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**Using High-Resolution Satellite Observations to Better Understand Surface
Melt Processes on the Greenland and Antarctic Ice Sheets**

A Dissertation submitted in partial satisfaction
of the requirements for the degree
Doctor of Philosophy

in

Earth Sciences

by

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2024

Using High-Resolution Satellite Observations to Better Understand Surface Melt
Processes on the Greenland and Antarctic Ice Sheets

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The dissertation of Philipp S. Arndt is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

University of California San Diego

2024

DEDICATION

To my coffee maker, Giulia.

TABLE OF CONTENTS

Dissertation Approval Page.....	iii
Dedication.....	iv
Table of Contents.....	v
List of Figures.....	xi
List of Tables.....	xiii
List of Abbreviations.....	xiii
Acknowledgements.....	xviii
Vita.....	xxii
Abstract of the Dissertation.....	xxiii
Chapter 1 Introduction.....	1
1.1 Motivation: the ice sheets and their role in the Earth system	1
1.1.1 The Greenland and Antarctic ice sheets	1
1.1.2 Ice sheet mass loss and global sea level rise	2
1.2 Surface melt as a major source of uncertainty in future ice sheet projections	5
1.2.1 Greenland surface melt and ice dynamics	6
1.2.2 Antarctic surface melt and ice shelf collapse	7
1.3 Environmental controls on supraglacial lake formation	12
1.3.1 Controls on surface temperature and melt	13
1.3.2 Controls on surface permeability and firn saturation	15
1.3.3 Controls on the presence of surface depressions	16
1.4 Satellite remote sensing of surface melt features	18
1.4.1 Methods for observing the spatial extent of meltwater	19

1.4.2	Methods for estimating meltwater depths	20
1.5	Summary of the dissertation	22
Chapter 2	A Framework for Automated Supraglacial Lake Detection and Depth Retrieval in ICESat-2 Photon Data Across the Greenland and Antarctic Ice Sheets.....	24
2.1	Introduction	25
2.2	Background	29
2.2.1	How supraglacial lakes affect ice sheet mass loss	29
2.2.2	Observations of supraglacial lake depths	32
2.3	Data and methods	34
2.3.1	ICESat-2	35
2.3.2	Supraglacial lake detection in ATL03: the FLUID algorithm	38
2.3.2.1	FLUID step 1: identification of flat water surfaces	39
2.3.2.2	FLUID step 2: removal of afterpulses	42
2.3.2.3	FLUID step 3: photon signal confidence estimation	47
2.3.2.4	FLUID step 4: secondary bathymetry peak detection	48
2.3.2.5	FLUID step 5: along-track aggregation of lake segments	51
2.3.3	Supraglacial lake depth determination: the SuRRF algorithm	53
2.3.3.1	SuRRF Robust Fit	54
2.3.3.2	SuRRF step 1: lake surface fit	56
2.3.3.3	SuRRF step 2: lakebed fit	57
2.3.3.4	SuRRF step 3: bathymetry signal confidence estimation	59
2.3.3.5	SuRRF step 4: water depth calculation	59
2.3.3.6	SuRRF step 5: lake segment quality estimate	60
2.3.4	Computational implementation of FLUID/SuRRF	61
2.3.5	Study regions and time span	63
2.4	Results and discussion	64
2.4.1	FLUID lake detection and accuracy	65
2.4.1.1	FLUID lake segment detection	65

2.4.1.2	Accuracy of FLUID lake segment detection	67
2.4.2	SuRRF depth retrieval and accuracy	73
2.4.2.1	SuRRF: meltwater depths	73
2.4.2.2	Accuracy of SuRRF depth retrievals and comparison with alternative methods	74
2.4.3	ICESat-2 bathymetry over other targets	80
2.4.4	Future studies	81
2.5	Summary	82
2.6	Code and data availability	83
2.7	Appendix A: photon density ratios in FLUID flatness check	85
2.8	Appendix B: photon signal confidences in FLUID	85
2.9	Appendix C: FLUID bathymetry check quality heuristics	87
2.10	Acknowledgements	91

Chapter 3 Five Years of ICESat-2 Supraglacial Lake Depth Measurements Across the Greenland Ice Sheet Improve Surface Meltwater Volume Estimates from Satellite Imagery 93

3.1	Introduction	94
3.2	Data and methods	96
3.2.1	ICESat-2 laser altimetry over supraglacial lakes	97
3.2.2	ICESat-2 lake detection and depth retrieval algorithm	98
3.2.3	Ice-sheet-wide retrieval of ICESat-2 lake depth measurements	99
3.2.4	Assessment of controls on spatiotemporal distribution and depth of ICESat-2 lake segments	100
3.2.5	Fusion of ICESat-2 depth measurements with Sentinel-2 imagery	104
3.2.6	Random forest model for predicting water depth from Sentinel-2	104
3.2.6.1	Feature engineering	104
3.2.6.2	Sample selection for training	105
3.2.6.3	Fitting the model	106

3.2.7	Random forest model validation	107
3.2.8	Comparison to previous empirical fitting methods: the band-ratio .	108
3.2.9	Comparison to independent RTE-based estimates	109
3.3	Results and discussion	110
3.3.1	Pan-Greenland ICESat-2 lake depths, 2019-23	110
3.3.1.1	Spatial distribution of lake segments across Greenland . .	111
3.3.1.2	Spatiotemporal patterns in lake depths	112
3.3.1.3	Distribution of lake depths with elevation	117
3.3.1.4	Timing and trends in lake formation	118
3.3.2	Random forest model performance	119
3.3.2.1	Cross validation	121
3.3.2.2	Validation against <i>in situ</i> data	122
3.3.2.3	Comparison to the band-ratio method	122
3.3.2.4	Comparison to independent RTE-based methods	126
3.4	Summary	130

Chapter 4 Lakes, Dolines and Benches: New Insights Into Antarctic Ice Shelf Mass Balance Processes Using High-Resolution 3D Satellite Observations 137

4.1	ICESat-2 supraglacial lake depth measurements across Antarctica	138
4.1.1	Introduction: surface melt on the Antarctic Ice Sheet	138
4.1.2	Data and methods	141
4.1.2.1	ICESat-2 lake detection and depth retrieval algorithm . .	142
4.1.2.2	Ice-sheet-wide retrieval of ICESat-2 lake depth measurements	142
4.1.3	Assessment of controls on spatiotemporal distribution and depth of ICESat-2 lake segments	144
4.1.4	Results and discussion	145
4.1.4.1	Spatial distribution of lake segments across Antarctica . .	148
4.1.4.2	Distribution of lake depths with elevation and distance from the grounding line	156

4.1.4.3	Timing and trends in lake formation	158
4.1.5	Summary and future work	162
4.2	Observations of ice doline formation	165
4.2.1	Antarctic surface melt and through-ice-shelf lake drainage	165
4.2.2	Early observations of ice doline features	165
4.2.3	Ice shelf collapse by hydrofracture	167
4.2.4	Direct observation of an ice doline formation on Amery Ice Shelf	168
4.2.5	Continent-wide satellite observations of ice doline formations	174
4.2.5.1	Compilation of the doline formation inventory	174
4.2.5.2	Spatiotemporal distribution and typical characteristics of doline observations	175
4.2.6	Observational data of ice shelf flexure	177
4.2.7	Implications for ice shelf stability	183
4.2.8	Summary and future work	186
4.3	ICESat-2 bathymetry measurements of ice shelf benches	187
4.3.1	Introduction: buoyancy-driven ice shelf flexure and calving	187
4.3.2	Data and methods	189
4.3.3	Results and discussion	189
4.3.4	Summary and future outlook	191
4.4	Acknowledgements	194
Chapter 5	Summary and Conclusions	195
5.1	Summary	195
5.2	Methodological and observational advancements	197
5.2.1	Leverage of ICESat-2's unique bathymetric capabilities	197
5.2.2	Generation of large-scale data products	198
5.2.3	Expansion of surface meltwater observations to high latitudes	199
5.2.4	Data fusion and machine learning for meltwater volume estimates	200
5.2.5	Observational strategies for Surface Topography and Vegetation	201

5.3	Geographical distribution, depths and temporal evolution of lakes on both ice sheets	202
5.3.1	Controls on geographical distribution of lakes	203
5.3.2	Controls on maximum lake depths	204
5.3.3	Intra-seasonal evolution of supraglacial hydrology	206
5.3.4	Greenlandification: insights from present-day Greenland for the future of Antarctica	208
5.4	Future work	209
5.4.1	Cross-ice-sheet data products and studies	210
5.4.2	Regionally-focused and process-scale studies	212
5.4.2.1	Regional drivers of lake formation and depth in Greenland	212
5.4.2.2	Hydrological processes on grounded ice in Antarctica . . .	213
5.4.2.3	Meltwater routing and ice shelf stability	213
5.4.2.4	Potential links between buoyancy-driven calving and hydrofracture	214
5.4.3	Recommendations for field measurements	215
5.4.3.1	Field campaigns in Greenland: focus on ICESat-2 validation	215
5.4.3.2	Field campaigns in Antarctica: focus on the impacts of lake drainage	216
5.4.4	Enabling data-driven polar exploration	217
5.5	Conclusion	219
	References	219

LIST OF FIGURES

1.1	Global mean sea level change in meters, relative to 1900	4
1.2	Impacts of melt-driven ice sheet processes on mass balance and stability . .	10
2.1	An Ice, Cloud and land Elevation Satellite 2 (ICESat-2) ATL03 data segment over a supraglacial lake	27
2.2	Study regions for testing the Flat Lake and Underlying Ice Detection (FLUID) / Surface Removal and Robust Fit (SuRRF) framework.	30
2.3	Flowchart of the FLUID/SuRRF framework.	36
2.4	Illustration of the FLUID “flatness check”	41
2.5	FLUID afterpulse removal	45
2.6	ATL03 photon signal confidence estimates	48
2.7	Illustration of the FLUID bathymetric signal check.	50
2.8	Illustration of the SuRRF algorithm for determining supraglacial lake depth	54
2.9	Maps and examples of FLUID/SuRRF outputs for Central West Greenland	68
2.10	Maps and examples of FLUID/SuRRF outputs for the Amery Catchment, East Antarctica	70
2.11	SuRRF lake segment depth statistics for two study regions in high and low melt years	74
2.12	Comparison between SuRRF water depth estimates, manually annotated ICESat-2 depths and results from other methods	76
S2.1	Illustration of ICESat-2’s beam geometry	92
3.1	Pan-Greenland ICESat-2 supraglacial lake depth dataset	102
3.2	Spatiotemporal variability and trends in the ICESat-2 supraglacial lake depth dataset	114
3.3	Validation of random forest depth predictions with <i>in situ</i> sonar data . . .	124
3.4	Comparison between random forest model predictions and RTE estimates for the depth of nine supraglacial lakes in Greenland and Antarctica	128
S3.1	Random forest performance during Recursive Feature Elimination	135
S3.2	ICESat-2 depths vs. depth predicted by random forest and the band-ratio method	136
S3.3	ICESat-2 depths vs. band-ratio for individual lake segments and Sentinel-2 scenes	136
4.1	Pan-Antarctic ICESat-2 supraglacial lake depth dataset.	146
4.2	Spatiotemporal variability and trends in the Antarctic-wide supraglacial lake depth dataset	152
4.3	Regional interannual trends in meltwater extent in the ICESat-2 data . . .	162
4.4	A schematic for the ice dooline formation mechanism	166
4.5	ICESat-2 data for an ice dooline formation on Amery Ice Shelf	170
4.6	First melt season after the ice dooline formation on Amery (2019/2020). . .	172

4.7	Locations of doline formation events observed by satellites	176
4.8	Comparison between ICESat-2 data over a doline and modeled ice shelf flexure	181
4.9	Two opposing effects of doline formation on ice shelf stability	183
4.10	Lagrangian elevation change measurements for four doline formation events, from WorldView Stereophotogrammetry.	184
4.11	Schematic of buoyancy-driven ice shelf flexure at a calving front with a sub- merged bench	188
4.12	Three examples of ICESat-2 observations of ice shelf benches in East Antarctica	192

LIST OF TABLES

2.1	Summary statistics for the ICESat-2 lake segments extracted by FLUID / SuRRF.	65
S3.1	Statistics for Greenland ICESat-2 lake depth segments by melt season and drainage basin	134
4.1	Statistics for Antarctic ICESat-2 lake depth segments by melt season and individual study regions	151
4.2	Satellite observations of doline formation events across Antarctica.	178

LIST OF ABBREVIATIONS

AI	Artificial Intelligence..... 91
AIS	Antarctic Ice Sheet 1
AOT	Aerosol Optical Thickness, Sentinel-2 L2A band 105
API	Application Programming Interface 61, 62
AR6	Sixth Assessment Report 25
ArcticDEM	Arctic Digital Elevation Model 63, 76, 79, 84, 99, 132
ATL03	ATLAS/ICESat-2 Global Geolocated Photon Data Product 24, 27, 29, 34, 35, 37–39, 41–48, 50, 52, 54, 56–58, 61, 62, 64, 67, 68, 70, 72, 75–78, 80, 81, 83, 84, 96, 98, 99, 102, 106, 111, 128, 131, 134, 142, 144–146, 151, 172, 181, 189, 192, 199
ATL06	ATLAS/ICESat-2 L3A Land Ice Height..... 37, 97, 98, 181
ATLAS	Advanced Topographic Laser Altimeter System 35, 37, 43, 45, 58, 72, 77, 97
AWS	Amazon Web Services 132
B-C	Antarctic IMBIE Drainage Basin Feeding into the Amery Ice Shelf, East Antarctica 30, 63, 65, 70, 149, 151
CMIP	Coupled Model Intercomparison Project..... 4
COVID-19	COronaVirus Disease of 2019 xix
CV	Cross-Validation..... 107
CW	Central West (Greenland drainage basin) 30, 63, 65
DEM	Digital Elevation Model 20, 34, 75, 78, 80, 84, 123, 169, 174, 177, 182
dHTC	distributed High-Throughput Computing 35, 62, 99, 144, 199
DNF	Did Not Finish (major frame data transfer error in the context of ICESat-2) 72
EAIS	East Antarctic Ice Sheet 1
EDGE	Earth Dynamics Geodetic Explorer 198
FINESST	Future Investigators in NASA Earth and Space Science xx
FLUID	Flat Lake and Underlying Ice Detection xi, xiii, 24, 25, 30, 34, 36, 38, 41, 42, 44, 45, 48–58, 61–68, 70, 72–75, 80–85, 87, 98, 99, 102, 105, 106, 110, 132, 141, 142, 145, 189, 191, 195, 196
GB	gigabyte 38
GEDI	Global Ecosystem Dynamics Investigation 197
GEE	Google Earth Engine..... 120, 131, 174
GIMP	Greenland Ice Mapping Project 99, 132
GPT	generative pre-trained transformer 91
GrIS	Greenland Ice Sheet 1

GT	Ground Track..... 35, 41, 45, 48, 50, 54, 67, 72, 74, 170, 172, 180
GTNX	ICESat-2 numbered Ground Track..... 35
HAJMPT	Hayden A. Johnson Memorial Picnic Table..... xviii
HDF5	Hierarchical Data Format version 5 62
ICESat	Ice, Cloud and land Elevation Satellite..... 174, 197
ICESat-2	Ice, Cloud and land Elevation Satellite 2 xi–xiii, xx, xxiv, 21, 22, 24–37, 39, 41–43, 45–55, 57–67, 69, 71–85, 87, 89, 91, 93–115, 117–119, 121–123, 125–135, 137, 138, 140–146, 148–152, 154–156, 158, 160–164, 168–170, 172, 174, 177, 178, 180–183, 188–192, 195–197, 202
IMBIE	Ice Sheet Mass Balance Inter-comparison Exercise... 30, 63, 99, 102, 142, 146, 178
InSAR	Interferometric Synthetic Aperture Radar..... 174, 179
IPCC	United Nations Intergovernmental Panel on Climate Change 4, 5, 25
ISEO	International Services and Engagement Office xix
ITS_LIVE	Inter-mission Time Series of Land Ice Velocity and Elevation... 169
K-D tree	K-Dimensional Tree 48
KML	Keyhole Markup Language..... 85, 132
kNN	k-Nearest Neighbors 48
L1C	Level-1C, data processing level for Sentinel-2 data products 104, 131
L2A	Level-2A, data processing level for Sentinel-2 data products 104, 105, 107, 131
LOWESS	LOcally WEighted Scatterplot Smoothing..... 54
MAE	Mean Absolute Error 75, 77, 78, 80, 120–122, 126
MEaSURES	Making Earth System Data Records for Use in Research Environments Program..... 169
MESOM	Marine Ecosystem Sensing, Observation and Modeling laboratory ... xviii
MICI	Marine Ice Cliff Instability 8, 32
ML	Machine Learning..... 94
MLP	Multi-Layer Perceptron..... 121
MODIS	Moderate Resolution Imaging Spectroradiometer.. 19, 146, 156, 174, 179
MSK_CLDPRB	Cloud Probability Mask, Sentinel-2 L2A band 105
MSK_SNWPRB	Snow Probability Mask, Sentinel-2 L2A band 105
NASA	National Aeronautics and Space Administration xx, xxiv, 21, 26, 83, 91, 94, 95, 132, 169
NDWI	Normalized Difference Water Index 105, 106
NSF	National Science Foundation..... xx

NSIDC	National Snow and Ice Data Center	61, 62, 84, 131, 132
OLS	Ordinary Least Squares	100, 117, 144
OSG	Open Science Grid . xx, 35, 36, 61, 62, 84, 91, 99, 111, 132, 144, 145, 199	
OSPool	Open Science Pool	xx, 35, 61, 99, 144, 199
PCE	Photon Counting Electronics	72
PGC	Polar Geospatial Center	132
PLS	Plain Language Summary	94
PMT	Photomultiplier Tube	37, 43, 45, 46
RAA	Relative Azimuth Angle	135
RACMO2	Regional Atmospheric Climate Model 2	165
REMA	Reference Elevation Model of Antarctica . 64, 84, 143, 174, 176, 179, 182	
RF	Random Forest	96
RFE	Recursive Feature Elimination	107, 119, 120
RGT	Reference Ground Track	37, 64, 97, 99, 143
RMSE	Root Mean Square Error	121, 122
RTE	Radiative Transfer Equation . . xi, 20, 33, 75, 76, 78–80, 93–97, 109, 110, 126–128, 130–132, 201	
s2cloudless	algorithm for computing cloud masks on Sentinel-2 imagery 104, 105, 135	
S3	Amazon Simple Storage Service	132
SAA	Solar Azimuth Angle	105
SALSA	Subglacial Antarctic Lakes Scientific Access	xx
SAR	Synthetic Aperture Radar	19, 175, 199
SCL	Scene Classification map, Seninel-2 L2A band	105
SDB	Satellite-Derived Bathymetry	80
SIO	Scripps Institution of Oceanography	xviii
SMB	Surface Mass Balance	165, 167
SROCC	Special Report on the Ocean and Cryosphere in a Changing Climate 5	
SSP	Shared Socioeconomic Pathways	4
STV	Surface Topography and Vegetation (NASA targeted observable) 202	
SuRRF	Surface Removal and Robust Fit xi, xiii, 24, 25, 30, 35, 36, 38, 53, 54, 56–58, 61–63, 65, 66, 68, 70, 72–84, 98, 99, 102, 106, 110, 132, 141, 142, 145, 146, 189, 191, 195, 196	
SZA	Solar Zenith Angle	105, 135
TB	terabyte	64, 99, 111, 144, 145
TG	Thank god it’s Friday happy hour	xviii

UAW	United Automobile Workers.....	xix
UCSD	University of California San Diego	xix
VAA	View Azimuth Angle	105
VZA	View Zenith Angle.....	105, 135
WAIS	West Antarctic Ice Sheet	xx, 1
Watta	ICESat-2-based supraglacial water depth algorithm developed by Tri Datta and Bert Wouters.....	76, 78, 79
WVP	Water Vapor Pressure, Sentinel-2 L2A band	105
YAPC	Yet Another Photon Classifier	47

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ABSTRACT OF THE DISSERTATION

Using High-Resolution Satellite Observations to Better Understand Surface Melt Processes on the Greenland and Antarctic Ice Sheets

by

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The Greenland and Antarctic ice sheets are losing mass at increasing rates and are projected to become the dominant contributors to global sea-level rise throughout the 21st century, with widespread impacts on coastal communities. Large uncertainties in future projections of the contributions of ice sheet mass loss make it challenging for policymakers and coastal planners to adopt adequate adaptation strategies. This uncertainty stems from poorly understood mass loss processes, many of which are driven by surface melt and

meltwater pooling in supraglacial lakes, which can drastically affect ice sheet stability but are not yet well represented in models of future ice sheet evolution. To better understand these processes, continuous monitoring of supraglacial lakes across the ice sheets is critical. Given the vast and remote nature of the ice sheets, satellite remote sensing is the only feasible tool for this task. While methods for monitoring meltwater extent are well established, determining meltwater volumes has been more difficult due to large uncertainties in indirect estimates of water depths. The launch of NASA's ICESat-2 laser altimeter in 2018 enabled the first direct measurements of water depths from space. This dissertation develops an automated framework for detecting supraglacial lakes and determining their depths using ICESat-2 data. Applied to both ice sheets from November 2018 to September 2023, this framework produces a comprehensive dataset of lake depths. The data are then used to train a machine learning model that estimates lake depths from passive optical imagery, reducing errors by 60 % compared to traditional methods. Additionally, the dissertation provides observational evidence of ice shelf flexure due to ice dooline formation and submerged benches along calving fronts, which cause buoyancy-driven flexure and calving. These results highlight the value of using multi-sensor, high-resolution satellite data in observing critical meltwater-driven ice sheet processes. We expect that they will contribute to improving model projections of sea level rise by providing a better understanding of complex ice sheet processes that have potentially dramatic impacts on mass loss and stability.

CHAPTER 1: INTRODUCTION

1.1. Motivation: the ice sheets and their role in the Earth system

1.1.1. The Greenland and Antarctic ice sheets

Ice sheets are vast masses of glacial land ice, defined as covering areas greater than $50,000 \text{ km}^2$, which move outward in all directions from a central accumulation zone (Rafferty, 2024). Currently, there are two primary ice sheets on Earth: the Greenland Ice Sheet (GrIS) in the Northern Hemisphere and the Antarctic Ice Sheet (AIS) in the Southern Hemisphere. The AIS is further subdivided into the WAIS and the East Antarctic Ice Sheet (EAIS). Collectively, these ice sheets store approximately 69% of the Earth's freshwater (Gleick, 1996), and over 99% of the planet's freshwater ice (Frezzotti and Orombelli, 2014). In many regions, the ice exceeds 2,000 m in thickness, with the thickest ice in East Antarctica reaching over 4,800 m (Fretwell et al., 2013). Accumulation of ice occurs primarily through snowfall in the interior regions, which then flows outward under the influence of gravity, deforming internally and sliding along the bedrock towards the coast (Rignot et al., 2011a).

A key difference between the GrIS and the AIS is their bed topography. While the Greenland Ice Sheet is largely grounded on bedrock above sea level (Morlighem et al., 2017), substantial portions of West Antarctica and parts of East Antarctica are grounded below sea level, with some areas extending more than 3,500 m below sea level (Allison et al., 2009; Morlighem et al., 2020). Much of the Greenland Ice Sheet's margin is located on land, with

land ice typically reaching the ocean via narrow fast-flowing outlet glaciers, where ice is lost via calving (Rignot et al., 2011a; Straneo and Heimbach, 2013). In contrast, around most of Antarctica, grounded ice flows across the coastline, where it starts floating atop the surrounding ocean, forming ice shelves that fringe 75% of the continent and cover an area comparable in size to the entire Greenland Ice Sheet (> 1.561 million km^2 ; Swithinbank, 1988; Barkov and Korotkevich, 1985). Ice shelves experience resistive forces through interactions with topography, which reduces the velocity of grounded ice flowing into the ocean compared to scenarios where no ice shelf is present (Scambos et al., 2004). This process, referred to as "buttressing" (e.g., Thomas, 1979; Gudmundsson, 2013; Goldberg, 2017), plays a critical role in regulating ice flow. The point at which grounded ice begins to float is called the grounding line (Van der Veen, 2013). As such, ice shelves act as the final barrier preventing grounded ice from flowing directly into the ocean and increasing sea levels.

The differences in ocean and atmospheric forcing, bed topography and ice dynamics between Greenland and Antarctica lead to distinct behaviors of these ice sheets, with Greenland's more temperate climate driving greater seasonal variability, while Antarctic mass loss is more influenced by ocean-driven ice shelf processes (Pfeffer et al., 2008; DeConto and Pollard, 2016).

1.1.2. Ice sheet mass loss and global sea level rise

Global sea levels have been rising for most of the 20th century, and the rate of sea level rise has been accelerating since the 1960s (Fig. 1.1; Church and White, 2006; Dangendorf et al., 2019). The main contributors to the global sea level rise are increased heat uptake and thermal expansion of the oceans (e.g., Cheng et al., 2019; Zanna et al., 2019) and losses in land ice from mountain glaciers and ice caps (e.g., Jacob et al., 2012;

Zemp et al., 2019), the Greenland Ice Sheet (e.g. Van den Broeke et al., 2016; The IMBIE Team et al., 2020) and the Antarctic Ice Sheet (e.g. Rapley, 2006; The IMBIE Team et al., 2018). Although glaciers and ice caps have historically been the largest contributors to global sea level rise from ice mass loss, recent acceleration in loss from the ice sheets suggests that ice sheets will become the dominant source of sea level rise throughout the 21st century (Rignot et al., 2011b). If the ice sheets were to melt completely, sea levels would rise by about 65 m, with a contribution of approximately 7 m (Morlighem et al., 2017) from Greenland and 58 m from Antarctica (Morlighem et al., 2020). While complete melting of the ice sheets will take place over millennia (Pattyn et al., 2018), their delayed long-term response to climate forcing suggests that future mass loss from the ice sheets is irreversible on timescales relevant for human planning (e.g., Ridley et al., 2010; Gregory et al., 2020; Garbe et al., 2020; Pattyn and Morlighem, 2020; Reed et al., 2024), leading to committed future sea level rise even if greenhouse gas emissions were to stop immediately (Golledge et al., 2015; Box et al., 2022a).

Even such moderate, sustained ice sheet mass loss and sea level rise can significantly increase the frequency and magnitude of coastal flooding during storm surges, threatening coastal populations and infrastructure (Vitousek et al., 2017; Neumann et al., 2015). Around the globe, approximately 700 million people live in low-elevation (< 10 m a.s.l.) coastal zones vulnerable to coastal flooding (Merkens et al., 2016), with that number projected to exceed 1 billion by 2050 (Oppenheimer et al., 2019). This forces policy makers and coastal planners to embrace costly adaptation strategies (Hinkel et al., 2014). Developing effective mitigation and adaptation strategies for future sea level rise requires accurate and actionable projections (Kopp et al., 2019). However, projections of ice sheet mass loss for the 21st century remain highly uncertain (Pattyn and Morlighem, 2020; Bamber et al., 2022), leading to significant uncertainties in future sea level rise estimates provided

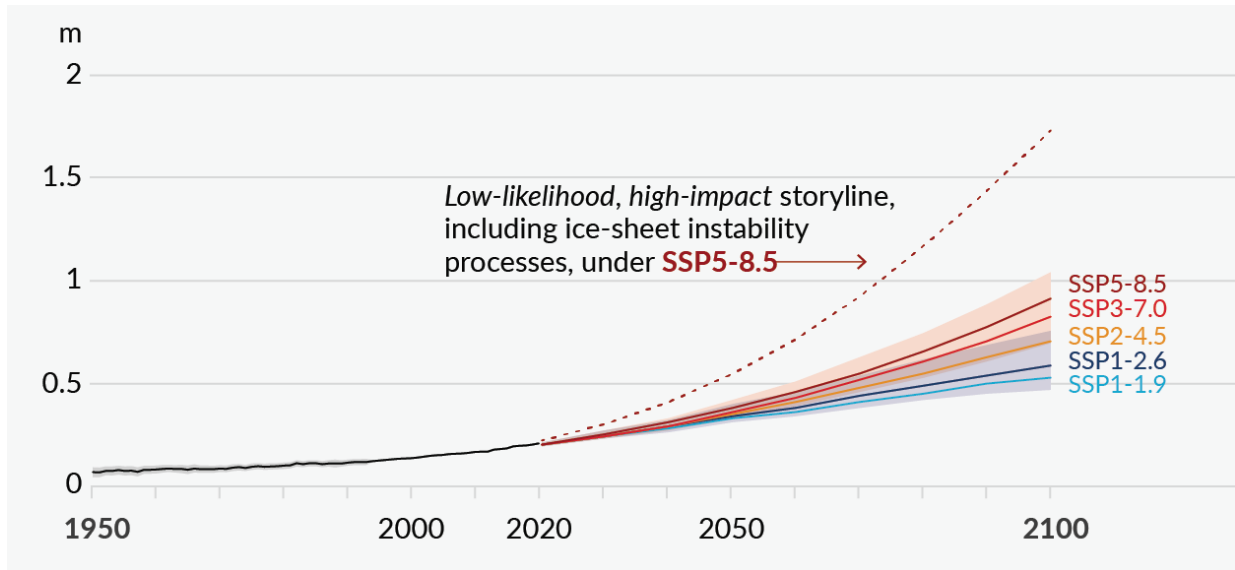


Figure 1.1: Global mean sea level change in meters, relative to 1900. The historical changes are observed (from tide gauges before 1992 and altimeters afterwards), and the future changes are assessed consistently with observational constraints based on emulation of Coupled Model Intercomparison Project (CMIP), ice-sheet, and glacier models. *Likely* ranges are shown for SSP1-2.6 and SSP3-7.0. Only *likely* ranges are assessed for sea level changes due to difficulties in estimating the distribution of deeply uncertain processes. The dashed curve indicates the potential impact of these deeply uncertain processes. It shows the 83rd percentile of SSP5-8.5 projections that include low-likelihood, high-impact ice-sheet processes that cannot be ruled out; because of *low confidence* in projections of these processes, this curve does not constitute part of a *likely* range. Changes relative to 1900 are calculated by adding 0.158 m (observed global mean sea level rise from 1900 to 1995–2014) to simulated and observed changes relative to 1995–2014. Reproduced from: Figure SPM.8 Panel (d) in IPCC, 2021: Summary for Policymakers. In: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*

to stakeholders, which complicates decision-making for coastal planners and policymakers (e.g., Fox-Kemper et al., 2021). The Antarctic Ice Sheet, in particular, represents the largest source of uncertainty, with sea level rise projections under high-end emissions scenarios ranging from 0.0 to 3.7 m by 2150 when including all possible ice sheet processes (DeConto et al., 2021; Fox-Kemper et al., 2021). Beyond 2100, uncertainty in the behavior of the Antarctic Ice Sheet increases even more sharply: over these longer timescales, various hypothesized instability processes could emerge, with the potential to destabilize extensive regions of Antarctica (Seroussi et al., 2024). This highly uncertain, but potentially very large contribution of the ice sheets to future sea level rise has been referred to as “*deep uncertainty*” in the United Nations Intergovernmental Panel on Climate Change (IPCC) Special Report on the Ocean and Cryosphere in a Changing Climate (SROCC; IPCC, 2019).

1.2. Surface melt as a major source of uncertainty in future ice sheet projections

A complex and poorly understood aspect of long-term ice sheet mass loss is the role of surface meltwater, especially when it pools on the surface of land ice in the form of supraglacial lakes (Hoffman et al., 2011; Bell et al., 2018). Melting of firn and ice at the surface, and subsequent transport of meltwater off the ice sheet directly contributes to mass loss as surface runoff, and this impact is well-constrained in models (e.g., The IMBIE Team et al., 2018, 2020). However, the indirect effects of supraglacial lakes and their drainage on ice dynamics and stability – which vary between the Greenland and Antarctic Ice Sheets – are much more uncertain.

1.2.1. **Greenland surface melt and ice dynamics**

In Greenland, melting of ice at the surface and direct runoff of meltwater is a significant direct contributor to the ice sheet’s overall mass balance, and has been significantly increasing since the 1990s (Hanna et al., 2008; The IMBIE Team et al., 2020). Meltwater can be efficiently transported off the ice sheet via runoff at the surface (e.g., Smith et al., 2015) or enter subglacial drainage systems through moulins and flow towards the ice sheet margins at the bedrock-ice interface (e.g., Chandler et al., 2021). Recent observations have confirmed a continuous expansion of the runoff area (Noël et al., 2019; Tedstone and Machguth, 2022), with supraglacial lakes advancing inland and migrating to higher elevations as climate warms (Leeson et al., 2015).

On grounded ice, rapid drainage of surface lakes by hydrofracture of the underlying glacier delivers pulses of meltwater to the base of the ice sheet, which has the potential to lubricate the bedrock and cause temporary acceleration of ice flow due to enhanced basal sliding (Zwally et al., 2002) and/or soften the ice through cryo-hydrologic warming (Phillips et al., 2013). Such short-term ice flow accelerations a well-studied phenomenon in Greenland (e.g., Das et al., 2008; Bartholomew et al., 2010; Tedesco et al., 2013; Davison et al., 2019; Maier et al., 2023), but the overall long-term impact of rapid lake drainage on the ice sheet’s mass balance is not fully understood (e.g., Sundal et al., 2011; Hoffman et al., 2011; Nienow et al., 2017). It has also been hypothesized that this could trigger “chain reaction”-like coupled drainage events that have the potential to quickly accelerate ice flow over large parts of the ice sheet (Christoffersen et al., 2018). However, modeling studies found stress-coupling length scales between draining lakes to be short, suggesting that this process may be limited in spatial extent (Das et al., 2024).

The volumes of water pulses delivered to the subglacial system by such rapid lake drainages are likely to increase in the future as temperatures become warmer and supraglacial

lakes continue expanding inland (Hageman et al., 2024). When subglacial freshwater discharge reaches the saltwater fjords at the base of marine-terminating glaciers, it rises to the surface, enhancing turbulent mixing and circulation of warmer ocean waters to the glacier terminus, thus intensifying frontal melting (Slater and Straneo, 2022). Consequently, outlet glaciers have accelerated, and solid ice discharge has increased (King et al., 2018; Mouginot et al., 2019).

1.2.2. Antarctic surface melt and ice shelf collapse

In contrast to Greenland, most surface melt in the colder Antarctic climate occurs in short, intermittent periods during austral summer (Trusel et al., 2013) driven by temporary atmospheric conditions such as foehn winds or atmospheric rivers (Cape et al., 2015; Wille et al., 2019). Almost all surface meltwater refreezes in the cold firn, resulting in negligible direct surface runoff (van den Broeke et al., 2023). However, many Antarctic ice shelves experience periods of summertime surface melt most years, and where melt is significant enough to saturate the firn at the surface, meltwater ponds in lakes and streams (Munneke et al., 2014; Kingslake et al., 2017; Stokes et al., 2019). Over the last several decades, surface melt has increased across most Antarctic ice shelves, progressively migrated towards locations further south, and is predicted to increase significantly in the future (Cook and Vaughan, 2010; Trusel et al., 2015; Gilbert and Kittel, 2021). Many Antarctic ice shelves are currently thinning (Paolo et al., 2015; Adusumilli et al., 2018; Smith et al., 2020), and on the Antarctic Peninsula some have disintegrated (Rott et al., 1996; Sergienko and Macayeal, 2005). Perhaps the most notable example of rapid ice shelf collapse was the Larsen B Ice Shelf, which lost most of its area within a few weeks towards the end of the anomalously warm 2001-2002 melt season (Scambos et al., 2004). Due to the widespread presence of melt lakes immediately prior to Larsen B’s disintegration, it is now widely believed that ponding of surface meltwater drives hydrofracture of ice shelves, which may

ultimately lead to their collapse (Scambos et al., 2004; MacAyeal et al., 2003; Banwell et al., 2013).

Hydrofracture on glaciers and ice shelves occurs when water infiltrates crevasses, filling them to a level at which hydrostatic pressure at the crack tip exceeds the fracture toughness of the ice (Weertman, 1973; Munneke et al., 2014; Alley et al., 2018). Melt lakes provide a large surface reservoir of water that may drain into downward-propagating fractures, thus further increasing pressure and leading to sustained fracture propagation (Krawczynski et al., 2009). When a melt lake on an ice shelf triggers hydrofracture that penetrates all the way to the base, the lake drains into the sub-ice-shelf ocean cavity, thereby removing mass from the ice shelf’s surface and leaving behind an empty lake basin (or “ice doline”) (Warner et al., 2021). The resulting local hydrostatic adjustment and upward bending of the floating ice shelf can subject it to further flexural stresses and nearly instantaneously change its surface hydrology, thereby potentially further weakening the ice shelf (Banwell and Macayeal, 2015; Banwell et al., 2019). Such sustained hydrofracture – fueled by pooling of meltwater in surface lakes and ice doline formation by through-ice-shelf lake drainage – can cause the formation of through-cutting fractures (called rifts), which significantly weaken ice shelves and can contribute to their rapid disintegration (Banwell et al., 2013; Robel and Banwell, 2019). With the ice shelf removed, the resulting loss of buttressing leads to accelerated flow of upstream grounded ice into the ocean, which causes sea level rise (De Angelis and Skvarca, 2003; Scambos et al., 2004; Rignot et al., 2004; Rott et al., 2018).

