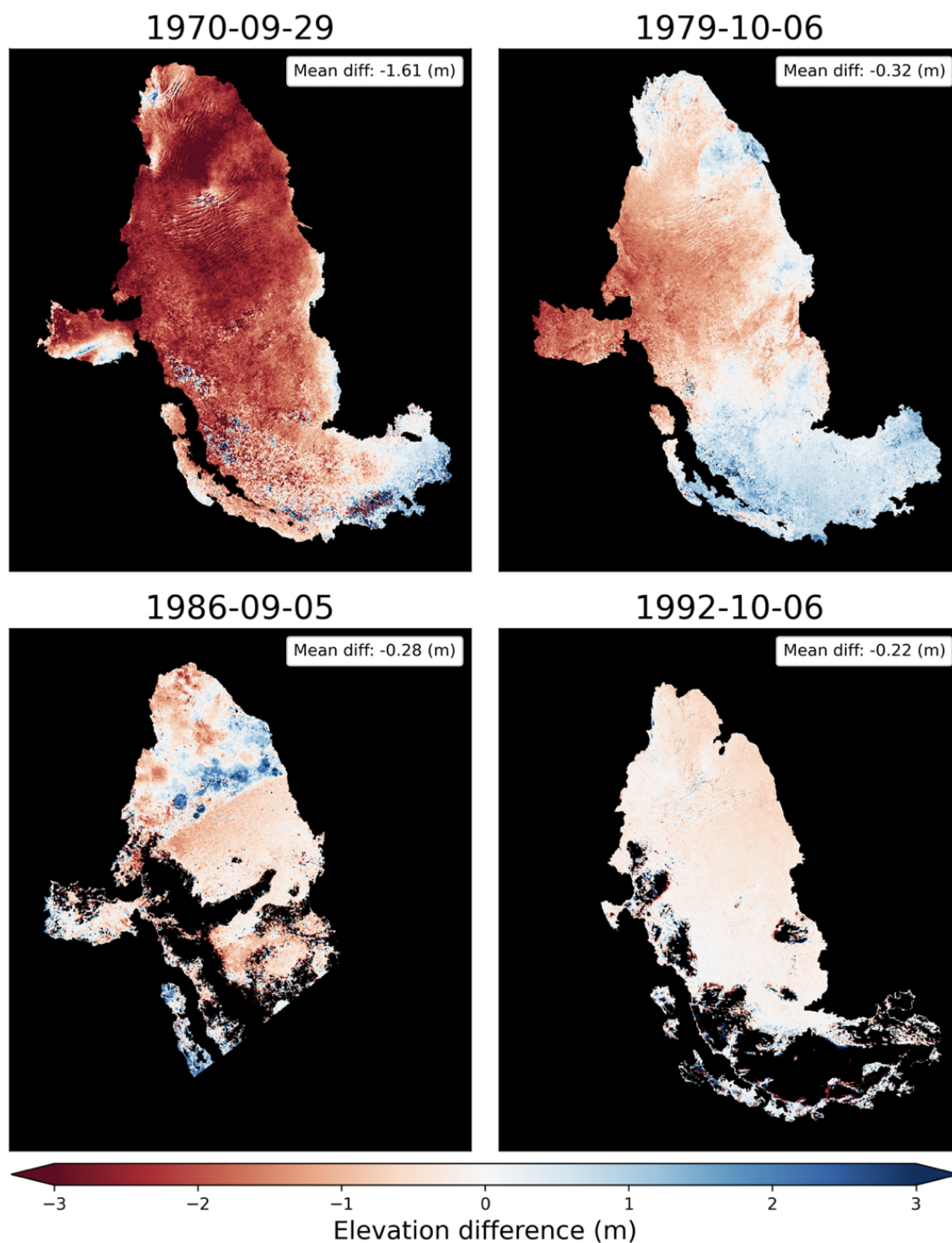


Figure A.7: Comparison of digital elevation models (DEMs) generated using the manual ground control point (GCP) method and Historical Structure from Motion (HSfM) for the same input images over South Cascade Glacier. Per-pixel elevation difference maps (manual GCP method minus HSfM) are clipped to the glacier outlines for 1970, 1979, 1986, and 1992 provided by the USGS (McNeil et al., 2022a; O’Neel et al., 2019). Red indicates that manual GCP method DEM is lower than the HSfM DEM, while blue indicates the opposite. Mean differences over the glacier surface range from -1.61 to -0.22 m.

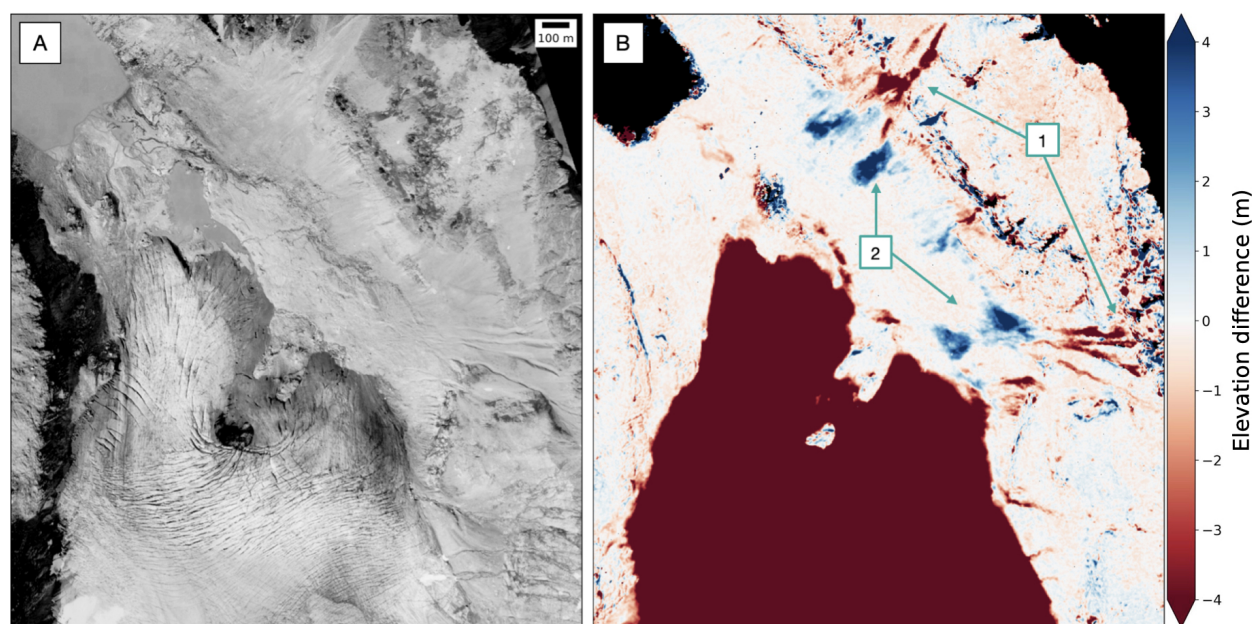


Figure A.8: (A) The 1994-09-06 North American Glacier Aerial Photography (NAGAP) orthomosaic over the South Cascade Glacier terminus. (B) Elevation difference between 1994-09-06 NAGAP digital elevation model (DEM) and the 2015 reference DEM, showing (B1) mass wasting and erosion of talus and (B2) associated deposits on the valley floor.

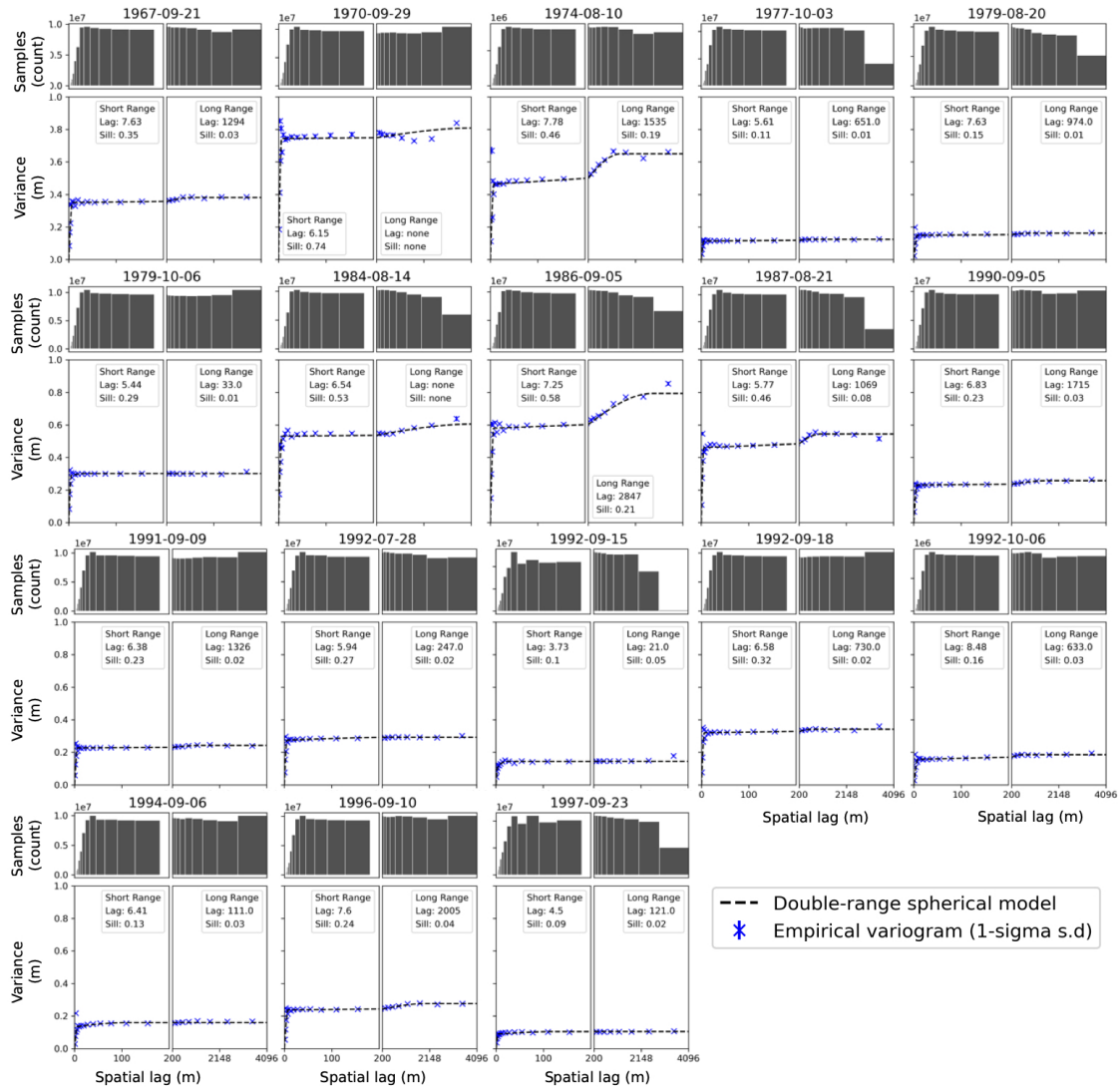


Figure A.9: Empirical variogram and model for each digital elevation model (DEM) at the South Cascade Glacier site. The 1970-09-29, 1974-08-10, 1984-08-14, 1986-09-05, and 1987-08-21 DEMs have higher spatially correlated error, as can be seen in the corresponding difference maps (Figure A.6) and Figure 7).