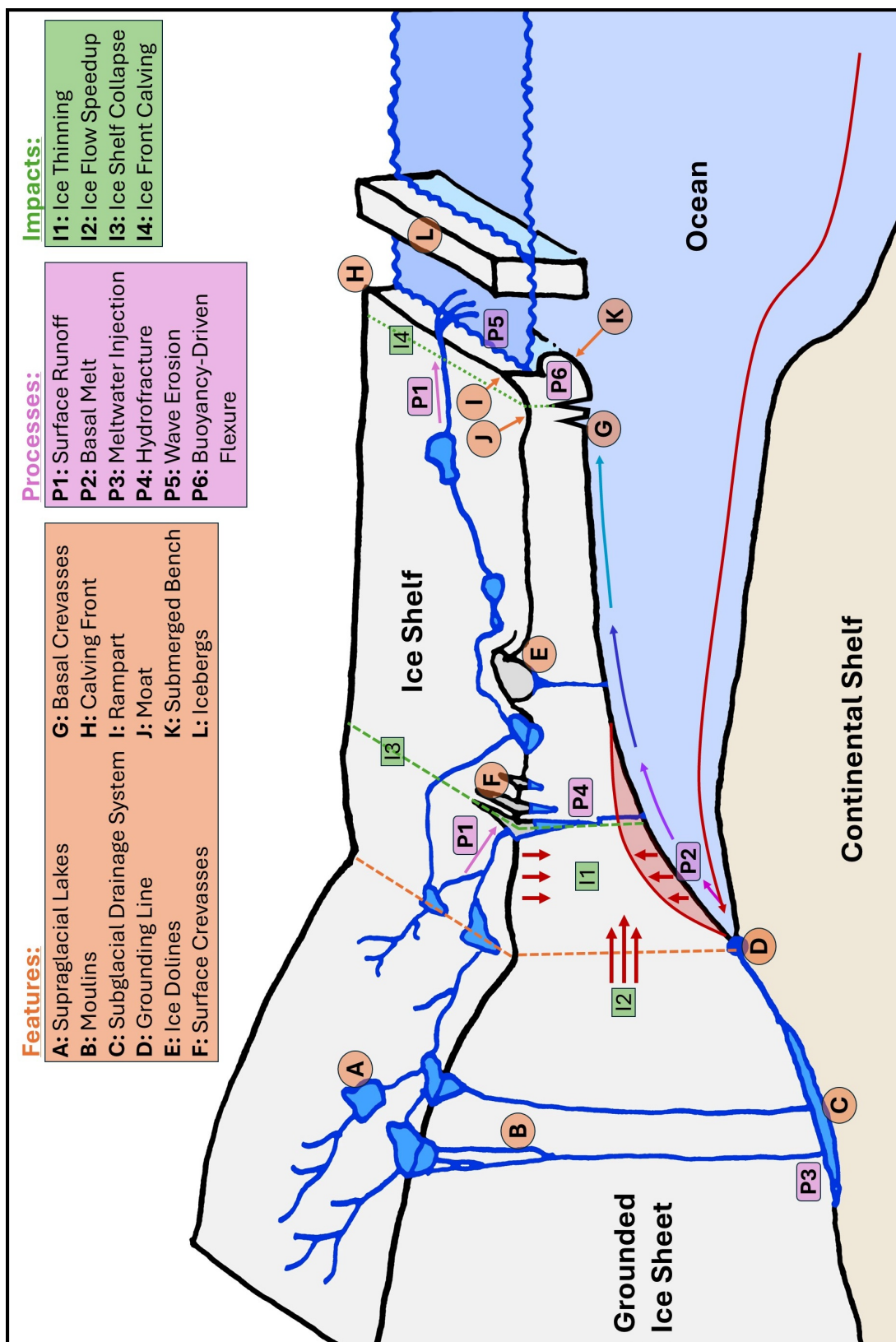
It has been hypothesized that Antarctic ice shelf collapse by hydrofracture has the potential to expose unstable ice cliffs and trigger rapid ice sheet collapse via the Marine Ice Cliff Instability (“MICI”; Bassis and Walker, 2012; DeConto and Pollard, 2016; Pollard et al., 2015). This phenomenon could lead to large increases in sea level rise projections;

however, it has not been observed and there is currently no consensus on whether it can occur in present-day Antarctica (Edwards et al., 2019; Morlighem et al., 2024). Due to these uncertain but potentially large indirect effects that supraglacial lakes can have on the stability of the Antarctic Ice Sheet and its ice shelves, it is crucial to closely monitor and accurately quantify melt water production and ponding, and to identify potential occurrences of hydrofracture.

While supraglacial lakes on Antarctica’s floating ice shelves have historically received most attention due to their critical role in ice shelf stability and collapse (e.g., Scambos et al., 2004; Banwell et al., 2013; Alley et al., 2018), recent observations have revealed that a significant fraction of lakes form on grounded ice upstream of the grounding line (Stokes et al., 2019; Tuckett et al., 2022). These lakes have the potential to influence ice dynamics, and it has been demonstrated that their drainage can trigger accelerations in ice flow (Tuckett et al., 2019; Boxall et al., 2022, 2024), akin to processes observed in Greenland (Zwally et al., 2002). The formation of such surface-to-bed hydraulic connections is projected to become more frequent in Antarctica, potentially transforming some grounded portions of the ice sheet into hydrological systems more closely resembling Greenland’s present-day ablation zones (Bell et al., 2018). This transition, often referred to as the "Greenlandification" of Antarctica (e.g., Mottram et al., 2021; Datta et al., 2023; Jones et al., 2023; Glaude et al., 2024), may drive an ice flow regime increasingly influenced by seasonal surface meltwater input to the subglacial system (Boxall et al., 2024). This suggests that in a warming climate, enhanced surface melting on grounded ice can be expected to play an increasingly important role in Antarctic ice mass loss processes (Trusel et al., 2018; Bell et al., 2018; Tuckett, 2023).

In summary, the processes through which surface meltwater impacts mass loss and ice sheet stability are different in Greenland and Antarctica; however, on both ice sheets

Figure 1.2: Impacts of melt-driven ice sheet processes on mass balance and stability. The main melt-driven processes (**P1–P6**) affecting ice dynamics and mass balance of marine-terminating outlet glaciers are illustrated schematically: Surface melting and runoff (**P1**), as well as basal melting (**P2**) lead to ice thinning (**I1**). Rapid supraglacial lake (**A**) drainage and meltwater injection (**P3**) to the subglacial drainage system (**C**) via moulins (**B**) has the potential to cause transient grounded ice flow accelerations (**I2**). Subglacial discharge at the grounding line (**D**) can drive sub ice shelf cavity ocean circulation and turbulent mixing in the buoyant melt plume, further increasing basal melting (**P2**). Drainage of supraglacial lakes (**A**) on the floating ice shelf through surface crevasses (**F**) and ice doline (**E**) formation can cause ice shelf collapse (**I3**) by hydrofracture (**P4**). At the ice shelf calving front (**H**), frontal melting driven by wave erosion (**P5**) can lead to the formation of a buoyant submerged bench (or “foot”, **K**), causing buoyancy-driven flexure (**P6**) and resulting in a rampart-moat (**I, J**) profile. The resulting flexural stresses at the base lead to the formation of basal crevasses (**G**), which drive iceberg (**L**) calving (**I4**). Ice front calving (**I4**) and ice shelf collapse (**I3**) can cause further accelerations of grounded ice flow (**I2**) and ice thinning (**I1**) through a loss of resistive “buttressing” backstresses.



surface melt has the potential to play a large indirect role in the future through mechanisms that are still poorly understood. Poorly understood processes governing ice sheet mass balance contribute to substantial uncertainties in future sea level rise projections. These uncertainties can be reduced with improved observational constraints. High-resolution satellite data now allow for the observation of small-scale changes in ice sheets over timescales ranging from weeks to decades. However, most prior studies have focused on reporting broad-scale, total mass changes over the satellite record, leaving localized and less-understood processes primarily to theoretical and modeling approaches. To enhance our understanding of ice sheet dynamics, improve models, and refine future projections, it is essential to fully leverage high-resolution satellite data capable of resolving these critical processes at finer scales.

1.3. Environmental controls on supraglacial lake formation

Supraglacial lakes form on ice sheets when surface meltwater accumulates in topographic depressions. Three primary conditions are necessary for their formation:

1. **Sufficiently warm temperatures:** Above-freezing surface temperatures lead to the generation of liquid meltwater on the ice sheet’s surface by melting snow and ice, or allow for liquid water to be added to the surface as rainfall (e.g., Braithwaite, 1995; Trusel et al., 2012).
2. **An impermeable surface layer or saturated firn:** Bare ice, meltwater-saturated firn and ice lenses or slabs can inhibit downward percolation of meltwater into deeper layers and thus allow for meltwater to remain at and be transported across the surface (e.g., Munneke et al., 2014; Machguth et al., 2016).
3. **Presence of surface depressions:** Topographic lows on the ice sheet’s surface allow meltwater to pool in basins and form lakes, rather than flowing downhill and being

lost from the ice sheet as runoff (e.g., Ignéczi et al., 2018; Arthur et al., 2020b).

1.3.1. Controls on surface temperature and melt

Surface temperatures largely depend on elevation and the surface energy balance, which is most strongly affected by the season and latitude. On the ice sheets, this means that the warmest conditions – and thus the conditions most conducive to surface melting and rainfall – are predominately encountered during summer, near the low-elevation fringes of the ice sheets, and at lower latitudes. This pattern is evident on both the Greenland and Antarctic ice sheets. For instance, the Greenland Ice Sheet experiences the most substantial melting during summer at its lower-elevation margins, with particularly extensive melting in the southern regions (van den Broeke et al., 2009). Similarly, in Antarctica, the Antarctic Peninsula and East Antarctic ice shelves, which extend to lower latitudes and have lower elevations, exhibit higher temperatures and more pronounced surface melting compared to the interior regions of the continent (Scambos et al., 2000; Saunderson et al., 2022).

Surface temperatures and melt are further influenced by the surface albedo: debris (Reznichenko et al., 2010) and algal growth (Cook et al., 2020) on the ice surface in ablation zones, as well as a lack of accumulation of highly reflective snow (Tedesco et al., 2011) increase the amount of absorbed solar shortwave radiation and thus result in warmer surface temperatures and production of larger amounts of meltwater (Box et al., 2012). The presence of supraglacial lakes further reduces ice sheet surface albedo, providing a positive feedback between surface melt and ice sheet ablation (Lüthje et al., 2006). In regions of high elevation and low latitude, where ambient temperatures are generally too low to allow surface melting, nunataks (exposed bedrock outcrops) can create localized warming that promotes melting (Kingslake et al., 2017). This warming effect likely occurs as the low-albedo exposed bedrock is heated by absorbing shortwave solar radiation and then

emits longwave radiation, which increases the temperature of the surrounding air and ice (Aubry-Wake et al., 2015).

Since snow and ice surfaces emit longwave radiation very efficiently and are highly reflective to solar shortwave radiation, the longwave cloud effect on the surface radiative balance generally dominates the shortwave cloud effect, so that cloud cover (somewhat paradoxically) results in a net warming of the surface (Bintanja and Van Den Broeke, 1995; Zhang et al., 1996), which also means that clouds over ice sheets can promote surface melting and reduce meltwater refreezing (Van Tricht et al., 2016; Kittel et al., 2021).

Finally, surface temperature and melt can also be enhanced by winds that advect warm air to a particular region of the ice sheet. Of particular importance are atmospheric rivers, which can transport large amounts of warm, moist tropical air towards the coasts and into the interiors of both the Greenland and Antarctic ice sheets, which can increase the amount of liquid water at the ice sheet surface by causing extreme melting events (Wille et al., 2022; Mattingly et al., 2023) and rainfall (Box et al., 2022b; MacLennan et al., 2022), but can also enhance snow accumulation and decrease surface albedo (Gorodetskaya et al., 2014; Hofer et al., 2017; Adusumilli et al., 2021). Intense surface melt events in both Greenland and Antarctica can also be caused by foehn conditions, during which warm, dry downslope winds increase air and surface temperatures (Cullather and Nowicki, 2018; Elvidge et al., 2020). These foehn conditions can be driven or further enhanced by atmospheric rivers (Bozkurt et al., 2018; Mattingly et al., 2023). On the Antarctic Ice Sheet in particular, katabatic (density-driven) winds warm as they descend from the ice sheet interior toward the coast, and displace cold, moist air near the ice surface, which can lead to surface melting (Lenaerts et al., 2017). Additionally, surface snow scouring by katabatic winds can lead to the formation of blue-ice zones upstream of the grounding lines of Antarctic ice shelves (Van Den Broeke and Bintanja, 1995), thereby enhancing localized

surface melting in these regions (Kingslake et al., 2017; Arthur et al., 2020a; Jakobs et al., 2021).

1.3.2. Controls on surface permeability and firn saturation

An impermeable surface that prevents meltwater retention below the surface can usually be found in bare ice regions where surface mass balance is negative, such as the ablation zone of the Greenland Ice Sheet (Ryan et al., 2019) or blue ice zones in Antarctica (Winther et al., 1996). For liquid water to remain at the surface in regions with firn cover, the near-surface firn layer needs to be either oversaturated with meltwater (Harper et al., 2012) or previous refreezing of liquid meltwater needs to have created layers of solid ice (ice slabs or ice lenses) that prevent meltwater from being stored below the surface by percolating into deeper layers (Machguth et al., 2016; Hubbard et al., 2016; Alley et al., 2018).

The development of impermeable layers within the firn can lead to two main outcomes: (1) subsurface transport and retention of meltwater in firn aquifers or, (2) pooling of meltwater due to excess runoff when near-surface saturation is reached (Machguth et al., 2016). In particular in regions with high snow accumulation and steep slopes, such as south-east Greenland, meltwater encountering impermeable ice slabs after percolating through the permeable near-surface firn can lead to the formation of firn aquifers that retain and transport meltwater below the surface, thereby reducing the likelihood of supraglacial lake formation (Miège et al., 2016; MacFerrin et al., 2019; Horlings et al., 2022; Miller et al., 2023). Conversely, in areas with lower snow accumulation and gentler slopes, like many of the Antarctic ice shelves, when percolating meltwater meets shallower impermeable ice lenses, firn saturation can occur at shallower depths and limit further downward infiltration (Hubbard et al., 2016; Buzzard et al., 2018; Bevan et al., 2017). When melt continues

over successive melt seasons, firn air content progressively decreases as the loss of pore space due to refreezing and densification outpaces the addition from snowfall (Ligtenberg et al., 2014). Once the firn reaches this air-depleted state, meltwater can no longer percolate through it, thus rendering it ineffective as a meltwater-absorbing buffer (Ligtenberg et al., 2014; Munneke et al., 2014). Under these saturated conditions, any further meltwater runoff from the surface floods the firn and can accumulate to form supraglacial lakes (Scambos et al., 2003; Mikkelsen et al., 2016; Dell et al., 2024; Glen et al., 2024).

1.3.3. Controls on the presence of surface depressions

Surface meltwater on grounded ice in Greenland and Antarctica frequently pools where subglacial bedrock undulations are transferred to the surface by the ice flow, forming depressions in which supraglacial lakes can form (Gudmundsson, 2003; Langley et al., 2016; Lampkin and VanderBerg, 2011). As a result, supraglacial lakes on grounded ice in both Greenland and Antarctica often form in the same locations each year (Echelmeyer et al., 1991; Gledhill and Williamson, 2018; Arthur et al., 2020b,a). These lake basins are defined by surface topography, which is primarily controlled by the underlying bedrock and modulated by factors such as ice thickness, surface slope, and basal slip ratio (Ignéczi et al., 2018).

Supraglacial lakes are more likely to form in areas with low surface slopes and moderate relief, where depressions that can contain lakes are more prevalent, and repeated filling of lake basins over successive melt seasons can deepen the basins through bottom ablation (Tedesco et al., 2012; Fan et al., 2024). In contrast, lakes are less common on steep slopes, as seen in southeastern Greenland, where backslopes, which favor lake formation (Nienow and Hubbard, 2006), are less likely to form, and where the resulting faster ice flow promotes fracturing and drainage of meltwater (Sundal et al., 2009). Regions with

significant basal meltwater production and high basal slip ratios, such as northern and central western Greenland, enhance the transfer of longer basal wavelengths to the surface through thicker ice, favoring the formation of larger and deeper lakes (Crozier et al., 2018; Ignéczi et al., 2018; Karlsson et al., 2021).

Downstream, where grounded ice transitions to floating ice shelves, the influence of bedrock topography on surface features diminishes. In the grounding zones of ice shelves, flexure at the slope break creates a local surface elevation minimum (Vaughan, 1994; Fricker and Padman, 2006), which enables meltwater to accumulate in the same locations over multiple seasons. This phenomenon is especially noticeable on ice shelves with a pronounced break in slope, such as the Amery Ice Shelf, where lakes in the grounding zone have been observed to repeatedly fill and drain (Trusel et al., 2022). On the freely floating parts of ice shelves, supraglacial lakes form in depressions that are advected with the ice flow (Macdonald et al., 2018) and hence their locations and geometries are influenced by surface flow-stripes and ridges inherited from grounded ice flow upstream (Glasser and Scambos, 2008). The locations and geometries of these depressions are further modified by variability in ice velocity, thickness, flexure, and internal stresses (LaBarbera and MacAyeal, 2011; Banwell et al., 2019). Surface depressions on ice shelves can also form above basal channels incised by basal melting (Dow et al., 2018) and basal crevasses (McGrath et al., 2012), because hydrostatic adjustment of the ice shelf in response to localized thinning results in surface lowering in these regions.

On the floating ice shelves, surface topography that directs meltwater flow and shapes the distribution of supraglacial lakes can change rapidly due to ice shelf flexure, particularly after rapid lake drainage events (Banwell and Macayeal, 2015; Banwell et al., 2019; Warner et al., 2021). The interplay between variability in ice shelf surface topography, surface and basal melting, lake drainage, meltwater routing and ice shelf flexure and their

control on the supraglacial hydrology remains an active area of research.

Overall, it can be concluded that numerous factors affect the spatial and temporal distribution and depths of supraglacial lakes on the ice sheets, including elevation, surface temperature, albedo, proximity to exposed rock, atmospheric circulation, snow accumulation, surface permeability, firn saturation, bedrock topography, surface slope, ice thickness, ice velocity, basal slip rate and ice shelf flexure. Many of these factors are interdependent, and changes in supraglacial lake distribution are driven by long-term climate trends and variability, which influence the complex interactions among these factors.

1.4. Satellite remote sensing of surface melt features

Earth’s ice sheets are vast and remote, thus making satellite remote sensing the only viable observational tool for continuous long-term monitoring of ice sheet change. Supraglacial hydrological systems are particularly difficult to observe on the ground, since they typically form seasonally in different locations and can rapidly evolve in complex and unpredictable patterns (Dirscherl et al., 2020; Gantayat et al., 2023), making even small-scale field studies logistically challenging and expensive. This means that our ice-sheet-scale knowledge of surface melt processes relies almost entirely on satellite observations (Mousavi et al., 2016). Monitoring meltwater volumes on the ice sheets require estimates of meltwater extent and depth. Methods for mapping the spatial extent are well-established (e.g., Sundal et al., 2009; Stokes et al., 2019; Corr et al., 2022; Tuckett et al., 2022; Dell et al., 2024); however, estimating meltwater depths from space remains challenging (Melling et al., 2024; Lutz et al., 2024). We review the various methods used to estimate these parameters, and provide an assessment of their advantages and disadvantages for monitoring supraglacial meltwater at ice-sheet scale.

1.4.1. Methods for observing the spatial extent of meltwater

Passive microwave sensors are able to detect the presence of liquid water in snow and firn and can therefore be used to map regions of the ice shelf surface that experience melting (e.g., Steffen et al., 2004; de Roda Husman et al., 2024); however, due to its coarse spatial resolution, this type of data cannot be used directly to map where any liquid water produced by surface melt saturates the firn and eventually pools in distinct lakes or streams. Therefore, it is challenging to use passive microwave data to monitor supraglacial hydrological systems, which could have large but uncertain impacts on future mass loss processes. Therefore, passive microwave sensor data is of limited use to assess the impacts that meltwater has on ice sheet dynamics and stability.

Passive optical imagery (e.g., MODIS, Landsat 8, Sentinel-2) is commonly used to detect the spatial extent of meltwater across the ice sheet, including supraglacial lakes, channels, streams, and slush areas (e.g., Williamson et al., 2017; Stokes et al., 2019; Corr et al., 2022; Tuckett et al., 2022; Dell et al., 2024). While these methods for mapping open-water areas from optical data are straightforward, accurate, and widely accessible, they are limited by their reliance on sunlight and their inability to capture the ice sheet surface when obscured by cloud cover.

In contrast, **Synthetic Aperture Radar** (SAR; e.g., Sentinel-1) provides year-round and all-weather observations, but methods attempting to monitor pooled meltwater extents typically struggle with precise delineation of lake boundaries and can overlook slush areas (e.g., Dirscherl et al., 2020). Hybrid approaches combining radar and optical data have been developed, and studies have demonstrated their potential to detect lakes buried beneath ice and firn layers (Miles et al., 2017; Dunmire et al., 2021).

1.4.2. Methods for estimating meltwater depths

While methods for mapping the spatial extent of meltwater on ice sheets are well-established, estimating meltwater depths from space remains challenging (Melling et al., 2024; Lutz et al., 2024). Various approaches have been proposed, each with distinct advantages and limitations.

- The **Radiative Transfer Equation (RTE)** is commonly used to estimate lake depth from optical imagery with broad spatial coverage, such as MODIS, Landsat and Sentinel-2 (Sneed and Hamilton, 2007; Moussavi et al., 2020; Leeson et al., 2020). This physics-based method allows for large-scale application but relies on uncertain parameters such as water attenuation coefficients and lakebed albedo, often leading to over- or underestimation in different environments (Brodský et al., 2022). For example, the RTE underestimated depths by 30-70 % on the Amery Ice Shelf (Fricker et al., 2021) but overestimated depths by up to 153 % in Southwest Greenland (Melling et al., 2024).
- **Empirical models**, based on regression between *in situ* depth measurements and optical imagery, offer another approach (Tedesco and Steiner, 2011; Legleiter et al., 2014; Pope et al., 2016). However, these models are limited by sparse *in situ* data, particularly in Antarctica, where no such data is available (Arndt and Fricker, 2024d), and by the geographical variability in the relationship between water depth and reflectance (Lutz et al., 2024), restricting their utility for large-scale applications.
- Using **Digital Elevation Models (DEMs)** of lakebed topography acquired before filling or after draining offers a method independent of water optical properties (Moussavi et al., 2016; Yang et al., 2019b). However, this approach is limited by the sporadic availability of DEMs and the inability to account for lakebed changes,

as well as being unsuitable for perennial lakes or lakes on floating ice shelves due to hydrostatic adjustments (Scambos et al., 2009; Warner et al., 2021).

- Launched in 2018, NASA’s **ICESat-2** laser altimeter became the first — and to date the only — satellite capable of directly and accurately measuring water depths from space. This is achieved through its use of green light, which penetrates water and enables the sensor to detect photons reflected from both the lake surface and the lakebed (Fig. 2.1; e.g., Fair et al., 2020; Fricker et al., 2021; Xiao et al., 2023; Arndt and Fricker, 2024d). ICESat-2 can measure water depths up to 41 m under optimal conditions (such as clear water and high bottom reflectivity), with typical accuracies around 0.5 m (Dietrich et al., 2024). Despite its unique ability to directly and accurately measure water depths, ICESat-2 is fundamentally limited by its spatial coverage. The data are confined to discrete, one-dimensional ground tracks that are widely spaced across the Earth’s surface, with a relatively infrequent revisit time of three months. As a result, ICESat-2 data alone cannot provide continuous monitoring of melt lake volumes. However, several case studies have demonstrated that ICESat-2 depth measurements can be used to constrain parameters in models that estimate lake volumes from satellite imagery (Datta and Wouters, 2021; Leeuwen, 2023; Lutz et al., 2024).

Combining the accuracy of ICESat-2 measurements with the broader spatial and temporal coverage of optical satellite data promises to offer the most effective approach for accurate meltwater depth monitoring across the ice sheets. This motivates much of the research presented in this dissertation.

1.5. Summary of the dissertation

In this dissertation we describe the use of ICESat-2 laser altimetry data and passive optical satellite imagery to quantify supraglacial meltwater depths across the ice sheets, and demonstrate how high-resolution satellite observations can put observational constraints on ice sheet processes that are still poorly understood but could have major impacts on future mass loss and stability. In **Chapter 2** we develop a scalable algorithm for automated detection and depth determination of supraglacial lakes in ICESat-2 photon data and provide a computational framework for its ice-sheet-wide implementation. To demonstrate its effectiveness in capturing spatial and temporal variability, we report results for two drainage basins in Greenland and Antarctica during two contrasting melt seasons. In the absence of ground truth data, we validate our results against manually annotated ICESat-2 depth estimates and compare our algorithm’s performance to alternative methods for meltwater depth estimation. In **Chapter 3** we apply our framework to the entire Greenland Ice Sheet, and present the resulting ice-sheet-wide dataset of ICESat-2-based supraglacial lake depth measurements between 2019 and 2023. We report patterns of spatiotemporal variability and trends in the lake depth data, and combine the ICESat-2-derived depths with passive optical imagery to create a machine learning training dataset. We use this data to train a model that can be used to predict supraglacial lake volumes from satellite imagery. To demonstrate that our data can be used to improve meltwater volume estimates across the ice sheets, we validate our model’s results against *in situ* data and compare its performance to traditional methods. In **Chapter 4**, we extend our analysis to the Antarctic Ice Sheet, presenting a continent-wide dataset of ICESat-2-based supraglacial lake depth measurements for melt seasons 2018-19 and 2022-23. We report patterns of spatiotemporal variability and trends in the Antarctic lake depth data, and contrast the results to those observed in Greenland. We further highlight how high-resolution three-dimensional

satellite data can provide observational insights into ice shelf flexure and damage resulting from through-ice-shelf lake drainage (doline formation) and provide observational evidence of ice shelf “benches” that are submerged in the ocean at their calving fronts and result in buoyancy-driven flexure and calving. These data put valuable observational constraints on mass loss processes and improve our understanding of the mechanical properties of ice shelves. Finally, in **Chapter 5** we provide a summary of the research presented in this dissertation, discuss how it has contributed to our understanding of surface melt processes and our ability to characterize them using satellite data, and explore avenues for future research.

CHAPTER 2: A FRAMEWORK FOR AUTOMATED SUPRAGLACIAL LAKE DETECTION AND DEPTH RETRIEVAL IN ICESAT-2 PHOTON DATA ACROSS THE GREENLAND AND ANTARCTIC ICE SHEETS

Abstract

Water depths of supraglacial lakes on the ice sheets are difficult to monitor continuously, due to the lakes' ephemeral nature and inaccessible locations. Supraglacial lakes have been linked to ice shelf collapse in Antarctica and accelerated flow of grounded ice in Greenland. However, the impact of supraglacial lakes on ice dynamics has not been quantified accurately enough to predict their contribution to future mass loss and sea level rise. This is largely because ice-sheet-wide assessments of meltwater volumes rely on models that are poorly constrained due to a lack of accurate depth measurements. Various recent case studies have demonstrated that accurate supraglacial lake depths can be obtained from ICESat-2's ATLAS/ICESat-2 Global Geolocated Photon Data Product (ATL03) photon-level data product. ATL03 comprises hundreds of terabytes of unstructured point cloud data, which has made it challenging to use this bathymetric capability at scale. Here, we present two new algorithms – Flat Lake and Underlying Ice Detection (FLUID) and Surface Removal and Robust Fit (SuRRF) – which together provide a fully automated and scalable method for lake detection and along-track depth determination from ATL03 data, and

establish a framework for its large-scale implementation using distributed high-throughput computing. We report FLUID/SuRRF algorithm performance over two regions known to have significant surface melt – Central West Greenland and Amery Ice Shelf catchment in East Antarctica – during two melt seasons. FLUID/SuRRF reveals a total of 1249 ICESat-2 lake segments up to 25 m deep, with more water during higher melt years. In absence of ground truth data, manual annotation of test data suggests that our method reliably detects melt lakes along ICESat-2’s ground tracks whenever the lakebed is visible or partially visible, and estimates water depths with a mean absolute error < 0.27 m. These results imply that our proposed framework has the potential to generate a comprehensive data product of accurate meltwater depths across both ice sheets.

2.1. Introduction

Earth is warming and both of its ice sheets (Greenland and Antarctica) are losing mass to the ocean at increasing rates (Rignot et al., 2011b; Smith et al., 2020), leading to sea level rise. There is growing evidence that some of this retreat is irreversible, thus committing coastal communities to embrace costly sea level rise adaptation strategies for decades and centuries to come (DeConto et al., 2021; Garbe et al., 2020; Gregory et al., 2020; Nordhaus, 2019). To address the resulting societal challenges, policy makers and coastal planners require accurate and actionable sea level rise projections (Moon et al., 2020). However, the projected contribution from the ice sheets is highly uncertain, to the point that the Sixth Assessment Report of the United Nations Intergovernmental Panel on Climate Change designated it as “*deep uncertainty*” (IPCC AR6; Fox-Kemper et al., 2021). Building confidence in projections of the ice sheets’ contribution to future sea level rise requires better mechanistic understanding of relevant mass balance processes for inclusion in ice sheet models (Golledge, 2020; Aschwanden et al., 2021). However, ice sheet

wide details of many of these processes are poorly known because they have been under observed in both space and time.

Supraglacial melting on the ice sheets is one example of a process which has a potentially important contribution to future sea level rise projections, yet has been under observed so is poorly understood. In a warming climate, supraglacial lakes have the potential to trigger positive feedback loops and catastrophic collapse (Gilbert and Kittel, 2021), yet the underlying mechanisms and associated likelihoods are vaguely defined due to a lack of high-quality observations (Arthur et al., 2020a). In particular, models that attempt to capture the influence of supraglacial hydrology on ice sheet behavior require accurate estimates of volumes of pooled surface meltwater as input (Zwally et al., 2002; Parizek and Alley, 2004; Krawczynski et al., 2009; Robel and Banwell, 2019). However, there are few direct *in situ* observations of supraglacial lake depths (none in Antarctica, and ten lakes up to 11.5 m deep in Greenland), which leads to errors in total water volume estimates. This introduces biases into model inputs for meltwater flow, impacting projections of future ice sheet evolution (Melling et al., 2024). To ensure that coupled hydrological-dynamical models accurately represent the underlying physics, it is important to find a method to acquire lake depths that are accurate, and also spatially and temporally and continuous.

Launched in 2018, NASA’s Ice, Cloud and land Elevation Satellite 2 (ICESat-2) laser altimeter became the first (and thus far only) satellite capable of making direct, accurate water depth measurements from space, due to its green light being able to penetrate water, which allows its sensor to register the elevation of photons that were reflected from both the lake surface and the lakebed (Fig. 2.1; e.g., Fair et al., 2020; Fricker et al., 2021; Xiao et al., 2023). This allows ICESat-2 to measure water depths up to 41 m under ideal conditions (very clear water and high bottom reflectivity), with typical accuracies of about 0.5 m (Dietrich et al., 2024).

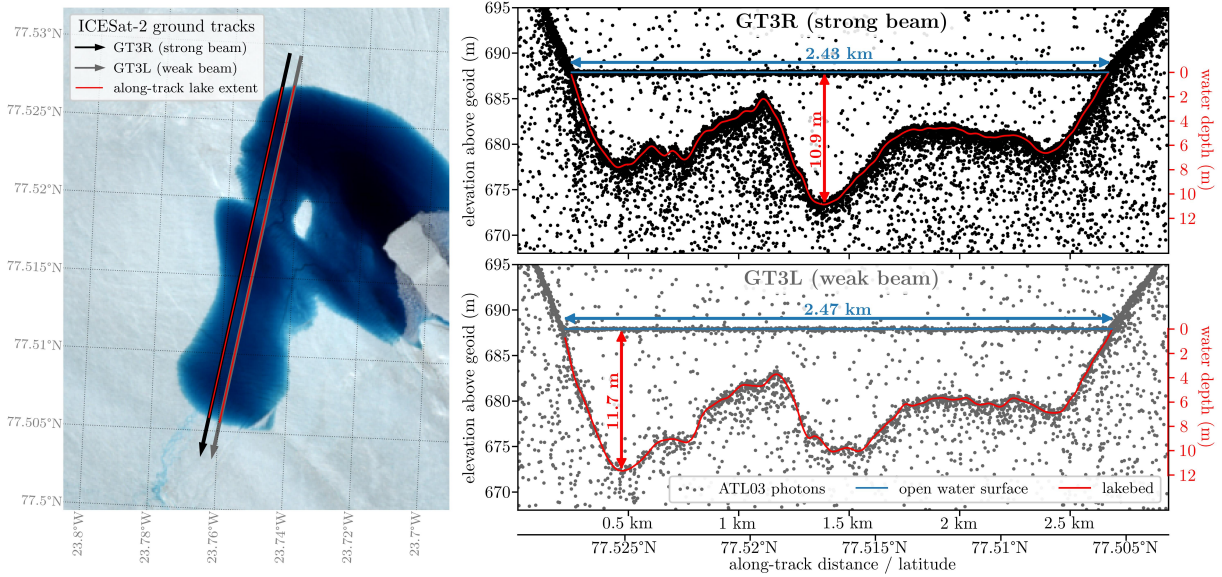


Figure 2.1: An ICESat-2 ATL03 data segment over a supraglacial lake, showing a particularly strong bathymetric return from the lakebed. (Data from ICESat-2 Track 406 on 20 July 2021; granule: ATL03_20210720053125_04061205_006_01.h5. The imagery in the left panel is a Sentinel-2 scene from the same day: S2B_MSIL2A_20210720T151809_N0301_R068_T27XVG_20210720T175839.)

While ICESat-2 has the unique capability to make direct and accurate measurements of water depth from space, its fundamental limitation is spatial coverage. ICESat-2 data are limited to discrete, one-dimensional ground tracks that are coarsely spaced on the Earth’s surface ($\sim 9.9\text{ km}$ between neighboring reference tracks and $\sim 3.3\text{ km}$ between all neighboring beam pair tracks at 70°N/S) with a relatively long revisit time of three months. This means that no supraglacial lake depth data product derived from ICESat-2 *alone* is able to provide samples of all (or even nearly all) supraglacial lakes on the ice sheets: ICESat-2’s track spacing means that the majority of lakes form in locations that ICESat-2 ground tracks never sample, and the three-month return period means that for a significant number of ground tracks ICESat-2 never passes over at the time at which melt lakes are visible. ICESat-2 is also unable to penetrate optically thick clouds, thus further limiting the amount of data available for water depth measurements.

While ICESat-2 data alone cannot be used to continuously monitor melt lake volumes, several case studies have shown that ICESat-2 depth measurements can be used to constrain parameters in models that estimate lake volumes from satellite imagery (Datta and Wouters, 2021; Leeuwen, 2023; Lutz et al., 2024). For instance, Datta and Wouters demonstrated that it is possible to accurately extrapolate depths along ICESat-2’s ground track segments to the full lake basins that these segments intersect. To be able to use ICESat-2 to improve depth estimates of supraglacial lakes in locations where (and at times when) ICESat-2 measurements are not directly available, it will be necessary to rely on statistical methods that can generalize the relationship between water depth and reflectance for a particular passive optical sensor under a wide variety of conditions and independently of the availability training data that are close-by in space and time (Hastie et al., 2009). For this to work effectively, the data that is used to train statistical learning models capable of multiple non-linear regression for representing a complex depth-reflectance relationship need to adequately cover the parameter space defined by the combination of predictors that are included (Markham and Rakes, 1998; Wang et al., 2022). Since ICESat-2 observations of melt lakes are relatively sparse, it is therefore crucial to obtain as many ICESat-2 depth estimates as possible from different locations and times (and thus under a wide variety of environmental conditions) to be able to effectively use ICESat-2 to improve monitoring of meltwater volumes across the ice sheets. This suggests that large-scale extraction of accurate supraglacial lake depths from a wide range of ICESat-2 photon-level data in combination with concurrent optical satellite imagery can provide a labeled training data set enabling the application of machine learning methods (e.g., Leeuwen, 2023) capable of generating a well-constrained data-driven model for ice-sheet-wide lake volume estimation (Melling et al., 2024).

While automated and scalable algorithms for lake detection and depth retrieval in

ATL03 photon data have been proposed (e.g., Datta and Wouters, 2021; Xiao et al., 2023), in practice no previous ICESat-2 studies have applied supraglacial lake depth estimation methods to more than a handful of manually picked lake segments or data granules, or presented a straightforward pathway to large-scale computational implementation across the ATL03 data catalog, which comprises hundreds of terabytes of unstructured point cloud data (Neumann et al., 2023a). To address this challenge, we present a framework for ice-sheet-wide implementation of our own fully automated and scalable algorithm for along-track lake segment detection and depth determination from ICESat-2 data. Here, we present this algorithm, apply it to two entire drainage basins in Greenland and Antarctica (Sect. 2.3.5, Fig. 2.2) using distributed high-throughput computing, and demonstrate its performance for two full melt seasons.

2.2. Background

2.2.1. How supraglacial lakes affect ice sheet mass loss

Supraglacial water has different roles in Greenland and Antarctic ice sheet mass loss processes, largely because of its different spatial extent on each ice sheet. Across most of the Greenland Ice Sheet’s ablation zone, meltwater pools in supraglacial lakes that extend from the ice margins up to about 2000 m on the plateau, and are forming further inland as temperatures increase (Leeson et al., 2015; Tedstone and Machguth, 2022). On the Antarctic Ice Sheet, pooling of surface meltwater in lakes is not as pervasive and is mostly observed on the floating ice shelves and at low elevations near their grounding zones (Stokes et al., 2019; Corr et al., 2022), with large regional and interannual variability (Arthur et al., 2022). Pooling and storage of meltwater in supraglacial lakes can affect ice sheet mass loss directly or indirectly in four ways:

1. *Surface runoff*: Supraglacial lake drainage and transport of water off the ice sheet

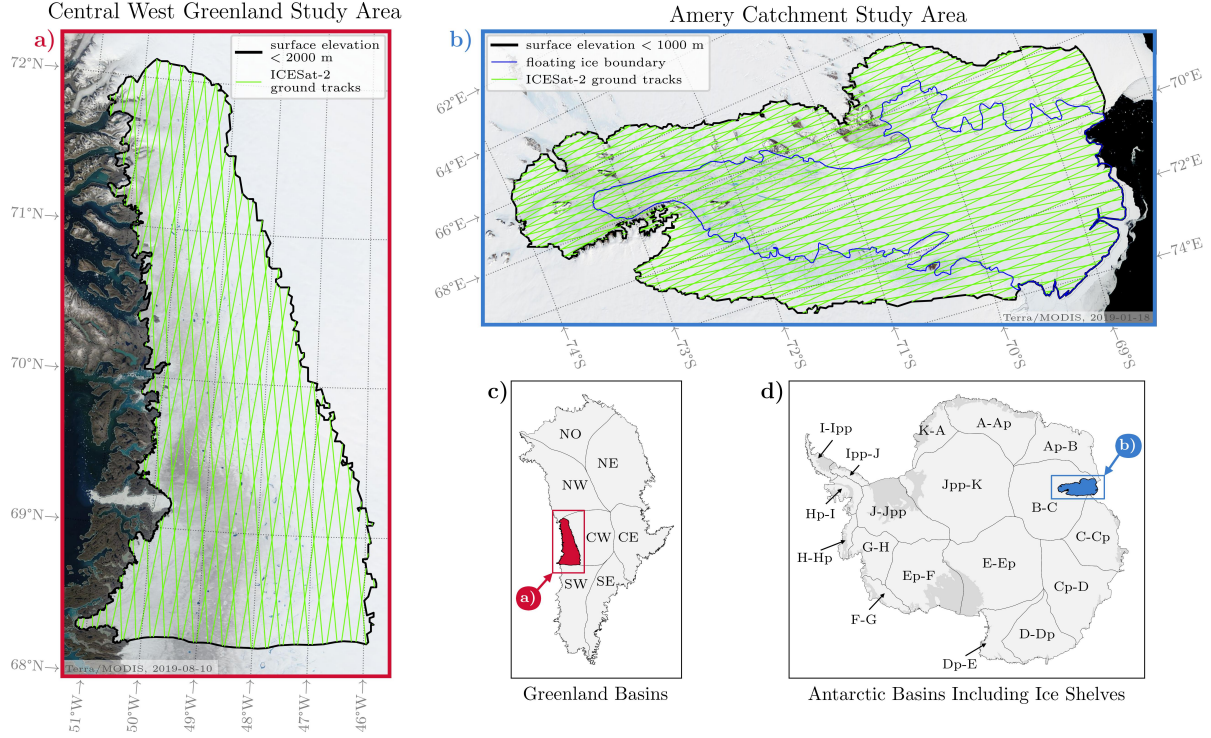


Figure 2.2: Study regions for testing the FLUID/SuRRF framework. a) and b) Maps of the two regions chosen for this study: Central West Greenland (CW drainage basin) and the Amery catchment (B-C drainage basin). The black outlines show the boundaries of the regions which were obtained by thresholding the corresponding ice sheet drainage basins (c and d) by the elevations shown in the legends. The green lines show ICESat-2 reference ground track coverage. c) and d): Maps of the Ice sheet Mass Balance Inter-comparison Exercise (IMBIE) drainage basins for Greenland (Mouginot and Rignot, 2019) and Antarctica (Mouginot et al., 2017). Insets show the locations of the two study areas.

through surface streams or englacial pathways contributes to mass loss directly as surface runoff. This is already a significant component of the Greenland Ice Sheet surface mass balance (The IMBIE Team et al., 2020), but has also been observed on the Antarctic Ice Sheet (Bell et al., 2017; Warner et al., 2021; Trusel et al., 2022) and could become more significant in a warming future (Kingslake et al., 2017; Bell et al., 2017). Such runoff also results in surface elevation lowering, which further increases meltwater production by exposing the ice sheet surface to the higher temperatures found at lower elevations (Levermann and Winkelmann, 2016; Bell et al., 2018).

2. *Surface albedo lowering:* Supraglacial lakes lower the surface albedo, which can further accelerate melting and result in a temperature increase in the adjacent ice column (Tedesco et al., 2012; Ryan et al., 2017; Stokes et al., 2019).
3. *Bedrock lubrication:* On grounded ice, rapid drainage of surface lakes by hydrofracture delivers pulses of meltwater to the base of the ice sheet, which has the potential to lubricate the bedrock and cause acceleration of ice flow due to enhanced basal sliding. This is a well-studied phenomenon in Greenland (e.g., Das et al., 2008; Bartholomew et al., 2010; Tedesco et al., 2013; Davison et al., 2019; Maier et al., 2023) but recent observations suggest that this mechanism is also driving ice flow speed-ups on the Antarctic Ice Sheet (Tuckett et al., 2019), where it could become an increasingly important mechanism as future warming will cause its hydrology to become more similar to Greenland’s current ablation zone (Bell et al., 2018).
4. *Ice shelf collapse:* In Antarctica, the ponding and draining of supraglacial lakes can weaken and fracture the floating ice shelves (Munneke et al., 2014; Banwell and Macayeal, 2015; Banwell et al., 2019; Lai et al., 2020), which, in extreme cases, has been linked to their collapse by hydrofracture (MacAyeal et al., 2003; Scambos et al., 2004; Banwell et al., 2013). The resulting loss of buttressing back-stresses leads

to accelerated discharge of upstream grounded ice into the ocean, which causes sea level rise (De Angelis and Skvarca, 2003; Scambos et al., 2004; Rignot et al., 2004; Rott et al., 2018). It has been hypothesized that these melt-driven hydrofracture processes could expose marine ice cliffs that are sufficiently tall and weakened to be prone to mechanical failure, which would trigger buoyancy-driven calving and could therefore lead to sustained, rapid ice sheet collapse, referred to as the Marine Ice Cliff Instability (MICI; Bassis and Walker, 2012; Pollard et al., 2015; DeConto and Pollard, 2016; Bassis et al., 2021, 2024).

Incorporating those processes through which surface meltwater ponding affects ice dynamics into ice sheet models can drastically increase projected future sea level rise (Martin et al., 2019; Edwards et al., 2021), yet they currently rely on poorly constrained parametrizations, making projections highly uncertain (Robel et al., 2019; Pattyn and Morlighem, 2020). This means that there is an urgent need to improve our understanding of the key underlying physical processes based on accurate observations (Hanna et al., 2024).

2.2.2. Observations of supraglacial lake depths

In situ observations of melt lake depths are scarce (e.g., Tedesco and Steiner, 2011) due to the challenging logistics and planning required to collect such data. Supraglacial hydrological systems on ice sheets form seasonally in some of Earth’s most remote and inaccessible locations, and they can rapidly evolve in complex and unpredictable patterns (Dirscherl et al., 2020; Gantayat et al., 2023), making survey planning difficult. Therefore, to obtain ice-sheet-wide observations of meltwater lake depths for each melt season, it is necessary to rely on satellite remote sensing techniques (Moussavi et al., 2016; Melling et al., 2024). Besides ICESat-2’s novel capability to directly observe water depths from photon refraction, various methods have been used to indirectly estimate lake depths from

satellite data, which all have different advantages and disadvantages.

One such method is to apply a **radiative transfer equation** (RTE, Philpot, 1987, 1989) to estimate lake depth from optical imagery (Sneed and Hamilton, 2007; Moussavi et al., 2020; Leeson et al., 2020). This approach has been widely used since optical imagery provides continuous spatial coverage at short temporal intervals and because it is assumed that its physics-based principles hold everywhere, which makes it possible to apply it at scale. However, the RTE approach relies on poorly constrained choices of water attenuation coefficients and lakebed albedo, and makes simplifying assumptions such as: no suspended particulate matter; a homogeneous lakebed albedo; no surface disturbances caused by wind; and the water column has vertically homogeneous optical properties (Brodskey et al., 2022). As a result, it has been shown that the RTE approach can significantly over- or underestimate lake depths in different environments: in Fricker et al. (2021) the RTE method underestimated depths by 30 to 70 % on Amery Ice Shelf in East Antarctica, whereas in Melling et al. (2024) it overestimated depths by up to 153 % in Southwest Greenland.

Another approach to estimating lake depths is using **empirical models** derived from regression of *in situ* depth measurements with optical imagery (e.g., Tedesco and Steiner, 2011; Legleiter et al., 2014; Pope et al., 2016). However, *in situ* measurements of supraglacial lake depths are very sparse, with (to the best of our knowledge and at the time of writing) no such data available for Antarctica, and data available for only ten lakes up to 11.5 m deep on the Greenland Ice Sheet between 2005 and 2024: Box and Ski (2007) sampled two lakes on Jakobshavn Isbræ and Sermeq Avannarleq in 2005, Sneed and Hamilton (2007) sampled one lake on Helheim Glacier in 2008, Tedesco and Steiner (2011) sampled one lake in Central West Greenland in Legleiter et al. (2014) sampled three supraglacial water bodies on Isunnguata Sermia, Russell Glacier in 2012 and Lutz et al. (2024) sampled three lakes on Zachariæ Isstrøm in 2022. This makes the observations

provided by Lutz et al. the only *in situ* depth data of supraglacial lakes that overlap with the Landsat 8 and Sentinel-2 missions. Further, it has been shown that the relationship between water depth and reflectance values in optical imagery can vary significantly by geographical region (Lutz et al., 2024). Thus, the regression coefficients of these empirical models are limited to the spatial area of the original *in situ* measurements, making them impractical for application on a larger, ice-sheet-wide scale.

A third approach is to use **digital elevation models** (DEMs) of a lake’s bed topography that were acquired before it filled or after it drained, and then to determine its fill level from imagery (Moussavi et al., 2016; Yang et al., 2019b). While this has the advantage of being independent of the optical properties of the water column, currently available DEM acquisitions are sporadic and the method cannot account for changes in the lakebed topography between acquisitions, due to, for example, bottom ablation (Tedesco et al., 2012). Because this approach requires acquisitions from before a lake fills or after it drains, it is not suitable for perennial lakes that freeze over and are buried in winter without draining (Koenig et al., 2015; Schröder et al., 2020; Leppäranta et al., 2013), and it cannot be directly applied to lakes on floating ice shelves, where any filling and draining events result in a hydrostatic adjustment that bends the ice surface (Scambos et al., 2009; Warner et al., 2021).

2.3. Data and methods

We use individual photon data from the ICESat-2 instrument, provided in a data product known as Global Geolocated Photons (ATL03; Sect. 2.3.1). Our method to extract water depths consists of two algorithms that are run consecutively on ATL03 data: (1) Flat Lake and Underlying Ice Detection (FLUID, Sect. 2.3.2) automatically detects the locations of supraglacial lakes visible in the point cloud data; (2) Surface Removal and

Robust Fit (SuRRF, Sect. 2.3.3) determines the along-track depth for each detected lake segment. To automatically compute results for large numbers of ATL03 data files over extensive geographical regions, we use the Open Science Grid’s (OSG) Open Science Pool (OSPool) for distributed High-Throughput Computing (dHTC) (Sect. 2.3.4; OSG, 2006; Pordes et al., 2007). Figure 2.3 summarizes the various steps of this method in a flowchart, and we describe each of them in more detail below.

2.3.1. ICESat-2

ICESat-2 was launched in September 2018 and carries the Advanced Topographic Laser Altimeter System (ATLAS) instrument, a photon-counting green light (532 nm) laser altimeter operating at a frequency of 10 kHz, which results in a 0.7 m along-track resolution (Markus et al., 2017). ATLAS divides the laser pulse it emits into six beams, forming three beam pairs, each of which consist of a weak and a strong beam (Fig. S2.1). The footprint of each beam is about 11 m in diameter on the ground (Magruder et al., 2021a). The six resulting ground tracks (GTNXs) are referred to as GT1L, GT1R, GT2L, GT2R, GT3L and GT3R, where the number N refers to the beam pair from left to right in direction of flight, and the X refers to the left (“L”) or right (“R”) track within each pair (Neumann et al., 2022). The three track pairs are separated 3.3 km on the ground, and the two tracks within a pair are separated by 90 m each. The ICESat-2 spacecraft can fly in either forward or backward orientation, and flips between the two approximately twice a year (Neumann et al., 2019; Smith et al., 2019). In forward orientation, ATLAS’s strong beams – numbered 1, 3 and 5 – are on the right side of each beam pair in the direction of flight and point to GTs 3R, 2R and 1R, respectively. Similarly, after a yaw flip to the backward orientation, the strong beams are on the left side of each beam pair and point to GTs 1L, 2L and 3L. This means that the data acquired along a particular GTNX can be associated with a strong or a weak beam, depending on the spacecraft orientation at the time of data acquisition. The

2.3. Data and methods

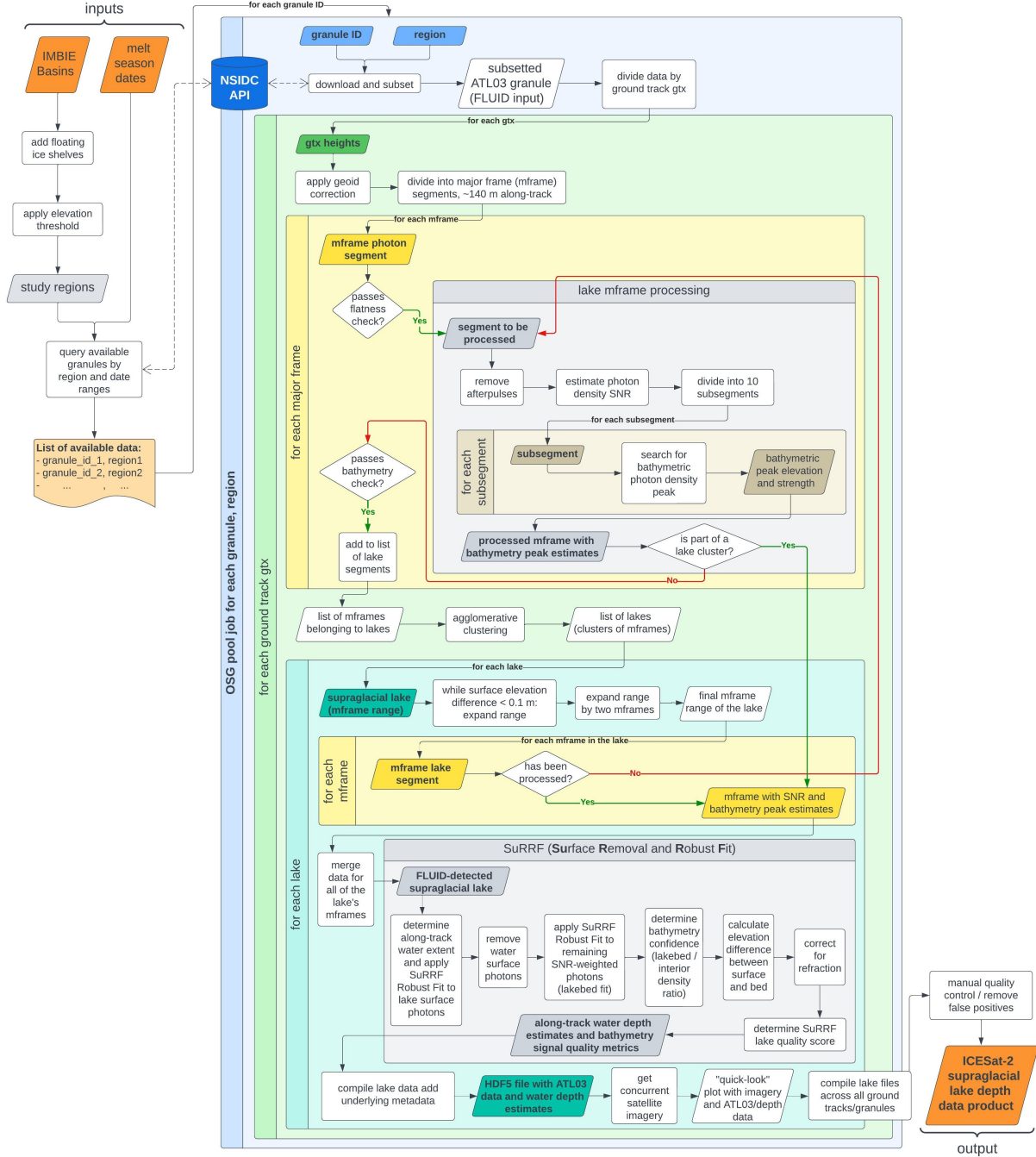


Figure 2.3: Flowchart of the FLUID/SuRRF framework for detecting and determining the depths of supraglacial melt lakes in ICESat-2 data for any melt season over any drainage basin of the Antarctic or Greenland ice sheets. All modules in the blue box can be parallelized for large amounts of input data granules, as a batch of compute jobs on a computer cluster or a platform for distributed High-Throughput Computing, such as the OSG Open Science Pool.

ATLAS receiver uses photomultiplier tubes (PMTs) designed to detect individual reflected photons, with 16 independent timing channels for each strong beam and four for each weak beam (Yang et al., 2019a). The strong beams have four times more energy than the weak beams, resulting in a correspondingly higher count of laser photons returned per shot.

ICESat-2 repeats its orbit every 91 days, after completing 1,387 distinct reference ground tracks (RGTs). Over land ice, ATLAS routinely points to these RGTs near its nadir to acquire repeat measurements (Magruder et al., 2021b). The satellite began targeting the planned RGTs in late March 2019, once the on-orbit pointing calibrations were finalized and updated in the onboard pointing control systems (Martino et al., 2019). Consequently, any observations during the 2018-19 Antarctic melt season do not align with the planned repeat tracks. ICESat-2 was in “safe-hold” from 26 June through 9 July 2019, which means that no data was collected during this 14-day period coinciding with the 2019 Greenland melt season.

Over shallow (< 41 m) and non-turbid water bodies, ATLAS’s green light is able to pass through the water column, which means that signal photons can be reflected from both the flat open-water surface and the lakebed (Fair et al., 2020; Fricker et al., 2021). Most land ice applications use the ATLAS/ICESat-2 L3A Land Ice Height (ATL06) data product designed for glacier and ice sheet surfaces (Smith et al., 2019). However, the ATL06 algorithm provides only one surface and thus cannot be used to extract meltwater depths. Also, over melt lakes ATL06 segments inconsistently track either the water surface or the lakebed, so the results are ambiguous (Fricker et al., 2021). To overcome this limitation and track both surfaces, our technique relies on the elevations of individual photons, which are distributed in the ATL03 data product (Neumann et al., 2023a). To keep the size of each individual ATL03 data file (or “granule”) manageable, each RGT orbit of ICESat-2 data is divided into 14 granule regions (Neumann et al., 2023b). This means

that each granule is limited to approximately 30 min of along-track data and rarely exceeds 10 gigabytes (GB) in size. ATL03 reports geolocated photon attributes such as longitude, latitude, along-track distance and height for each individual photon detection event, thus providing an along-track point cloud of photon locations. Geophysical corrections (such as geoid height) are reported at a 20 m along-track segment rate, and parameters related to on-board data processing (such as telemetry window ranges) are reported at the 50 Hz (≈ 140 m along-track) “major frame” rate (Martino et al., 2022b). In an ATL03 point cloud, signal photons being reflected both from a lake’s water surface and its lakebed results in characteristic double returns, which are used by FLUID to detect along-track data segments containing supraglacial lakes and by SuRRF to generate depth estimates for those lake segments. While the strong beam data have a higher signal to noise ratio, we have designed our FLUID/SuRRF method to work well with both strong and weak beams whenever a bathymetric return from the lakebed is discernible, i.e. for lakes with a visible or partly visible lakebed.

2.3.2. Supraglacial lake detection in ATL03: the FLUID algorithm

The Flat Lake and Underlying Ice Detection (FLUID) algorithm takes an ATL03 granule as input, searches for locations that contain potential supraglacial lakes with a bathymetric signal, and then returns along-track segments of the data for all detections. FLUID exploits two unique characteristics of supraglacial lake segments in ATL03 data:

1. photons which are reflected back from an open water surface cluster around a flat line (Sect. 2.3.2.1, Fig. 2.4) and
2. a bathymetric return signal must present as a secondary peak in photon density below such a flat surface (Sect. 2.3.2.4, Fig. 2.7).

To search for supraglacial lake segments in ATL03, FLUID divides the photon data into

140 m along-track segments aligning with ICESat-2’s “major frames” and selects those that satisfy both of the above requirements. Then, adjacent major frames are iteratively clustered into larger along-track data segments that likely represent all available ATL03 data for an entire supraglacial lake (Sect. 2.3.2.5).

2.3.2.1 FLUID step 1: identification of flat water surfaces

This step uses the fact that the surface slope of a stationary body of open water is close to zero in geopotential coordinates (i.e. using orthometric photon heights), in contrast to the surrounding ice sheet or ice shelf which mostly have slopes greater than 0.01° (Shen et al., 2022; Fan et al., 2022). This simple property enables a computationally inexpensive calculation (a “flatness check”) to be applied to geoid-corrected ATL03 height data to check for possible candidate lake segments.

To perform this flatness check, we apply the ATL03-provided geoid correction to photon heights, and divide the data of each of ICESat-2’s six ground tracks into approximately 140 m along-track segments aligning with ICESat-2’s major frames. For each major frame, we bin photon elevations in 0.01 m intervals and smooth the resulting histogram using a gaussian filter with a standard deviation of 0.05 m, then normalize it by dividing by its largest value. If the smoothed histogram has a single peak with prominence > 0.1 , we record the elevation of this peak h_{peak} as the surface elevation at which a flat surface reflector would be located. In the case of a melt lake segment with a bathymetric return signal, it is possible that the return from the lakebed is stronger than the surface return. Therefore, if the smoothed histogram has multiple peaks with prominence > 0.1 , we choose h_{peak} from the two most prominent peaks, and set it to the elevation of the one located at a higher elevation.

The flatness check is based on ratios between photon densities d_i that we calculate

for various elevation bands around h_{peak} (Appendix 2.7). As illustrated in the lower panels of Fig. 2.4, d_0 is the photon density within an elevation band of $\pm w_{\text{peak}} = 0.1$ m around the photon density peak. If a major frame contains the flat surface of a lake, then most of the surface signal photons should be contained in this “lake surface elevation band”, making d_0 significantly larger than the photon density in surrounding elevation bands (see Fig. 2.4, panel b). d_1 and d_2 are the photon densities within elevation bands of width $w_{\text{buffer}} = 0.35$ m just below and above the lake surface elevation band, respectively. Due to multiple scattering in the water column of a lake, we expect that over supraglacial lake segments the photon density just below the surface (d_1) can take on larger values than the photon density just above the surface (d_2). d_3 is the photon density within the entire telemetry window except for the lake surface elevation band, and d_4 is the photon density between the top of the lake surface elevation band and the top of the telemetry window. Over a lake segment, most of the telemetry window outside the lake surface elevation band contains only background noise photons, so we expect that the photon densities d_3 and d_4 need to be significantly smaller than the surface photon density (d_0) if the major frame contains a flat lake surface. Since d_3 can still contain photons below the lake surface due to multiple scattering and a bathymetric signal, we expect that over supraglacial lake segments d_3 can take on larger values than d_4 . Based on these assumptions, and using a trial-and-error approach, we defined the following thresholds on the density ratios that need to hold for a major frame to pass the flatness check: $d_0/d_1 \geq 2$, $d_0/d_2 \geq 5$, $d_0/d_3 \geq 10$ and $d_0/d_4 \geq 100$. As part of this trial-and-error approach, we manually assessed the effects of tweaking the above thresholds on a number of hand-picked granules, which we judged to be likely representative of various possible environments, to ensure adequate performance (i.e. granules without surface melt vs. pervasive surface melt, granules with smooth vs. rough background topography, granules containing ice-covered and partially ice-covered lakes, granules containing slush areas, granules containing exposed bedrock,

partially cloudy granules, weak vs. strong beam data, night- vs. daytime acquisitions, etc.). Panels a and b of Fig. 2.4 illustrate the outcome of the flatness check for all the major frames within a short along-track segment of ATL03 data that crosses a partially ice-covered supraglacial lake. Panels b and c show examples of major frames that pass the flatness check and fail the flatness check, respectively, and illustrate the elevation bands that were used to calculate photon density ratios.

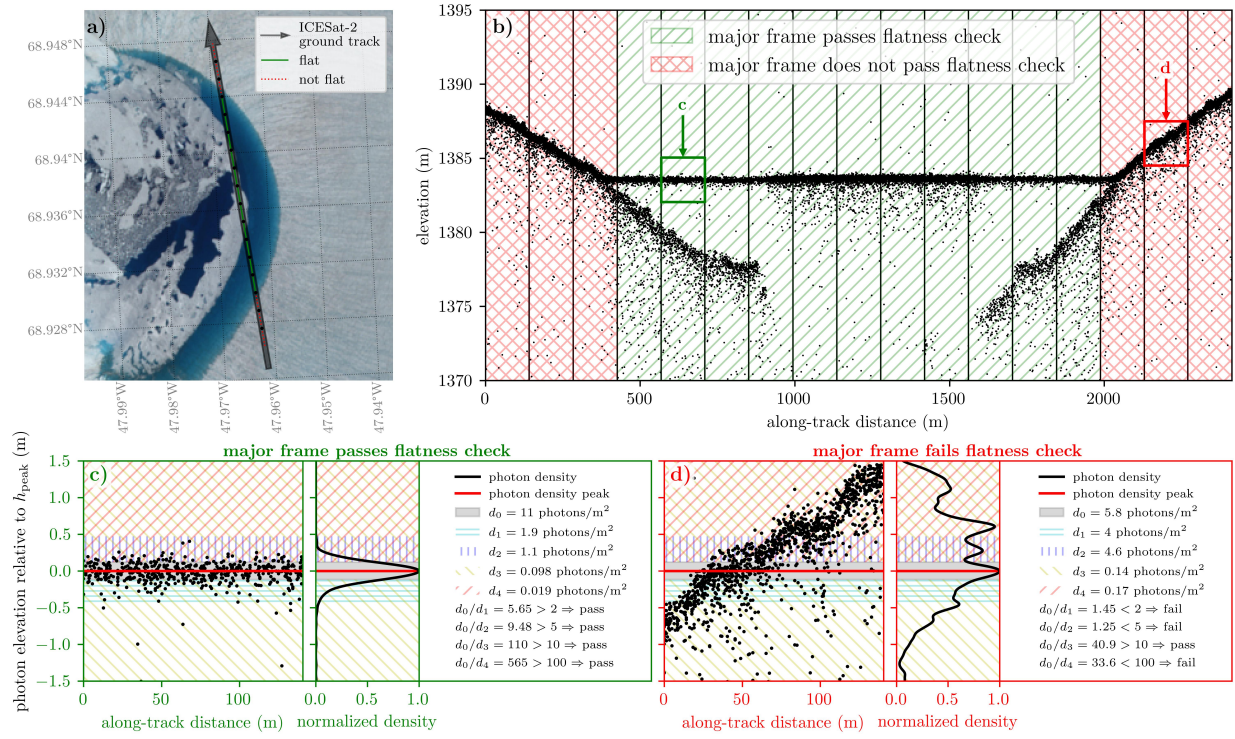


Figure 2.4: FLUID “flatness check” applied to every ATL03 major frame for identifying potential supraglacial lake segments. a) Ground track of an along-track segment of ATL03 data over the Greenland Ice Sheet, crossing a partially ice-covered supraglacial lake; b) Corresponding along-track photon elevations, with major frame boundaries marked by vertical black lines and flatness check outcomes shown in hatching; c) and d) Photon density ratios for a passing and a failing segment, respectively. (Data from ICESat-2 Track 216 GT1L on 12 July 2019 and centered at 68.9370°N, 47.9657°W; granule: ATL03_20190712052659_02160403_006_02.h5, imagery: Sentinel-2 on 13 July 2019)

Since FLUID assesses the flatness of the surface of full major frames that cover an along-track distance of ~ 140 m, lake segments with shorter open-water surfaces are

not guaranteed to be detected by FLUID. However, lake segments that are significantly shorter than 140 m are regularly detected by FLUID in practice. This is because the return signal from flat water surfaces is typically much stronger than the return signal from the surrounding ice surfaces, which makes even very short, flat water surfaces dominate the overall distribution of photon elevations within a major frame. The presence of a flat surface within a major frame is a necessary condition for detecting supraglacial bathymetry data, but it is not sufficient. There are many types of surfaces that would pass the flatness test but are not supraglacial lake segments with a bathymetric signal. This includes areas of slush, frozen-over supraglacial lakes covered in ice and snow, any areas of sea ice, ocean water or ice-marginal lakes erroneously included in the ice mask used for subsetting data, and other short along-track sections over firn or glacial ice that happen to be extremely flat by chance. For example, a lake may have partial ice cover, which prevents ICESat-2 from obtaining a bathymetric return (Fig. 2.4). However, since the ice cover here appears to be thin and flat, the corresponding major frames still pass the flatness check despite the absence of any useful bathymetry data in those segments. This means that the flatness check presented in this chapter serves as a preliminary screening method, helping to efficiently narrow down the number of along-track segments that could potentially contain useful supraglacial bathymetry data. This process makes it computationally feasible to determine whether a bathymetric signal is actually present by performing more complex operations on only the data that remain after checking for a sufficiently flat surface. The following sections describe these methods, which are at first only applied to those major frames that passed the initial flatness check.

2.3.2.2 FLUID step 2: removal of afterpulses

The second step removes artefacts in the ATL03 photon data known as “afterpulses”, which appear as additional lines below and parallel to the primary surface return,

due to the specifics of the ATLAS sensor (Luthke, 2023; Lu et al., 2021; Martino et al., 2022a). Afterpulses only become noticeable when the sensor is nearly or fully saturated, which means they often appear in ATL03 data over supraglacial lakes because smooth open water surfaces (i.e. the surface of stationary water bodies that are not affected by wind) can result in specular reflection. This suggests that the presence of wind ripples increases the likelihood of detecting a lake segment with a clear bathymetric signal in ATL03 data by preventing sensor saturation and afterpulsing (Lu et al., 2019; Tilling et al., 2020) and also explains why we observe afterpulsing more frequently near the (more wind-shielded) margins of melt lakes than over their (more wind-exposed) interior. Figure 2.5 (panels d-h) shows an example of an ATL03 data segment over a supraglacial lake in which these afterpulses are clearly visible below the flat water surface. There are three different mechanisms that can cause afterpulses:

1. *Dead-time* afterpulses appear in saturated pulses due to the ATLAS receiver channels only being able to register one photon event roughly every 3 ns. If the return signal is strong enough that all receiver channels register photon events during a time span shorter than this “dead-time”, ATLAS cannot register any photons until the receiver channels have recovered. This means that for saturated pulses, afterpulses can appear in intervals of about 3 ns of photon flight time, equivalent to ~ 0.45 m of elevation (Lu et al., 2021).
2. *Internal reflection* afterpulses are found in ATL03 data around 2.36 m, 4.27 m and 6.59 m below the surface return (Martino et al., 2022a). These are due to optical reflections internal to the ATLAS receiver.
3. *PMT ionization* afterpulses appear as a broad peak ~ 12 –40 m below the surface when pulses are strongly saturated and cause ionization of the Photomultiplier Tubes (PMTs), which triggers false photon detection events.

Since all of these afterpulses present as secondary peaks in photon density below the primary surface return, they can be mistaken for or obscure any real bathymetric signal returns. Therefore, they need to be removed before determining whether a bathymetric signal is present in the data. ATL03 provides the parameter `quality_ph` that is designed to allow users to filter out afterpulses. However, this parameter does not remove most dead-time afterpulses and naively removes all data more than 2 m below the surface for saturated returns (Neumann et al., 2022). This means that using the ATL03-provided `quality_ph` flag is not appropriate when searching for sub-surface return signals in saturated pulses, as it would fail to remove dead-time afterpulses that could be misidentified as bathymetric signals and could remove actual bathymetric signals at depths greater than 2 m (Fig. 2.5 panel e). Therefore, we developed an improved afterpulse removal routine that is tailored to bathymetric applications.

Afterpulse removal: We first estimate the saturation level of each pulse, based on the sensor dead-time t_{dead} which is provided for each beam in the ATL03 data product. Let n_{ch} be the number of receiver channels, i.e. $n_{\text{ch}} = 4$ for weak beams and $n_{\text{ch}} = 16$ for strong beams. If the total number of photons in a pulse $n_{\text{ph}} \geq n_{\text{ch}}$ we can calculate the minimum vertical distance spanned by any n_{ch} photons, and denote it by Δh . We then estimate the sensor saturation ratio as $r_{\text{sat}} = t_{\text{dead}}c/(2\Delta h)$ if $n_{\text{ph}} \geq n_{\text{ch}}$ and zero otherwise, where c is the speed of light in a vacuum. This means that for saturated pulses ($r_{\text{sat}} \geq 1$), all receiver channels registered a photon within a time frame of $t_{\text{dead}}/r_{\text{sat}}$. For all saturated pulses, we calculate the elevation of the saturated return, h_{sat} as the mean elevation of the n_{ch} photons that span Δh .

To determine the typical locations of afterpulses relative to h_{sat} in saturated pulses, we compiled a data set of saturated pulses from melt lake segments using an earlier version of FLUID (Arndt and Fricker, 2022), which did not include afterpulse removal. For each

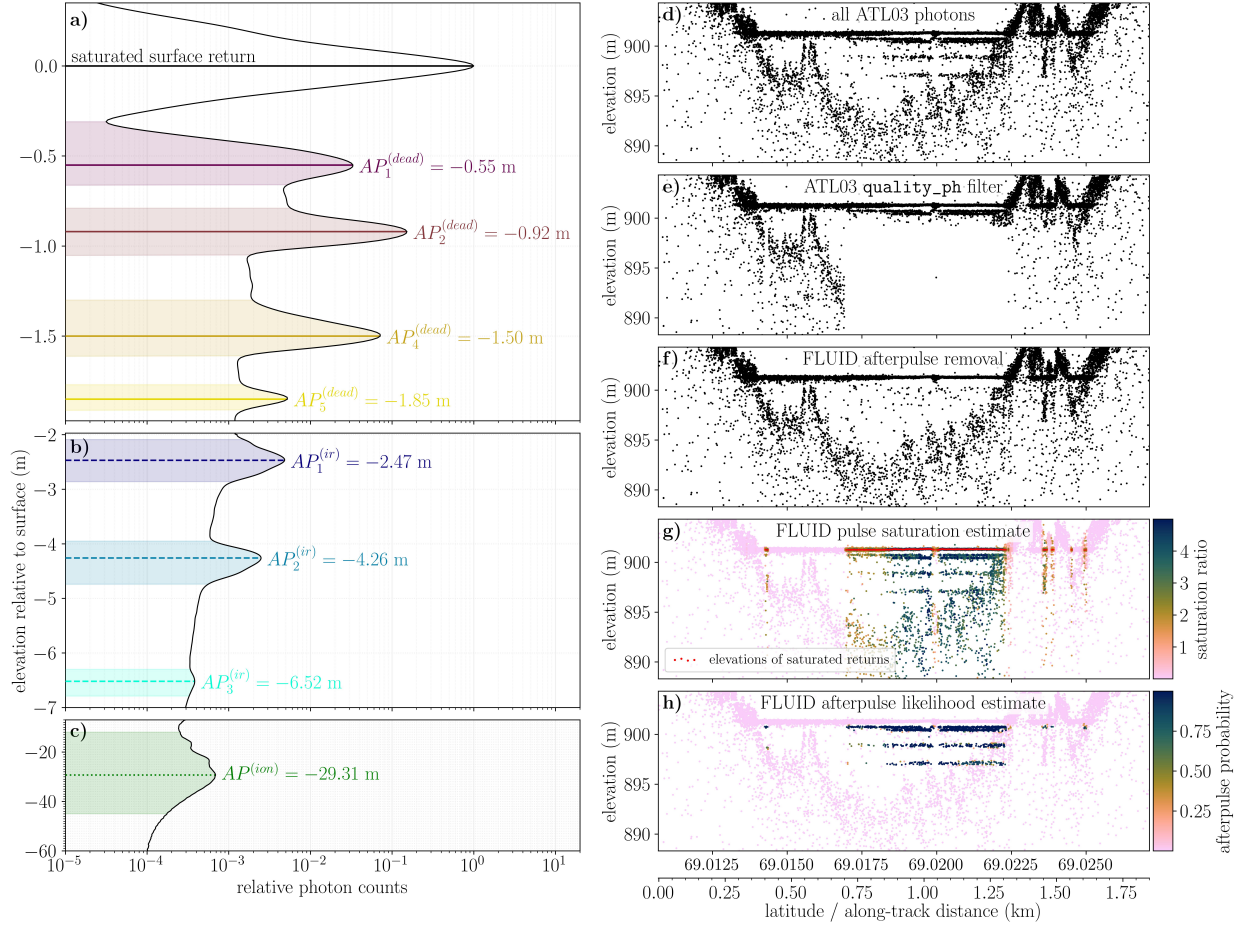


Figure 2.5: FLUID afterpulse removal. (a) to (c): Histogram of photon elevations in saturated pulses from ICESat-2 melt lake segments, relative to the elevation at which saturation occurred. The secondary peaks that appear below the saturated surface return are afterpulses that are caused by (a) dead-time of the ATLAS sensor; (b) internal reflections in the instrument; and (c) PMT ionization. Note that (a), (b) and (c) have different vertical scales. d) to h): Implementation of FLUID’s afterpulse removal for a short along-track segment of ATL03 data that crosses a supraglacial lake, with sections of highly saturated (specular) pulses. Known locations of ATLAS afterpulses (a) to (c) are used to remove likely afterpulse photons. (Data from ICESat-2 Track 1222 GT2L on 17 June 2019 and centered at 69.0189° N, 49.0444° W; granule: ATL03_20190617064249_12220303_006_02.h5)

saturated pulse, we subtracted h_{sat} from the photon elevations and created a histogram of photon counts weighted by r_{sat} (Fig. 2.5, panels a-c). The strong peaks in this histogram correspond to the elevations at which afterpulses occur relative to the surface. We found that dead-time afterpulses occurred at four depths: $AP_1^{(\text{dead})} = 0.55$ m, $AP_2^{(\text{dead})} = 0.92$ m, $AP_3^{(\text{dead})} = 1.50$ m and $AP_4^{(\text{dead})} = 1.85$ m. Only the first two of the internal reflection afterpulses were strong enough to significantly contaminate bathymetric data in saturated or near-saturated pulses, at $AP_1^{(\text{ir})} = 2.46$ m and $AP_2^{(\text{ir})} = 4.25$ m below the surface. While the third internal reflection afterpulse is also visible at $AP_3^{(\text{ir})} = 6.52$ m, it appears that this afterpulse is not typically strong enough to be confused for a bathymetric return signal. The broad peak associated with PMT ionization around $AP^{(\text{ion})} \approx 29 \pm 15$ m only became noticeable at the typical length scales of ICESat-2 melt lake segments when $r_{\text{sat}} > 3.5$. For such strongly saturated pulses, we simply discarded any photons > 12 m below the surface.

With the locations of the main afterpulses known, we can use a simple empirical method to remove afterpulses from ATL03 data for all major frames that passed the flatness check and for which at least 100 photons are attributed to saturated pulses. For each major frame, we follow the above weighted histogramming procedure and examine the heights of the seven most prominent peaks; if any of these peaks align with the relative elevations of the known afterpulses, we consider it evidence for likely afterpulsing and remove any photons that belong to saturated pulses in that elevation band (Fig. 2.5, panel h). Since this procedure removes photons in saturated pulses only, true bathymetric signals that overlap with the elevation of a known afterpulse are still retained as long as they appear in any unsaturated pulses. However, if all pulses within an along-track section of the data are saturated, any true bathymetric signals from a flat lakebed at the elevation of a known afterpulse will be removed from the data because they are practically indistinguishable from the afterpulses that we expect to see in the point cloud under such highly saturated

conditions.

While more sophisticated approaches for afterpulse removal are certainly possible, we found that in practice our purely empirical approach strikes a good balance between effectively removing enough afterpulse photons to prevent bathymetric surface fitting methods from considering afterpulses a signal, while also retaining enough photons to prevent removal of actual signal returns whenever it is possible to discern the two.

2.3.2.3 FLUID step 3: photon signal confidence estimation

Once flat “candidate” segments have been identified and afterpulses have been removed, the next step is to assign a signal confidence score to the remaining photons. ATL03 contains many noise photons from various sources, such as solar background noise, atmospheric backscatter, and multiple scattering in translucent media (Neumann et al., 2019; Yang et al., 2023). Release 006 of the ATL03 data product provides two measures that can help discriminate between signal and noise photons. Over the ice sheets, the `signal_conf_ph` parameter gives an estimate of how likely it is that a photon is part of the land ice surface signal, based on slant histogramming (Neumann et al., 2019). This parameter, however, does not consider the possibility of two distinct reflective surfaces that are both signal, and therefore often labels lakebed return photons over supraglacial lakes as noise (Fig. 2.6, panel a). Since release 006, ATL03 also includes the `weight_ph` parameter, which provides a local metric for relative photon density based on the Yet Another Photon Classifier method (YAPC; Neumann et al., 2022; Sutterley and Gibbons., 2021). For each target photon, the YAPC weight calculation is based on a rectangular window ± 3 m in elevation around the photon location. This can result in sharp photon weight discontinuities 3 m above and below highly reflective flat surfaces, which are inconsistent with relative local photon density (Fig. 2.6, panel b). Due to these drawbacks of the ATL03-provided param-

eters, we developed a new density-based method for photon signal confidence estimation that is more accurate for ICESat-2 melt lake segments (Fig. 2.6, panel c). This method is based on the inverse euclidean distances between a photon and its k -nearest neighbors (kNN) within a search radius that depends on the background noise rate (Appendix 2.8).