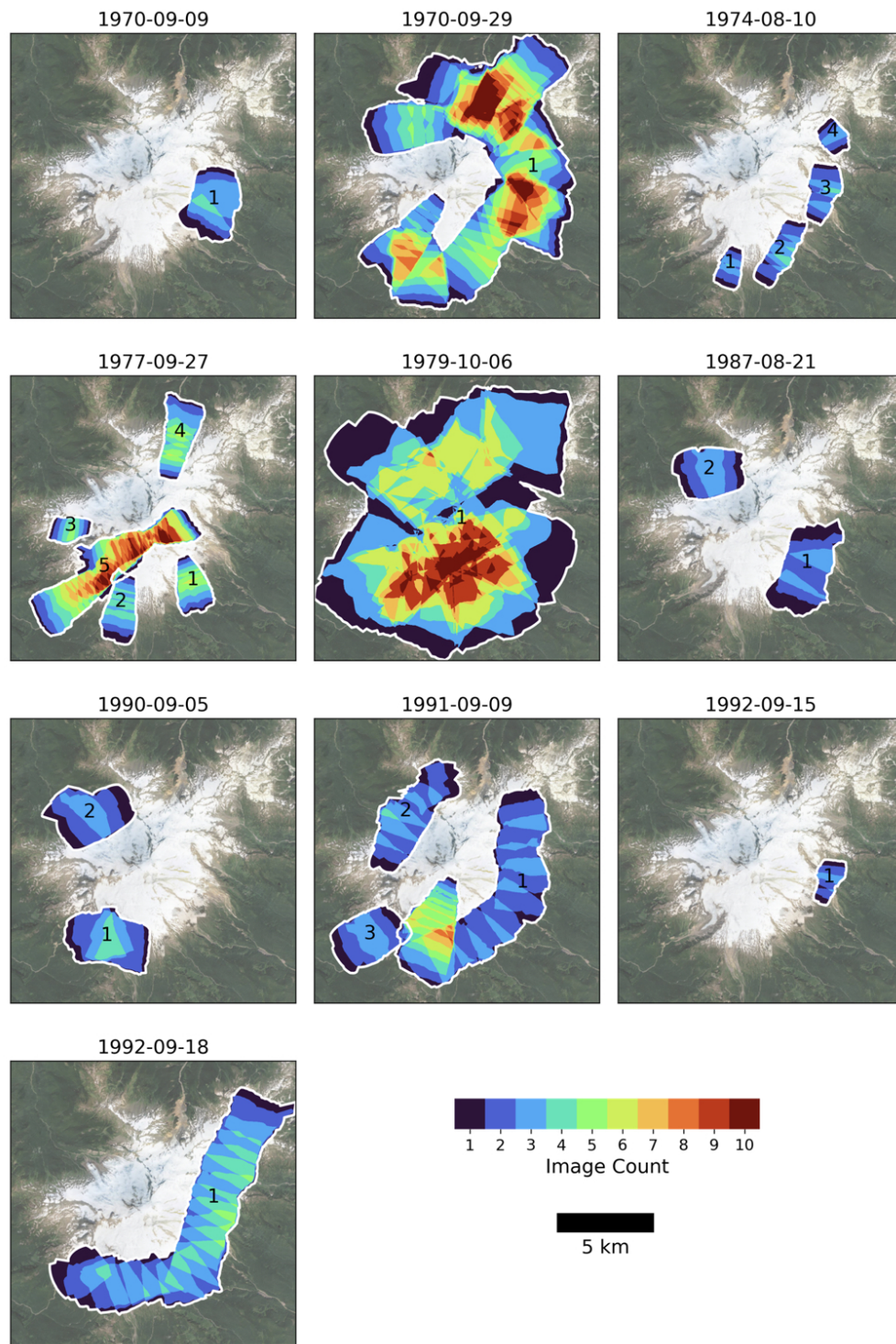


Figure A.10: Orthoimage footprint count maps for all blocks over the Mount Baker site. Non-overlapping blocks for a single date are numbered and outlined with a white border.

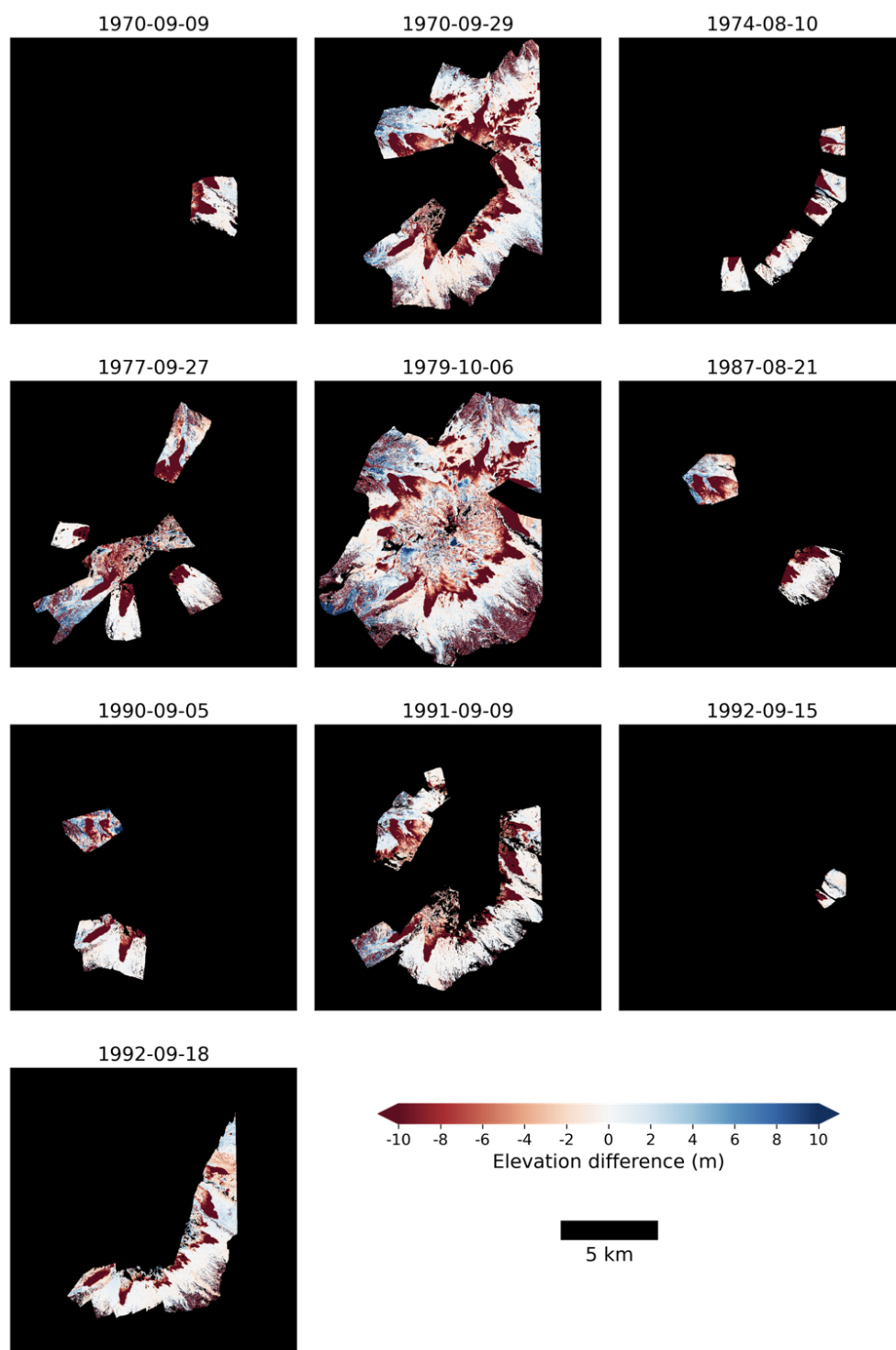


Figure A.11: Elevation difference maps for the Mount Baker site (2015 reference digital elevation model (DEM) minus historical DEM).