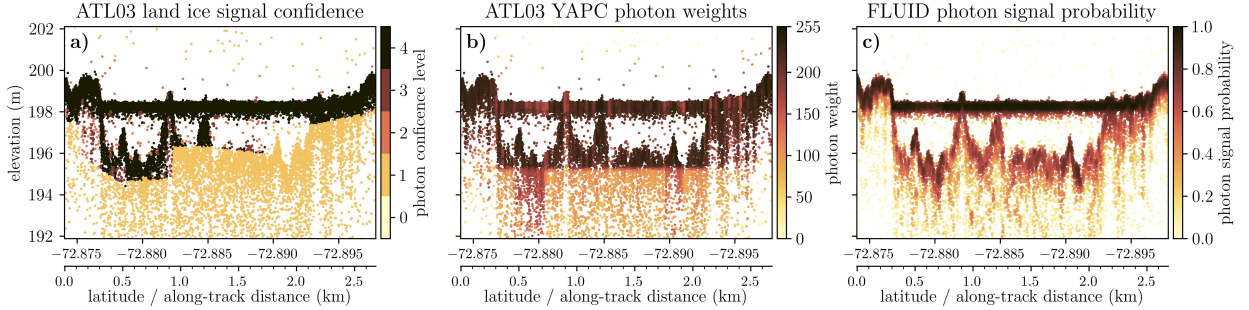


Figure 2.6: Comparison between photon signal confidence estimates: ATL03-provided values and our method for melt lake segments in FLUID. (Data from ICESat-2 Track 81 GT2L on 2 January 2019 and centered at 72.8859°S, 67.3082°E; granule: ATL03_20190102184312_00810210_006_02.h5)

In FLUID, we implement this photon signal probability estimation using a K-D tree approach for querying nearest neighbors of photons, applied to individual major frames. To calculate photon densities within a major frame, we consider additional photons within a sufficiently wide buffer in along-track distance to avoid penalizing photons that are near the major frame margins by not taking into account all their nearest neighbors. Panel c) of Fig. 2.6 shows the resulting density-based photon signal probabilities for a supraglacial melt lake segment on Amery Ice Shelf.

2.3.2.4 FLUID step 4: secondary bathymetry peak detection

To determine which major frames amongst the ones that pass the flatness check are likely to provide useful bathymetry data, FLUID checks for secondary peaks in photon density below the flat surface return. To do so, we divide each major frame into 10 along-track sub-segments of equal length (i.e. about 14m per sub-segment). For each sub-

segment we use the FLUID photon-level signal probabilities to calculate photon signal confidence as an empirical smooth function of elevation. To determine whether a potential bathymetric signal is present below the lake surface, we determine the elevation of the most prominent below-surface peak in this function for every sub-segment. Based on the along-track locations, elevations and prominences of all peaks that were identified in a given major frame, we define four quality heuristics q_i for different components that we found to affect the overall quality of the bathymetric return (Appendix 2.9). The q_i all take on values between zero and one, with higher values implying a “better” bathymetric signal. We designed the expressions for the quality heuristics such that q_1 penalizes major frames with smaller numbers of detected subsurface peaks, q_2 penalizes major frames with less prominent peaks, q_3 penalizes major frames with a very large overall spread of peak elevations, and q_4 penalizes major frames with peak elevations that do not align along a smooth surface. We then define the overall bathymetric quality summary q_s of a major frame as the product of the four q_i . We consider the secondary bathymetric peak in photon density strong and coherent enough to pass the bathymetric signal check for any major frames with $q_s \geq 0.1$.

We illustrate this procedure for an along-track segment over Central West Greenland that crosses a supraglacial lake with a bathymetric return signal that varies in strength along the ground track (Fig. 2.7). In this example, most of the major frames that cover the supraglacial lake’s interior pass the bathymetric signal check, with bathymetric photon density peaks smoothly tracing the apparent lakebed. However, two of the major frames within the lake’s interior do not have a strong-enough signal of photons reflected from the lakebed to be passing the bathymetric signal check during this step, in which FLUID initially considers each major frame in isolation. These two major frames visibly overlap with the location of a thin partial ice cover near the lake’s northern shore (Fig. 2.7, panel

2.3. Data and methods

a), which explains why some of the lakebed is occluded. While such areas, where part of the lakebed is occluded, may not pass the bathymetry check, they are later included in the data that make up a full ICESat-2 lake segment, as explained in the next section.

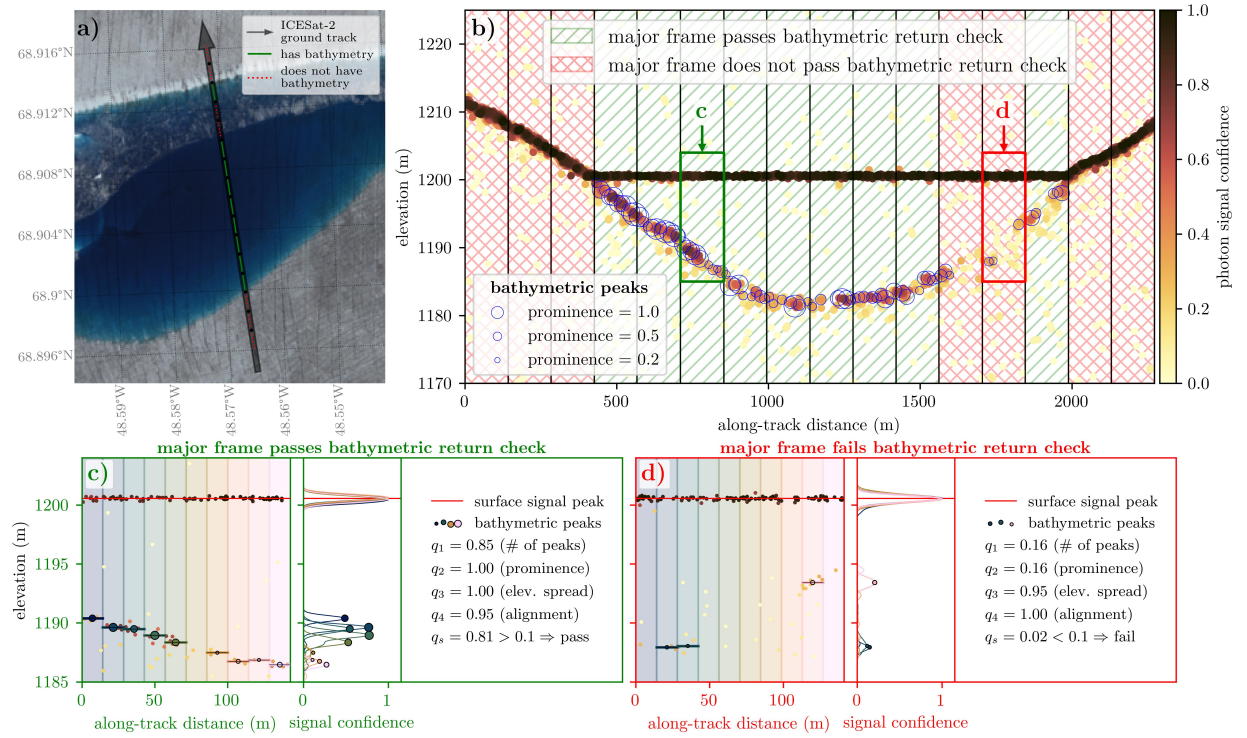


Figure 2.7: FLUID's bathymetric signal check run on every ATL03 major frame that has passed the flatness check. a) Ground track for an along-track segment of ATL03 data over the GrIS, which crosses a supraglacial lake that has a thin partial ice cover near its northern shore. b) Corresponding along-track photon elevations, and locations of detected bathymetric photon density peaks. The vertical black lines are the major frame boundaries, and hatching indicates whether major frames passed the bathymetric signal check or not. c) and d) Bathymetric peak-finding procedure from photon density and associated values of the bathymetric return quality heuristics described in the text and defined in Appendix 2.9, for a passing and a failing major frame, respectively. (Data from ICESat-2 Track 277 GT3R on 16 July 2019 and centered at 68.9062° N, 48.5689° W; granule: ATL03_20190716051841_02770403_006_02.h5, imagery: Sentinel-2 on 16 July 2019)

2.3.2.5 FLUID step 5: along-track aggregation of lake segments

Given the collection of major frames that individually pass the bathymetric signal check along a ground track, FLUID aggregates major frames into clusters, each of which likely represents a transect of an entire supraglacial lake. To achieve this, we use an agglomerative clustering scheme based on two simple assumptions: (i) the water surface elevation within a single ICESat-2 lake segment should be nearly constant along the ground track, and (ii) a ground track rarely crosses the same lake in two distinct locations that are separated by more than about 1.5 km. At the start of the clustering process, each major frame that passed the initial bathymetric return check is considered a singleton cluster with a water surface elevation h_{surf} equal to the single major frame's surface photon density peak h_{peak} , and major frame start and end IDs $m_{\text{start}} = m_{\text{end}}$ that are both equal to the single major frame's ID. This means that a cluster can be expressed as

$$\mathcal{C}^{(i)} = \{h_{\text{surf}}^{(i)}, m_{\text{start}}^{(i)}, m_{\text{end}}^{(i)}\} \quad (2.1)$$

where the index $i \in 1, 2, \dots, n_{\text{clusters}}$ is assigned to the i^{th} cluster when sorting all n_{clusters} clusters by their respective values of m_{start} . Since major frame IDs are numbers that strictly increase with along-track distance, this means that $m_{\text{end}}^{(i)} < m_{\text{start}}^{(i+1)}$ for all clusters. Now, clusters that are adjacent to each other in along-track coordinates are compared in a pairwise fashion. For all uneven numbers $i < n_{\text{clusters}}$, if

$$\left| h_{\text{surf}}^{(i)} - h_{\text{surf}}^{(i+1)} \right| \leq \Delta h_{\text{max}} = 0.1 \text{ m} \quad (2.2)$$

and

$$m_{\text{start}}^{(i+1)} - m_{\text{end}}^{(i)} \leq \Delta m_{\text{max}} = 10, \quad (2.3)$$

clusters $\mathcal{C}^{(i)}$ and $\mathcal{C}^{(i+1)}$ are merged into a new cluster

$$\mathcal{C}^{(i')} = \left\{ \left(h_{\text{surf}}^{(i)} + h_{\text{surf}}^{(i+1)} \right) / 2, m_{\text{start}}^{(i)}, m_{\text{end}}^{(i+1)} \right\}. \quad (2.4)$$

Equation 2.2 states that neighboring clusters are only merged if their respective lake surface elevations are within 0.1 m of each other, and Eq. 2.3 states that neighboring clusters are further only merged if they are separated by ten major frames that did not pass the bathymetry check, or less (about 1.5 km). This means that if FLUID encounters the unlikely but possible scenario in which a ground track crosses two arms of the same lake, which are separated in along-track distance by more than 10 major frames, then these two crossings are considered to be separate lake segments and returned as two separate files in the output data rather than being merged together into one lake segment. If these two conditions do not result in any two clusters being merged, then the same pairwise comparison is carried out for all even numbers $i < n_{\text{clusters}}$. After an iteration of merging clusters, the indices of the remaining n'_{clusters} clusters are re-set to $1, 2, \dots, n'_{\text{clusters}}$, and the same procedure is repeated until no more clusters can be merged based on the conditions above.

The resulting final clustering is now considered the set of ICESat-2 supraglacial lake segments that have been found on each ground track. Note that for simplicity we here use the term “*ICESat-2 lake segment*” (or simply “*lake segment*”) to refer to any single-ground-track segment of ATL03 data with visible bathymetry from one supraglacial lake. If multiple ICESat-2 ground tracks contain data from the same supraglacial lake, the distinct ground track segments are still considered different “ICESat-2 lake segments” for the purpose of this algorithm. For example, the two ATL03 profiles acquired by the two neighboring ground tracks of the center beam pair shown in Fig 2.1 would be considered two distinct “lake segments” despite ICESat-2 having acquired their underlying data during the same overpass and from the same supraglacial lake. Since multiple ICESat-2 lake segments

can be associated with the same supraglacial lake, the total number of unique supraglacial lakes sampled by ICESat-2 is smaller than the total number of supraglacial lake segments reported by FLUID-SuRRF (Sect. 2.4.1, Table 2.1).

Since every lake segment that was detected this way is characterized by an along-track range of major frame IDs $[m_{\text{start}}, m_{\text{end}}]$, FLUID extends these ranges outwards to make sure that no bathymetry data were missed near the edges of any lake segment. To do so, each lake segment's range is extended to include any major frames for which $|h_{\text{peak}} - h_{\text{surf}}| < 0.2 \text{ m}$ as long as such major frames exist within three major frames of the lake segment's range. At the end of this process we add another four major frames as a buffer, two to each side of the lake segment. Since this expansion of the along-track ranges of lake segments can create lake segments that overlap, the set of buffered lake segments is corrected by separating partially overlapping lake segments at the midpoint of their along-track overlap and removing any lake segments that are fully contained within another lake segment. We apply FLUID steps 2, 3 and 4 (afterpulse removal, signal confidence estimation and bathymetric return check) to all major frames in the buffer (i.e. now included in the along-track range of a lake segment but had not initially passed the flatness check). The resulting final set of lake segments across all ground tracks in the input granule is the output of FLUID.

2.3.3. Supraglacial lake depth determination: the SuRRF algorithm

To estimate the along-track depth for each detected lake segment, we developed the Surface Removal and Robust Fit (SuRRF) algorithm, updated from Fricker et al. (2021). The central idea of SuRRF is to use a robust fitting procedure (Sect. 2.3.3.1) to first fit a smooth line to all photons returned from the lake surface and the surrounding topography (Sect. 2.3.3.2), then remove all photons that are part of the water surface and fit another

smooth line to the remaining photons to determine the location of the lakebed (Sect. 2.3.3.3). The along-track water depth estimate is the elevation difference between the fits to the water surface and the lakebed, corrected for the refractive index for the speed of light in water (Sect. 2.3.3.5). In Fig. 2.8, we illustrate the main steps of SuRRF using an example of ATL03 along track data, which was determined to be a supraglacial lake segment by FLUID. We summarize the main steps of SuRRF in the following sections.

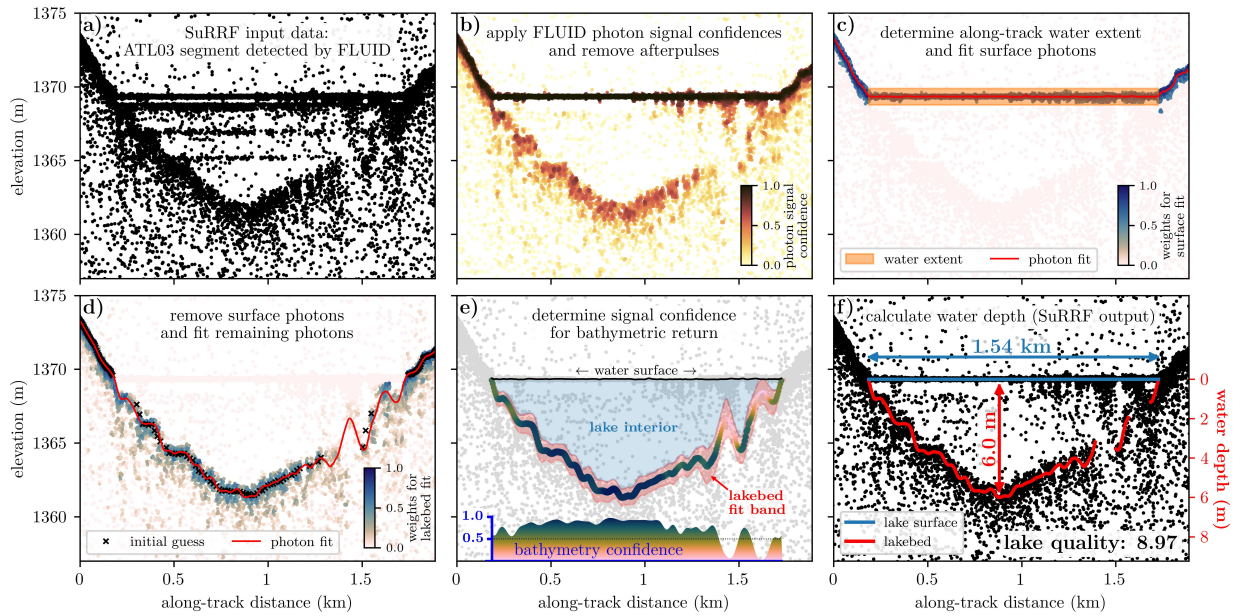


Figure 2.8: SuRRF algorithm for determining supraglacial lake depth from an along-track segment of ATL03 data that was detected by FLUID. (Data from ICESat-2 Track 277 GT2L on 13 July 2020 and centered at 68.1923° N, 48.5134° W; granule: ATL03_20200713115804_02770803_006_01.h5)

2.3.3.1 SuRRF Robust Fit

In SuRRF steps 1 and 2 (Sect. 2.3.3.2 and 2.3.3.3), we use a tailored robust non-parametric regression method to locate the lake surface and lakebed. The SuRRF Robust Fit is based on Locally Weighted Regression and Smoothing Scatterplots (LOWESS, Cleveland, 1979), which is applied to the data iteratively, while removing outliers during

each iteration to converge to an along-track fit that smoothly tracks the elevation of highest photon density. For each evaluation location x_{fit} in along-track coordinates, we fit a locally weighted n^{th} -degree polynomial regression to the photons that are at a distance of at most x_{max} in along-track coordinates. The value of x_{max} is the minimum distance from x_{fit} within which there are n_{ph} photons i with a nonzero FLUID-derived signal confidence p_i , or a minimum along-track fitting window length of x_{min} , whichever is larger. To achieve smooth local weighting, the along-track weight of a photon i at location x_i is calculated using the tri-cube weight function $w_i^{(\text{x})} = \left(1 - |(x_i - x_{\text{fit}})/x_{\text{max}}|^3\right)^3$. If the method is provided with an initial guess for the first iteration, we calculate the residuals e_i as the difference between each photon's elevation and the linear interpolation of the initial guess elevations to each photon's along-track location. In this case, we consider only photons whose absolute residuals are at most h_{max} , and calculate their residual-based weights as $w_i^{(\text{h})} = \left(1 - (|e_i|/h_{\text{max}})^3\right)^3$. In absence of an initial guess, we set $w_i^{(\text{h})} = 1$ for all photons in the first iteration. The photon weights that are used for the regression are $w_i = p_i w_i^{(\text{x})} w_i^{(\text{h})}$. We evaluate the resulting regression model at each fit location x_{fit} to obtain an along-track estimate of the fit to the photon heights. For each consecutive iteration, we calculate the residuals e_i as the difference between each photon's elevation and the elevation of the linearly interpolated elevation fit of the previous iteration. Let σ be the standard deviation of residuals, weighted by the previous iteration's weights. To achieve a robust fit, we now consider only photons whose absolute residuals are at most n_{std} standard deviations, and calculate the residual-based weights $w_i^{(\text{h})}$ as defined above, using $h_{\text{max}} = n_{\text{std}}\sigma$. We run this nonparametric weighted regression for a number of n_{iter} iterations to obtain a smooth fit that tracks the along-track elevation of highest photon density.

2.3.3.2 SuRRF step 1: lake surface fit

To fit an elevation profile to just the surface of a lake segment detected with FLUID, we calculate the along-track extent of photons that belong to the flat lake surface, remove all photons below the lake surface, and then apply the SuRRF Robust Fit to the remaining photons (Fig. 2.8, panel c). We determine the extent of the open water surface by calculating the photon density within an elevation band of ± 0.225 m around the lake's surface elevation at 1 m along-track resolution, as well as the corresponding photon densities within the remaining telemetry window and within 2 m above the surface elevation band. We smooth all photon densities using an along-track gaussian window with a 15 m standard deviation. We then consider a location along the ground track to contain a water surface if the photon density within the surface elevation band is at least ten times as large as the other photon densities for any continuous along-track section of at least 100 m in length. Within the resulting estimate of along-track water extent, we remove all photons that are more than 0.4 m below the lake's surface elevation from the surface fit by setting their signal confidence $p_i = 0$.

To obtain an along-track fit to the lake's surface and its surrounding topography, we apply the SuRRF Robust Fit (Sect. 2.3.3.1) to all remaining photons with a signal confidence > 0.5 at evenly spaced locations x_{fit} along the ground track, at 5 m resolution. In this step, we use a linear regression ($n = 1$) and run it for $n_{\text{iter}} = 10$ iterations, with no initial guess. We here choose $x_{\text{min}} = 20$ m and let n_{ph} decrease linearly from $n_{\text{ph}}^{(\text{start})} = 300$ in the first iteration to $n_{\text{ph}}^{(\text{end})} = 100$ in the last iteration. Similarly, we choose $n_{\text{std}}^{(\text{start})} = 10$ and $n_{\text{std}}^{(\text{end})} = 4$. We illustrate this surface-fitting procedure by showing an example of a supraglacial lake segment in ATL03 with photons color-coded by their surface fit weights p_i , along with the detected along-track water surface extent and the final smooth photon fit to the lake surface and surrounding topography (Fig. 2.8, panel c).

2.3.3.3 SuRRF step 2: lakebed fit

To fit an elevation profile to just the lakebed, we remove all photons that belong to the lake’s water surface, and then again apply the SuRRF Robust Fit to the remaining photons (Fig. 2.8, panel d). In this case, we remove all photons that fall within the along-track water surface extent that was determined in the previous step, and are located at an elevation of 0.35 m below the lake’s surface or higher. Note that this imposes a theoretical minimum depth threshold for detection on lake segments: ATL03 segments need to exhibit a bottom return signal at least 0.35 m below the lake surface (or 0.26 m in refraction-corrected water depth) at their deepest along-track point to be considered by SuRRF. However, in practice, such shallow lake segments do not have a discernible bathymetric signal since typical depth retrieval accuracies for ICESat-2 are on the order of 0.5 m (Dietrich et al., 2024). To provide the SuRRF Robust Fit with an initial guess, we combine the locations of the bathymetric peaks found by FLUID that have a peak prominence value of at least 0.5 and fall within the lake’s along-track water extent with those locations of the smooth surface fit from Sect. 2.3.3.2 that fall outside of the lake’s along-track water extent. We then smooth the values of the initial guess using a running mean with a window of five data points to decrease the influence of any potential outliers. To decrease the influence of near-surface photons from multiple scattering, we further reduce the signal confidence values p_i of any photons that are between a lower bound of one meter above the initial guess and an upper bound of the lake surface elevation by multiplying them by a factor that linearly decreases from one to zero between the lower and the upper bound. To fit the lakebed, we apply the SuRRF Robust Fit (Sect. 2.3.3.1) to the same evaluation locations x_{fit} that were used to fit the lake surface. We here use a third-degree polynomial regression ($n = 3$) and SuRRF Robust Fit parameters $n_{\text{iter}} = 20$, $x_{\text{min}} = 100$ m, $n_{\text{std}}^{(\text{start})} = 10$, $n_{\text{std}}^{(\text{end})} = 3$, and $h_{\text{max}} = 10$ m in the first iteration. In this step we choose different values for $(n_{\text{ph}}^{(\text{start})}, n_{\text{ph}}^{(\text{end})})$

depending on ATLAS beam strength: (200, 100) for strong beam data and (100, 50) for weak beam data. We illustrate this lakebed-fitting procedure by showing photons color-coded by their lakebed fit weights p_i , along with the initial guess and the final smooth photon fit to the lakebed (Fig. 2.8, panel d).

Previous studies have hypothesized that ICESat-2-based depth retrieval algorithms placing the lakebed fit at the along-track elevation of highest subsurface photon density may be biased towards slightly overestimating total water depths due to multiple scattering within the water column (Fricker et al., 2021; Xiao et al., 2023). To address this, we provide an optional correction, which places the lakebed fit at a higher elevation where the initial SuRRF lakebed fit included photons further below the initial lakebed fit than would be expected from bathymetric signal photons. To achieve this, we remove any photons located at a vertical distance below the initial SuRRF lakebed fit by more than the sum of (1) ICESat-2’s single-photon time-of-flight precision (~ 12 cm in ATL03 photon heights or 800 ps; Markus et al., 2017), and (2) the elevation range within ICESat-2’s footprint diameter (~ 11 m Magruder et al., 2021a) obtained by projecting the footprint onto the along-track lakebed topography estimated by the initial SuRRF lakebed fit. We then reapply the lakebed fit to the remaining photons as described above, while supplying the SuRRF Robust Fit (Sect. 2.3.3.1) with the uncorrected SuRRF lakebed fit as the initial guess. Since the presence or magnitude of this hypothesized overestimation of water depths cannot be established without any ground truth *in situ* data available along any ICESat-2 lake segments, we provide this scattering correction for reference only, and do not apply it to the water depths presented in this study. If such validation data becomes available in the future, our scattering correction can be tuned to better match observations, and can be readily applied to FLUID-SuRRF output data.

2.3.3.4 SuRRF step 3: bathymetry signal confidence estimation

To estimate the signal confidence of the fit to the lakebed, we calculate the photon density ratio between the lower half of the interior of the lake and the elevation band within $\pm n_{\text{std}}^{(\text{end})} \sigma$ of the last iteration of the lakebed fit for each fit location $x_{\text{fit}} \pm 5$ m along the ground track. Here, we consider the interior of the lake to be the elevation range between the top of the elevation band of the lakebed fit and the surface elevation of the lake. For any along-track points for which there are no lakebed photons or for which the elevation band of the lakebed fit includes the lake surface, we set the ratio to 1. We then set the bathymetry confidence to one minus the density ratio, clip it to the range $[0, 1]$, set it equal to one wherever the lakebed fit is at a higher elevation than the lake surface elevation (i.e. wherever the estimated water depth is zero), and smooth it using an along track gaussian filter with a standard deviation of 10 m. Wherever the elevation range of the interior of the lake is less than the width of the elevation band of the lakebed fit, we further decrease the confidence by multiplying it by the ratio between the two elevation ranges. We illustrate this bathymetry signal confidence estimation procedure by visualizing both the elevation band of the final lakebed fit and the interior of the lake, and showing the resulting along-track confidence estimates for the bathymetric return (Fig. 2.8, panel e).

2.3.3.5 SuRRF step 4: water depth calculation

To determine the along-track water depth, we take the difference between the lake's surface elevation and the fit to the lakebed, and divide it by the refractive index for the speed of 532 nm light in 0 °C freshwater (≈ 1.336 ; Mobley, 1995). For any locations along the lake segment where the final lakebed fit (Sect. 2.3.3.3) returns a higher elevation than the surface elevation of the lake, we record a water depth of zero meters (i.e. no water

is present). We do not correct water depths for the effect of lakebed return geolocation errors caused by refraction, since ICESat-2 is nadir-pointing to its reference ground tracks over land ice, making the water depth correction due to the angle of refraction negligibly small (≈ 0.003 of the total water depth for the slightly off-nadir-pointing outer beam pairs, which is about 9 cm for a water depth of 30 m; Parrish et al., 2019). Final along-track water depths can be selected by applying a threshold to the bathymetry signal confidence (Sect. 2.3.3.4). Here, we select a confidence threshold of 0.5. For the lake segment example shown, this results in a maximum along-track depth of 6.0 m and gaps in along-track depth data in locations where no bathymetric return is evident (Fig. 2.8, panel f).

2.3.3.6 SuRRF step 5: lake segment quality estimate

To provide a relative indication of data quality, we provide an estimate for a summarized quality measure for each lake segment. Let $h_x^{(\text{surf})}$ and $h_x^{(\text{bed})}$ be the surface and bed fits at along-track measurement location x . For all x where $\Delta h_x = h_x^{(\text{surf})} - h_x^{(\text{bed})} > 0$, we calculate a histogram of photon counts within a 5 m along-track window for 300 elevation bins that are evenly spaced between $h_x^{(\text{bed})} - \Delta h_x$ and $h_x^{(\text{surf})} + \Delta h_x$. We then normalize the associated bin elevations $\tilde{h}$ such that $h_x^{(\text{bed})}$ corresponds to $\tilde{h} = 0$ and $h_x^{(\text{surf})}$ corresponds to $\tilde{h} = 1$, and take the per-bin sum across all x . We smooth the resulting elevation-normalized histogram using a gaussian filter with a standard deviation of three bins, and calculate the quality ratio r_q as the ratio between the value at $\tilde{h} = 0$ and the mean of the first quartile of the lowest values in $0 > \tilde{h} > 1$.

The “quality ratio” can be considered an along-track average estimate for the photon density ratio between the lakebed and the lowest-photon-density part of the interior of the lake. We classify lake segments with $r_q \leq 2$ as “zero quality” lake segments. Similarly, we classify lake segments with $r_q > 2$ as “high quality” lake segments, for which we report

the lake segment quality score as $r_q - 2$. This means that a lake segment is assigned a non-zero quality by SuRRF if the along-track averaged strength of the return signal from the lakebed is at least twice as large as the along-track averaged background noise rate within the interior of the lake. While “zero quality” lake segments might still include a clear bathymetric return along a small part of their associated along-track extent, a quality score of zero is meant to indicate that there may be significant issues with data quality. In the example shown, this results in SuRRF classifying the given lake segment as high quality, with a score of 9.0 (Fig. 2.8, panel f). We show more examples of FLUID/SuRRF output lake segments and their associated quality scores in a range from 0.2 to 115.5 in Figs. 2.9 and 2.10 (Sect. 2.4.1).

2.3.4. Computational implementation of FLUID/SuRRF

To facilitate large-scale use of FLUID/SuRRF, we implemented the algorithms as a Python routine that can be run on any ATL03 data granule, and developed a framework that allows for estimating all ICESat-2 lake depths for a given region of interest and time span. Given a polygonal region of interest (e.g.; a particular glacier, ice shelf, drainage basin, or other study region) and time span (e.g.; a typical melt season), we use the National Snow and Ice Data Center’s Data Access and Service API (NSIDC API) (NSIDC, 2021) to query for a list of all available ATL03 data granules that satisfy the spatio-temporal search parameters. To obtain all desired ICESat-2 lake depths, we can subset these ATL03 granules to the region of interest, run FLUID/SuRRF on each subsetted granule individually, and collect all output melt lake segment and their associated along-track depth data. This allows for parallel processing of data granules.

To apply FLUID/SuRRF to all identified granules in an efficient, cost-effective and reproducible manner, we use the OSG Open Science Pool (OSPool) for distributed High-

Throughput Computing (dHTC) (OSG, 2006; Pordes et al., 2007) Since batches of OSG compute jobs run on heterogeneous hardware, we run all jobs in a Singularity container (Kurtzer et al., 2017) that we designed for use with FLUID/SuRRF. We run one OSG compute job per ATL03 granule, where each job receives as input the producer ID of the granule and a shapefile of the corresponding region of interest. Each job makes a request to the NSIDC API to subset the specified granule to the given shapefile, and downloads the subsetting granule. The job then runs FLUID/SuRRF on the downloaded granule for each of ICESat-2’s six ground tracks, and sends back individual HDF5 files of output water depths for each lake segment that was detected by FLUID.

Each output file reports water depth estimates at a 5 m along-track resolution with associated values for longitude, latitude, along-track distance, bathymetry signal confidence and elevations of the lakebed and surface fit to the photon data. We also include lake segment properties such as: surface elevation, SuRRF quality score, and various metadata such as the granule name, beam, time of data acquisition, center longitude/latitude. For reference, we add the underlying ATL03 photon heights and locations with FLUID estimates of photon signal probability, saturation level and afterpulse probability, as well as calculated FLUID parameters at the major frame rate. In addition to each lake segment’s data file, we also create an associated “quick look” plot of the photon data with surface and lakebed fits and the ground track shown over the closest available cloud-free Landsat 8/9 or Sentinel-2 imagery (e.g.; Fig. 2.9, a-j and 2.10, a-j). The availability of these for all returned lake segments makes it possible to add a final manual quality control step to our method, based on visual inspection of the plots in a custom-made streamlit app. We use this to remove clear false positives from the output data.

2.3.5. Study regions and time span

To evaluate the performance of our method, specifically whether it is able to capture spatial and temporal variability while reliably extracting supraglacial lake depths at scale, we focus on one drainage basin on each of the ice sheets and compare a high-melt with a low-melt season for each. For both the Greenland and Antarctic ice sheets, we define our study regions using the Ice sheet Mass Balance Inter-comparison Exercise (IMBIE) drainage basins (Fig. 2.2, Mouginot et al., 2017; Mouginot and Rignot, 2019). Since we do not expect significant surface meltwater pooling beyond a certain elevation, we apply elevation thresholds to the drainage basins prior to running FLUID/SuRRF.

In Greenland, we focus on the Central West (CW) drainage basin, and compare ICESat-2 lake depths between the exceptionally warm 2019 melt season (Tedesco and Fettweis, 2020) and the 2020 melt season, which experienced comparatively little surface melt and runoff (Druckenmiller et al., 2021). During these two summers, Central West Greenland experienced a particularly stark contrast in observed surface runoff elevation limits, with surface runoff extending to significantly higher elevations in 2019 than in 2020 (Tedstone and Machguth, 2022). For Central West Greenland, we use an elevation threshold of 2000 m based on Zhang et al. (2023), who reported a mean elevation limit of surface water of 1609 m above sea level in this region during the anomalously warm 2019 melt season. We apply this threshold based on the ArcticDEM digital elevation model (Morin et al., 2016).

In Antarctica, we focus on the B-C drainage basin, including Amery Ice Shelf and its surrounding grounded ice catchment, which on average experiences more meltwater pooling than any other Antarctic ice shelf. We compare the 2018-19 and 2020-21 melt seasons, which exhibit positive and negative anomalies in terms of open-water melt extent, respectively (Tuckett et al., 2022). For the Amery catchment, we use an elevation threshold

of 1000 m, based on Tuckett et al. (2021), who reported $> 95\%$ of lakes at elevations below 500 m in the 2004–20 time period, and only a handful of small lakes above 1000 m even during high-melt summers. We apply this threshold based on the Reference Elevation Model of Antarctica (REMA) digital elevation model (Howat et al., 2019).

Our two study areas cover latitudes from 68.2°N to 72.1°N in Greenland and latitudes from 68.4°S to 74.0°S in Antarctica, meaning that ICESat-2 track spacing is similar over the two regions: in Central West Greenland RGT spacing varies from $\sim 8.8\text{ km}$ in the north to $\sim 10.8\text{ km}$ in the south; over the Amery Catchment RGT spacing varies from $\sim 7.9\text{ km}$ in the south to $\sim 10.7\text{ km}$ in the north. The total area of the Central West Greenland study region is about $650,000\text{ km}^2$ with a coverage of 50 distinct ICESat-2 reference ground tracks, and the area of the Amery catchment study region is about 3.5 million km^2 with a coverage of 74 distinct ICESat-2 reference ground tracks.

For Greenland, we consider the annual melt season to be the 5-month period between the first day of May and the last day of September of a given year. Similarly, for Antarctica, we define the melt season to be the 5-month period between the first day of November and the last day of March of the following year. Based on these spatiotemporal parameters, we processed a total of 447 ATL03 granules with a total size of 1.15 terrabytes (TB), amounting to a total along-track distance about 760,000 km and comprising nine billion individual photon locations.

2.4. Results and discussion

Using FLUID, we identified a total of 1249 supraglacial lake segments over our two study areas in the available ATL03 data during the four melt seasons we considered (Table 2.1). We found that FLUID reliably detects potential supraglacial lake segments, with the number of detected lake segments varying with the strength of the melt season and

Table 2.1: Summary statistics for the ICESat-2 lake segments extracted by FLUID/SuRRF for our regions and melt seasons of interest.

melt season	Amery catchment (B-C)		Central West Greenland (CW)	
	2018-19	2020-21	2019	2020
amount of surface melt	high	very low	high	low
Landsat 8 melt extent	1872 km ²	100 km ²	1127 km ²	431 km ²
total ICESat-2 lake segments	721	28	325	175
unique lakes sampled	385	25	198	114
high-quality segments	165	5	196	109
percent high-quality	23 %	18 %	60 %	62 %
median depth	1.85 m	1.48 m	2.77 m	3.43 m
maximum depth	10.4 m	17.3 m	25.8 m	15.1 m

their locations aligning well with imagery-derived melt extents (Sect. 2.4.1). Along-track lake depths determined by SuRRF agree well depths obtained by manually annotating ATL03 segments of supraglacial lakes, with deeper lakes in Central West Greenland than in the Amery catchment (Sect. 2.4.2). Our method is effective for detection and depth determination of supraglacial lakes over the ice sheets; however, it is not designed for ICESat-2 bathymetry over other targets, for which different methods have been developed (Sect. 2.4.3). Applying our method at an ice-sheet-wide scale and combining the results with satellite imagery would make it possible to develop data-driven models for accurate estimation of the volume of pooled surface meltwater across the ice sheets at high resolution and spatial coverage (Sect. 2.4.4).

2.4.1. FLUID lake detection and accuracy

2.4.1.1 FLUID lake segment detection

Out of the 1249 supraglacial lake segments that we detected in the ICESat-2 data analyzed in this study, 500 were located in Central West Greenland and 749 in the Amery

catchment. The number of lake segments that we detected using FLUID varied with strength of the melt season (Figs. 2.9 and 2.10). Over Central West Greenland, we identified 325 lake segments during the high-melt 2019 boreal summer versus only 175 during the low-melt 2020 boreal summer. Over the Amery catchment, we identified 721 lake segments during the high-melt 2018-19 austral summer versus only 28 during the (very) low-melt 2020-21 austral summer. To estimate how many unique supraglacial lakes were sampled by these detected ICESat-2 lake segments during each melt season, we calculated the maximum surface meltwater extent for each of the melt seasons independently using Landsat 8 imagery, based on the methods detailed in Tuckett et al. (2021) (blue regions in Fig. 2.9 and 2.10). We then matched each detected ICESat-2 lake segment to a lake basin in these imagery-based melt extents and counted the number of total basins that were sampled by at least one ICESat-2 lake segment (see supplemental maps; Arndt and Fricker 2024a). Over Central West Greenland, this resulted in 196 unique supraglacial lakes being sampled by our data in 2019, and 109 lakes in 2020. Over the Amery Catchment, FLUID-SuRRF segments sampled 165 unique melt lakes in 2018-19 and 25 lakes in 2020-21.

Across all the data that we analyzed, FLUID and SuRRF determined on average 0.12 % of total distance along the ICESat-2 ground tracks to be meltwater surfaces. During the high-melt summers this number was 0.22 % and 0.21 % for Central West Greenland and the Amery catchment, respectively. The corresponding numbers for low-melt summers were 0.088 % and 0.0057 %. SuRRF assigned a non-zero quality score to 475 of these lake segments, indicating that they likely contain high-quality bathymetric measurements. The fraction of non-zero quality lake segments was significantly higher for Central West Greenland (61 %) than for the Amery catchment (22.7 %). This is likely because the locations of supraglacial lake basins on Greenland’s grounded ice are primarily controlled by bedrock topography (Lampkin and VanderBerg, 2011), which allows for well-defined lake basins to

develop in the same locations every year. In contrast, lake basins on Antarctica’s floating ice shelves are more difficult to distinguish from their much flatter surrounding topography, on which they usually form sporadically and in different locations each year (Arthur et al., 2022) with existing basins typically being advected to locations significantly further downstream from one melt season to the next (Arthur et al., 2020b). Furthermore, an appreciable portion of meltwater across Antarctic ice shelves is stored as slush (Dell et al., 2024), which often appears in ATL03 data with a surface return that is flat enough to look similar to a supraglacial lake, with large amounts of scattered photons below the surface that can be mistaken for a bathymetric signal.

2.4.1.2 Accuracy of FLUID lake segment detection

To validate the spatial extents of ICESat-2-derived supraglacial lake segments, we also used the Landsat-8-based maximum surface meltwater extents for each of the melt seasons (blue regions in Fig. 2.9 and 2.10). We found a high correspondence between these estimates: For Central West Greenland, the ground tracks of 97.0 % of high-quality ICESat-2 lake segments coincided with the Landsat-8-derived maximum seasonal melt extent. The corresponding percentage for the Amery catchment was 95.8 %.

Since there are no ground truth data of water depths available for any ICESat-2 data over supraglacial lakes, it is necessary to evaluate the performance of our method by manually examining the data in representative granules. We report results for ICESat-2 track 81, GT2L on 2 January 2019 over the Amery catchment, which was also studied in Fricker et al. (2021) and Xiao et al. (2023). To evaluate whether FLUID detects all supraglacial lake segments that have bathymetric data in this ATL03 ground track, we manually inspected the ATL03 data for any evidence of meltwater and determined whether any such along-track contained a return signal from a lakebed. Out of 25 along-track

Figure 2.9: Maps and examples of FLUID/SURRF outputs for Central West Greenland. Center maps: FLUID/SuRRF algorithm testing in Greenland. Locations of melt lake segments detected in ATL03 data for the Greenland Ice Sheet’s Central West drainage basin for melt seasons 2019 and 2020, mapped over the corresponding seasons’ maximum meltwater extent from Landsat 8. Panels a-j: Examples showing the underlying ATL03 photon clouds and water depths calculated by SuRRF, for some of the lake segments shown on the maps. Numbers in lower right of panels are SuRRF lake segment quality scores.

2. Automated Supraglacial Lake Detection and Depth Retrieval in ICESat-2 Data

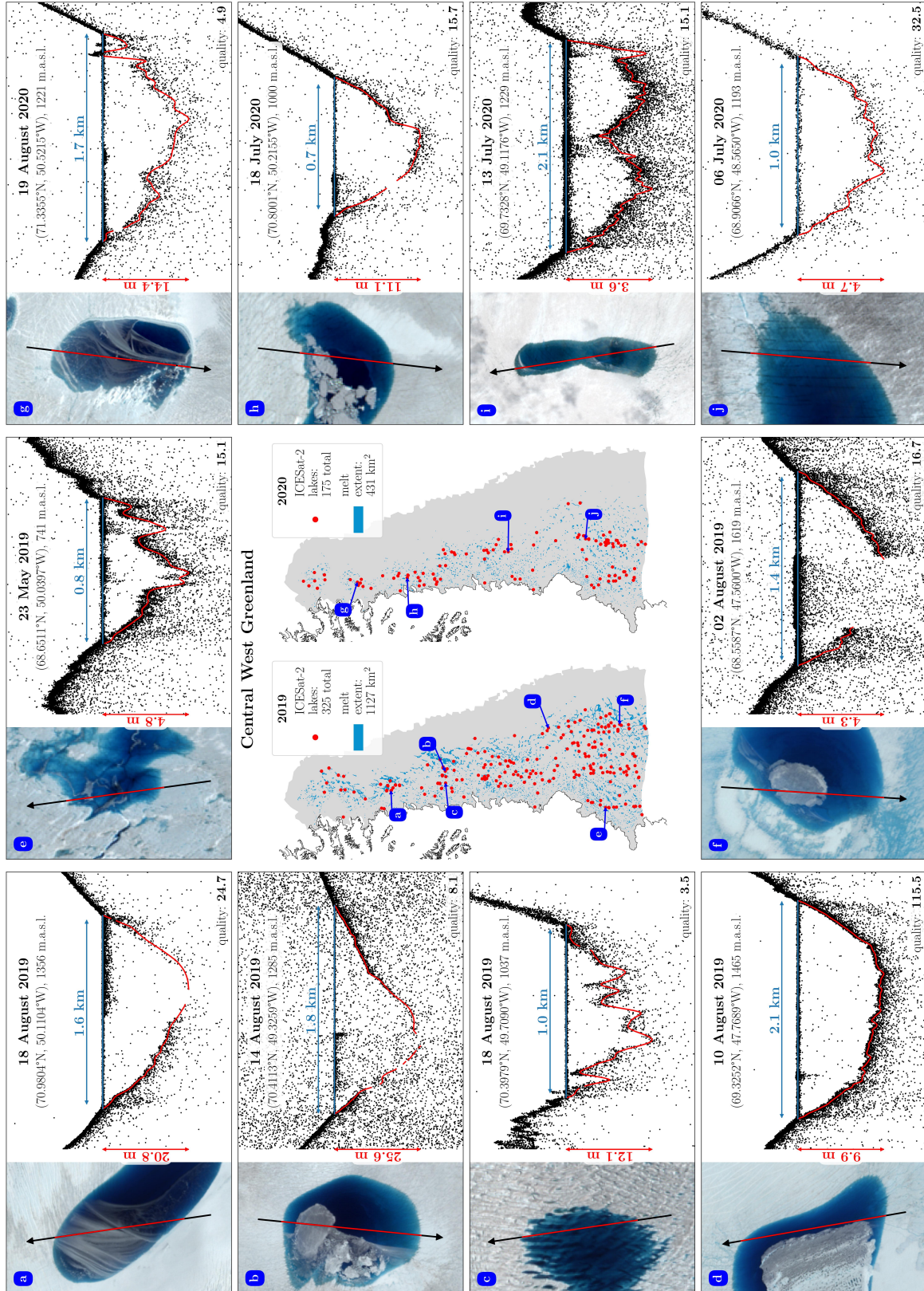
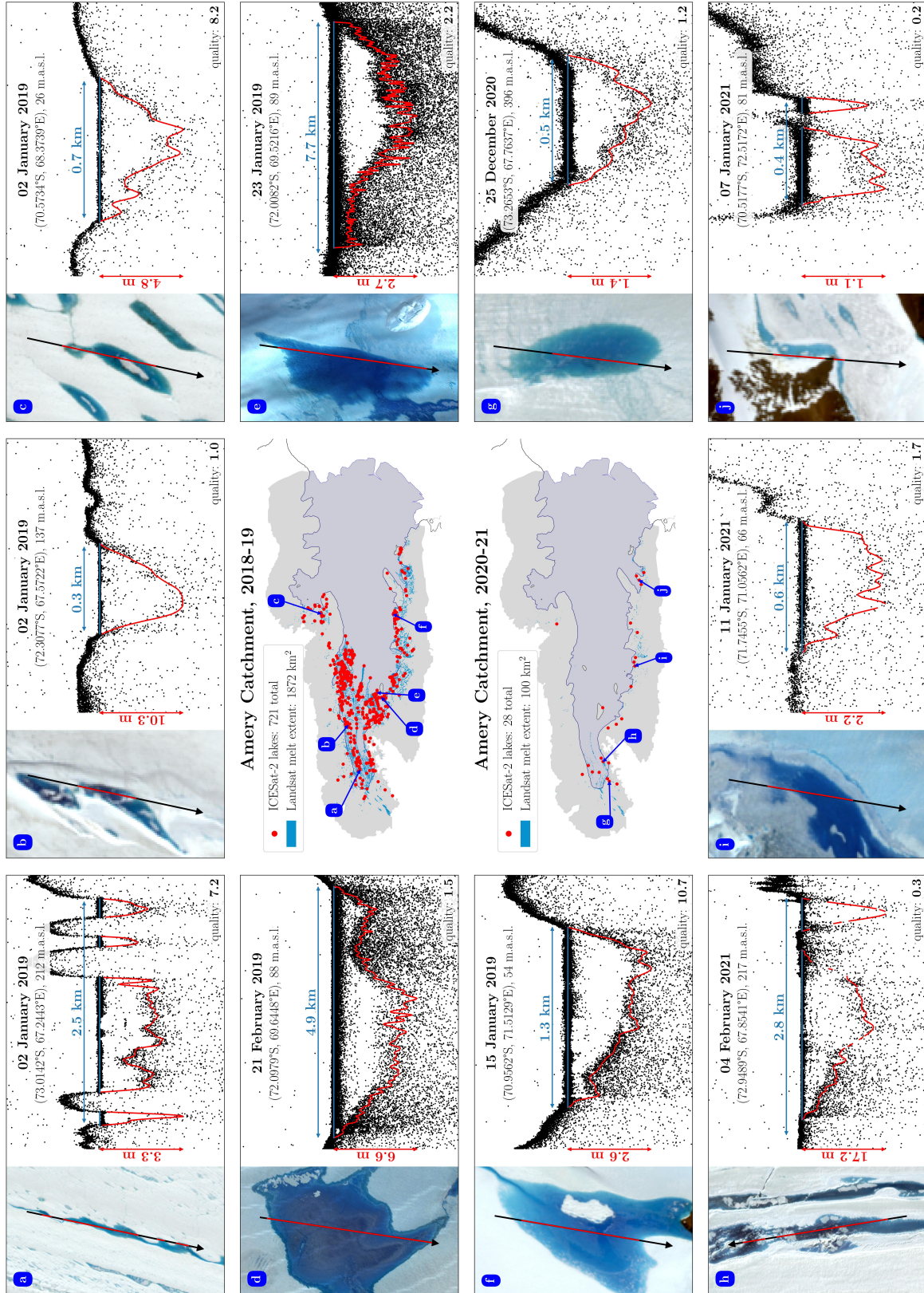


Figure 2.10: Maps and examples of FLUID/SURRF outputs for the Amery Catchment, East Antarctica. Center maps: FLUID/SuRRF algorithm testing in Antarctica. Locations of melt lake segments that FLUID detected in ATL03 data for the Antarctic Ice Sheet’s B-C drainage basin for melt seasons 2019-20 and 2020-21, mapped over the corresponding seasons’ maximum meltwater extent from Landsat 8. Panels a-j: Examples showing the underlying ATL03 photon clouds and water depths calculated by SuRRF, for some of the lake segments shown on the maps. Numbers in lower right of panels are SuRRF lake segment quality scores.

2. Automated Supraglacial Lake Detection and Depth Retrieval in ICESat-2 Data



segments with meltwater, we judged that only eight were supraglacial lake segments with a discernible bathymetric signal. We further evaluated whether the ATL03 photon cloud misses any supraglacial lakes that track 81 GT2L crosses, by mapping it over a mosaic of Sentinel-2 scenes from the same day (same as used in Fricker et al. 2021). Based on visual inspection, the ICESat-2 ground track crossed supraglacial lakes that were clearly distinguishable in the imagery only in the same eight locations that we had also judged to be lake segments in the ATL03 data. Most other ICESat-2 segments that showed evidence of surface water in ATL03 also showed some evidence of meltwater in the imagery, and were associated with ice-filled crevasses, narrow melt channels, likely areas of slush, or melt lakes with an opaque ice cover (for which depth determination is not possible). FLUID found 16 potential melt lake segments within the same ground track, which all showed evidence of meltwater, but only the eight that we had also manually picked were classified as high-quality lake segments.

Out of all lake segments that FLUID detected, we deemed 308 to be false positives, many of which showed evidence of surface water but no distinguishable bathymetric return. However, we found that lake segments classified by SuRRF as “high quality” contain few false positives, with only 15 such segments that we manually removed from the data. The majority (11) of these were due to our study region erroneously extending past the calving front of the Amery Ice Shelf in Antarctica or marine-terminating outlet glaciers in Greenland, or due to ice-marginal lakes being included in the study region. Of the remaining four false positives, three were likely due to random noise and one showed a supraglacial lake but the data seemed to be affected by a “Did Not Finish Major Frame” (DNF) data transfer error in the ATLAS Photon Counting Electronics (PCE) (Magruder et al., 2024). While testing our algorithm, we found that false positives may also arise when ICESat-2’s footprint includes two surfaces at different elevations for a substantial

along-track distance, which is possible when the ground track passes over a flat calving front or crevasses with a bottom return at an acute angle. Where the study region extends past an ice shelf calving front, FLUID/SuRRF can also falsely classify the bathymetric return of a submerged “bench” as a supraglacial lake segment (Buck, 2024).

2.4.2. SuRRF depth retrieval and accuracy

2.4.2.1 SuRRF: meltwater depths

The meltwater depths determined by SuRRF suggest that supraglacial lakes in Central West Greenland are generally deeper than those in the Amery catchment: The median of along-track maximum water depths of lake segments in Greenland was 3.09 m versus only 1.84 m in Antarctica. Median lake segment depth in the Amery catchment was greater during the high-melt season (1.85 m) than it was during the low-melt season (1.48 m). In contrast, median lake segment depth in Central West Greenland was less during the high-melt season (2.77 m) than it was during the low melt season (3.43 m) (Fig. 2.11, a). We hypothesize that this opposite behavior is due to different relationships between lake elevations and depths in these regions. A linear regression of lake segment depth on surface elevation in our data suggests that lake depth decreases with elevation in Central West Greenland ($p = 0.12$), while it increases with elevation in the Amery catchment ($p = 0.093$) (Fig. 2.11, b). In Greenland, where supraglacial lake basin locations are controlled by bedrock topography, lakes in a low-melt season are more likely to form at lower elevations, where repeated filling, bottom ablation and draining during most prior melt seasons has resulted in well-defined, deep lake basins (Lampkin and VanderBerg, 2011; Tedesco et al., 2012). In a high-melt season, surface melt extends further upwards above the ablation zone, where lake basins are less well-defined, forming smaller, shallower lakes and slush areas (Glen et al., 2024). On an Antarctic ice shelf, lakes in a low-melt season are more likely to form

at lower elevations, where the ice is floating and the surface topography is very flat, resulting in mostly shallow lakes (Banwell et al., 2014). In a high-melt season, melt extends further upward of the grounding line where lakes form in deeper basins that are controlled by the bedrock topography (similar to lakes in Greenland; Bell et al., 2018), thus resulting in deeper lakes.

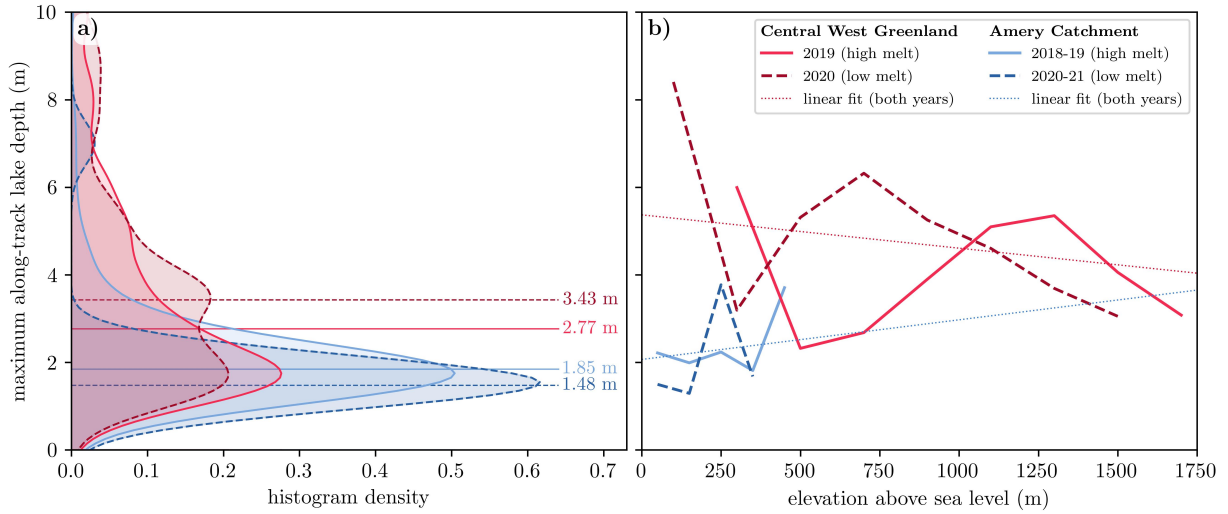


Figure 2.11: SuRRF lake segment depth statistics for two study regions in high and low melt years. a): Density of maximum lake depth distributions. The numbers shown are median lake segment depths during the corresponding melt season and study region. b): Elevation-binned means of maximum lake segment depths for each season and study region. The dotted lines are the linear fit to all data for the corresponding study region.

2.4.2.2 Accuracy of SuRRF depth retrievals and comparison with alternative methods

For the 16 potential melt lake segments that FLUID identified in ICESat-2 track 81, GT2L on Jan 2nd, 2019 over the Amery catchment (Sect. 2.4.1.2 Fricker et al., 2021), SuRRF assigned a nonzero quality score only to the eight data segments which we had manually determined to be supraglacial lake segments with a discernible bathymetric signal.

For four of the lake segments identified in this granule, Fricker et al. (2021) established manually annotated baseline depth estimates, which were used to assess the performance of automated algorithms in the absence of any ground truth data. In addition to these four lake segments, Melling et al. (2024) used a similar method to establish manual estimates for five more segments in Southwest Greenland. We here use the manual annotations from both of these method comparison studies to evaluate SuRRF’s depth estimation performance for all nine lake segments, and to briefly compare SuRRF to other methods whose results were included in these two comparative studies (Fig. 2.12). For a detailed comparison between various ICESat-2 lake depth algorithms (including an earlier version of SuRRF) and RTE-methods, we refer the reader to Fricker et al. (2021). For in-depth discussions comparing manually picked ICESat-2 depths to RTE methods, DEM-based approaches as well as empirical methods using *in situ* data, we refer the reader to Melling et al. (2024) and Lutz et al. (2024).

When run on the corresponding ATL03 granules, FLUID automatically detects all nine lake segments, and the SuRRF depth estimates track the general shape of the manually outlined lakebeds well (Fig. 2.12). This is also demonstrated by an average Pearson’s correlation coefficient of $R = 0.992$ between the SuRRF and manual depth estimates for the nine lake segments examined here, with averages of $R = 0.989$ for the segments on Amery catchment and $R = 0.994$ for the segments in Southwest Greenland. SuRRF depth estimates show an average bias of 0.26 m deeper than the manually picked values, with a mean absolute error (MAE) of 0.27 m. This results in SuRRF reporting a total amount of water that is 10 % larger than the estimate given by the manual baseline. For the lake segments on Amery Ice Shelf, the average bias is 0.29 m and the MAE is 0.29 m. For the lake segments in Southwest Greenland, the average bias is 0.23 m and the MAE is 0.24 m. When applying the correction for multiple scattering (Sect. 2.3.3.3) to SuRRF depth estimates,

2.4. Results and discussion

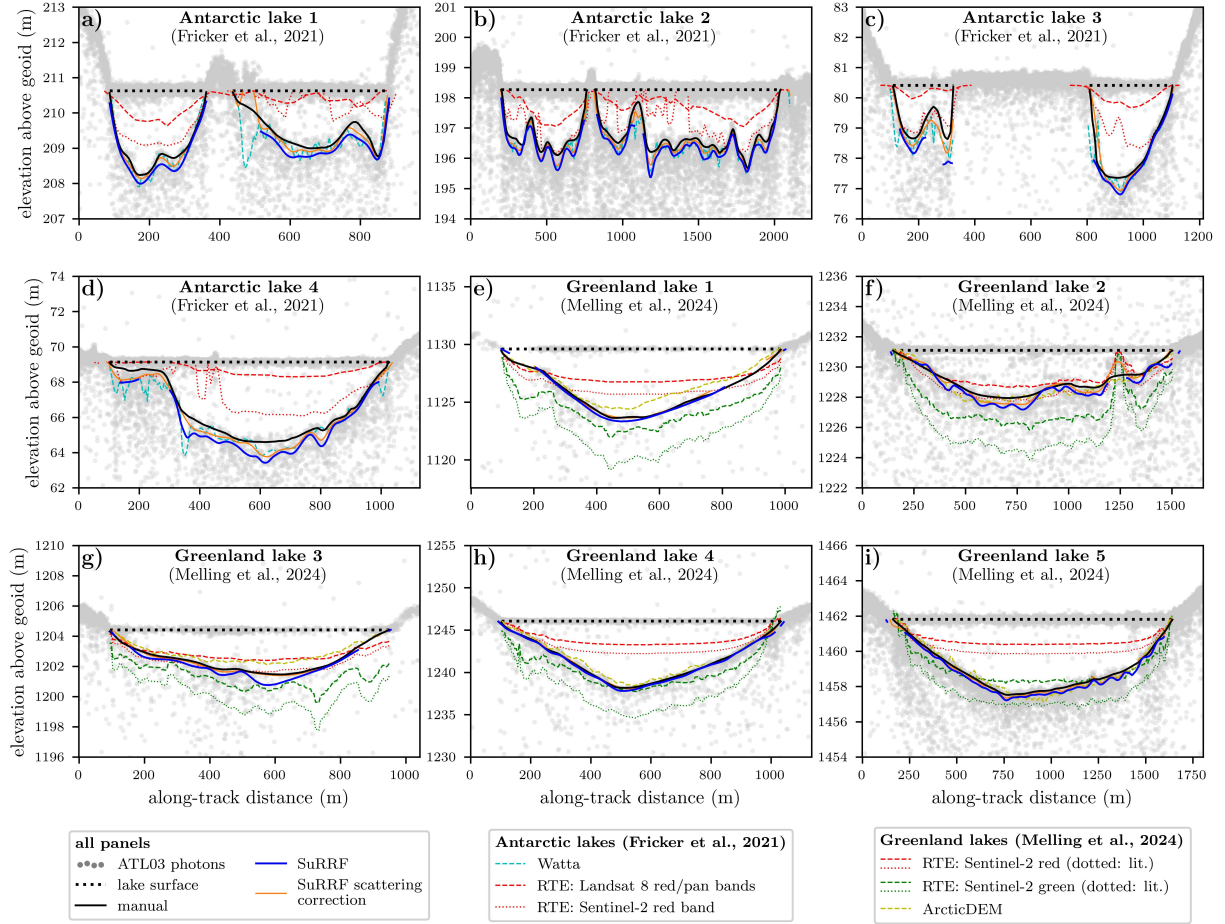


Figure 2.12: Comparison between SuRRF water depth estimates, manually annotated ICESat-2 depths and results from other methods for meltwater depth estimation for lakes in Antarctica and Greenland. a)-d): ICESat-2 melt lake segments on the Amery Ice Shelf, Antarctica, with manual annotations from Fricker et al. (2021). Other meltwater depth estimates that were reported by Fricker et al. are shown for the Watta algorithm (based on ICESat-2; Datta and Wouters, 2021) and for the RTE method applied to the average of Landsat 8’s red and panchromatic bands (Spergel et al., 2021) and to Sentinel-2’s red band (Moussavi et al., 2020). e)-i): ICESat-2 melt lake segments in Southwest Greenland with manual annotations from Melling et al. (2024). Other meltwater depth estimates that were reported by Melling et al. are shown for the RTE method individually applied to both Sentinel-2’s red and green bands, as well as estimates from post-drainage lakebed topography in ArcticDEM (based on Bowling et al. 2019). SuRRF depth estimates are shown only where the estimated bathymetric signal confidence exceeds 0.5. To align along-track depths with the ATL03 photons (gray dots), the elevations of photons below the water surface elevation of each lake (black dotted lines) were corrected by dividing their vertical distance from the lake’s surface by the refractive index for the speed of light in water.

the average bias is reduced to 0.07 m deeper than the manually picked values, with a mean absolute error (MAE) of 0.15 m and a Pearson’s correlation coefficient of $R = 0.993$. This results in the scattering-corrected version of SuRRF reporting a total amount of water that is 3 % larger than the estimate given by the manual baseline.

Based on the nine lake segments that were used to assess the accuracy of depth estimates, most algorithms (including SuRRF) seem to estimate slightly greater depths than the manually picked values (Xiao et al., 2023). When the bathymetric returns in the ATL03 point cloud are “fuzzy” the difference between the manual baseline and SuRRF water depth estimates tends to become larger. The majority of algorithms for lake depth retrieval from ATL03 operate on the assumption that the elevation with the locally highest photon density corresponds to the elevation of the ice-water interface at the lakebed, yet most altimetry experts placed the secondary return signal higher up in the point cloud, where the photon density first significantly increases below the water surface (Fricker et al., 2021). We agree that the true location of the lakebed is likely at a higher elevation than the along-track elevation of highest photon density, since multiple scattering increases the photon density below the elevation of the lakebed. However, the elevation at which the photon density first significantly increases represents the highest point within ICESat-2’s 11 m footprint and furthermore tracks the upper bound of ATLAS’s single-photon time-of-flight uncertainty of 800 ps (Markus et al., 2017), which corresponds to about 12 cm in photon height uncertainty. We therefore believe that the true water depth falls somewhere in between our (deeper) SuRRF estimates and the (more shallow) manual baseline estimates from Fricker et al. (2021) and Melling et al. (2024). Our scattering correction to SuRRF depth estimates is an attempt to reconcile this disparity between depth estimates. However, in the absence of ground truth *in situ* validation data for ICESat-2 lake segments, the correct magnitude of this correction remains unknown. This demonstrates an urgent need

for *in situ* meltwater depth data that can be used to reliably validate the accuracy of ICESat-2 estimates.

Since many lakes on the Greenland Ice Sheet are transient and drain late in season (Johansson et al., 2013), it could be possible to obtain independent ICESat-2-based meltwater depth estimates by comparing “full vs empty” repeat-track measurements along ICESat-2 lake segments before and after the drainage. However, this approach would suffer from many of the same drawbacks that affect depth estimation from DEMs of a lake’s bed topography that were acquired after it drained (Sect. 2.2.2), for example: effects of lake-bottom ablation, surface elevation change from precipitation and blowing snow deposits, as well as across-track advection of surface topographical features. Furthermore, this approach would not be feasible in Antarctica, where lake drainage is very rare, in particular on grounded ice. In cases where melt lake drainage is observed on the floating ice shelves, obtaining water depth from repeat-track elevation change is not possible due to the advection of surface topography with the ice flow and post-drainage flexural rebound (Warner et al., 2021). Due to these complexities, we do not attempt to validate ICESat-2 lake depth measurements using this method.

In addition to SuRRF and manual depth estimates, panels a)-d) of Fig. 2.12 show depth estimates for Antarctic lakes that were reported in Fricker et al. (2021), for the Watta algorithm (based on ICESat-2; Datta and Wouters, 2021) and for the RTE method applied to the average of Landsat 8’s red and panchromatic bands (Spergel et al., 2021) and to Sentinel-2’s red band (Moussavi et al., 2020). Both SuRRF and Watta track the general shape of lakebed returns in the ATL03 photon clouds well (Pearson’s correlation coefficients of $R = 0.99$ and 0.94 , respectively), and largely agree with manually determined along-track water depths (MAEs of 0.29 m and 0.30 m, respectively). In contrast to SuRRF, Watta appears to have a tendency to overfit where photon density near the lakebed is

high with a large elevation spread, resulting in an unreasonably “wiggly” lakebed fit (e.g., Antarctic lake 1, 500-800 m). SuRRF’s smoother fit under these conditions is likely due to the fact that it utilizes an adaptive kernel for its robust fit, whose width increases as the number of photons that narrowly cluster around the previous iteration’s fit decreases (Sect. 2.3.3.1). In contrast to SuRRF, Watta also attempts to fit the lakebed across the entire lake basin, even where the lakebed is not visible or indistinguishable from noise, which can sometimes result in arbitrary, unrealistic depth estimates (e.g., Antarctic lake 1, around 450 m). Under such conditions SuRRF assigns a low confidence score to the lakebed fit and discards associated depth estimates to prevent arbitrary results. However, in some cases this results in SuRRF discarding depth estimates where Watta appears to fit the lakebed reasonably well (e.g., Antarctic lake 3, 250-300 m). The RTE approach based on Landsat 8’s red/panchromatic band average consistently underestimates water depths, reporting a total amount of water that is $\sim 73\%$ lower than the manual baseline. The RTE approach based on Sentinel-2’s red band also underestimates water depths, and reports a total amount of water that is 34% lower than the manual baseline.

Panels e)-i) of Fig. 2.12 also show non-ICESat-2 depth estimates for Greenland lakes that were reported in Melling et al. (2024), for the RTE method individually applied to both Sentinel-2’s red and green bands, as well as estimates from post-drainage lakebed topography in ArcticDEM (based on Bowling et al. 2019). The RTE approach based on Sentinel-2’s red band generally underestimates depths and reports a total amount of water that is 42% lower than the manual baseline (similar to this method’s performance over Antarctic lakes). In contrast, the RTE approach based on Sentinel-2’s green band generally overestimates depths and reports a total amount of water that is 34% larger than the manual baseline. However, Melling et al. also note that when using values of tuneable parameters that have been commonly used in the literature in the past (Sneed and Hamilton,

2007; Georgiou et al., 2009; Pope et al., 2016), the RTE approach for Sentinel-2’s green band overestimates lake depths even more, which results in reporting a total amount of water that is 84 % larger the manual baseline, with individual depths being overestimated by up to 153 %. This implies that RTE-based methods, while being popular for their simplicity, can potentially result in highly inaccurate meltwater volume estimates. The depth estimates derived from DEMs of emptied lake basins match the ICESat-2 manual baseline reasonably well, and when compared with it underestimate the total amount of water by 6 % with a MAE of 0.34 m. Since this method’s performance is comparable to that of ICESat-2-based methods, this implies that DEM-based methods could be used supplement ICESat-2 depth measurements for labeling reflectance in passive optical imagery with supraglacial water depths, at least on the Greenland Ice Sheet where melt lakes on grounded ice drain regularly (Johansson et al., 2013).

2.4.3. ICESat-2 bathymetry over other targets

Beyond estimating the depth of supraglacial lakes, ICESat-2’s bathymetric capabilities have been used for various other applications. Many algorithms employed for depth retrieval from ATL03 share significant similarities, enabling method development for ICESat-2-derived bathymetry to benefit from broader cross-discipline collaboration (Parrish et al., 2022). Methods similar to FLUID-SuRRF have been used for satellite-derived nearshore ocean bathymetry (SDB) (e.g.; Parrish et al., 2019; Ma et al., 2020; Thomas et al., 2021), estimating water depths of inland waters (e.g.; Li et al., 2019; Xu et al., 2020; Jasinski et al., 2023) and tracking the evolution of melt pond depths on sea ice (e.g.; Farrell et al., 2020; Tilling et al., 2020; Herzfeld et al., 2023; Buckley et al., 2023). However, there are also notable differences between bathymetric applications of ICESat-2 in different environments that have led to the development of specialized approaches, in particular for their large-scale implementation. For nearshore and inland bathymetry applications, the locations of

the desired bathymetry estimates are usually known *a priori* and the bottom topography is often considered constant, so bathymetric measurements can be accumulated over time and compared to non-concurrent validation data. In contrast, the ephemeral nature of supraglacial lakes on the ice sheets and melt ponds on sea ice makes it necessary to automatically detect their locations directly from ATL03 and makes it more difficult to reliably validate depth estimates. Our FLUID algorithm addresses this issue for supraglacial lakes on the ice sheets: it automatically detects the locations of lakes by relying on the fact that the water surface reflection over open water presents as a flat line in geoid-corrected ICESat-2 elevation data, while the surrounding topography on the ice sheets is almost always sloped. This makes our algorithm efficient over the ice sheets by discarding most non-lake photon segments in the first “flatness check” step. However, it makes our algorithm less suited for detecting lakes on sea ice, where most segments over the open ocean and thin sea ice would likely pass the flatness threshold.

2.4.4. Future studies

Our ICESat-2-derived water depths are the first comprehensive dataset of supraglacial lake depths directly measured from a satellite. However, these along-track observations alone are too sparsely spaced in space and time to allow for the calculation of lake volumes or the continuous tracking of meltwater throughout the progression of a melt season. The large volume and wide variety of data that our method provides suggest that ICESat-2-based depth measurements obtained from applying FLUID-SuRRF at ice-sheet-wide scale could be used to better constrain parameters in existing methods which estimate meltwater volumes from high-resolution, spatially continuous satellite imagery. Furthermore, our method could be used to extract pan-ice-sheet meltwater depths and combine them with concurrent satellite imagery, thus providing a training data set that would enable the development of data-driven models of the relationship between meltwater depth and

satellite imagery reflectances, based on statistical learning methods. Since in the absence of ground truth validation data our depth validation efforts were based on manual annotation of the data, we acknowledge that there may be a small but potentially significant bias towards overestimating water depths with FLUID-SuRRF. This highlights an urgent need for ground truth *in situ* water depth measurements of supraglacial lakes that coincide with ICESat-2 overpasses, to enable calibration and validation of depth estimates.

2.5. Summary

Supraglacial lakes form seasonally around most of the margins of the Greenland and Antarctic ice sheets. In a warming climate, these lakes have the potential to significantly impact the future stability of both ice sheets through processes that are not yet understood well enough to be included into models. To confidently project future sea-level rise, better satellite observations of surface meltwater are needed to enable science that produces a better mechanistic understanding of how ice dynamics are impacted by the pooling of surface meltwater in lakes. Until recently, any available methods used to estimate supraglacial lake depth from satellite data have been required to make strong assumptions and to use poorly constrained parameters, making it difficult to accurately assess the distribution of meltwater volumes across ice surfaces. Multiple case studies have successfully demonstrated that supraglacial lake depths can now be directly measured from photon refraction in ICESat-2's laser altimetry data. However, ICESat-2 data had not previously been used at scale for this purpose because its photon-level product comprises hundreds of terabytes of unstructured point cloud data along spatially discrete ground tracks, which makes it difficult to integrate the data with spatially continuous data in existing workflows.

To address this challenge, we have proposed a computational framework that allows users to detect lake segments and determine their water depths across all available

ICESat-2 data for any desired ice sheet drainage basins and melt seasons. Using distributed high-throughput computing, this framework applies the fully automated, two-step FLUID/SuRRF algorithm to large numbers of ICESat-2 ATL03 photon data granules in parallel. To test our method, we applied FLUID-SuRRF to all available ICESat-2 data over two drainage basins, one on the Antarctic Ice Sheet and one on the Greenland Ice Sheet, for a high-melt and a low-melt summer. We have demonstrated the following for our method:

1. It reliably detects supraglacial lake segments based on the flatness of their surface and the presence of a lakebed return.
2. There is a potential for false positives, but their impact can be effectively mitigated by filtering for the strength of the bathymetric signal.
3. Water depth estimates are accurate based on manual validation of the data, however, there is an urgent need for *in situ* data for definitive ground truthing.
4. It can be applied at scale by leveraging distributed high-throughput computing.
5. The resulting data effectively capture spatial and temporal variability in meltwater extent and depth.

Our framework can be used to generate a comprehensive data product of supraglacial lake depths for Greenland and Antarctica since the launch of ICESat-2, which would enable the development of data-driven models of meltwater volumes in satellite imagery.

2.6. Code and data availability

The FLUID/SuRRF source code is freely available at <https://doi.org/10.5281/zenodo.10905941> (Arndt and Fricker, 2024c). To execute this code, users need to create a free NASA Earthdata login for ICESat-2 data access. The source code contains a

singularity container in which this version of FLUID/SuRRF can be executed. The main Python script `detect_lakes.py` can be run either locally on any individual ATL03 granule, or on many granules in parallel on any computing cluster that supports the specified computing environment or the use of singularity containers. In this study we present our implementation of FLUID/SuRRF on the OSG Open Science Pool because it provided us with free computational infrastructure. Due to funding mandates, free access to the OSG Open Science Pool is limited to researchers contributing to a US-based project at an academic, government, or non-profit organization, or researchers affiliated with any project or institution that operates its own local access point. This means that to implement FLUID/SuRRF on the OSG Open Science Pool as described here, you need to have at least one collaborator on your team to whom these criteria apply. This collaborator can register your project with OSG on the Open Science Pool. Then, anyone contributing to the project can register for an account on OSG Connect to gain access to the Open Science Pool. For more information, see https://osg-htc.org/services/open_science_pool.html and <https://osg-htc.org/about/organization/>. More information is also included in the README file. The supraglacial meltwater depth estimates and associated “quicklook” plots for all 1249 lake segments identified in this study are available at <https://zenodo.org/doi/10.5281/zenodo.10901737> (Arndt and Fricker, 2024b). All data and code needed to reproduce the figures in this study, as well as supplementary figures, are available at <https://doi.org/10.5281/zenodo.10901826> (Arndt and Fricker, 2024a). ICESat-2 ATL03 data is available at NSIDC (Neumann et al., 2023a). Sentinel-2 and Landsat imagery were accessed via Google Earth Engine (Gorelick et al., 2017). Drainage basins for Greenland are available at DRYAD (Mouginot and Rignot, 2019). Drainage basins for Antarctica are available at NSIDC (Mouginot et al., 2017). ArcticDEM mosaics for elevation thresholding are available at <https://www.pgc.umn.edu/data/arcticdem/> (Porter et al., 2023) and REMA DEM mosaics are available at

<https://www.pgc.umn.edu/data/rema/> (Howat et al., 2022a). ICESat-2 ground track KML files are available at <https://\gls{ICESat-2}.gsfc.nasa.gov/science/specs>.

2.7. Appendix A: calculation of photon density ratios in FLUID flatness check

For a given major frame, let $l_{\text{mframe}} \approx 140$ m be the along-track length of the major frame, and let P be the set of photons with h_i denoting the geoid-corrected height of photon $i \in P$. We calculate the five photon densities used in the flatness check as:

$$d_0 = \frac{\sum_{i \in P} [|h_i - h_{\text{peak}}| \leq w_{\text{peak}}]}{2w_{\text{peak}}l_{\text{mframe}}} \quad (2.5)$$

$$d_1 = \frac{\sum_{i \in P} [0 < h_i - h_{\text{peak}} - w_{\text{peak}} \leq w_{\text{buffer}}]}{w_{\text{buffer}}l_{\text{mframe}}} \quad (2.6)$$

$$d_2 = \frac{\sum_{i \in P} [-w_{\text{buffer}} \leq h_i - h_{\text{peak}} + w_{\text{peak}} < 0]}{w_{\text{buffer}}l_{\text{mframe}}} \quad (2.7)$$

$$d_3 = \frac{\sum_{i \in P} [|h_i - h_{\text{peak}}| > w_{\text{peak}}]}{(h_{\text{max}} - h_{\text{min}} - 2w_{\text{peak}})l_{\text{mframe}}} \quad (2.8)$$

$$d_4 = \frac{\sum_{i \in P} [h_i - h_{\text{peak}} > w_{\text{peak}}]}{(h_{\text{max}} - h_{\text{peak}} - w_{\text{peak}})l_{\text{mframe}}} \quad (2.9)$$

where $w_{\text{peak}} = 0.1$ m is the width of the density peak, $w_{\text{buffer}} = 0.35$ m is the width of the buffer around the peak, and h_{min} and h_{max} are the bottom and the top of the telemetry window, respectively. Here $[\cdot]$ are Iverson brackets, which evaluate to 1 if the condition inside the brackets is true, and to 0 otherwise.