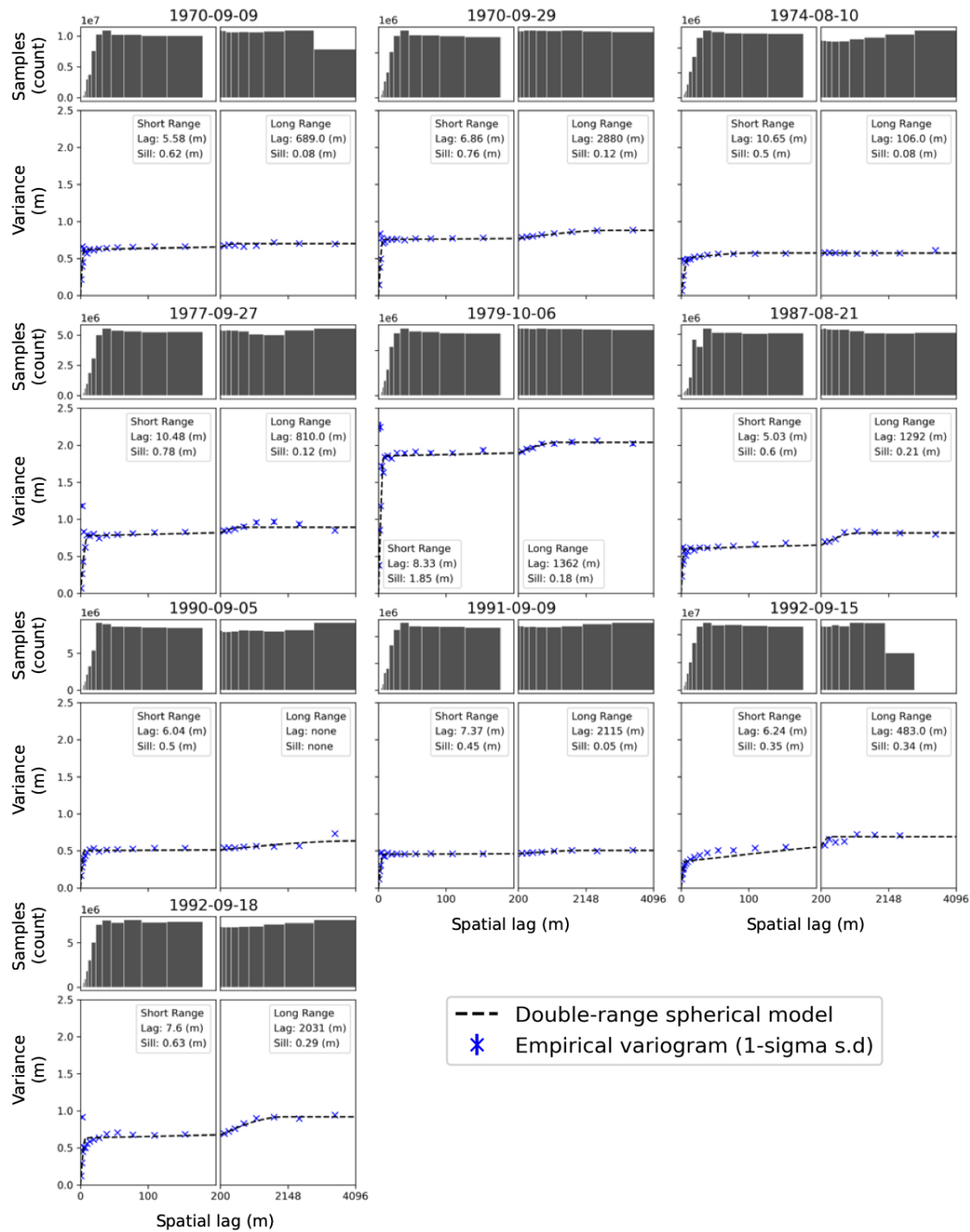


Figure A.12: Empirical variogram and model for each digital elevation model (DEM) at the Mount Baker site. The 1970-09-29, 1974-08-10, 1984-08-14, 1986-09-05, and 1987-08-21 DEMs have higher spatially correlated error, as can be seen in the corresponding difference maps (Figure A.6 and Figure 7). The large 1979-10-06 DEM has the largest errors with highest spatial autocorrelation.

Appendix B

SUPPLEMENTARY MATERIAL FOR CHAPTER 2: ARE PARTIAL DEMS USEFUL? A MEMORY-EFFICIENT METHOD TO ESTIMATE LONG-TERM GLACIER SURFACE ELEVATION CHANGE FROM SPATIALLY AND TEMPORALLY SPARSE MEASUREMENTS

B.1 Functions

The Matérn function is defined as:

$$k(x_i, x_j) = \frac{1}{\Gamma(\nu)2^{\nu-1}} \left(\frac{\sqrt{2\nu}}{l} d(x_i, x_j) \right)^\nu K_\nu \left(\frac{\sqrt{2\nu}}{l} d(x_i, x_j) \right) \quad (\text{B.1})$$

where ν controls the smoothness of the fit, $d(\cdot, \cdot)$ is the Euclidean distance, $K_\nu(\cdot)$ is a modified Bessel function, and $\Gamma(\cdot)$ is the gamma function (Pedregosa et al., 2011).

The Radial Basis Function kernel is defined as:

$$k(x_i, x_j) = \exp \left(-\frac{d(x_i, x_j)^2}{2l^2} \right) \quad (\text{B.2})$$

where l is the length scale of the kernel and $d(\cdot, \cdot)$ is the Euclidean distance (Pedregosa et al., 2011).

The periodic ExpSineSquared function is defined as:

$$k(x_i, x_j) = \exp \left(-\frac{2 \sin^2(\pi d(x_i, x_j)/p)}{l^2} \right) \quad (\text{B.3})$$

where l is the length scale of the kernel, p the periodicity of the kernel, and $d(\cdot, \cdot)$ is the Euclidean distance (Pedregosa et al., 2011).

B.2 Tables

Table B.1: South Cascade Glacier. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs.

Date	Resolution (m)	NMAD (m)	Stable ground coverage (%/100)	RGI coverage (%/100)	Source
1958-08-13	9.83	5.79	0.97	0.99	USGS
1967-09-21	1.0	0.5	0.62	0.98	HSfM
1970-09-29	1.0	0.75	0.96	1.0	HSfM
1974-08-10	1.0	0.73	0.41	0.85	HSfM
1977-10-03	1.0	0.3	0.25	0.56	HSfM
1979-08-20	1.0	0.35	0.23	0.79	HSfM
1979-10-06	1.0	0.45	0.97	1.0	HSfM
1984-08-14	1.0	0.6	0.38	0.37	HSfM
1986-09-05	0.8	0.98	0.41	0.77	USGS
1987-08-21	1.0	0.59	0.28	0.57	HSfM
1990-09-05	1.0	0.44	0.63	0.5	HSfM
1991-09-09	1.0	0.38	0.71	0.64	HSfM
1992-07-28	1.0	0.48	0.74	0.61	HSfM
1992-09-15	1.0	0.34	0.17	0.38	HSfM
1992-09-18	1.0	0.48	0.73	0.76	HSfM
1992-10-06	0.59	0.51	0.37	0.94	USGS
1994-09-06	1.0	0.34	0.63	0.98	HSfM
1996-09-10	1.0	0.42	0.66	0.99	HSfM
1997-09-23	1.0	0.28	0.28	0.64	HSfM
2001-09-20	0.28	1.07	0.4	0.97	USGS
2004-09-26	5.0	1.38	0.69	1.0	USGS

Continued on next page

Table B.1: South Cascade Glacier. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs.
(Continued)

Date	Resolution (m)	NMAD (m)	Stable ground coverage (%/100)	RGI coverage (%/100)	Source
2008-10-01	2.0	0.34	0.97	0.99	USGS
2009-06-01	2.0	2.29	1.0	1.0	EarthDEM
2012-07-05	2.0	2.46	0.95	0.89	EarthDEM
2012-09-06	2.0	0.49	1.0	1.0	EarthDEM
2013-06-16	2.0	2.38	0.86	0.98	EarthDEM
2014-05-11	2.0	3.29	0.8	0.92	EarthDEM
2014-08-24	2.0	0.4	0.72	0.82	EarthDEM
2014-09-06	2.0	0.5	0.98	0.98	EarthDEM
2015-05-01	2.0	2.0	0.19	0.01	EarthDEM
2015-05-04	2.0	2.02	0.86	1.0	EarthDEM
2015-06-06	2.0	0.82	0.98	0.98	EarthDEM
2015-08-17	2.0	0.55	0.98	0.98	EarthDEM
2015-10-14	2.0	0.18	0.97	0.98	USGS
2015-12-01	2.0	0.94	0.48	0.66	EarthDEM
2016-01-06	2.0	1.5	0.53	0.89	EarthDEM
2016-01-09	2.0	2.29	0.7	1.0	EarthDEM
2016-03-18	2.0	2.98	0.98	1.0	EarthDEM
2016-04-06	2.0	2.56	0.2	0.0	EarthDEM
2016-04-08	2.0	2.33	1.0	1.0	EarthDEM
2016-04-19	2.0	2.7	1.0	1.0	EarthDEM
2016-05-08	2.0	3.28	0.13	0.0	EarthDEM
2016-05-12	2.0	1.48	0.07	0.0	EarthDEM

Continued on next page

Table B.1: South Cascade Glacier. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs.
(Continued)

Date	Resolution (m)	NMAD (m)	Stable ground coverage (%/100)	RGI coverage (%/100)	Source
2016-06-19	2.0	1.21	0.7	0.37	EarthDEM
2016-06-22	2.0	1.59	0.98	0.97	EarthDEM
2016-07-28	2.0	0.51	0.92	0.66	EarthDEM
2016-08-29	2.0	0.37	0.97	0.97	EarthDEM
2016-09-27	2.0	0.5	0.91	0.98	EarthDEM
2016-10-22	2.0	0.7	0.8	0.99	EarthDEM
2017-04-03	2.0	2.48	0.99	1.0	EarthDEM
2017-05-22	2.0	2.67	1.0	1.0	EarthDEM
2017-06-22	2.0	1.99	1.0	1.0	EarthDEM
2017-07-18	2.0	0.79	0.82	0.7	EarthDEM
2017-08-20	2.0	0.44	0.69	0.45	EarthDEM
2017-09-28	2.0	0.54	1.0	1.0	EarthDEM
2018-03-11	2.0	2.33	1.0	1.0	EarthDEM
2018-04-24	2.0	2.9	0.86	1.0	EarthDEM
2018-05-25	2.0	2.78	0.18	0.0	EarthDEM
2018-05-27	2.0	2.43	1.0	1.0	EarthDEM
2018-07-19	2.0	0.57	0.76	0.81	EarthDEM
2018-08-17	2.0	0.4	0.9	0.8	EarthDEM
2018-09-17	2.0	0.42	0.9	1.0	EarthDEM
2019-05-05	2.0	1.93	0.92	0.99	EarthDEM
2019-07-25	2.0	0.52	0.94	0.95	EarthDEM
2019-08-08	2.0	0.33	1.0	1.0	EarthDEM

Continued on next page

Table B.1: South Cascade Glacier. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs.
(Continued)

Date	Resolution (m)	NMAD (m)	Stable ground coverage (%/100)	RGI coverage (%/100)	Source
2019-08-22	2.0	0.89	0.28	0.28	EarthDEM
2019-10-10	2.0	0.63	0.85	0.77	EarthDEM
2020-04-09	2.0	3.71	0.86	0.98	EarthDEM
2020-07-13	2.0	1.49	0.99	1.0	EarthDEM
2020-12-06	2.0	1.41	0.67	0.18	EarthDEM
2021-08-13	2.0	0.4	0.98	0.99	USGS

Table B.2: Mount Baker. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs.