2.8. Appendix B: calculation of photon signal confidences in FLUID

Let P be the set of photons within an along-track segment (e.g., a major frame), and for each photon $i \in P$, let x_i and h_i be the along-track distance and elevation, respectively. To give appropriate relative weights to the two spatial dimensions when calculating photon

densities, we need to adjust along-track distance by an aspect ratio parameter r_a . We found that for typical supraglacial lake segments, a value of $r_a = 30$ works well. Denote by $\tilde{x} = x/r_a$ the aspect-ratio-adjusted along-track distance. We now want to express a photon's signal confidence as the average of the inverse euclidean distances between the photon and up to $k_{\max}$ nearest neighbors within a search radius of r_s , where distances are normalized and clamped to this search radius. Let K_i be the set of photons including i and its $k_{\max}$ nearest neighbors, i.e. $K_i \subseteq P$ s.t. $|K_i| = k_{\max} + 1$ and

$$d_{i,j} \geq \max_{n \in K_i} d_{i,n} \quad \forall j \in P \setminus K_i \quad (2.10)$$

where

$$d_{i,j} = \sqrt{(\tilde{x}_j - \tilde{x}_i)^2 + (h_j - h_i)^2} \quad (2.11)$$

is the aspect-ratio-adjusted euclidean distance between photons i and j . Then, the signal probability of photon i is estimated as

$$p_i = \frac{1}{k_{\max}} \left(k_{\max} - \sum_{j \in K_i} \left(\frac{\min(d_{i,j}, r_s)}{r_s} \right) + 1 \right). \quad (2.12)$$

Note that this implies $p_i \in [0, 1]$. In particular, $p_i = 0$ if photon i does not have any neighbors within a radius of r_s , and p_i would be equal to 1 only for a “perfect photon”, whose location coincides exactly with that of $k_{\max}$ other photons. To effectively discriminate between signal and noise, we need to choose $k_{\max}$ and r_s in a way such that typical background noise photons are assigned a small target value, which we set to $p_{\text{noise}} = 0.05$.

Assuming that a major frame contains only noise photons and a flat surface with a signal photon spread of $w_{\text{signal}} = 0.3$ m, we can estimate the aspect-ratio-adjusted mean

area per background photon (i.e. the inverse photon density) as

$$a = \frac{(h_{\max} - h_{\min} - 2w_{\text{signal}}) l_{\text{mframe}}}{r_a \sum_{i \in P} [|h_i - h_{\text{peak}}| > w_{\text{signal}}]}. \quad (2.13)$$

If background noise photons follow a random uniform distribution, this means that to find an expected k neighbors around a typical background photon, one would have to search within a radius of $r(k) = \sqrt{a(k+1)/\pi}$ around that photon. Using the fact that the average inverse distance of a point in a circle with radius R to its origin is $R/3$ (Stone, 1991), we can set

$$r_s = \sqrt{3p_{\text{noise}}} r(k_{\max}) = \sqrt{\frac{3ap_{\text{noise}}(k_{\max} + 1)}{\pi}} \quad (2.14)$$

to ensure that $p_i \leq p_{\text{noise}}$ for typical background noise photons. We found that setting $k_{\max} = 15$ strikes a good balance between being sensitive enough to small-scale signals, and being too sensitive to small amounts of noise photons clustering together by random chance.

2.9. Appendix C: calculation of quality heuristics in FLUID bathymetry check

To detect any potential bathymetric returns in a major frame, we divide it into $n_{\text{seg}} = 10$ along-track sub-segments of equal length. For each sub-segment, we calculate the median of the FLUID photon-level signal probability p_i for photons i within 0.1 m elevation bins, assigning a value of zero whenever there are no photons within any bin. This results in an empirical function that relates signal probability to elevation h , which we here denote by $p(h)$. In addition, we calculate the analogous function of photon density $d(h)$ as a simple histogram for 0.01 m elevation bins. Let $d'(h) = d(h) \forall h : |h - h_{\text{peak}}| > w_{\text{signal}}$ and zero otherwise. Denote by $\cdot|_l$ a smoothing operator using a gaussian window with standard

deviation of l . Now calculate signal confidence as a function of h as

$$c(h) = p(h)|_l \min \left(\frac{d(h)|_l}{\max_h d'(h)|_l}, 1 \right), \quad (2.15)$$

where $p(h)$ is linearly interpolated to match the domain of $d(h)$. Note that this implies $p(h) \in [0, 1] \forall h$ in the telemetry window. To determine whether a potential bathymetric signal peak is present, we find peaks in $c(h)$. If there are at least two peaks with prominence $\rho \geq 0.1$, and the elevation of the peak closest to h_{peak} is found within an elevation difference of w_{signal} , then out of the peaks whose elevation is below $h_{\text{peak}} - w_{\text{signal}}$ the peak with the highest prominence is considered a potential bathymetric peak. Denote by n_{peaks} the number of potential bathymetry peaks found in the major frame, and let h_i be the elevation and ρ_i the prominence of peak $i \in [1, 2, \dots, n_{\text{peaks}}]$. We only consider the major frame to be potentially part of a lake segment if $n_{\text{peaks}} \geq 3$. In this case, we define the following heuristics for different components that affect the quality of the bathymetric return within the major frame.

$$q_1 = f^{3/2} \quad (2.16)$$

$$q_2 = \min \left(\frac{\sum_i \rho_i}{n_{\text{peaks}}} 2(\min(\{2f, 1\}) - 1) + 1, 1 \right) \quad (2.17)$$

$$q_3 = \min \left(\frac{1}{\log_5(\max(\Delta h, 1.1))}, 1 \right) \quad (2.18)$$

$$q_4 = \frac{1}{1 + \frac{d_h}{\max(\Delta h, 0.5n_{\text{seg}})}} \quad (2.19)$$

where $f = n_{\text{peaks}}/n_{\text{seg}}$ is the fraction of sub-segments for which a potential bathymetric peak was detected, $\Delta h = \max_i h_i - \min_i h_i$ is the elevation spread of the detected peaks,

and

$$d_h = - \sum_{i=2}^{n_{\text{seg}}-1} \frac{|h_i - h_{i-1}| + |h_{i+1} - h_i|}{2} \max(\text{sgn}(h_i - h_{i-1}) \text{sgn}(h_{i+1} - h_i), 0). \quad (2.20)$$

Note that the quality heuristics $q_i \in [0, 1] \forall i$, with higher values implying a “better” bathymetric signal. The expressions used here were derived by trial-and-error and designed such that q_1 penalizes major frames with smaller numbers of detected bathymetry peaks, q_2 penalizes major frames with less prominent peaks, q_3 penalizes major frames with a very large overall spread of peak elevations, and q_4 penalizes major frames with peak elevations that do not align along a smooth surface. Based on these quality heuristics for the major frame, we calculate a quality summary $q_s = \prod_{i=1}^4 q_i$ for each major frame.

While the quality heuristics q_i were obtained by trial-and-error, the starting points for this approach were based on the following assumptions and observations:

- The starting point for q_1 was the idea that major frames with a smaller number of detected bathymetry peaks are less likely to have a consistent signal from a lakebed. The way the equation for q_1 is designed, major frames with a very small fraction of detected bathymetry peaks (0 to 30 % of sub-segments) are disproportionately penalized, since such small numbers of peaks are much more likely to be noise.
- The starting point for q_2 was the idea that major frames with less prominent peaks represent either a weak, inconsistent bathymetric signal or noise. Here, q_2 is equal to the mean prominence of peaks when the fraction of detected bathymetry peaks $f \leq 0.5$. However, for fractions larger than 0.5, the assumption is that the bathymetric signal is consistent enough that even smaller mean peak prominence suggests that the bathymetric signal is clearly visible.
- The starting point for q_3 was the observation that in most cases supraglacial lake

segments with a usable bathymetric signal have fairly small lakebed slopes. Therefore, we do not expect the lakebed elevation of a major frame with a good signal to span a large elevation range. In contrast, we observed that major frames with detected potential bathymetric peaks that span a very large elevation range are often due to noise in the data. Based on this, we designed the equation for q_3 such that its value drops off once the total elevation range of detected bathymetry peaks within the major frame (of length ≈ 140 m) exceeds 5 m. There are, however, some lake segments with a clear bathymetric signal that do exhibit a large range of lakebed elevations (often due to a single burst of noise being detected as a potential bathymetric peak). Therefore, we made sure that the value for q_3 is large enough for major frames to still pass the bathymetry check if Δh is very large but its other quality heuristics q_i are closer to 1.

- The starting point for q_4 was the idea that in most cases bathymetry peak elevations will align along a smooth surface in the along-track distance direction rather than randomly fluctuate (which is usually the case for noise). Here, we penalize every “direction change” (i.e., wherever a peak has two neighbors and its elevation constitutes a local minimum or maximum). We allow for random fluctuations of up to 0.5 m per peak detection without a large penalty, since we observed that a vertical photon spread of up to about this value is quite possible even for lake segments with a somewhat “fuzzy”, yet clearly distinguishable return signal from the lakebed.

A figure that illustrates these quality heuristics is available in the supporting information at <https://doi.org/10.5281/zenodo.10901826> (Arndt and Fricker, 2024a).

2.10. Acknowledgements

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Chapter 2, in full, is a reprint of the material as it appears in: Arndt, P.S. and Fricker, H.A. (2024). “A Framework for Automated Supraglacial Lake Detection and Depth Retrieval in ICESat-2 Photon Data Across the Greenland and Antarctic Ice Sheets.” *The Cryosphere*, 18(11), 5173-5206. DOI: 10.5194/tc-18-5173-2024. The dissertation author was the primary investigator and author of this manuscript.

Supplementary information

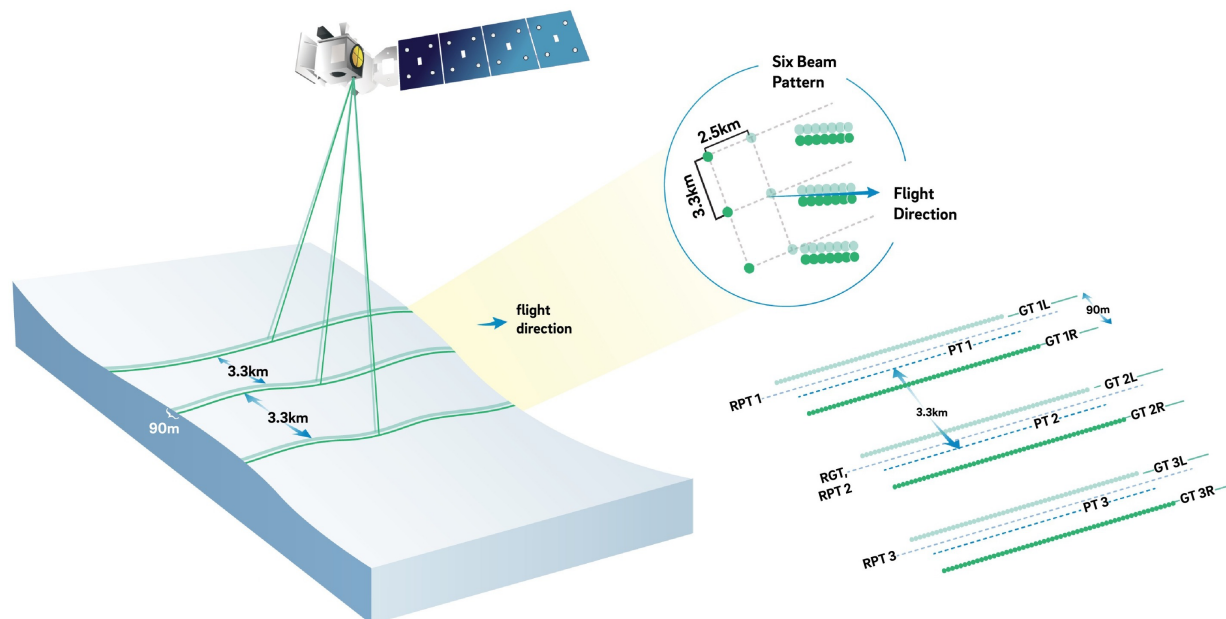


Figure S2.1: Illustration of ICESat-2's beam geometry, as described in Sect. 2.3.1. Reproduced from Smith et al. (2019).

CHAPTER 3: FIVE YEARS OF ICESAT-2 SUPRAGLACIAL LAKE DEPTH MEASUREMENTS ACROSS THE GREENLAND ICE SHEET IMPROVE SURFACE MELTWATER VOLUME ESTIMATES FROM SATELLITE IMAGERY

Key points:

- We present a dataset of 7,395 ICESat-2-derived supraglacial lake depth segments across the Greenland Ice Sheet 2019-23, up to 33 m deep
- A random forest model trained on Sentinel-2 imagery predicts water depth with a mean error ~ 0.5 m, validated against in situ sonar data
- Our model reduces errors by over 60% compared to traditional RTE methods for water volume estimation and generalizes to Antarctic melt lakes

Abstract

Accurate estimation of supraglacial lake volumes is critical for quantifying this mass budget process to understand its role in ice sheet dynamics. Current estimates of water depths are inferred from satellite imagery based on poorly constrained radiative transfer equation (RTE) models. We present a comprehensive dataset of 7,395 supraglacial lake depth transects estimated from ICESat-2 photon data across the Greenland Ice Sheet from 2019 to 2023. Our dataset shows lakes up to 33 m deep and reveals a trend of deeper lakes at lower elevations, with maximum depths decreasing by approximately 0.5 m per 100 m elevation

gain. We use this ICESat-2 dataset to train a random forest regression model to predict water volumes from Sentinel-2 imagery. Cross-validation suggests that this model predicts water depth with a mean absolute error of 0.52 ± 0.04 m, validated against *in situ* sonar data with a mean error of 0.50 m. Our model significantly outperforms traditional RTE methods and generalizes effectively to Antarctic melt lakes.

Plain language summary (PLS)

When ice melts on ice sheets, it often forms lakes that can crack the ice and drain through it, speeding up glacier flow into the ocean, and contributing to sea level rise. Studying these lakes is important for future sea level projections, but their remote locations and short-lived nature make them hard to observe directly. Fortunately, NASA’s ICESat-2 satellite can measure the depth of these lakes from space by using a green laser that is able to “see” through the water. We use a method to automatically detect these lakes and measure their depth in ICESat-2 data covering the entire Greenland Ice Sheet from 2019 to 2023. In total, we identify 7,395 lake transects, some as deep as 33 meters (109 ft). To improve continuous meltwater volume monitoring, we use this rather sparse but accurate ICESat-2 data from across Greenland to train a machine learning (ML) model to predict lake depths from satellite images – essentially based on how “deep blue” their color appears. The resulting model outperforms traditional methods and can even estimate lake depths in Antarctica, helping us better understand the impact of these lakes on ice sheet stability and future sea level rise.

3.1. Introduction

Monitoring supraglacial lake volumes is essential for understanding the impact of surface meltwater on ice sheet mass balance and dynamics (Joughin et al., 2013), especially given the accelerating ice loss from the Greenland and Antarctic ice sheets (Leeson

et al., 2015; Smith et al., 2020). Supraglacial lakes can drive significant changes in ice sheet flow (Dow et al., 2015; Maier et al., 2023) and may trigger “chain reaction”-like drainage events that have the potential to quickly destabilize parts of the ice sheets (Banwell et al., 2013; Christoffersen et al., 2018). Due to a lack of accurate, continuous observations, these processes remain insufficiently understood to be incorporated into models for predicting future sea level rise in a warming climate (Fox-Kemper, 2021; Aschwanden et al., 2021; Dunmire et al., 2024). Direct *in situ* measurements of supraglacial lake depths are logistically challenging, and impractical on a large scale due to the ephemeral nature of the lakes and their remote locations. Therefore, satellite remote sensing techniques are necessary for continuous monitoring of supraglacial lake volumes (Moussavi et al., 2016; Melling et al., 2024). Traditionally, at ice-sheet scale, water depths have been inferred from satellite imagery using the radiative transfer equation (RTE; Philpot, 1987), due to their ease of application and the broad spatial coverage and high temporal resolution of passive optical imagery. However, this approach relies on poorly constrained parameters, often leading to significant over- or underestimations depending on the environmental context (Fricker et al., 2021; Melling et al., 2024; Lutz et al., 2024).

The launch of NASA’s ICESat-2 laser altimeter in 2018 marked a significant advancement in supraglacial lake monitoring by providing the first direct and accurate depth measurements from space (e.g.; Fair et al., 2020; Fricker et al., 2021; Datta and Wouters, 2021). While ICESat-2’s bathymetric measurements are highly accurate (~ 0.5 m Dietrich et al., 2024), their utility is limited by ICESat-2’s sparse spatial coverage and the complexity of processing its large amount of unstructured point cloud data (Melling et al., 2024; Arndt and Fricker, 2024d). To leverage the advantages of both passive optical satellite imagery (broad spatial coverage, higher temporal resolution, and ease of application) and active laser altimetry (direct, accurate measurements), integrated approaches are needed

that use ICESat-2 to improve image-based depth estimates. Previous case studies have demonstrated optical imagery can be used to extrapolate depths along ICESat-2’s ground track segments to entire lake basins (Datta and Wouters, 2021), and that statistical models can learn the depth-reflectance relationship in satellite imagery to predict lake depth (Leeuwen, 2023; Lv et al., 2024). However, these previous studies have been limited to small datasets and regions. Given that the relationship between surface reflectance and water depth varies significantly by geographical region (Lutz et al., 2024), statistical learning models for ice-sheet-wide water volume estimation need to generalize this relationship across diverse conditions, independent of the availability of nearby training data in space and time. Effective generalization requires large, diverse training datasets that capture the full range of expected patterns and variations (Hastie et al., 2009). Since ICESat-2 observations of melt lakes are sparse, it is crucial to obtain as many depth estimates as possible from various locations, times, and environmental conditions to effectively use ICESat-2 to improve monitoring of meltwater volumes across the ice sheets.

In this paper, we present a comprehensive new dataset of ICESat-2-derived supraglacial lake depth estimates across the Greenland Ice Sheet for five melt seasons, from 2019 to 2023. We analyze trends in these data to assess spatial and temporal variability in lake depths. We train a supervised random forest (RF) regression model for lake depth prediction from satellite imagery on the ICESat-2-provided labels and validate the results against *in situ* data, demonstrating that they can significantly improve meltwater volume estimates compared to traditional RTE methods.

3.2. Data and methods

We used the ICESat-2 Global Geolocated Photon Data product (ATL03; Sect. 3.2.1) to extract supraglacial lake depths (Sect. 3.2.3). We combined these ICESat-2 depths with

concurrent Sentinel-2 imagery (Sect. 3.2.5) and used the fused dataset to train a random forest model for predicting lake depth from imagery (Sect. 3.2.6). To evaluate model performance, we cross-validated predictions on the full training dataset and independently validated predictions against *in situ* sonar data (Sect. 3.2.7). We compared model performance to RTE-based methods and against manually annotated ICESat-2 water depths on both ice sheets, including Antarctic data for testing whether our model successfully generalizes to a different domain (Sect. 3.2.9).

3.2.1. ICESat-2 laser altimetry over supraglacial lakes

ICESat-2, launched in September 2018, carries the Advanced Topographic Laser Altimeter System (ATLAS), a photon-counting green light (532 nm) laser altimeter operating at a frequency of 10 kHz, resulting in a 0.7 m along-track resolution (Markus et al., 2017). ATLAS emits laser pulses divided into six beams, forming three beam pairs, each consisting of a weak and a strong beam. The strong beams have four times the energy of weak beams, yielding a correspondingly higher return photon count per shot. Each beam’s footprint is about 11 m in diameter (Magruder et al., 2021a). ICESat-2 repeats its orbit every 91 days, covering 1,387 distinct reference ground tracks (RGTs). Over land ice, ATLAS routinely targets these near-nadir RGTs to obtain repeat measurements (Magruder et al., 2021b). From 26 June through 9 July 2019, ICESat-2 was in “safe-hold”, meaning no data were collected within this 14-day period during the 2019 Greenland melt season. ATLAS’s green light can penetrate shallow (< 41 m) and non-turbid water bodies, allowing signal photons to reflect from both the open-water surface and the lakebed (Fair et al., 2020; Dietrich et al., 2024).

Most land ice studies (e.g., Becker et al., 2021; Li et al., 2021a,b; Siegfried and Fricker, 2021; Khan et al., 2022) use the ATLAS/ICESat-2 L3A Land Ice Height (ATL06)

data product and higher-level products derived from ATL06, designed for glacier and ice sheet surfaces (Smith et al., 2019). However, ATL06 provides only a single surface that inconsistently tracks either the water surface or the lakebed over melt lakes, which means it cannot be used to determine meltwater depths (Fricker et al., 2021). Therefore, bathymetry applications rely on the elevations of individual ICESat-2 photons, available in the Global Geolocated Photons (ATL03) data product (Neumann et al., 2023a). In an ATL03 point cloud, signal photons reflected from both the surface and lakebed create a transect of the water column with characteristic double returns (e.g.; Fig. 3.1 a-t), which we use to derive along-track supraglacial lake depths.

3.2.2. ICESat-2 lake detection and depth retrieval algorithm

To extract ICESat-2 along-track segments of supraglacial lake depth measurements from ATL03 data across the entire ice sheet for all melt seasons from 2019 to 2023, we used the Flat Lake and Underlying Ice Detection (FLUID) and Surface Removal and Robust Fit (SuRRF) framework presented in Arndt and Fricker (2024d). The FLUID algorithm automatically identifies the locations of supraglacial lakes in the point cloud data by detecting flat water surfaces and subsurface peaks in photon density caused by reflections from the lakebed. The SuRRF algorithm then determines water depth for each detected along-track lake segment by fitting robust non-parametric regressions to both the photons from both the lake surface and the lakebed. The output from FLUID/SuRRF consists of along-track segments of ATL03 data, with the elevation of the lake surface and lakebed posted at a 5 m along-track resolution (blue and red lines in Fig. 3.1, a-t). Water depth is calculated by taking the elevation difference between the lake surface and the lakebed, adjusted for the refractive index of 532 nm light in 0°C freshwater (≈ 1.336 ; Mobley, 1995). Although ground truth data for ICESat-2 supraglacial lake segments are unavailable, validation with manually annotated data indicates that FLUID/SuRRF can extract lake depths with an

absolute error of less than < 0.27 m (Arndt and Fricker, 2024d).

3.2.3. Ice-sheet-wide retrieval of ICESat-2 lake depth measurements

To implement the FLUID/SuRRF algorithm across the entire Greenland Ice Sheet, we subsetting the available ATL03 data to geographic areas and time periods for which surface melt is typically observed.

Spatial subsetting: We defined the Greenland-wide study region using the Ice sheet Mass Balance Inter-comparison Exercise (IMBIE) drainage basins (Mouginot and Rignot, 2019). To include areas with floating ice tongues, we added regions from the Greenland Ice Mapping Project (GIMP) ice mask (Howat et al., 2014) that border the IMBIE drainage basins. We limited the study region to the ice sheet margins where supraglacial lakes typically form by applying a 2200 m elevation threshold using the ArcticDEM digital elevation model (Morin et al., 2016). This value is based on Zhang et al. (2023), who reported a maximum basin-mean elevation limit of surface water at 1967 m in Central West Greenland during the anomalously warm 2019 melt season, with surface water extending beyond 2000 m in some areas. The resulting ice-sheet-wide study area spans latitudes from 60.1° N to 82.7° N, leading to RGT spacing that varies from ~ 14.4 km in the south to ~ 3.7 km in the north.

Temporal subsetting: We defined the annual melt season as the 5-month period from May 1 to September 30 of each year.

Applying these spatiotemporal parameters to the ATL03 catalog resulted in a total of 11,304 ATL03 granules totaling 31 TB in size, covering a combined along-track distance of 12 million kilometers and comprising 171 billion individual photon locations. To process this large amount of data, we implemented FLUID/SuRRF on the Open Science Grid’s (OSG) Open Science Pool (OSPool) for distributed High-Throughput Computing (dHTC)

(Pordes et al., 2007; Sfiligoi et al., 2009; OSG, 2015), yielding a dataset of 7,395 ICESat-2 lake depth segments (Fig. 3.1).

3.2.4. Assessment of controls on spatiotemporal distribution and depth of ICESat-2 lake segments

To assess how variations in the spatiotemporal distribution and depth of supraglacial lake segments in the ICESat-2 data are related, we performed various ordinary least squares (OLS) linear fit to relate latitudes, elevations, depths and the days of the year where supraglacial lakes were detected in ATL03. Since there is a strong correlation between latitude and the observed distribution of supraglacial lakes with elevation (Sundal et al., 2009), lake depths and timing of lake occurrences are evaluated against elevation residuals after accounting for the effect of latitude. The uncertainties and p-values that we report were calculated in the standard way, under the assumption of unbiased and uncorrelated sampling. We compare our results to various previous studies, which have estimated supraglacial lake extents and depths from passive optical satellite imagery (e.g., Sundal et al., 2009; Selmes et al., 2011; Hu et al., 2021; Zhang et al., 2023; Fan et al., 2024) and explore meaningful physical explanations for our results using past literature and concepts reviewed in Sect. 1.3.

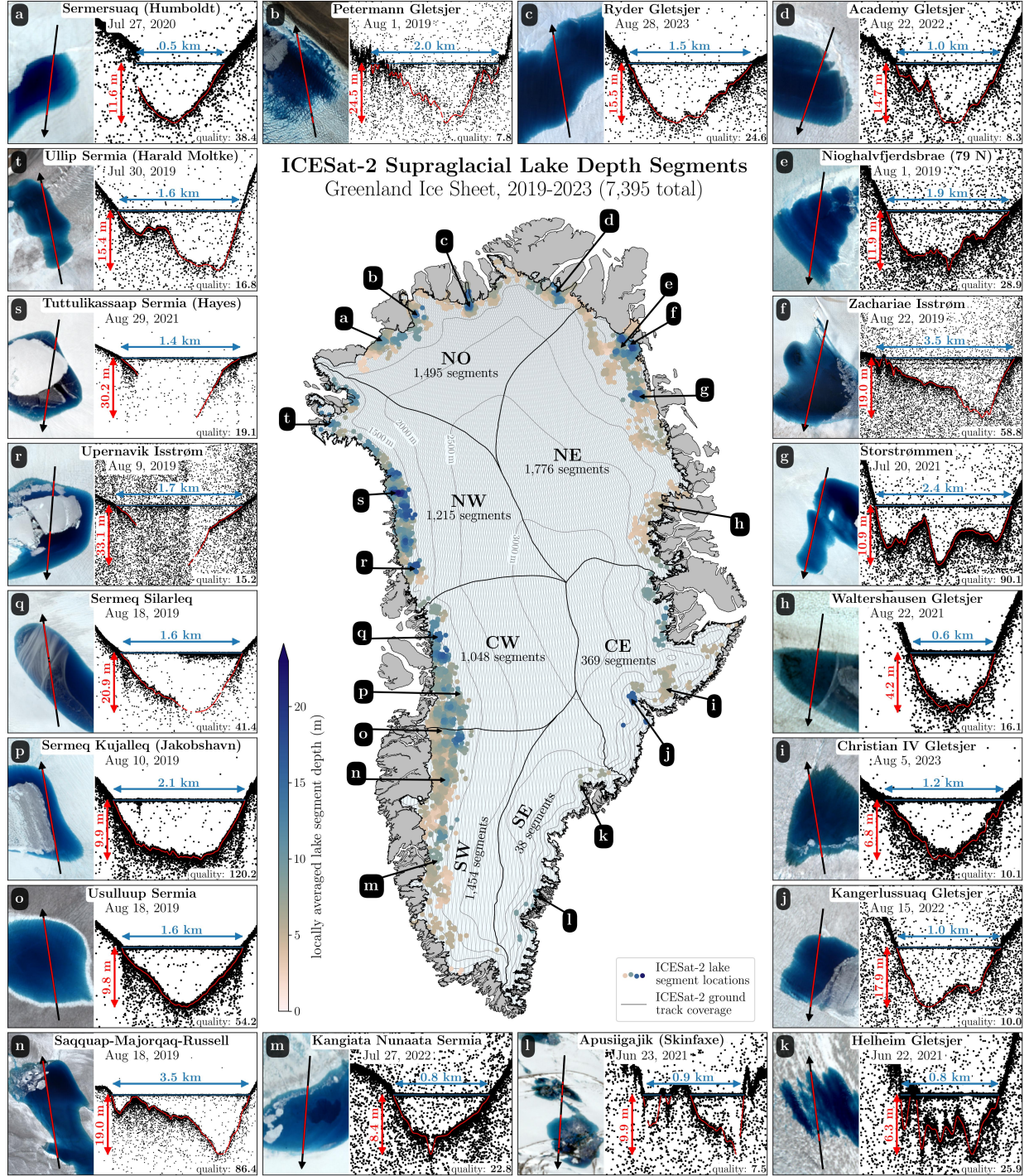
Since ICESat-2 ground track density increases at higher latitudes (Sect. 3.2.3), it has to be noted that ICESat-2 is more likely to sample supraglacial lakes at higher latitudes and therefore lakes further north are overrepresented in our dataset of lake segments. This means that our continent-wide results are also biased towards being more representative of higher-latitude lakes, as compared to a random sample of the full Greenland-wide distribution of supraglacial lakes. ICESat-2 is also unable to obtain supraglacial lake data in the presence of optically thick clouds, which means that regions with more frequent cloud cover are also underrepresented in our dataset.

These orbit- and cloud-dependent biases are not unique to ICESat-2, and also apply to passive optical imagery-based studies. Many previous imagery-based studies of supraglacial lake extents and imagery-based depth estimates on the ice sheets have suffered from a similar track-density bias when extracting meltwater features from individual scenes, since larger overlap areas between adjacent scenes in areas of denser ground track spacing lead to an increase in temporal resolution at higher latitudes (e.g., Moussavi et al., 2020; Stokes et al., 2019; Corr et al., 2022). Due to the higher inclination of passive optical satellites such as the Landsat satellites or Sentinel-2, this latitude-dependent sampling bias is larger in such imagery-based studies than it is for our ICESat-2-based dataset (Irons et al., 2012; Agency, 2015; Markus et al., 2017). For imagery-based studies, however, this bias can be partially corrected by calculating maximum extents or depths over longer time periods (e.g., Hu et al., 2021; Arthur et al., 2022; Tuckett et al., 2022; Zhang et al., 2023). This, however, decreases the overall temporal resolution of the data and makes it difficult to assess trends within the melt season. Further, since the probability of observing a lake (or observing it at its highest fill level) increases with temporal resolution, some sampling bias with respect to latitude and cloud cover remains when aggregating maximum extents over time. Recent work has presented an approach that aims to further reduce potential sampling biases and correlations with cloud cover by calculating lake visibility metrics for each scene (Tuckett et al., 2021).

In summary, while our ICESat-2-based supraglacial lake dataset is affected by an obvious sampling bias with respect to latitude, most comparable satellite remote sensing data products are affected by various biases and correlations with many climatic, dynamic and geologic factors remain. This underscores the importance to carefully assess whether and how results inferred from such satellite remote sensing data are physically meaningful.

Figure 3.1: Pan-Greenland ICESat-2 supraglacial lake depth dataset. Center map: Locations of all lake depth segments extracted from ATL03 data across the Greenland Ice Sheet from 2019 to 2023, using the FLUID/SuRRF framework. Dots representing lake segment locations are colored by depth, with the top quartile of maximum depth among each segment’s 30-nearest neighbors used as a locally averaged measure. The map is divided into seven sub-regions, defined by the IMBIE basins (Mouginot and Rignot, 2019). ICESat-2 reference ground tracks are shown to illustrate that ICESat-2 coverage increases with latitude. Side panels a-t: Examples of individual ICESat-2 lake depth segments extracted by FLUID/SuRRF. Left: Segment ground tracks over concurrent Sentinel-2 imagery. Right: ATL03 photon locations (black dots) with SuRRF fits to the lake surface (blue line) and lakebed (red line, shown where the bathymetry confidence score exceeds 0.3). Horizontal blue arrows indicate the along-track extent, and vertical red arrows show the maximum segment water depth. Numbers on the lower right represent the segment’s quality score.

3. Improving Supraglacial Lake Volume Estimates Using ICESat-2 Data Across Greenland



3.2.5. Fusion of ICESat-2 depth measurements with Sentinel-2 imagery

To create a training dataset for supervised machine learning that relates satellite imagery parameters (the input predictors) to ICESat-2-derived supraglacial lake depths (the output labels), we used Google Earth Engine to select Sentinel-2 Level-2A (L2A) surface reflectance scenes that coincide with ICESat-2 water depth measurements.

For each ICESat-2 lake segment, we selected Sentinel-2 scenes acquired with the following criteria: within 7 days of the ICESat-2 overpass; a maximum cloud probability score of 20 % within the segment’s bounding box, based on the s2cloudless algorithm (Zupanc, 2017); and sun elevation angle $\geq 20^\circ$, following previous studies of supraglacial lakes (Moussavi et al., 2020; Tuckett et al., 2021; Arthur et al., 2022).

Using the filtered collection of scenes, we calculated the zonal mean value (Winsemius and Braaten, 2023) of each Sentinel-2 band within a 7.5 m radius for every ICESat-2 along-track depth measurement from the Sentinel-2 scene acquired closest in time to the ICESat-2 data. We interpolated all solar and satellite view zenith and azimuth angles supplied in the Sentinel-2 Level-1C (L1C) metadata to the ICESat-2 ground track. This resulted in a tabular dataset with each ICESat-2-derived meltwater depth data point matched with the corresponding closest-in-time reflectance values for all Sentinel-2 L2A bands, the s2cloudless score, solar angles and per-band satellite view angles.

3.2.6. Random forest model for predicting water depth from Sentinel-2

3.2.6.1 Feature engineering

To create predictive features for linking Sentinel-2 data to water depth, we processed the Sentinel-2 samples in the fused dataset as follows:

- **Log-transformation of reflectance values:** We applied a log transformation to

the reflectance values of all Sentinel-2 bands (bands 1-12), Aerosol Optical Thickness (AOT), Water Vapor Pressure (WVP), and the s2cloudless score.

- **Cosine-transformation of angles:** For each band, we performed a cosine transformation on four angles: the solar zenith angle (SZA); the view zenith angle (VZA); the view azimuth angle (VAA) relative to the solar azimuth angle (SAA); and the phase angle between the incident solar radiation and the satellite sensor.
- **Calculation of ratios and indices:** We computed the log ratios and differences between all visible bands (bands 2, 3, and 4). We calculated the Normalized Difference Water Index (NDWI) using the red and blue bands.
- **Inclusion of classification maps and probability masks:** We included the Scene Classification Map (SCL) and the cloud and snow probability masks (MSK_CLDPRB and MSK_SNOWPRB) exactly as provided in the Sentinel-2 L2A data product.

This resulted in a training dataset consisting of approximately 1.2 million samples, each relating 62 Sentinel-2 predictors to an ICESat-2-derived water depth labels. About 55 % of the samples had a nonzero ICESat-2 depth, while the rest represented surrounding areas where no surface meltwater was detected. Using a grid-optimized NDWI threshold of 0.125, 89.2 % of Sentinel-2 samples aligned with ICESat-2 in detecting the presence of surface meltwater.

3.2.6.2 Sample selection for training

To ensure that our model is trained on a high-quality subset of the ICESat-2 depth labels, we removed samples with the following criteria before training:

1. **Unreliable ICESat-2 depths:** We removed (i) all samples from FLUID lake seg-

ments with a SuRRF quality score less than 2.0, indicating that the averaged ATL03 photon density along the fitted lakebed is less than twice the photon density in the lake’s interior (Arndt and Fricker, 2024d) and (ii) individual along-track depth samples with a SuRRF bathymetry confidence score less than 0.3, indicating lake segment locations where the lakebed fit is unreliable (Arndt and Fricker, 2024d).

2. **Sentinel-2 scenes that poorly match ICESat-2 observations:** Since it is possible that lakes drain, flood, or have significant changes to ice cover during the time between an ICESat-2 depth measurement and a Sentinel-2 scene acquisition, we limit the training data to Sentinel-2 data samples acquired within 48 hours of an ICESat-2 overpass as well as FLUID lake segments with a NDWI-based surface water presence agreement with ICESat-2 greater than 85% and a minimum Pearson’s correlation coefficient $r \geq 0.75$ between ICESat-2 depth and the log-transformed reflectance of at least one visible band.

These filtering steps yield a cleaned training dataset containing about 420,000 samples from 2,241 distinct ICESat-2 lake segments. With a grid-optimized NDWI threshold of 0.144, ICESat-2 and Sentinel-2 now agree on the presence of surface meltwater for 97.6 % of these remaining samples.

3.2.6.3 Fitting the model

Random forest models are generally considered to achieve outstanding “out of the box” empirical performance (Wager, 2016) due to their high level of robustness to both correlated and irrelevant features (Gregorutti et al., 2017), and since they generally perform well without the need for extensive hyperparameter tuning (Probst et al., 2019). Random forests further reveal which input features are most relevant due to their inherent process of producing variable importances (Grömping, 2009).

To predict water depth from the extracted Sentinel-2 features, we trained a random forest regression model (Breiman, 2001) on the cleaned training data using the scikit-learn package in Python (Pedregosa et al., 2011). The model is an ensemble of 1000 individual decision tree regressors, each trained on 5% of the samples and selecting 40% of the predictors at each split, and can be used to make predictions on any Sentinel-2 L2A data on a per-pixel basis.

To verify that our model is robust to potentially irrelevant and highly correlated features in the training data, we use Recursive Feature Elimination (RFE; Guyon et al., 2002), an iterative process during which a model is fit at each step, and then the least important feature is dropped. This process has been shown to effectively select relevant features for random forest models, both when irrelevant features are present and when features are correlated (Gregorutti et al., 2017). To evaluate whether the removal of less relevant features would lead to increases in predictive performance in our model, we monitor 10-fold cross-validation model accuracy throughout this process as increasingly many features are removed from the set of predictors that the model is trained on.

3.2.7. Random forest model validation

To assess our selected random forest model’s predictive performance on the depth-labeled Sentinel-2 data, we use 10-fold cross validation CV (Kohavi, 1995). Since we expect the samples spaced 5 m apart along individual ICESat-2 lake segment ground tracks to be highly autocorrelated, we randomly split the training data by ICESat-2 lake segment rather than by individual depth sample. This approach is used to train the model to better generalize across different lakes, providing cross-validation statistics that more accurately represent the model’s predictive performance on new supraglacial lakes from previously unseen Sentinel-2 data, rather than simply its ability to “fill in” predicted depths along

lake segments after being trained on about 90 % of each segment’s data.