Date	Resolution (m)	NMAD (m)	Stable ground coverage (%/100)	RGI coverage (%/100)	Source
1947-09-14	3.75	4.0	0.97	0.77	HSfM
1950-09-02	1.88	4.38	0.98	0.77	HSfM
1970-09-09	1.0	0.73	0.08	0.05	HSfM
1970-09-29	1.0	0.83	0.72	0.46	HSfM
1974-08-10	1.0	0.58	0.22	0.05	HSfM
1977-09-27	1.0	0.51	0.29	0.27	HSfM
1979-10-06	1.0	1.19	0.87	0.94	HSfM
1987-08-21	1.0	0.74	0.15	0.11	HSfM
1990-09-05	1.0	0.63	0.17	0.1	HSfM
1991-09-09	1.0	0.58	0.52	0.31	HSfM
1992-09-15	1.0	0.67	0.03	0.0	HSfM

Continued on next page

Table B.2: Mount Baker. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs. (Continued)

Date	Resolution (m)	NMAD (m)	Stable ground coverage (%/100)	RGI coverage (%/100)	Source
1992-09-18	1.0	0.82	0.43	0.19	HSfM
2013-09-11	2.0	0.47	1.0	0.98	EarthDEM
2013-09-13	2.0	1.09	0.99	1.0	EarthDEM
2014-05-14	2.0	2.67	0.91	0.84	EarthDEM
2014-08-23	2.0	0.82	0.9	0.98	EarthDEM
2014-11-01	2.0	0.68	0.58	0.76	EarthDEM
2014-11-07	2.0	1.19	0.51	0.77	EarthDEM
2014-11-11	2.0	0.77	0.93	0.78	EarthDEM
2015-04-17	2.0	1.9	0.76	0.8	EarthDEM
2015-08-27	1.0	0.0	1.0	1.0	WADNR
2015-09-11	2.0	0.76	1.0	1.0	EarthDEM
2015-09-28	2.0	0.5	0.9	0.99	EarthDEM
2015-09-30	2.0	0.47	0.39	0.31	EarthDEM
2015-12-16	2.0	1.32	0.99	0.99	EarthDEM
2016-01-19	2.0	2.61	0.95	0.8	EarthDEM
2016-03-05	2.0	2.76	0.65	0.83	EarthDEM
2016-04-01	2.0	2.54	0.74	0.91	EarthDEM
2016-06-04	2.0	2.27	0.67	0.78	EarthDEM
2016-07-28	2.0	1.09	0.79	0.93	EarthDEM
2016-08-01	2.0	0.96	0.9	0.99	EarthDEM
2016-09-09	2.0	0.73	0.78	0.88	EarthDEM
2016-10-11	2.0	0.58	0.99	0.92	EarthDEM
2017-04-09	2.0	2.64	0.53	0.73	EarthDEM

Continued on next page

Table B.2: Mount Baker. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs. (Continued)

Date	Resolution (m)	NMAD (m)	Stable ground coverage (%/100)	RGI coverage (%/100)	Source
2017-08-20	2.0	0.61	0.09	0.18	EarthDEM
2017-09-02	2.0	0.82	0.93	1.0	EarthDEM
2018-01-03	2.0	1.41	0.94	0.93	EarthDEM
2018-03-07	2.0	2.54	0.64	0.3	EarthDEM
2018-04-23	2.0	2.9	0.88	0.92	EarthDEM
2018-07-08	2.0	1.3	0.0	0.0	EarthDEM
2018-07-23	2.0	0.81	0.42	0.14	EarthDEM
2018-07-24	2.0	0.78	0.71	0.99	EarthDEM
2018-07-27	2.0	1.0	0.45	0.92	EarthDEM
2018-07-30	2.0	0.6	1.0	1.0	EarthDEM
2018-08-17	2.0	0.61	0.84	0.95	EarthDEM
2018-09-27	2.0	0.61	0.99	0.92	EarthDEM
2019-05-08	2.0	2.26	0.7	0.73	EarthDEM
2019-06-16	2.0	1.07	0.59	0.83	EarthDEM
2019-07-20	2.0	0.81	0.65	0.87	EarthDEM
2019-08-03	2.0	0.55	0.66	0.94	EarthDEM
2019-10-11	2.0	0.61	0.99	0.88	EarthDEM
2020-04-13	2.0	2.32	0.25	0.1	EarthDEM
2020-06-22	2.0	1.91	0.98	0.99	EarthDEM
2020-09-05	2.0	0.49	0.78	0.94	EarthDEM
2020-12-12	2.0	1.12	0.9	0.92	EarthDEM

Table B.3: Mount Rainier. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs.

Date	Resolution (m)	NMAD (m)	Stable ground coverage (%/100)	RGI coverage (%/100)	Source
1951-08-16	1.8	2.41	0.31	0.33	HSfM
1955-09-15	4.0	4.81	0.95	0.82	HSfM
1957-09-15	3.6	4.41	0.32	0.13	HSfM
1959-07-14	3.2	3.38	0.19	0.04	HSfM
1961-08-19	1.8	2.13	0.29	0.32	HSfM
1966-08-21	1.6	2.23	0.18	0.31	HSfM
1967-09-19	0.7	1.13	0.08	0.08	HSfM
1969-08-30	1.4	2.47	0.56	0.2	HSfM
1970-08-29	0.5	2.92	0.04	0.07	HSfM
1970-09-15	2.4	2.71	0.95	0.8	HSfM
1973-09-24	1.05	0.82	0.23	0.24	HSfM
1975-09-19	4.8	4.2	0.25	0.12	HSfM
1979-09-14	5.2	3.37	0.98	0.91	HSfM
1980-10-09	1.06	0.66	0.02	0.01	HSfM
1987-08-21	1.36	3.59	0.05	0.03	HSfM
1988-08-21	0.8	1.66	0.02	0.01	HSfM
1990-09-13	0.8	1.6	0.15	0.07	HSfM
1991-09-09	0.98	0.65	0.22	0.17	HSfM
1992-07-28	0.6	1.41	0.17	0.1	HSfM
1992-10-06	0.7	2.31	0.25	0.22	HSfM
2008-10-01	2.0	0.0	0.0	1.0	HSfM
2008-09-05	2.0	1.13	1.0	0.0	EarthDEM
2014-04-18	2.0	2.64	0.3	0.62	EarthDEM

Continued on next page

Table B.3: Mount Rainier. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs. (Continued)

Date	Resolution (m)	NMAD (m)	Stable ground coverage (%/100)	RGI coverage (%/100)	Source
2014-05-22	2.0	2.51	0.94	0.97	EarthDEM
2014-06-25	2.0	2.59	0.5	0.53	EarthDEM
2014-06-30	2.0	1.72	0.98	0.98	EarthDEM
2014-07-17	2.0	1.35	0.95	0.98	EarthDEM
2014-08-03	2.0	0.88	0.73	0.86	EarthDEM
2014-08-08	2.0	1.32	0.29	0.53	EarthDEM
2014-08-09	2.0	1.11	0.56	0.73	EarthDEM
2014-08-27	2.0	1.47	0.48	0.76	EarthDEM
2014-08-28	2.0	0.91	0.63	0.91	EarthDEM
2014-10-18	2.0	0.72	0.36	0.61	EarthDEM
2014-11-01	2.0	0.89	0.49	0.84	EarthDEM
2014-12-03	2.0	0.94	0.31	0.12	EarthDEM
2015-04-18	2.0	1.75	0.86	0.95	EarthDEM
2015-07-06	2.0	0.97	0.01	0.0	EarthDEM
2015-07-18	2.0	0.89	0.85	0.98	EarthDEM
2015-08-18	2.0	0.88	0.57	0.81	EarthDEM
2015-08-21	2.0	0.78	0.47	0.79	EarthDEM
2015-08-25	2.0	0.91	0.52	0.75	EarthDEM
2015-09-07	2.0	63.63	0.0	0.0	EarthDEM
2015-09-11	2.0	0.73	0.83	0.97	EarthDEM
2015-09-30	2.0	0.81	0.58	0.72	EarthDEM
2015-10-27	2.0	0.84	0.69	0.73	EarthDEM
2015-11-21	2.0	1.14	0.05	0.0	EarthDEM

Continued on next page

Table B.3: Mount Rainier. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs. (Continued)

Date	Resolution (m)	NMAD (m)	Stable ground coverage (%/100)	RGI coverage (%/100)	Source
2015-12-01	2.0	0.91	0.68	0.78	EarthDEM
2016-01-02	2.0	1.94	0.86	0.96	EarthDEM
2016-03-05	2.0	2.78	0.83	0.66	EarthDEM
2016-04-01	2.0	3.39	0.71	0.75	EarthDEM
2016-04-06	2.0	2.84	0.46	0.51	EarthDEM
2016-06-06	2.0	1.76	1.0	1.0	EarthDEM
2016-07-06	2.0	1.66	0.31	0.61	EarthDEM
2016-07-24	2.0	1.09	0.98	0.98	EarthDEM
2016-08-01	2.0	0.98	0.47	0.54	EarthDEM
2016-08-06	2.0	0.86	0.17	0.13	EarthDEM
2016-08-23	2.0	0.89	0.08	0.0	EarthDEM
2016-09-09	2.0	2.88	0.01	0.0	EarthDEM
2016-09-14	2.0	0.99	0.59	0.78	EarthDEM
2016-10-22	2.0	0.99	0.64	0.84	EarthDEM
2017-04-02	2.0	2.67	0.34	0.52	EarthDEM
2017-04-15	2.0	3.23	0.63	0.93	EarthDEM
2017-05-19	2.0	2.69	0.34	0.51	EarthDEM
2017-05-22	2.0	3.9	0.33	0.38	EarthDEM
2017-05-23	2.0	2.7	0.8	0.65	EarthDEM
2017-08-08	2.0	0.98	0.84	0.96	EarthDEM
2017-09-11	2.0	0.92	0.84	0.97	EarthDEM
2017-12-21	2.0	1.34	0.77	0.76	EarthDEM
2018-03-05	2.0	2.77	0.25	0.69	EarthDEM

Continued on next page

Table B.3: Mount Rainier. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs. (Continued)

Date	Resolution (m)	NMAD (m)	Stable ground coverage (%/100)	RGI coverage (%/100)	Source
2018-03-10	2.0	2.78	0.79	0.89	EarthDEM
2018-04-19	2.0	2.95	0.25	0.66	EarthDEM
2018-05-24	2.0	2.46	0.39	0.76	EarthDEM
2018-07-19	2.0	0.74	0.5	0.89	EarthDEM
2018-08-04	2.0	0.92	0.5	0.81	EarthDEM
2018-08-09	2.0	1.49	0.72	0.96	EarthDEM
2018-08-20	2.0	0.7	0.89	0.98	EarthDEM
2018-09-25	2.0	0.61	0.82	0.94	EarthDEM
2019-05-07	2.0	2.07	0.7	0.84	EarthDEM
2019-05-09	2.0	1.92	0.88	0.79	EarthDEM
2019-06-13	2.0	1.75	0.54	0.48	EarthDEM
2019-06-16	2.0	1.39	0.52	0.67	EarthDEM
2019-07-29	2.0	0.97	0.82	0.84	EarthDEM
2019-08-15	2.0	1.07	0.32	0.68	EarthDEM
2019-10-10	2.0	1.82	0.78	0.81	EarthDEM
2019-11-21	2.0	0.79	0.67	0.69	EarthDEM
2019-11-28	2.0	0.8	0.52	0.83	EarthDEM
2020-04-09	2.0	4.48	0.13	0.01	EarthDEM
2020-04-16	2.0	2.9	0.25	0.19	EarthDEM
2020-06-19	2.0	1.84	0.22	0.04	EarthDEM
2020-07-21	2.0	1.38	0.17	0.22	EarthDEM
2020-07-22	2.0	1.05	0.0	0.0	EarthDEM
2020-08-02	2.0	1.4	0.03	0.03	EarthDEM

Continued on next page

Table B.3: Mount Rainier. Table with acquisition date, resolution, NMAD, stable ground area coverage, RGI outline coverage, and source for input DEMs. (Continued)

Date	Resolution (m)	NMAD (m)	Stable ground coverage (%/100)	RGI coverage (%/100)	Source
2020-08-15	2.0	0.91	0.67	0.7	EarthDEM
2020-09-01	2.0	0.78	0.35	0.35	EarthDEM

B.3 Figures

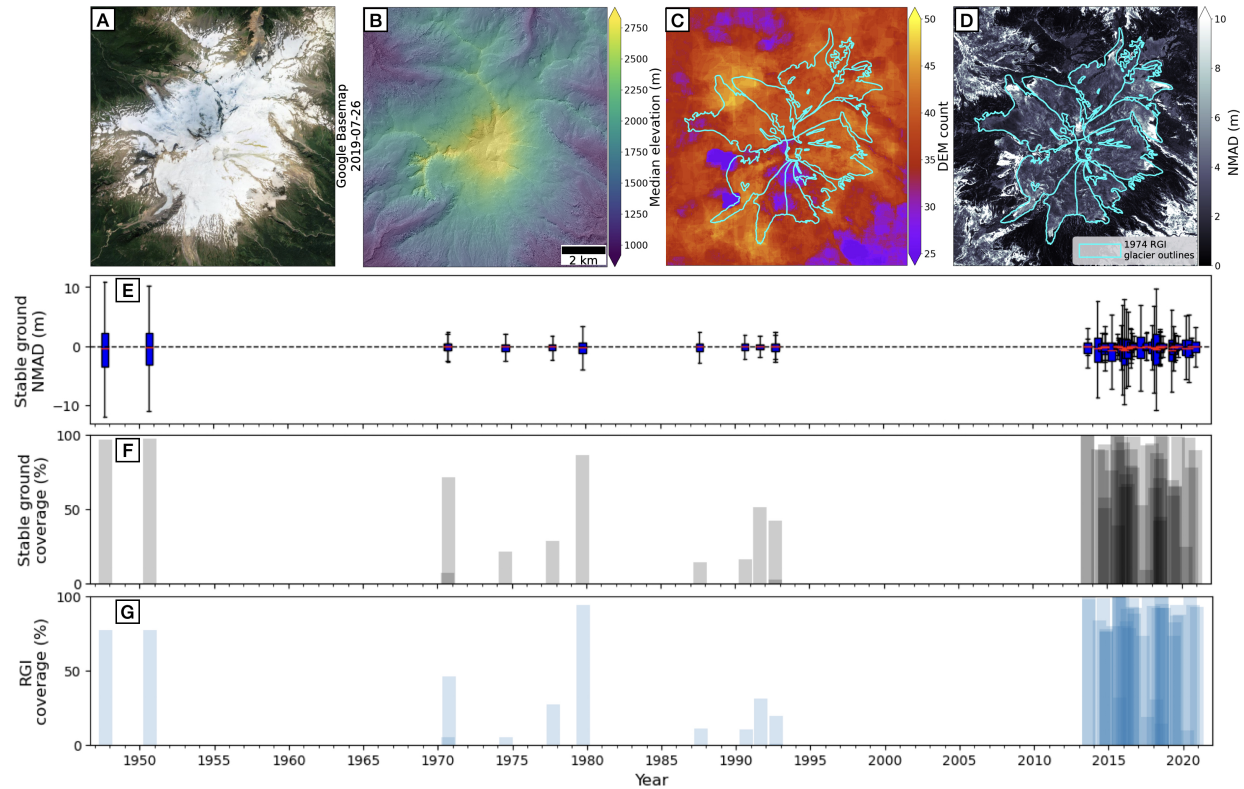


Figure B.1: A. Google satellite basemap for the Mount Baker site (imagery source date 2019-07-26). B. Median surface elevation of the 55 Digital Elevation Models (DEMs) in the 73-year time series stack (1947-09-14 to 2020-12-12). C. Per-pixel DEM count. D. Per-pixel normalized median absolute deviation (NMAD) of residuals between stable ground in DEMs and reference DEM. Both C. and D. show 1974 RGI glacier outlines in blue. E. Absolute accuracy metrics over stable ground surfaces for each DEM (DEM minus reference DEM). Boxes show interquartile range, with median values in red and whiskers at 1.5 times the interquartile range. F. Percent coverage of stable ground surface area (34.67 km²) in (129.31 km²) scene over which statistics shown in E are computed. G. Percent coverage of the 1974 RGI glacierized extent (39.75 km²) seen in C.

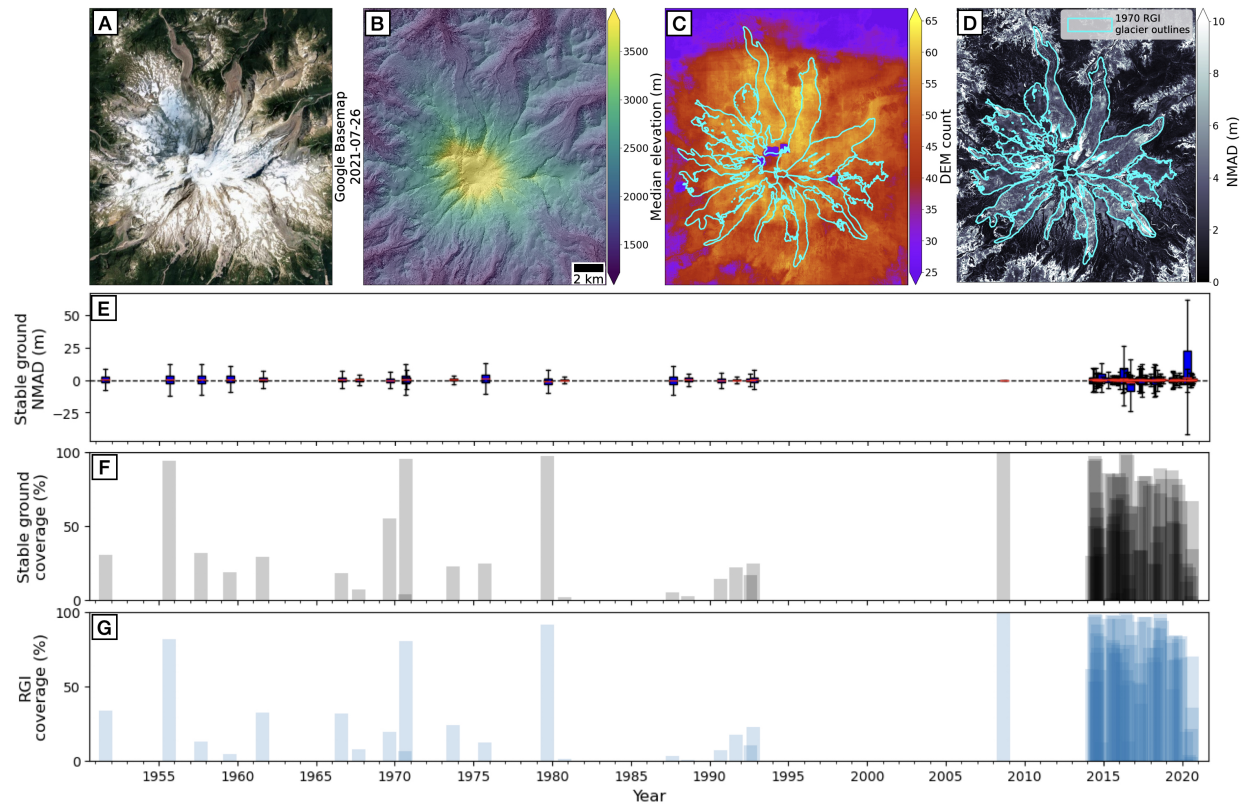


Figure B.2: A. Google satellite basemap for the Mount Rainier site (imagery source date 2021-07-26). B. Median surface elevation of the 94 Digital Elevation Models (DEMs) in the 69-year time series stack (1951-08-16 to 2020-09-01). C. Per-pixel DEM count. D. Per-pixel normalized median absolute deviation (NMAD) of residuals between stable ground in DEMs and reference DEM. Both C. and D. show 1970 RGI glacier outlines in blue. E. Absolute accuracy metrics over stable ground surfaces for each DEM (DEM minus reference DEM). Boxes show interquartile range, with median values in red and whiskers at 1.5 times the interquartile range. F. Percent coverage of stable ground surface area (134.42 km²) in (311.57 km²) scene over which statistics shown in E are computed. G. Percent coverage of the 1970 RGI glacierized extent (79.89 km²) seen in C.