To validate the ICESat-2-trained random forest model independently of ICESat-2-derived depth estimates, we use *in situ* sonar depth measurements of three supraglacial lakes in Northeast Greenland, acquired during the 2022 melt season, as presented in (Lutz et al., 2024, Fig. 3.3). At the time of writing, these sonar measurements are the only *in situ* supraglacial lake depth data over the ice sheets for the Sentinel-2 period. We use the same zonal statistics approach used for ICESat-2 lake segments to extract Sentinel-2 data for each point along the sonar track, for all scenes that meet the conditions described in Sect. 3.2.5. After removing scenes affected by rapid drainage or flooding of a lake before or after the sonar data acquisition, we use the random forest model to predict depths for all remaining scenes. To best estimate predicted lake depth at the exact time of the sonar data acquisition, we evaluate the intercept of a linear regression of predicted water depth on the time difference between the Sentinel-2 acquisition and the sonar data acquisition for each point along the sonar track.

3.2.8. Comparison to previous empirical fitting methods: the band-ratio

We compare the performance of our random forest model to the simpler band-ratio method that has previously been proposed for empirical fits between passive optical imagery reflectances and water depths for near-shore ocean bathymetry (Dierssen et al., 2003), rivers (Legleiter et al., 2009) and supraglacial lakes on the Greenland Ice Sheet (Legleiter et al., 2014). It has been shown that the logarithm of the ratio of reflectances recorded in two bands is relatively constant across variable lakebed types, as changes in bottom albedo affect both bands similarly (Legleiter et al., 2009). This logarithmically transformed band ratio $X = \ln \left(\frac{R(\lambda_1)}{R(\lambda_2)} \right)$, where $R(\lambda_i)$ is recorded the reflectance value at the wavelength λ_i of a particular band i , is then assumed to be quadratically related to depth $D = aX^2 + bX + c$

(e.g., Legleiter et al., 2009; Pope et al., 2016).

Previous studies have shown that the quadratic fit to the band ratio between the blue and green bands resolves depths more accurately than other band combinations than other band combinations (Moussavi et al., 2016; Pope et al., 2016). For the Sentinel-2 data we therefore calculate the band ratio X using $R(\lambda_1) = B2$ and $R(\lambda_2) = B3$, where B2 is the reflectance of Sentinel-2’s blue band (band 2) and B3 is the reflectance of the green band (band 3). Since this simple, parametric fit to the data is unlikely to result in overfitting on our large amount of ICESat-2-derived depths, we evaluate the performance of the band-ratio method on the entire training dataset. Since the band-ratio X is not well-defined as the reflectance in the denominator becomes zero, we discard all data points where this happens for the purpose of evaluating the performance of the band-ratio method. This, however, means that application of the band-ratio method to imagery data would result in missing data where the green band becomes saturated, which is most likely for the deepest supraglacial lakes (Melling et al., 2024).

We further compare our results for the empirical band-ratio fit to our training data to the results of Fan et al. (2024), who used a similar ICESat-2-based training dataset to estimate the relationship between spectral reflectance in Landsat data to supraglacial lake depth.

3.2.9. Comparison to independent RTE-based estimates

To compare the performance of our random forest model to traditional RTE methods we compare predictions against nine ICESat-2 lake segments with “baseline” water depth labels provided by an ensemble of manual annotations by ICESat-2 altimetry experts for comparison and validation (Fig. 3.4; Arndt and Fricker, 2024d):

1. **Five segments located in Southwest Greenland** (3.4, a-e), first presented in

Melling et al. (2024) alongside depth estimates using the RTE method individually applied to Sentinel-2’s red and green bands with values of tunable parameters that have been commonly used in the literature (Sneed and Hamilton, 2007; Georgiou et al., 2009; Pope et al., 2016).

2. **Four segments located on Amery Ice Shelf, East Antarctica** (3.4, f-i), first presented in Fricker et al. (2021) alongside depth estimates using the RTE method applied to the average of Landsat 8’s red and panchromatic bands (based on Spergel et al., 2021) and to Sentinel-2’s red band (based on Moussavi et al., 2020). For these lake segments, the manual baseline depths from Fricker et al. (2021) provided an opportunity to evaluate whether our random forest model trained on ICESat-2 data from Greenland only is able to effectively generalize and also make accurate depth predictions for supraglacial lakes on Antarctic ice shelves.

To compare our method’s depth predictions to the RTE-based estimates, we calculated the random-forest-predicted depth at the time of the ICESat-2 overpass for along-track data points at a 5 m resolution as described in Sect. 3.2.7. Since the Greenland lake segments used here are all already included in our ICESat-2-derived training dataset, we make depth predictions for these five segments using a separate random forest model trained as described in Sect. 3.2.6 while omitting the five segments used for comparison from the training data.

3.3. Results and discussion

3.3.1. Pan-Greenland ICESat-2 lake depths, 2019-23

Our implementation of FLUID/SuRRF across the entire Greenland Ice Sheet between 2019 and 2023 yielded a dataset of 7,395 ICESat-2 lake depth segments with water depth measurements up to 33 m (Fig. 3.1). Across all processed granules, only 0.033 % of

along-track distance corresponds to surfaces of supraglacial lakes with a lakebed visible in ATL03, amounting to 4060 km of along-track lake depth data. The overall small proportion of usable ICESat-2 supraglacial bathymetry measurements relative to the total processed ATL03 data underscores the need for efficient, large-scale methods that can automatically detect and extract ICESat-2 supraglacial lake segments. Such approaches are essential for building a large and diverse training dataset for machine learning models, enabling robust predictions of meltwater depths from spectral reflectance in optical imagery and facilitating broader spatial and temporal scaling of lake volume estimates. Processing all available ATL03 data (11,304 granules totaling 31 TB in size), took less than a day on the OSG Open Science Pool.

3.3.1.1 Spatial distribution of lake segments across Greenland

Between 2019 and 2023, we found the highest number of lake segments in the Northeast (1,776), North (1,495) and Southwest (1,454) drainage basins and only a very small number of lake segments (38) in the Southeast. This is similar to results from Hu et al. (2021), who reported the largest quantity of supraglacial lakes between 2016 and 2018 in the Northeast, Southwest and Northwest and also a strikingly small number of lakes in the Southeast. It has to be noted, however, that lakes at higher latitudes are more likely to be sampled by ICESat-2, due to the ICESat-2's track spacing being denser at higher latitudes (3.1). Relative to the total amount of data analyzed, we found the largest proportion of supraglacial lake data (lake density) in the Central West (0.09 % of along-track distance), followed by the Southwest, Northeast and Northwest, in order (Fig. 3.2, a). This aligns with Hu et al. (2021), who reported the highest lake density along the western basins and the Northeast. We observed the lowest density of lakes in the Southeast, where only 0.002 % of total along-track distance was supraglacial lake data.

The high density of lakes in the Central West and Southwest basins, compared to other regions of the Greenland Ice Sheet, can be attributed to several key characteristics of these areas. These basins have extensive bare-ice ablation zones and runoff areas that extend far inland and to high elevations (Ryan et al., 2019; Zhang et al., 2023), an early onset and prolonged duration of surface melt (Sundal et al., 2009; Mernild et al., 2011), high rates of summer ice thinning (Slater et al., 2021), high rainfall amounts (Box et al., 2023), and relatively low ice-surface slopes with moderate topographic relief, which favors the development of lake basins (Ignéczi et al., 2018). These factors collectively enhance the potential for meltwater to accumulate in supraglacial lakes over large areas and for extended periods (Sect. 1.3).

In contrast, the paucity of supraglacial lakes in Southeast Greenland, as reported in previous studies (e.g., Sundal et al., 2009; Zhang et al., 2023; Fan et al., 2024), is likely due to the region’s steep surface slopes, abundance of crevassing, and thick, permeable firn layer, which is sustained by snowfall rates near the coast that are approximately five times higher than in other parts of the ice sheet (Gallagher et al., 2022). These conditions favor meltwater infiltration and the formation and drainage of firn aquifers (Poinar et al., 2017; Miller et al., 2022), thereby reducing the likelihood of surface meltwater pooling in supraglacial lakes. Overall, the Central West and Southwest basins experience substantial negative surface mass balance, whereas the Southeast basin largely maintains a positive surface mass balance (van den Broeke et al., 2017; Van Kampenhout et al., 2019), underscoring a strong relationship between lake occurrence and surface mass loss processes.

3.3.1.2 Spatiotemporal patterns in lake depths

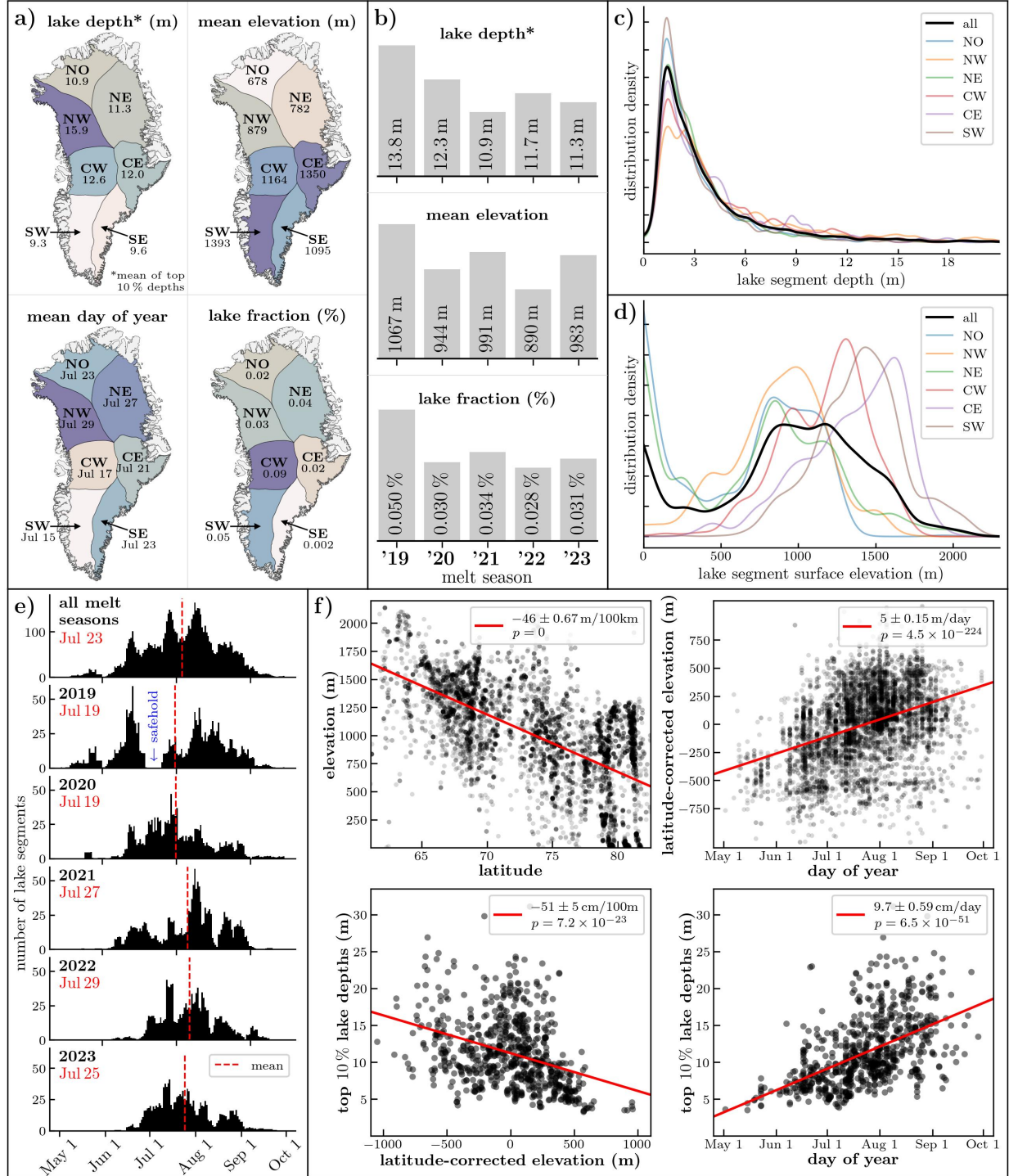
Because ICESat-2 ground tracks intersect supraglacial lake basins at arbitrary locations, they often do not sample the deepest part of the lake. As a result, the maximum

depth measured along a lake segment is typically less than the actual maximum depth of the entire lake, with many tracks only sampling the shallower margins. This means that for shallower depths, the overall distributions of maximum along-segment depths are largely similar across regions with both shallow and deep lakes, but significant differences appear in the upper tails of these distributions. Therefore, when reporting depth statistics, we consider the mean depth of the top 10 % deepest segments, d_{10} , as an indicator for how deep supraglacial lakes tend to grow across a particular region. Although the absolute value of d_{10} has no intrinsic physical meaning, this metric allows for meaningful comparisons of the maximum depths that typical supraglacial lakes reach across different regions and time periods.

Our results show that the deepest supraglacial lakes form in Northwest Greenland ($d_{10} = 15.9$ m), while lakes remain shallowest in the Southwest ($d_{10} = 9.3$ m). The presence of deepest lakes in Northwest Greenland is likely driven by the influence of bedrock topography on surface depressions, modulated by ice flow dynamics. The margin of the Northwest drainage basin is characterized by rough basal topography and fast-flowing ice (Rippin, 2013). High basal meltwater production in this region (Karlsson et al., 2021), combined with a spatially variable basal slip ratio (i.e., featuring both “sticky spots” and “slippery spots”; Bons et al., 2018; MacGregor et al., 2022), facilitates the transfer of longer basal wavelengths to the ice surface through thicker ice (Sergienko, 2013; Ignéczi et al., 2018). This process can generate large and deep surface depressions that have the potential to accumulate significant meltwater, forming particularly deep supraglacial lakes. Recent research further indicates that lakes in Northwest Greenland drain less frequently than those in other basins (Dunmire et al., 2024), suggesting that surface depressions in this region accumulate excess surface runoff for extended periods, allowing lakes to grow deeper over time.

Figure 3.2: Spatiotemporal variability and trends in the ICESat-2 supraglacial lake depth dataset. a): Depth, elevation, timing and spatial density of supraglacial lakes by drainage basin. Reported values are statistics based on all ICESat-2 lake segments found in each basin. Lake depths are reported as the mean of the top 10 % of maximum along-track lake segment depths. b): Same statistics as in a), by melt season. c): Distribution of maximum along-track segment depths for the full dataset and by drainage basin. d): Distribution of lake segment surface elevations for the full dataset and by drainage basin. e): Histograms of the day of year for lake segment ICESat-2 overpasses, for the full dataset and by melt season. The empirical lake segment depth and surface elevation probability distributions (c,d) are not shown for the Southeast (SE) basin, since not enough lake segments were detected in this region. f): Estimates for the relationship between various parameters in the dataset. Upper left: lake segments' surface elevations versus the day of the latitude of each observation. Upper right: Latitude-corrected elevations (the residuals from linearly regressing elevation on latitude) versus the day of the year of each observation. Lower left: top 10 % of the lake segment depths versus latitude-corrected lake segment surface elevation. Lower right: top 10 % of the lake segment depths versus the day of the year. Values in the legends are the slopes of the linear fits (red line) to the data and uncertainties are standard errors of the slopes. Uncertainties and p-values were calculated in the standard way using `statsmodels.api.OLS` for linear model fitting, under the assumption of unbiased and uncorrelated sampling, with standard errors and p-values derived from the model fit.

3. Improving Supraglacial Lake Volume Estimates Using ICESat-2 Data Across Greenland



In contrast, the tendency of lakes in Southwest Greenland to remain comparatively shallow can be attributed to a weaker influence of bedrock undulations on surface topography and meltwater routing. This region is characterized by smoother basal topography, lower ice velocities, and reduced basal meltwater production (Rippin, 2013; Karlsson et al., 2021). These factors contribute to fewer deep surface depressions in the percolation zones of southern and southwestern Greenland (Ignéczi et al., 2016). Additionally, the presence of thick ice slabs in this region promotes the development of surface streams (MacFerrin et al., 2019; Jullien et al., 2023), which efficiently transport meltwater off the ice sheet (Smith et al., 2015). Supporting this, a recent study found that the recurrence rate of supraglacial melt lakes – defined as the fraction of years during which lakes form in the same location – is significantly lower in the southern Greenland Ice Sheet compared to central and northern regions (Fan et al., 2024). This lower recurrence rate suggests that bedrock topography has a reduced influence on lake distribution in the south, and prevents the long-term deepening of lake basins through lake bottom ablation over consecutive melt seasons (Tedesco et al., 2012).

We found the most amount of melt in 2019, which had an along-track lake density 65 % higher than during the remaining four years (Fig. 3.2, b). The 2019 melt season also features the deepest lakes, and lakes forming at the highest elevations (Fig. 3.2, b). This is consistent with 2019 having been an exceptionally warm melt season across Greenland, with lower than average snow and ice surface reflectivity (Elmes et al., 2021) and low snow accumulation in the previous winter (Tedesco and Fettweis, 2020), which implies high levels of surface meltwater production and a reduced capacity of the surface firn to retain meltwater.

3.3.1.3 Distribution of lake depths with elevation

On the grounded Greenland Ice Sheet, most lakes (75 %) are located at elevations between 750 m and 1700 m (Fig. 3.2, d), which is consistent with previous studies (e.g., Hu et al., 2021) and with the findings of Ignéczi et al. (2018) who demonstrated that lakes tend to form in regions of moderate ice-surface relief where depressions that can hold lakes are most abundant. In the North and Northeast a significant number of generally smaller and shallower lakes (19 %) also formed on or near the floating ice tongues of marine-terminating glaciers, at elevations < 200 m. Similar observations of supraglacial lakes on Greenland’s floating ice tongues have previously been reported by Macdonald et al. (2018) for Petermann Gletsjer and Turton et al. (2021) for Nioghalvfjærdsbrae.

Our data suggest that lake segments on grounded ice are generally found at higher elevations further south on the ice sheet, consistent with results from Leeson et al. (2015) and with Fan et al. (2024), who reported that supraglacial lakes on the northern Greenland Ice Sheet form approximately 300 to 400 m in elevation lower than in the south. In our ICESat-2 data, however, the difference between mean lake segment elevation on grounded ice in the southern basins (1390 m) and the northern basins (840 m) is larger (~ 550 m), which is likely due to the fact that Fan et al. (2024) consider maximum melt extent in July and August only, while our data includes observations from May through September. We performed an ordinary least squares (OLS) linear fit to the ICESat-2 data, which confirmed that mean lake surface elevation increases in southward direction ($p = 0.0$), at a rate of 46 ± 0.67 m every 100 km, where the uncertainty range denotes the standard error of the estimated slope (3.2, f).

After correcting for the relationship between latitude and surface elevation, a linear regression of the maximum 10 % lake depths against surface elevation residuals indicates that maximum lake depths decrease significantly with elevation ($p = 7.2 \times 10^{-23}$) at a rate

of 51 ± 5.0 cm every 100 m of elevation gain. This inverse relationship between lake depth and surface elevation is likely influenced by several factors, including duration and extent of surface melt, firn saturation, and differing levels of bedrock control on surface topography.

Low-elevation regions near the ice sheet margins are characterized by thinner ice, faster flow rates, and high basal slip ratios (MacGregor et al., 2022), driven by significant basal meltwater production and active surface-to-bed hydraulic connections in the ablation zone (Banwell et al., 2016; Davison et al., 2019; Karlsson et al., 2021). These conditions enhance the transfer of bedrock undulations to the ice surface, forming deeper closed topographic depressions (Gudmundsson, 2003; Ignéczi et al., 2018). Additionally, low-elevation areas experience higher average temperatures and longer durations of above-freezing conditions during the melt season (Mernild et al., 2011), enabling more runoff to accumulate in these depressions and form deeper supraglacial lakes. The strong influence of bedrock topography on lake locations increases the likelihood of lakes forming repeatedly in the same depressions across multiple melt seasons, promoting further deepening of lake basins through lake bottom ablation (Tedesco et al., 2012). This effect is particularly pronounced at lower elevations, where higher temperatures accelerate melt rates. In contrast, supraglacial lakes at higher elevations typically form on smoother topography with a more permeable firn layer and are less likely to recur over consecutive melt seasons (Glen et al., 2024), limiting the development and growth of deep lake basins.

3.3.1.4 Timing and trends in lake formation

Our dataset contains valuable information about the spatial and temporal variability of water depths. Considering all five melt seasons, the average acquisition time of ICESat-2 lake segments suggests that Greenland melt seasons typically peak around July 23 each year (Fig. 3.2, e). Within each individual melt season, there is a trend in supraglacial

lake depth with time, with lakes generally appearing at higher elevations as the season progresses (Sundal et al., 2009). A linear regression of the day of year of ICESat-2 lake observations against surface elevation residuals supports this ($p = 4.5 \times 10^{-224}$), showing an average upward migration rate of the locations of supraglacial lakes of 5.0 ± 0.15 m/day. This upward migration of supraglacial lake locations can be explained by surface melt, firn saturation and pooling of excess runoff reaching progressively higher elevations in late summer, combined with supraglacial lakes at low elevations being more likely to drain early in the melt season (Yang et al., 2021; Dunmire et al., 2024). The ICESat-2 data also suggest that the deepest supraglacial lakes tend to grow even deeper as the melt season progresses. A linear regression of maximum 10 % lake depths on the day of the year indicates that maximum lake depths increase ($p = 6.5 \times 10^{-51}$) at a rate of 9.7 ± 0.59 cm/day. This is likely due to basins of low-elevation lakes that do not drain during summertime reaching progressively higher fill levels as excess runoff accumulates throughout the melt season, thus favoring the formation of deepest lakes late in the melt season.

Overall, our findings are consistent with previously-reported general patterns in the spatiotemporal distribution of supraglacial lake locations on the Greenland Ice Sheet (Elmes et al., 2021; Leeson et al., 2015; Sundal et al., 2009), and add valuable new insights related to water depths.

3.3.2. Random forest model performance

Recursive Feature Elimination (RFE) demonstrated that our model is robust to less relevant and highly correlated features. Throughout the feature elimination process, model performance did not improve (i.e., cross-validated mean absolute errors did not decrease) as less important and strongly correlated features were excluded from training and prediction (Fig. S3.1). This observation aligns with the general understanding that random forest

models are inherently robust to irrelevant features and multicollinearity, particularly when the number of features randomly considered at each split is sufficiently large (Gregorutti et al., 2017; Probst et al., 2019). Notably, however, the predictive performance of our model did not significantly decline until approximately 20 of the total 62 features remained. This indicates that, for efficient large-scale implementation, the model could be simplified by including fewer predictors with minimal loss in predictive performance.

The final three most relevant variables during RFE highlight that the majority of information related to water depth is captured in the visible spectrum (blue, green, and red bands) and that both band ratios and band differences enhance predictive performance. Specifically, the log-reflectance of the green band, $\ln(B3)$, the band ratio between the green and blue bands, $\ln\left(\frac{B3}{B2}\right)$, and the difference between the log-reflectances of the green and red bands, $\ln(B3) - \ln(B4)$, were identified as the three most critical features (Fig. S3.1). These variables incorporate absolute reflectance values, band ratios, and band differences, leveraging complementary information from the three visible bands.

Interestingly, the 20 most relevant features identified by RFE included only one band’s phase angle, one band’s view zenith angle, and one band’s relative azimuth angle, suggesting that the relative solar and satellite view angles across different bands provide largely redundant information. These features could likely be replaced by cross-band averages of the relative angles, further streamlining the model without sacrificing much predictive accuracy. During RFE, the MAE increased by only 4 cm – or less than 10 % – before all features related to solar and satellite view angles were excluded. Eliminating these angle-related features altogether would negate the need to download associated metadata and enable a lake depth prediction workflow fully within Google Earth Engine. This would significantly simplify both the model and the data curation process, achieving a substantial reduction in complexity at a relatively low cost to predictive performance.

3.3.2.1 Cross validation

10-fold cross-validation of the random forest model on the training dataset suggested that our random forest model is able to predict supraglacial lake depths with a mean absolute error (MAE) of 0.52 ± 0.04 m, a root mean square error (RMSE) of 0.95 ± 0.08 m and a small overall bias towards underestimating water depth by 0.04 ± 0.05 m, where the reported uncertainties are the standard deviations across the 10 cross-validation folds. The Pearson correlation coefficient between ICESat-2-provided depth labels and random forest predictions was 0.96 ± 0.01 across all cross-validation folds. Since the error statistics include the effects of actual lake depth changes between the acquisition times of ICESat-2 and Sentinel-2, the reported performance is likely a conservative estimate for our algorithm’s ability to reproduce ICESat-2 depth estimates from Sentinel-2 data alone.

These cross-validation results indicate that our model outperforms a recent machine learning approach presented by Fan et al. (2024), which employs a Multi-Layer Perceptron (MLP) with three hidden layers (“deep learning” model) to predict ICESat-2-derived lake depths from Landsat 8 spectral reflectances. In their study, the authors report a MAE of 0.85 m and RMSE of 1.26 m on the validation set, along with a Pearson correlation coefficient of 0.92 between the ICESat-2 depth labels and model predictions. However, Fan et al. (2024) provide limited information about their training data, including its size, distribution, and the method used to split samples for training and validation. This makes it challenging to determine whether the observed differences in predictive performance arise from disparities in the size or quality of the training data itself, or from differences in the chosen machine learning models.

3.3.2.2 Validation against *in situ* data

Validation of the random forest model against *in situ* sonar data over three lakes presented in (Lutz et al., 2024) shows that our depth predictions fit the ground truth data well (Fig. 3.3): gridded per-pixel predictions of lake depth (d-f) visually agree with true-color images of each sonar track’s surroundings (a-c) and along-sonar-track depth predictions follow the shape of the sonar data depth profiles to a high degree of accuracy (g-l), which is also supported by a Pearson’s correlation coefficient of $r = 0.94$ across all three lakes. The corresponding MAE is 0.50 m, with a bias towards underestimating water depths by 0.13 m, resulting in an underestimate of the total amount of water by 3 %. Among the three individual lakes, biases range from a 7 % overestimate for lake 522 to a 12 % underestimate for lake 610b. This significant inter-lake variability in prediction bias may be due to the fact that all three lakes were actively filling at the time of the sonar measurements (Fig. 3.3, g-i) making interpolation of predicted lake depths to the exact time of the sonar data acquisition challenging. The *in situ* validated mean error of our ICESat-2-trained random forest model is comparable to typical accuracies of direct ICESat-2 bathymetry measurements (0.5 m; Dietrich et al., 2024), implying that the model is able to successfully predict supraglacial water depths within the uncertainty inherent to the training data.

3.3.2.3 Comparison to the band-ratio method

The band-ratio method, calibrated across all of our training data, performs relatively poorly, yielding a MAE of 1.36 m, a RMSE of 2.20 m, and a Pearson correlation coefficient of 0.70 (Fig. S3.2). These results align with those of Fan et al. (2024), who evaluated a blue and green band-ratio method for Landsat 8 calibrated to ICESat-2-derived lake depths. In their study, the authors reported a MAE of 1.33 m, consistent with the relatively poor

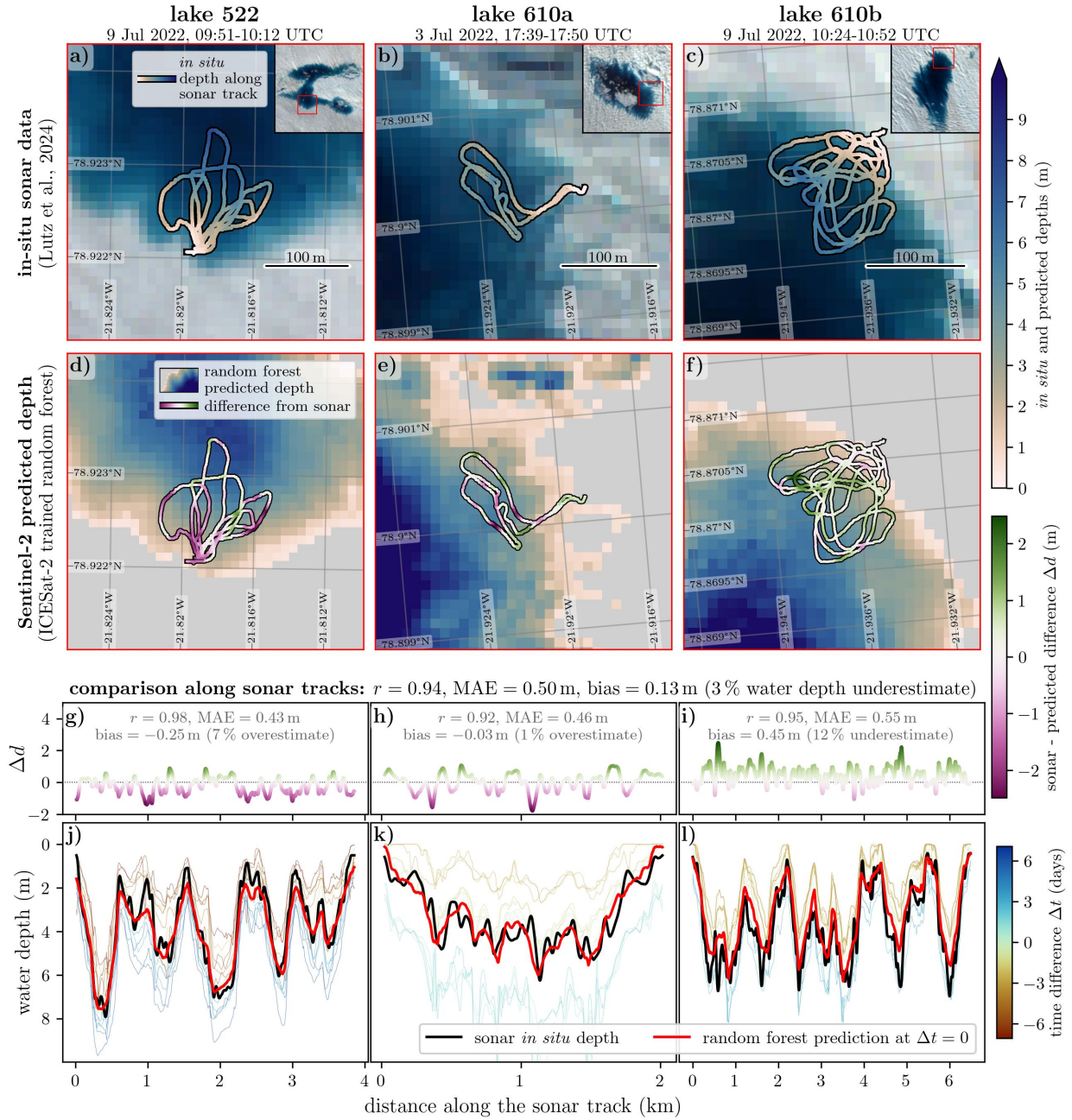
performance observed here.

Our data indicate that the band-ratio method exhibits significant limitations when applied across large spatial extents and diverse datasets. While the relationship between the band-ratio and water depth is well-defined for individual lakes and even multiple lakes within a single imagery scene, this relationship varies substantially across different lakes and scenes (Fig. S3.3). Although the band-ratio performs reasonably well for shallow depths (< 5 m) across distinct lakes and scenes, its accuracy diminishes significantly for deeper lakes. This degradation in performance is likely due to band-ratio values becoming excessively large when the denominator reflectance approaches zero, a scenario more common in deep lakes. Consequently, attempting to fit a unified model to the band-ratio and water depth relationship across all of Greenland and multiple melt seasons results in poor overall predictive performance. These findings are consistent with the observations of Lutz et al. (2024), who reported that the parameters in simple models relating lake depth to passive optical spectral reflectances vary significantly by geographic region. Additionally, our results suggest that the acquisition conditions of individual imagery scenes introduce further variability, preventing a consistent band-ratio-to-depth relationship across scenes.

In comparison to previous studies, the performance limitations of the band-ratio method observed in this study is likely attributable to the broader spatial and depth ranges of our dataset. Earlier works were geographically constrained and relied on a limited number of lakes and imagery scenes for model calibration and validation. For instance, Tedesco and Steiner (2011) and Pope et al. (2016) relied on *in situ* data from a single lake, and Legleiter et al. (2014) applied the same method to three lakes. Moussavi et al. (2016) used depth estimates from DEMs of seven post-drainage lake beds for calibration, all within a small study region. Notably, these studies were limited to relatively shallow lakes, generally up to ~ 5 m deep, where the band-ratio method performs considerably

Figure 3.3: Validation of random forest depth predictions with *in situ* sonar data. a-c): *In situ* water depths from Lutz et al. (2024) plotted along the sonar track. Background images are median composites of Sentinel-2 around the *in situ* data acquisition date. d-f): Gridded water depths predicted by the random forest model. The sonar track overlays are colored by depth differences between sonar validation data and predicted depths. g-i) Differences between validation and predicted data plotted along the full distances of the sonar tracks, with performance statistics shown for each individual lake. j-l) Full depth profiles along the sonar tracks. Bold lines are *in situ* sonar measurements (black) and random forest estimates interpolated to the time of the sonar data acquisition (red). Thin lines are individual random forest depth predictions from Sentinel-2 scenes up to 7 days before and after the sonar data acquisition.

Validation with *in situ* sonar data



better. However, deeper water exhibits a more variable relationship between band-ratio and depth across multiple imagery scenes (Fig. S3.3). Moreover, the quadratic fits often used in band-ratio approaches lack physical meaning, making them prone to overfitting for individual lakes or small, geographically-limited datasets. While such fits may appear to work well in limited contexts, they fail to generalize to large-scale, pan-Greenland datasets, where variability in environmental conditions and imagery acquisition significantly impacts performance.

3.3.2.4 Comparison to independent RTE-based methods

To assess the performance of our random forest model’s predictions and compare them to RTE-based estimates we evaluated results for five lakes in Greenland and four lakes in Antarctica (Fig. 3.4). Since our model had not seen any training data in Antarctica, we included these four lakes to determine whether it is able to generalize to a different domain.

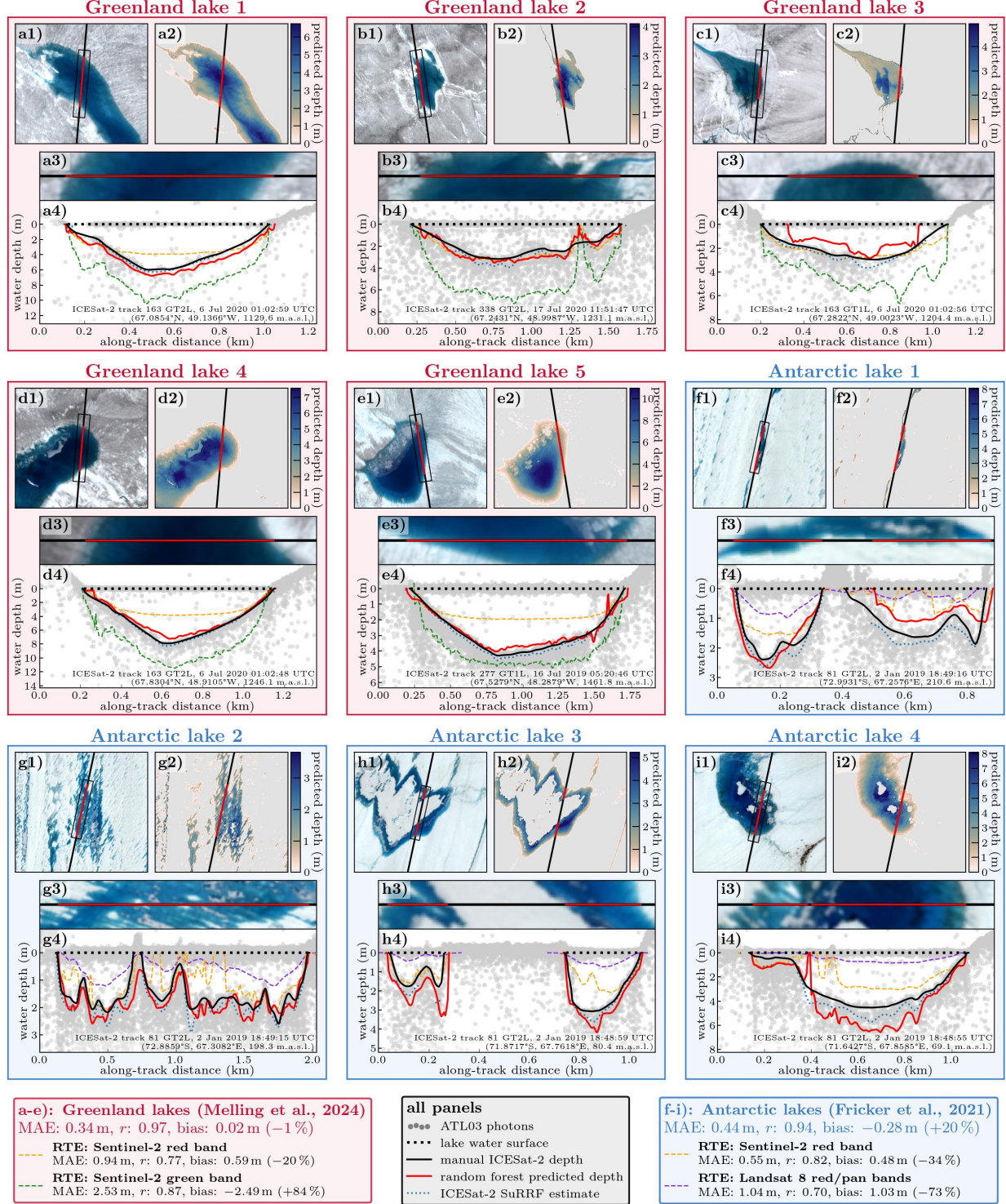
Greenland lakes: For the five Greenland lakes with manual depth annotations to the ATL03 data, our random forest model predicts water depth with a MAE of 0.34 m, compared to 0.94 m and 2.53 m for Sentinel-2 red and green-band RTE estimates, respectively. This means that our model reduces the total errors by 64 % when compared to the traditional red-band RTE estimates, and by 87 % when compared to the green one. The random forest predictions robustly match the shape of the lakebeds, as indicated by a Pearson correlation coefficient of $r = 0.97$. In contrast, the red and green-band RTE methods show lower correlation values (0.77 and 0.87), suggesting these methods are less effective at retrieving the shape of the lakebed compared to our model. The exception is lake 3 (Fig. 3.4, c1-4), which was in the process of rapidly draining during the ICESat-2 overpass. The average bias of our random forest model across the five lakes is negligibly small (0.02 m, < 1 % water underestimate). In contrast, the red-band RTE method

underestimates water depths by 20 % (bias of 0.59 m), with a particularly large bias for water depths exceeding approximately 3 m. This occurs due to the strong attenuation of red light in water, which leads to significant underestimation in lake areas deeper than the red saturation point (Melling et al., 2024; Lutz et al., 2024). Conversely, the green-band RTE overestimates depths, with an average bias of 2.49 m, resulting in an overestimation of water volume by 84 %. These results suggest that our ICESat-2-trained random forest model outperforms traditional single-band RTE methods that are not informed by ICESat-2, which can lead to a reduction of errors in depth estimates by over 60 %, where the exact amount depends on which particular band and parameters are used in these alternative RTE approaches. While some earlier studies have used a band-averaging technique (e.g., Pope et al., 2016; Williamson et al., 2018), such an approach may conceal specific effects unique to individual bands, such as a plateauing effect found in the red-band RTE and consistent overestimation in the green-band RTE (Melling et al., 2024). Consequently, although band-averaging might yield a better fit for certain lakes, it is not appropriate to average the RTE depths from the green and red bands.