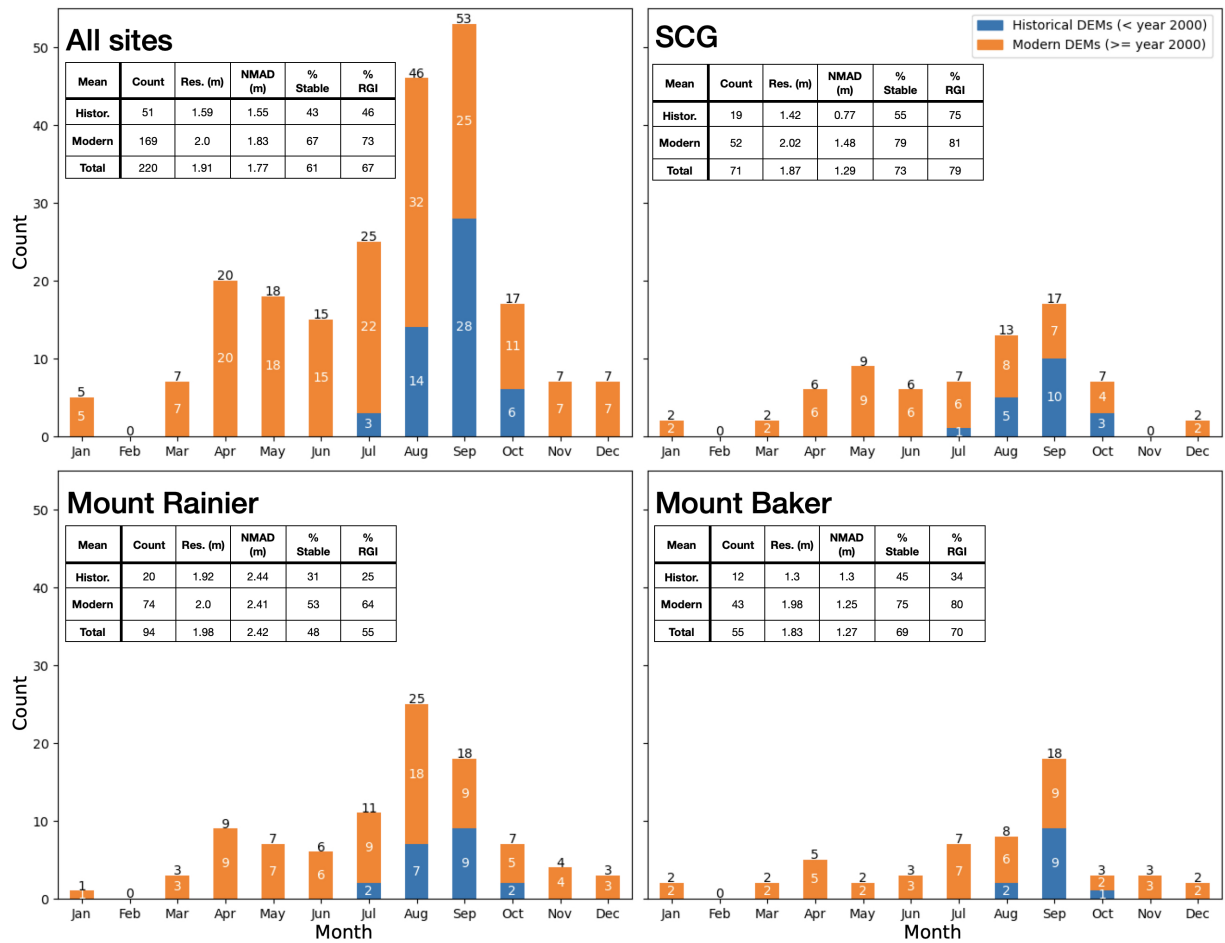


Figure B.3: Digital Elevation Model (DEM) count binned by month. Historical (pre year 2000) DEM bins in blue. Modern (year 2000 or after) DEM bins in orange. Total count per month listed at the top of each bin.

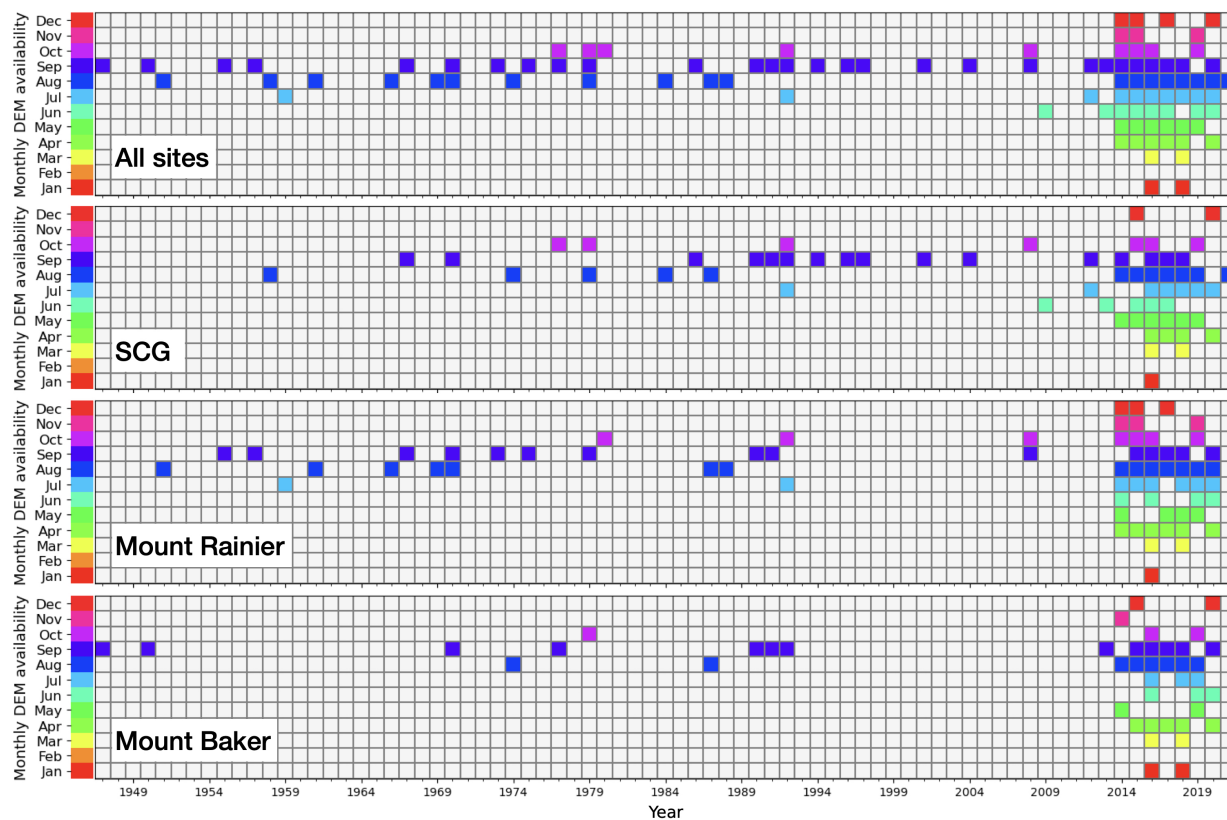


Figure B.4: Monthly DEM coverage by year.

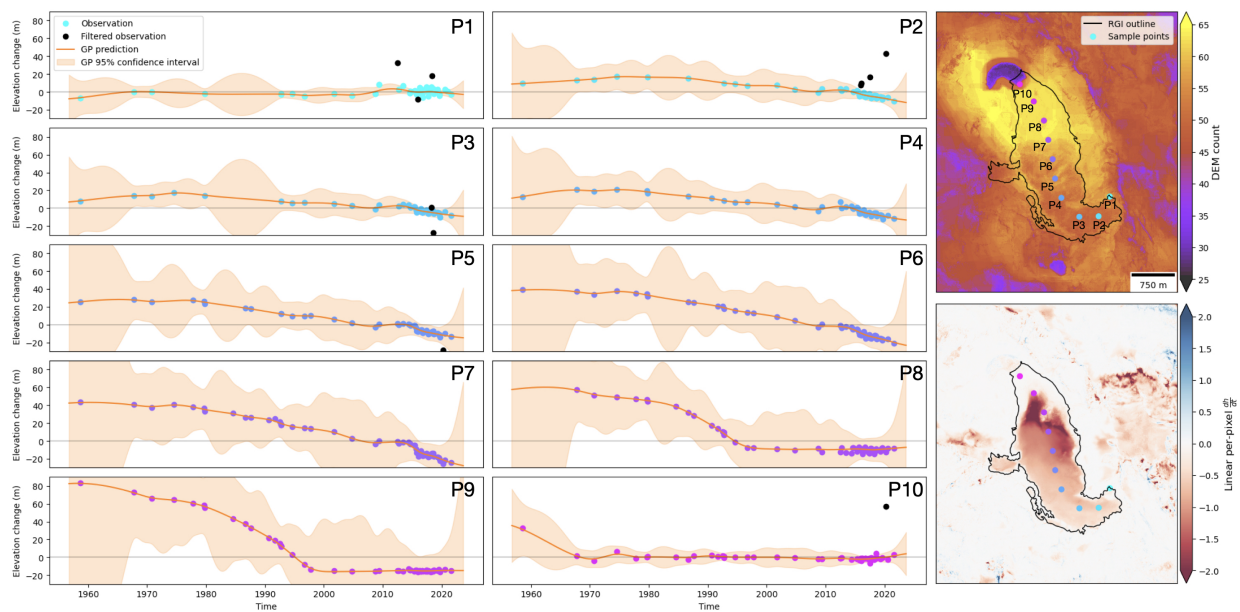


Figure B.5: A. Elevation change relative to mean elevation for ten points (P1-10) sampled along South Cascade glacier centerline with Gaussian Process (GP) prediction without periodic kernel shown with orange line and 95% confidence interval. Filtered outliers outside 3σ threshold shown in black. The σ value is the standard deviation for each estimate returned by the GP regression. C. Per-pixel DEM count and sample points. C. Per-pixel linear elevation change trend (1958-2021) and sample points.

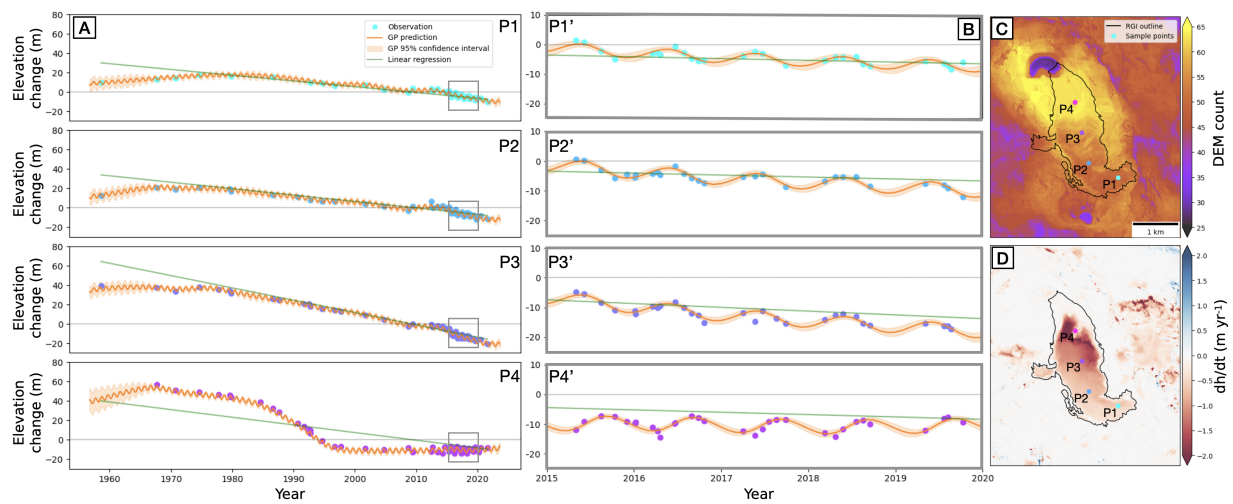


Figure B.6: Elevations at four points (P1-4) sampled along South Cascade Glacier centerline with Gaussian Process (GP) estimation shown with orange line and 95% confidence interval. Here, the dependant values (elevation) are not normalized by the *GaussianProcessRegressor* prior to GP regression, which results in a smaller confidence interval (Section 2.7.3.1). Column A. shows the full time series at each location. Column B. shows seasonal variability in a zoomed in temporal window from 2015 to 2020. C. Per-pixel DEM count and sample points. C. Per-pixel linear elevation change trend (dh/dt) from 1958 to 2021 and sample points.

Appendix C

**SUPPLEMENTARY MATERIAL FOR CHAPTER 3:
MEASURING LONG-TERM GEODETIC GLACIER MASS
BALANCE AND KINEMATICS AT HIGH SPATIOTEMPORAL
RESOLUTION**

C.1 Figures

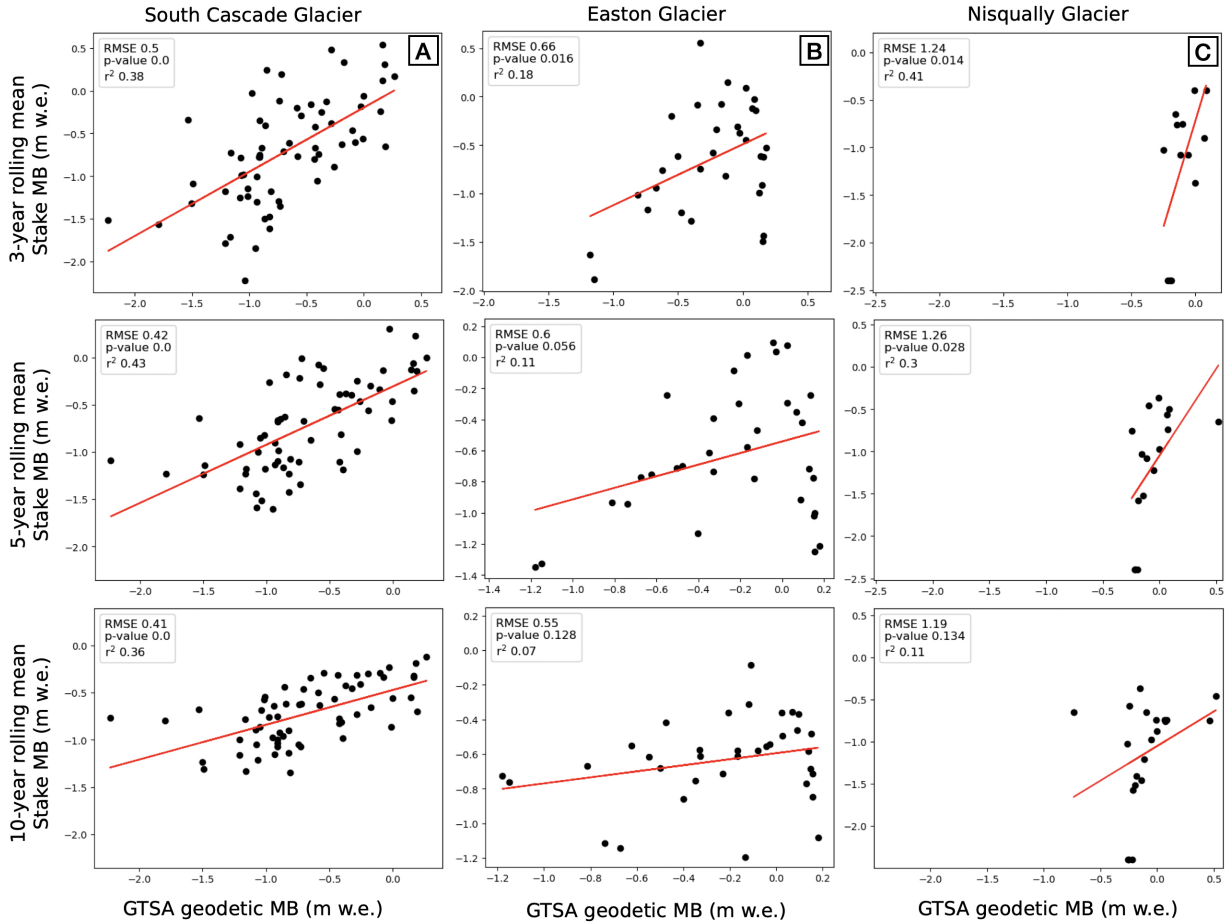


Figure C.1: Squared Pearson correlation coefficient (r^2), root mean squared error (RMSE), and p-values for 3, 5, and 10 year in-situ mass balance averages compared with geodetic mass balance derived from subtracting surfaces interpolated with Gaussian Process (GP) regression. Columns A, B, and C plot the time averaged in-situ mass balance on the y-axis and geodetic mass balance on the x-axis. The red line represents the least-squares regression line. South Cascade Glacier shows the highest r^2 (0.43) for the the 5-year averaging window. Easton Glacier and Nisqually Glacier show the highest r^2 (0.18 and 0.41, respectively) for the 3-year averaging window.

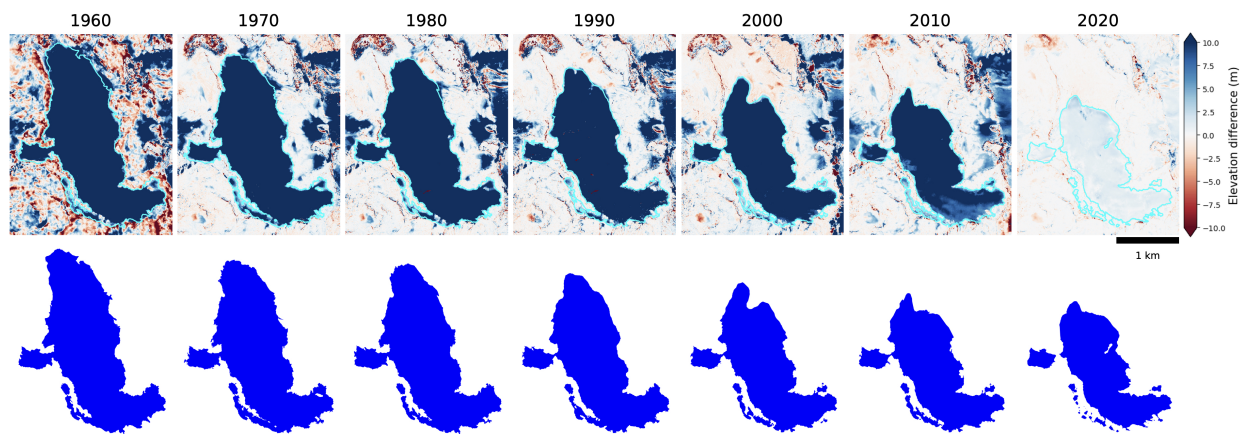


Figure C.2: Example glacier area outlines (7 of 63) for the South Cascade Glacier time series (1958–2021). Outlines were delineated from DEM difference maps created by subtracting the DEM with minimum glacier extent (2021). Top row shows DEM difference maps and glacier outline in light blue for first year in each decade (1960–2020). Bottom row shows glacier outline in blue.

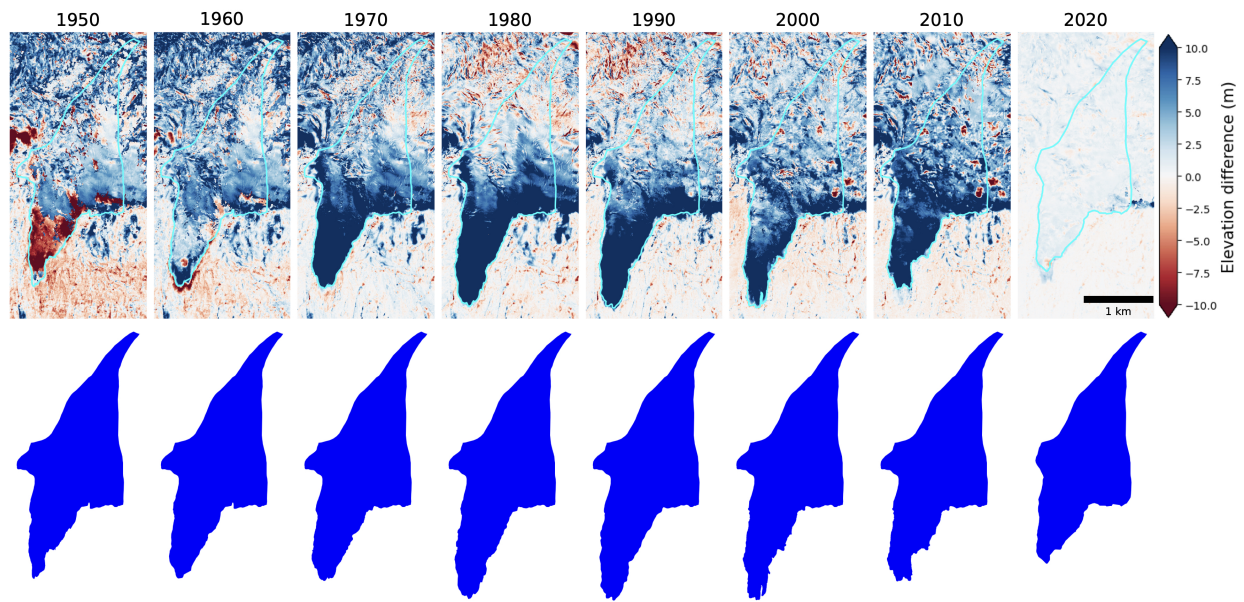


Figure C.3: Example glacier area outlines (8 of 73) for the Easton Glacier time series 1947–2020. Outlines were delineated from DEM difference maps created by subtracting a DEM with minimum glacier extent (2021). To obtain a synthetic DEM and compute the 2020 DEM difference map and outline, we used the Gaussian Process regression to estimate a synthetic surface for 2021, which is beyond the temporal bounds of the input DEM time series. Top row shows DEM difference maps and glacier outline in light blue for first year in each decade (1950–2020). Bottom row shows glacier outline in blue.

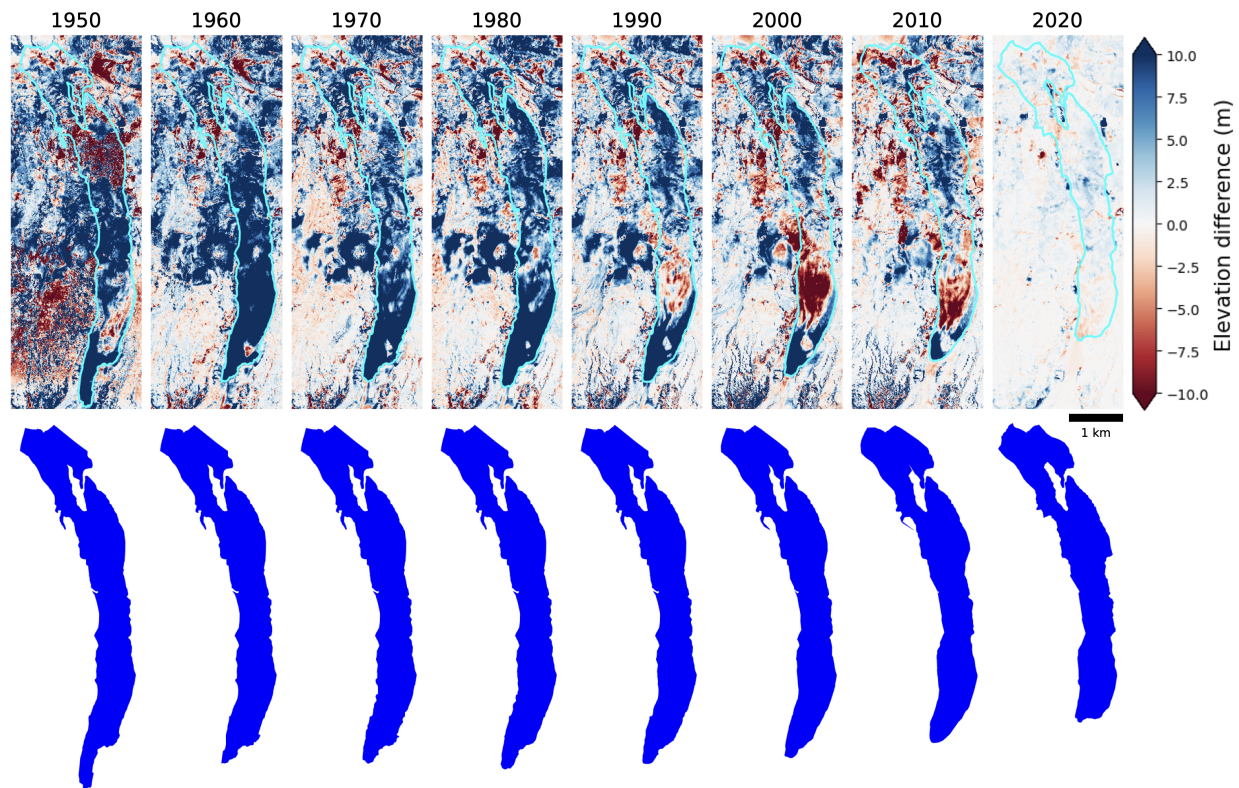


Figure C.4: Example glacier area outlines (8 of 69) for the Nisqually Glacier, time series 1947–2020. Outlines were delineated from DEM difference maps created by subtracting DEM with minimum glacier extent (2021). To obtain a synthetic DEM and compute the 2020 DEM difference map and outline, we used the Gaussian Process regression to estimate a synthetic surface for 2021, which is beyond the temporal bounds of the input DEM time series. Top row shows DEM difference maps and glacier outline in light blue for first year in each decade (1950–2020). Bottom row shows glacier outline in blue.

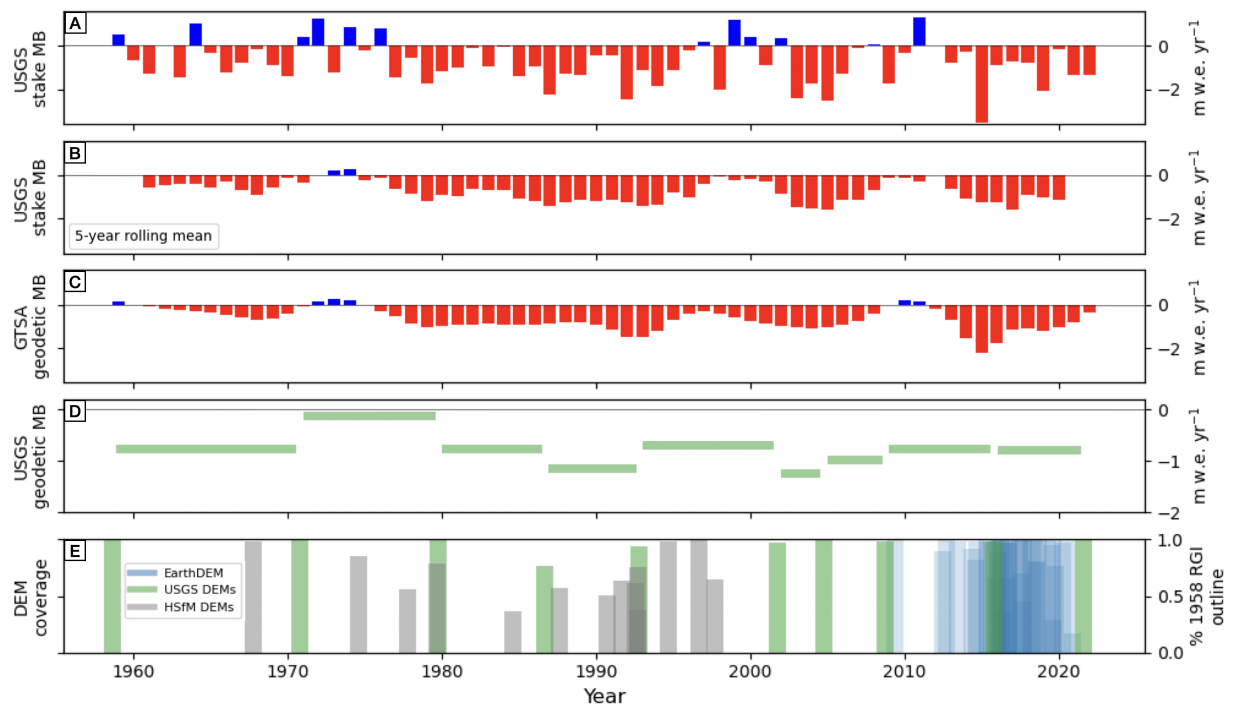


Figure C.5: Enhanced temporal resolution of geodetic mass balance. A. Annual in-situ mass balance time series at South Cascade Glacier (SCG, McNeil et al., 2022b). B. Five-year point-centered rolling mean of A. C. Annual geodetic mass balance from DEM surfaces interpolated with Gaussian Process regression. D. Geodetic mass balance from USGS geodetic data release (McNeil et al., 2022a). E. Percent coverage of RGI SCG glacier extent (RGI60-02.18778, 2.92 km², dated 1958). The geodetic mass balance in D is computed from the USGS DEMs with full glacier coverage shown in E. Panel C. shows the enhanced temporal resolution of geodetic mass balance computed from the augmented and interpolated DEM time series.

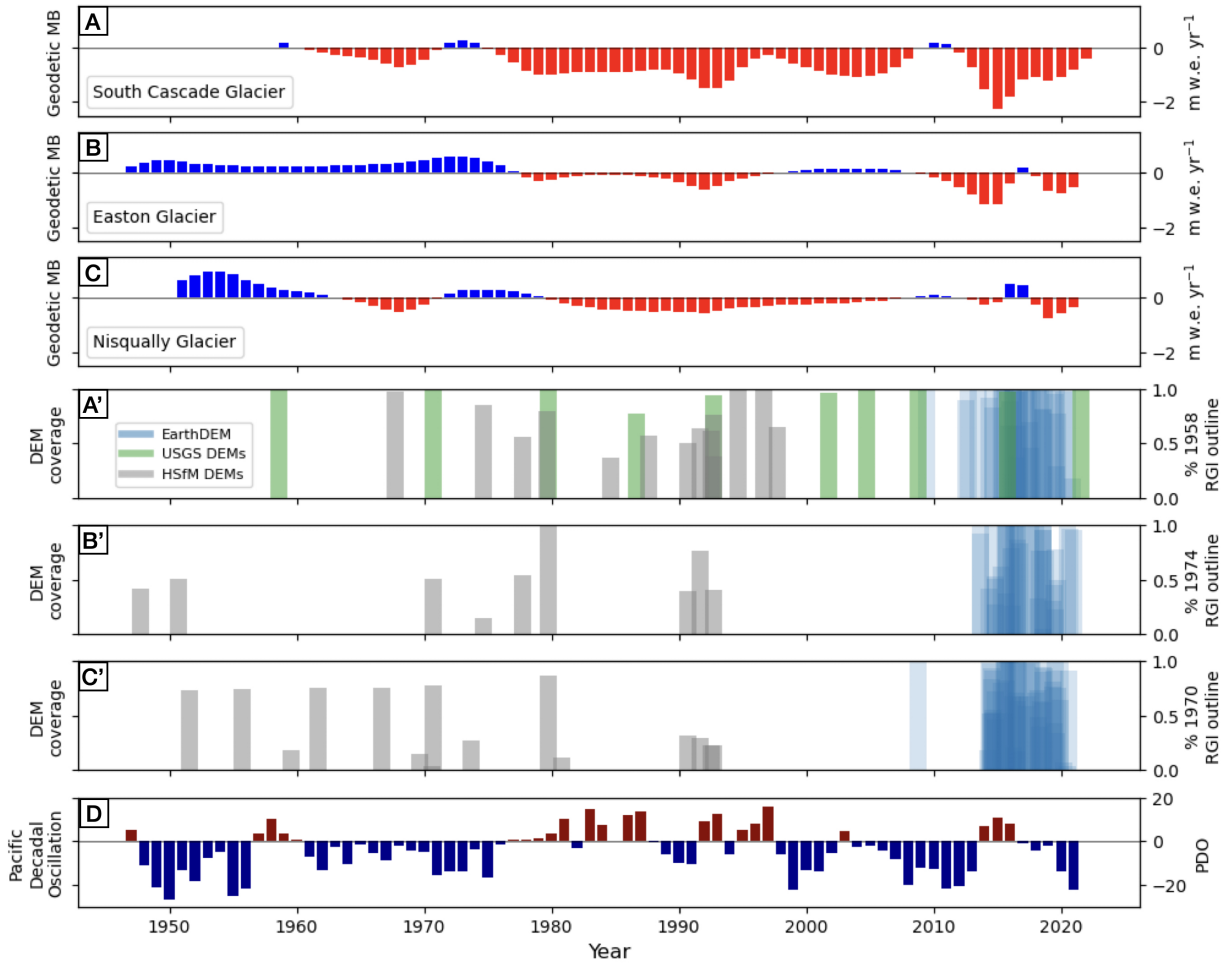


Figure C.6: Annual geodetic mass balance from DEM surfaces interpolated with Gaussian Process regression at A. South Cascade Glacier, B. Easton Glacier, and C. Nisqually Glacier. Panels A', B', and C' show the respective input DEM coverage of RGI outlines (RGI60-02.18778, RGI60-02.17739, RGI60-02.14336). D. Pacific Decadal Oscillation (PDO).