Antarctic Lakes: For the four Antarctic lakes, our random forest model outperforms both the Sentinel-2 red-band RTE and the Landsat 8 red/panchromatic-band RTE on all performance metrics, although the margins are smaller compared to Greenland (Fig. 3.4, f-g). The most notable difference is that for the Antarctic lakes, our random forest model predicts depths with a significant bias, overestimating lake depths by 0.28 m (or 20 %). While this indicates that our random forest model, trained exclusively on Greenland data, generalizes sufficiently well to improve predictions of lake depths in Antarctica compared to traditional RTE estimates, the significantly better performance in Greenland suggests that future efforts to estimate Antarctic lake volumes would benefit from including training examples from the Antarctic in our random forest model.

Figure 3.4: Comparison between random forest model predictions and RTE estimates for the depth of nine supraglacial lakes in Greenland and Antarctica. a-e): ICESat-2 segments in Southwest Greenland with manual depths from Melling et al. (2024). RTE estimates are shown for Sentinel-2’s red and green band. f-i): ICESat-2 segments on Amery Ice Shelf, Antarctica, with manual depths from Fricker et al. (2021). RTE estimates are shown for the average of Landsat 8’s red and panchromatic bands and Sentinel-2’s red band. Sub-panels 1): ICESat-2’s ground tracks over Sentinel-2 imagery. Sub-panels 2): Gridded random forest depth predictions. Sub-panels 3): Zoomed-in imagery, rotated to match along-track ICESat-2 data. Sub-panels 4): Water depth estimates along the ICESat-2 ground tracks, plotted over ATL03 photon data. Performance statistics for random forest predictions on both ice sheets are reported in legend captions. Performance statistics for all RTE-based methods are reported in their respective legend entries. Photon elevations are shifted to place the water surface at zero meters, and elevations below the surface are corrected for the refractive index for speed of light in water. Ground tracks are shown in red where the random forest model predicts pooled surface water and black elsewhere.

3. Improving Supraglacial Lake Volume Estimates Using ICESat-2 Data Across Greenland



Together, these comparisons demonstrate that our random forest model significantly outperforms traditional RTE-based methods in Greenland on all performance statistics, and that it also generalizes sufficiently well to perform better than RTE methods in Antarctica.

3.4. Summary

We have presented the first comprehensive ice-sheet-scale dataset of ICESat-2-derived supraglacial lake depth measurements, spanning the entire Greenland Ice Sheet for five melt seasons from 2019 to 2023. The ICESat-2 data confirm previously reported patterns in spatial and temporal variability of supraglacial lake extent, and provide new insights into patterns of meltwater depth. Deepest lakes are found on low elevation grounded ice late in the melt season, with maximum depths decreasing about 0.5 m every 100 m in altitude and increasing throughout the progression of the annual melt season at a rate of about 0.1 m/day. Our results confirm that supraglacial lakes are most abundant in regions with low surface slopes that experience a significantly negative surface mass balance. In these regions, summertime meltwater production tends to be large, and the higher likelihood of bare ice surfaces, impermeable ice layers or meltwater-saturated firn favor the pooling of excess runoff in surface depressions and formation of supraglacial lakes, thus underscoring a strong relationship between lake occurrence and surface mass loss processes. We have further demonstrated that deepest supraglacial lakes form in regions of rough bedrock topography where large driving stresses and high levels of subglacial meltwater production result in fast ice flow and high basal slip ratios, thus enabling the transfer of larger-scale bedrock undulations to the surface.

To test whether the ICESat-2 data can be used to improve meltwater volume estimates across the ice sheets from satellite imagery, we used it to train a data-driven (random forest regression) model for predicting supraglacial lake depths from Sentinel-2 imagery. We

have demonstrated that this model is capable of reproducing ICESat-2 depth measurements with a mean absolute error of 0.52 m and negligibly small bias. We validated our model against *in situ* sonar data, suggesting that it predicts true water depths with a mean absolute error of 0.50 m and a small bias of about 3 % towards underestimating total amounts of water. We compared model predictions to RTE-based estimates in both Greenland and Antarctica, and showed that our ICESat-2-based data-driven method drastically outperforms traditional RTE approaches, which are prone to introducing significant biases into estimates of the total volume of meltwater. Our model outperformed RTE-based methods on both ice sheets, implying that it effectively generalizes to previously unseen data from a different continent.

Our study demonstrates that the Greenland-wide ICESat-2 supraglacial lake depth dataset can significantly improve large-scale estimates of surface meltwater volumes. This improvement enables the development of more accurate models to assess the impact of supraglacial lakes on future ice sheet stability and sea level rise. We conclude that approaches combining machine learning methods with large-scale data fusion of laser altimetry observations and passive optical imagery are an effective strategy for accurate and continuous large-scale monitoring of shallow bathymetry, even in challenging environments such as remote and rapidly evolving supraglacial hydrological networks.

Open Research Section

ICESat-2 ATL03 data is available at NSIDC (Neumann et al., 2023a). Sentinel-2 L2A (surface reflectance) imagery data were accessed via the `COPERNICUS_S2_SR_HARMONIZED` and `COPERNICUS/S2_CLOUD_PROBABILITY` collections in Google Earth Engine (GEE) (Gorelick et al., 2017). Associated satellite view angle grids and solar angle grids were accessed through Sentinel-2 L1C metadata files in the Copernicus Dataspace Amazon Web Ser-

vices (AWS) Simple Storage Service (S3) bucket at `s3://eodata/Sentinel-2/MSI/`. The *in situ* sonar validation data for the water depths of three supraglacial lakes in North-west Greenland are available at <https://doi.org/10.1594/PANGAEA.971782> (Lutz et al., 2024). Drainage basins for Greenland are available at DRYAD (Mouginot and Rignot, 2019). The GIMP ice mask is available at NSIDC (Howat, 2017). ArcticDEM mosaics for elevation thresholding are available at PGC (Porter et al., 2023). ICESat-2 ground track KML files are available at <https://icesat-2.gsfc.nasa.gov/science/specs>.

Acknowledgements

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Chapter 3, in full, is currently being prepared for submission for publication of the

3. Improving Supraglacial Lake Volume Estimates Using ICESat-2 Data Across Greenland

material: Arndt, P.S. and Fricker, H.A. (2024). “Five Years of ICESat-2 Supraglacial Lake Depth Measurements Across the Greenland Ice Sheet Improve Surface Meltwater Volume Estimates from Satellite Imagery.” *In prep. for Geophysical Research Letters*. The dissertation author was the primary investigator and author of this material.

Supplementary Information

Table S3.1: Statistics for Greenland ICESat-2 lake depth segments by melt season and drainage basin. The depth percentage is the percentage of total ICESat-2 along-track distance where water is present and the lakebed is visible in the ATL03 data.

		Percent Depths	Mean of Top 10% Depths (m)	Mean Elevation (m)	Mean Day
	total	0.034	12.1	981	Jul 22
basin	CE	0.017	12.0	1350	Jul 21
	CW	0.089	12.6	1164	Jul 17
	NE	0.038	11.3	782	Jul 27
	NO	0.023	10.9	678	Jul 23
	NW	0.033	15.9	879	Jul 29
	SE	0.002	9.6	1095	Jul 23
	SW	0.053	9.3	1393	Jul 15
melt season	2019	0.050	13.8	1067	Jul 18
	2020	0.030	12.3	944	Jul 18
	2021	0.034	10.9	991	Jul 26
	2022	0.028	11.7	890	Jul 28
	2023	0.031	11.3	983	Jul 24

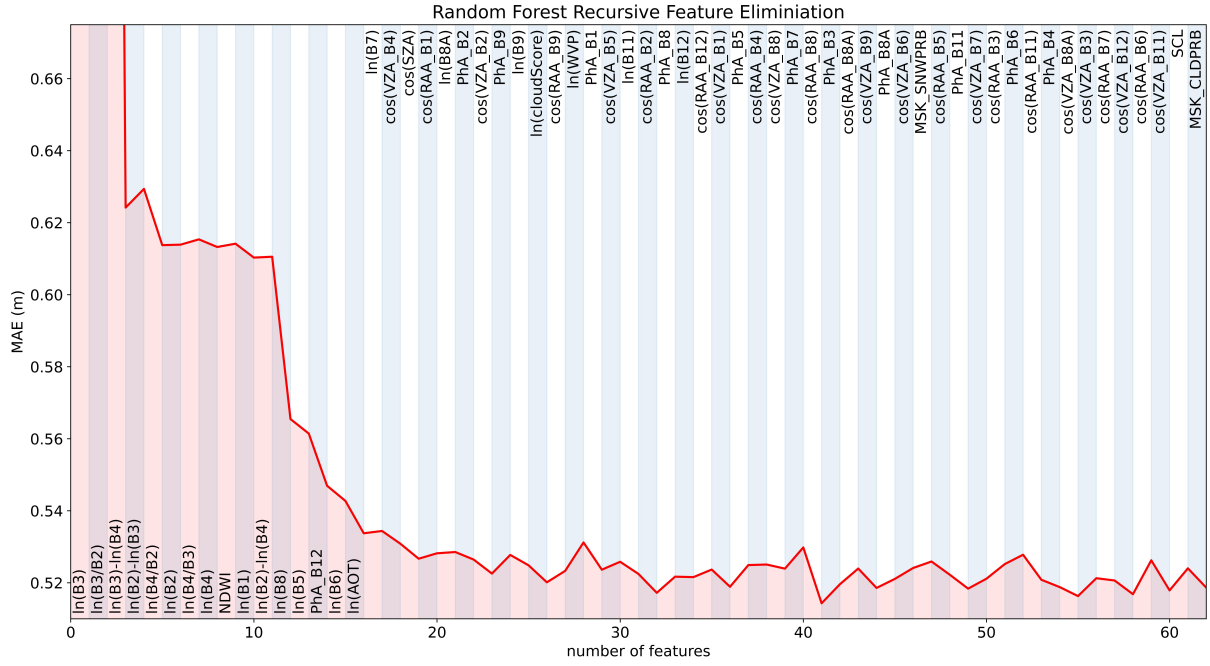


Figure S3.1: Random forest cross validation performance during Recursive Feature Elimination. The red line shows the 10-fold cross validation mean absolute error (MAE) during successive rounds of model fits, where after each iteration the feature with lowest variable importance was dropped. The MAE for two or less remaining features is greater than 1.25m and omitted from this figure. The feature cloudScore refers to the s2cloudless cloud probability, and abbreviations for solar and view angle-related features are PhA (Phase Angle), RAA (Relative Azimuth Angle), VZA (View Zenith Angle), and SZA (Solar Zenith Angle).

3.4. Supplementary Information

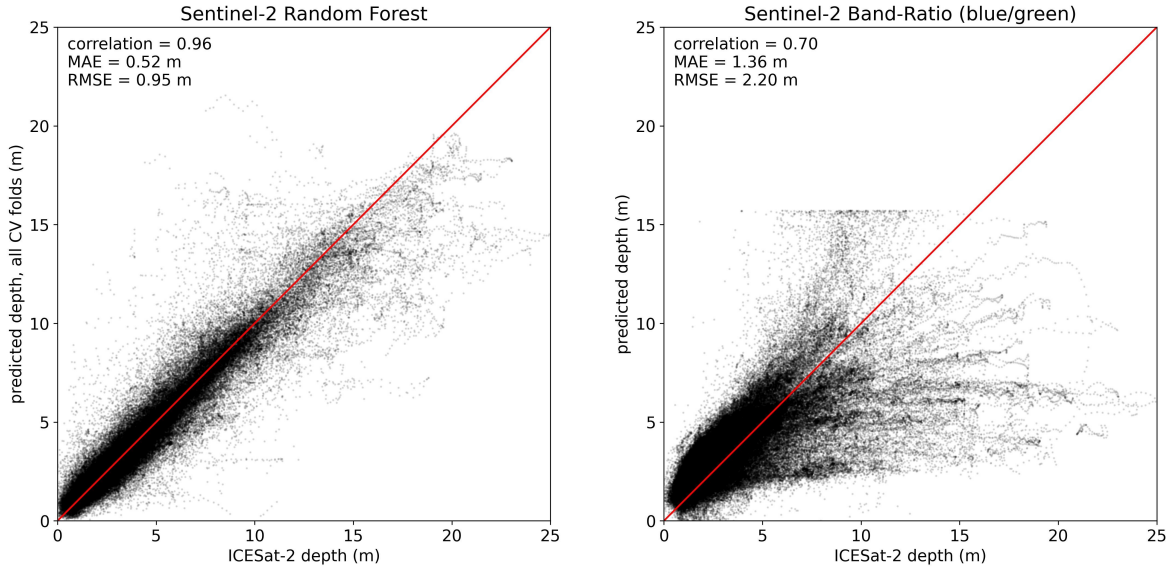


Figure S3.2: ICESat-2 depths vs. depth predicted by random forest and the band-ratio method. Random forest depths (left) show predictions on the validation sets for all cross validation folds. Band-ratio depths (right) show the predicted values for a quadratic fit on the entire training dataset.

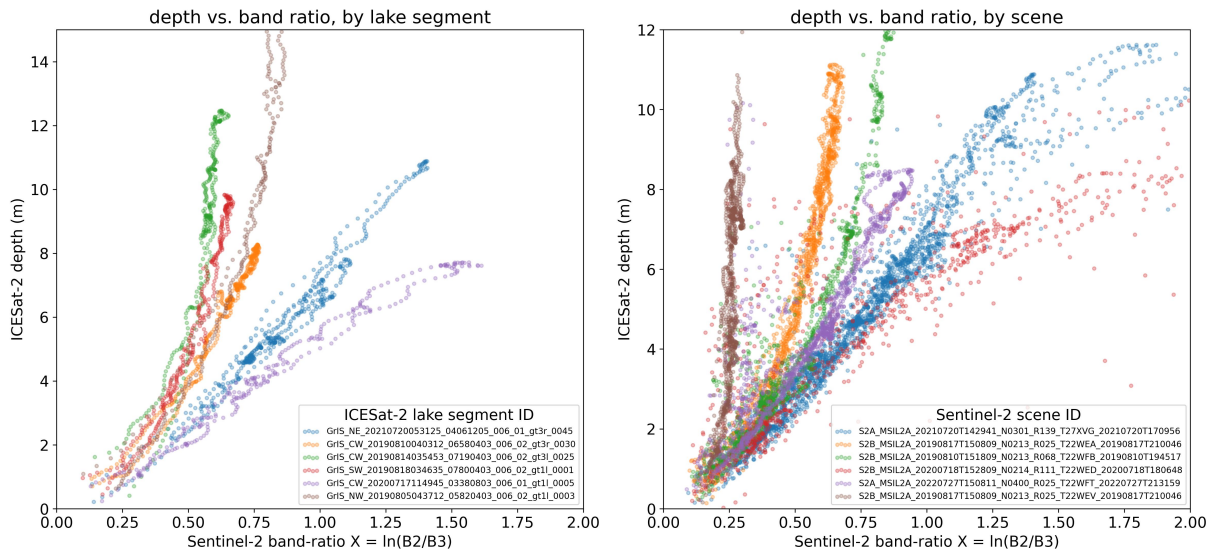


Figure S3.3: ICESat-2 depths vs. band-ratio for individual lake segments and Sentinel-2 scenes. Left: ICESat-2 depths plotted against Sentinel-2 blue/green band-ratio for six individual lake segments. Right: ICESat-2 depths plotted against Sentinel-2 blue/green band-ratio for all samples (from multiple lakes) that appear in six distinct Sentinel-2 scenes.

CHAPTER 4: LAKES, DOLINES AND BENCHES: NEW INSIGHTS INTO ANTARCTIC ICE SHELF MASS BALANCE PROCESSES USING HIGH-RESOLUTION 3D SATELLITE OBSERVATIONS

This chapter is divided into three sections, each of which describes use of high-resolution 3D satellite observations to understand three ice shelf features related to processes that can have a significant impact on Antarctic ice shelf mass:

Supraglacial lakes (Sect. 4.1): *“Five Years of ICESat-2 Supraglacial Lake Depth Measurements Across the Antarctic Ice Sheet, 2018/19 to 2022/23”*. In this section we present a comprehensive new dataset of ICESat-2-derived supraglacial lake depth estimates across the Antarctic Ice Sheet for five melt seasons, from 2019 to 2023. We analyze trends in these data to assess spatial and temporal variability in lake depths.

Ice dolines (Sect. 4.2): *“Altimetry and Stereophotogrammetry Observations of Doline Formation”*. Ice dolines form when surface meltwater lakes drain through Antarctica’s floating ice shelves into the ocean below. Their formation can have a large impact on ice shelf stability, yet this process has been largely overlooked in continent-wide observational studies. In this section, we present an inventory of satellite observations of doline formations around Antarctica, which suggest that through-ice-shelf drainage of supraglacial lakes is more widespread than previously thought, and providing insights into the mechanics

of this process.

Calving fronts (Sect. 4.3): *“New Insights Into Buoyancy-Driven Ice Shelf Flexure and Calving from ICESat-2 Bathymetry Measurements at Ice Shelves’ Calving Fronts”*. In this section we briefly communicate our discovery of ICESat-2 observations that confirm the presence of a submerged “bench” at the front of some Antarctic ice shelves.

Taken together, the results in this chapter demonstrate how high-resolution 3D satellite observations can improve our understanding of each of these features, and outline future work that is needed to take full advantage of such observations across Antarctica.

4.1. Five years of ICESat-2 supraglacial lake depth measurements across the Antarctic Ice Sheet, 2018/19 to 2022/23

4.1.1. Introduction: surface melt on the Antarctic Ice Sheet

Surface melting is a small part of the Antarctic ice sheet’s mass balance, but many of its floating ice shelves in particular experience it to a significant degree (Rignot et al., 2019; Kingslake et al., 2017). When firn becomes saturated with meltwater at the surface, the water begins to pool and develop extensive areas of slush, melt streams and supraglacial lakes (Munneke et al., 2014; Dell et al., 2024; Pitcher and Smith, 2019; Arthur et al., 2020a). In a warming climate, these supraglacial hydrological networks are expected to expand across more ice shelves, discharge more meltwater, and migrate to higher elevations and further inland upstream of the grounding line. (Cook and Vaughan, 2010; Bell et al., 2018; Gilbert and Kittel, 2021). In contrast to Greenland, surface melt on the Antarctic Ice Sheet currently produces negligible quantities of direct mass loss from surface runoff (van den Broeke et al., 2023) and occurs on lower elevations during short events of intermittent melt (Trusel et al., 2013) caused by atmospheric conditions such as strong foehn winds or atmospheric rivers (Cape et al., 2015; Wille et al., 2019).

On Antarctica’s ice shelves, ponding of meltwater in lakes has the potential to bend and fracture the ice (Weertman, 1973; Banwell and Macayeal, 2015). In extreme cases, supraglacial lakes can drain through the ice shelf into the ocean beneath via through-cutting rifts in a chain-reaction of repeated fracture, drainage and bending, leading to the rapid disintegration of entire ice shelves (Banwell et al., 2013). This process was most dramatically observed when Larsen B Ice Shelf rapidly disintegrated at the end of a record melt season in February 2002, following an extended period of warm summer temperatures, surface melting and migration of melt lakes toward its calving front (Skvarca et al., 2004; Sergienko and Macayeal, 2005; Leeson et al., 2020). In the future, more ice shelves are projected to become vulnerable to this type of collapse (Lai et al., 2020; Naughten et al., 2023; Zheng et al., 2024). While the disintegration of the floating ice shelves does not directly contribute to sea level rise, their ability to hold back flow of grounded ice into the ocean via buttressing backstresses is reduced as they thin and weaken, and lost when they collapse (De Angelis and Skvarca, 2003; Munneke et al., 2014; Rignot et al., 2004; Scambos et al., 2004). Furthermore, it has been hypothesized that rapid ice shelf disintegration by hydrofracture has the potential to expose unstable ice cliffs and trigger further rapid ice sheet collapse (Bassis and Walker, 2012; DeConto and Pollard, 2016; Pollard et al., 2015). However, this phenomenon has not been observed and there is currently no consensus on whether it can occur in present-day Antarctica (Edwards et al., 2019; Morlighem et al., 2024). This means that surface meltwater ponding on Antarctica’s floating ice shelves has the potential to have a large indirect effect on future ice sheet mass loss, but the underlying processes are currently poorly understood, making it difficult to integrate them into models of future ice sheet evolution and projections of global sea level rise (Golledge, 2020; Aschwanden et al., 2021).

Historically, studies of Antarctic supraglacial lakes have predominantly focused on

those forming on the floating ice shelves, given their critical role in ice shelf stability and collapse (e.g., Scambos et al., 2004; Banwell et al., 2013; Alley et al., 2018). However, recent observations have revealed extensive supraglacial lakes on grounded ice near the grounding line along Antarctica’s periphery (Stokes et al., 2019; Tuckett et al., 2022). It has been shown that drainage of these lakes has the potential to induce both short-term (Tuckett et al., 2019) and seasonal (Boxall et al., 2022, 2024) accelerations in ice flow, similar to the processes observed in Greenland’s ablation and percolation zones (Zwally et al., 2002). As the climate warms, enhanced surface melting is anticipated to play an increasingly prominent role in driving mass loss from the Antarctic Ice Sheet (Trusel et al., 2018), and the formation of surface-to-bed hydraulic connections around Antarctica is expected to become more frequent, suggesting that both supraglacial and subglacial hydrology in some regions of Antarctica could start to resemble Greenland’s present-day ablation and percolation zones (Bell et al., 2018). This shift could signify a transition toward an ice flow regime more heavily influenced by seasonal surface meltwater input (Boxall et al., 2024), a phenomenon described as the "Greenlandification" of the Antarctic Ice Sheet (e.g., Mottram et al., 2021; Datta et al., 2023; Jones et al., 2023; Glaude et al., 2024). As supraglacial lakes on grounded ice may play an increasingly significant role in influencing ice dynamics and contributing to future mass loss from the Antarctic Ice Sheet, it is crucial to closely monitor these lakes and to deepen our understanding of controls on their formation and behavior.

To better understand surface hydrological processes in Antarctica and to integrate them into models of future ice sheet evolution that can confidently predict future sea level rise, more extensive and accurate observations of meltwater are needed across the entire Antarctic Ice Sheet, including both its grounded portions and its floating ice shelves (Arthur et al., 2020a; Tuckett, 2023). Since these supraglacial hydrological systems form in remote,

inaccessible regions and evolve quickly, efforts to continuously monitor them need to rely on satellite remote sensing data (Moussavi et al., 2020). While the spatial extent of surface meltwater lakes can be readily observed in satellite imagery (e.g., Stokes et al., 2019; Corr et al., 2022; Arthur et al., 2022; Tuckett et al., 2022), it has been much more challenging to accurately estimate water depth, resulting in current methods often drastically over- or underestimating total water volumes (Fricker et al., 2021; Melling et al., 2024; Lutz et al., 2024).

To address this challenge, we applied our FLUID/SuRRF framework, previously demonstrated for Greenland in Chapter 3, to ICESat-2 data from the austral summers of 2018-19 to 2022-23. This allowed us to generate a comprehensive, Antarctic-wide dataset of ICESat-2-derived supraglacial lake depths for the same period. These new data offer valuable insights into the spatiotemporal variability and trends in meltwater depths across Antarctica’s grounded and floating land ice, providing a level of observation that has not been available before, and highlighting the critical role of these data in understanding Antarctic surface processes.

4.1.2. Data and methods

The methods used to extract supraglacial lake depths from ICESat-2 data across Antarctica are analogous to those used for the same purpose across the Greenland Ice Sheet, as described in Chapter 3. We therefore refer the reader to the previous chapter (Sect. 3.2) for details, and predominantly focus on the Antarctica-specific methods and data in the following sections.

4.1.2.1 ICESat-2 lake detection and depth retrieval algorithm

To extract along-track segments of supraglacial lake depth measurements from ICESat-2 ATL03 data across the Antarctic Ice Sheet for all melt seasons from 2018-19 to 2022-23, we employed the Flat Lake and Underlying Ice Detection (FLUID) and Surface Removal and Robust Fit (SuRRF) framework introduced by Arndt and Fricker (2024d). The FLUID algorithm identifies supraglacial lakes in the point cloud data by detecting flat water surfaces and subsurface peaks in photon density caused by reflections off the lakebed. SuRRF then calculates water depth for each along-track lake segment by fitting robust non-parametric regressions to the photons reflected from both the lake surface and lakebed. The FLUID/SuRRF output consists of ATL03 data along-track segments, with the lake surface and lakebed elevations provided at a 5-meter resolution (shown as blue and red lines in Fig. 4.1, a-p). Water depth is computed as the elevation difference between the lake surface and the lakebed, corrected for the refractive index of 532 nm light in 0°C freshwater (≈ 1.336 ; Mobley, 1995). While no ground truth data are available for ICESat-2 supraglacial lake segments, validation against manually annotated data shows that FLUID/SuRRF can estimate lake depths with an absolute error of less than 0.27 m Arndt and Fricker (2024d). This is the same method that we used for extracting ICESat-2 lake segments from ATL03 over Greenland (Chapter 3).

4.1.2.2 Ice-sheet-wide retrieval of ICESat-2 lake depth measurements

To implement the FLUID/SuRRF algorithm across the Antarctic Ice Sheet, we subsetting the ATL03 data to focus on geographic regions and time periods where surface melt is commonly observed.

Spatial subsetting: We defined the Antarctic-wide study area using the Antarctic Ice Sheet IMBIE drainage basins Mouginot et al. (2017). By default, this dataset includes

only the main contiguous grounded part of the ice sheet in the definition of the major drainage basins, thus excluding the floating ice shelves, ice rises and areas of grounded ice on adjacent islands. The IMBIE data, however, provides a shapefile with the geographic extent of all ice shelves and islands, in which most of the ice shelves are labeled with their associated upstream (grounded) drainage basins. We use these ice shelf associations to add areas of floating ice to their respective grounded drainage basins. Ice shelves without an IMBIE-provided basin association were merged into the basin with which they share the longest boundary. Similarly, in the next step, ice rises and islands directly bordering any of the merged basins (now including all their associated ice shelves) were added to the one with which they share the longest boundary. The details of our definition of Antarctic basins are provided in (Arndt and Fricker, 2024c). To focus on areas where supraglacial lakes typically form, we limited the study area to the ice shelves and the grounded ice sheet margins, applying a 1000-meter elevation threshold based on the REMA digital elevation model (Howat et al., 2019). This threshold is informed by (Stokes et al., 2019, supporting data), who found that 99.7 % of supraglacial lake area was located below 1000 m across the East Antarctic Ice Sheet in January 2017, and Corr et al. (2021), who obtained a corresponding value of 99.6 % across the West Antarctic Ice Sheet and the Antarctic Peninsula. Our final study region spans latitudes from 63.2°S to 86.1°S, with ICESat-2 Reference Ground Track (RGT) spacing ranging from approximately 13.0 km in the northern coastal areas to about 2.0 km in the southern interior (see Fig. 3.1 for an illustration of track spacing decreasing at higher latitudes).

Temporal subsetting: We defined the annual melt season as the 5-month period from November 1 to March 31 the following year. Since austral summer spans two calendar years, we refer to each Antarctic melt season by both years (e.g.; “2018-19” for the melt season ranging from November 1, 2018 to March 31, 2019).

By applying these spatial and temporal criteria to the ATL03 dataset, we identified a total of 42,752 ATL03 granules, totaling 107 TB in size. These granules cover a combined along-track distance of 55 million kilometers and contain 594 billion photon locations. To process this large volume of data, we used the Open Science Grid’s (OSG) Open Science Pool (OSPool) for Distributed High-throughput Computing (dHTC) (Pordes et al., 2007; Sfiligoi et al., 2009; OSG, 2015).

4.1.3. Assessment of controls on spatiotemporal distribution and depth of ICESat-2 lake segments

Analogously to the results presented in Chapter 3, to investigate the factors controlling the spatiotemporal distribution and depth of Antarctic supraglacial lake segments detected by ICESat-2, we conducted a series of ordinary least squares (OLS) linear regressions. These analyses examine relationships between lake elevations, proximity to the grounding line, water depths, and the day of year when lakes were observed in ATL03. Uncertainties and p-values were computed using standard statistical methods, assuming unbiased and uncorrelated sampling. We contextualize the results by comparison with prior studies estimating supraglacial lake extents and depths using passive optical satellite imagery (e.g., Stokes et al., 2019; Corr et al., 2022; Arthur et al., 2022; Tuckett, 2023), and we explore physical explanations for the observed patterns using concepts reviewed in Sect. 1.3.

Due to the higher density of ICESat-2 ground tracks at higher latitudes (Sect. 4.1.2.2), supraglacial lakes located further south are overrepresented in our dataset. Consequently, our results are biased toward being more representative of higher-latitude lakes, rather than reflecting the full continent-wide distribution of Antarctic supraglacial lakes. Furthermore, ICESat-2 cannot obtain lake data in regions with optically thick cloud cover, resulting in the underrepresentation of areas with frequent cloud cover in the dataset.

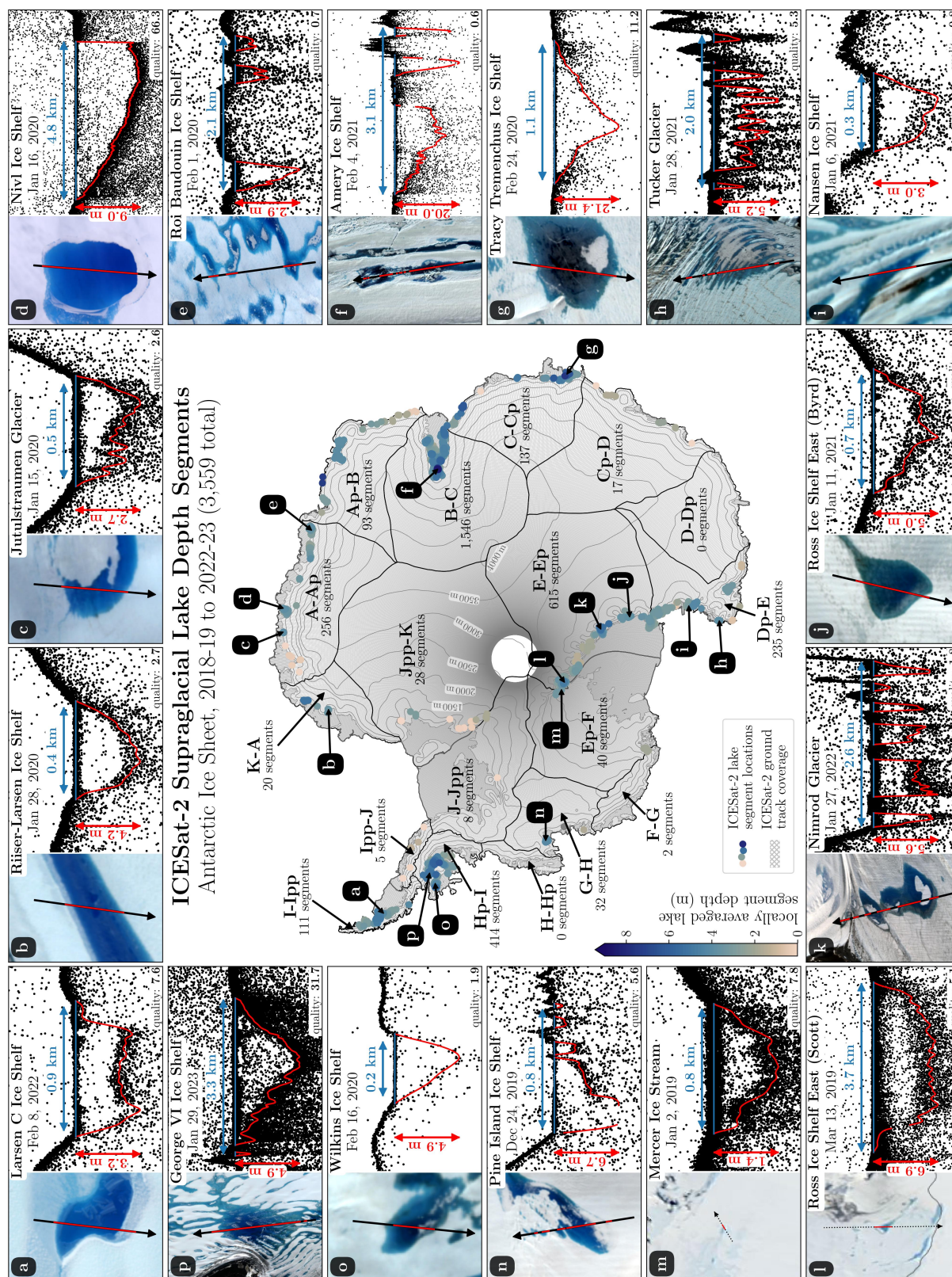
As explained in detail in Sect. 3.2.4, these biases, driven by satellite orbit and cloud conditions, are not unique to ICESat-2, and similar limitations apply to passive optical satellite imagery-based studies. However, recent imagery-based studies have attempted to mitigate these biases by aggregating data over extended time periods (e.g., Arthur et al., 2022) or incorporating visibility metrics for each scene (Tuckett et al., 2021). While these methods represent significant progress, most satellite-based supraglacial lake datasets remain subject to biases and correlations with climatic, dynamic, and geologic factors. This underscores the need for careful evaluation of whether and how results inferred from such datasets are physically meaningful.

4.1.4. Results and discussion

Our implementation of FLUID/SuRRF across the entire Antarctic Ice Sheet for all melt seasons between 2018-19 and 2022-23 yielded a dataset of 3,559 ICESat-2 lake depth segments with water depth measurements up to 21 m (Fig. 4.1). Across all processed granules, 0.0039% of along-track distance corresponds to surfaces of supraglacial lakes with a lakebed visible in ATL03, amounting to 2117 km of along-track lake depth data. The relatively low proportion of usable ICESat-2 supraglacial bathymetry measurements compared to the total processed ATL03 data highlights the critical need for scalable, automated methods to detect and extract ICESat-2 supraglacial lake segments. Processing all available ATL03 data (42,752 ATL03 granules, totaling 107 TB in size), took less than two days on the OSG Open Science Pool.

Analogously to the results presented in Chapter 3, we report depth statistics using the mean depth of the top 10% deepest segments, d_{10} , as an indicator of the typical maximum depth that supraglacial lakes reach within a particular region. This choice reflects the sampling limitations inherent to ICESat-2 ground tracks, which intersect supraglacial

Figure 4.1: Pan-Antarctic ICESat-2 supraglacial lake depth dataset. Center map: Locations of all ICESat-2 lake depth segments, 2018-19 to 2022-23. Lake segment locations are colored by depth, with the top quartile of maximum depth among each segment’s 30-nearest neighbors used as a locally averaged measure. The Antarctic Ice Sheet is divided into 18 sub-regions, defined by the IMBIE basins. ICESat-2 reference ground tracks illustrate that ICESat-2 coverage increases poleward as the ground tracks become more closely spaced. Side panels a-t: Examples of individual ICESat-2 lake depth segments. Left: Segment ground tracks over concurrent satellite imagery. l) and m) are Moderate Resolution Imaging Spectroradiometer (MODIS) images, d) is a Landsat 8 image, and all other images are from Sentinel-2. Right: ATL03 photon locations (black dots) with SuRRF fits to the lake surface (blue line) and lakebed (red line, shown where the bathymetry confidence score exceeds 0.3). Horizontal blue arrows indicate the along-track extent, and vertical red arrows show the maximum segment water depth. Numbers on the lower right represent the segment’s quality score.



lake basins at arbitrary locations. Consequently, these tracks often miss the deepest part of a lake and predominantly sample shallower margins. This limitation means that the maximum depth measured along a lake segment is usually less than the actual maximum depth of the entire lake. The d_{10} metric addresses this challenge by focusing on the upper tails of the depth distribution, where significant differences emerge between regions with predominantly shallow versus deep lakes. While the absolute value of d_{10} does not have any intrinsic physical meaning, it provides a consistent and comparative measure of how deep lakes tend to become across regions and time periods, enabling robust assessments of regional and temporal variability in supraglacial lake depths.

The mean of the top 10 % lake depths across Antarctica is $d_{10} = 5.7$ m (Table 4.1), which is considerably lower than the corresponding value for Greenland ($d_{10} = 12.1$ m; Chapter 3, Table S3.1). This suggests that supraglacial lakes across Antarctica typically grow less deep than those in Greenland, which is consistent with previous comparative studies for smaller regions on each ice sheet (Banwell et al., 2014; Arndt and Fricker, 2024d).

4.1.4.1 Spatial distribution of lake segments across Antarctica

We found the highest number of lake segments (2,947) in East Antarctica, making up 83 % of segments in the pan-Antarctic dataset. This finding is comparable to Tuckett et al. (2022), who report 75.3 % of Antarctic surface melt extent between 2006 and 2021 in East Antarctica, as well as Stokes et al. (2019) and Corr et al. (2022), whose results, when taken together, provide an estimate of 86.5 % of Antarctic supraglacial melt features in January 2017 being located in East Antarctica. We found only 82 lake segments in West Antarctica, making up 2 % of all identified segments. The remaining 530 lake segments (15 %) were located on the Antarctic Peninsula. Relative to the total amount of data

analyzed, the proportion of supraglacial lake data (e.g., lake density) was similar in East Antarctica, where lakes covered 0.0079 % of ICESat-2 along-track distance, and at the Peninsula, where the corresponding number was 0.0073 %. Lake density was significantly lower in West Antarctica, where only 0.00016 % of ICESat-2 data had measurements of supraglacial bathymetry.

Regions experiencing significant melt: The B-C drainage basin, which includes the Amery Ice Shelf and is known for experiencing significant surface melt most years (Phillips, 1998; Spergel et al., 2021), featured significantly more lakes than any other basin, with a total of 1546 lake segments, making up 43% of the entire Antarctic-wide dataset. The B-C drainage basin stands out with an along-track density of lake depth measurements more than six times as high as the value for any other drainage basin (Table 4.1). Other regions of significant melt included the George VI and Wilkins Ice Shelves on the Peninsula, the coastal margins of the Queen Maud Land and Enderby Land, as well as the Shackleton Ice Shelf in East Antarctica. While the E-Ep drainage basin features the second most ICESat-2 lake segments in our data, with most lakes clustering around the eastern margin of the Ross Ice Shelf, this number is likely due to sampling bias, with melt in this region extending furthest south where the coverage of ICESat-2 ground track is much denser than in any other locations that experience significant surface melt (Fig. 4.1).

The spatial distribution of supraglacial lakes identified in our dataset broadly aligns with findings from numerous prior studies, which have reported high concentrations of meltwater features to consistently form on ice shelves along the Antarctic Peninsula, including the Larsen (Luckman et al., 2014; Leeson et al., 2020), George VI (Banwell et al., 2021; Barnes et al., 2021), and Wilkins (Scambos et al., 2009; Braun et al., 2009) ice shelves. Similar patterns have been observed on several lower-latitude ice shelves in East Antarctica, such as the Shackleton (Arthur et al., 2020b; Saunderson et al., 2022), Amery

(Spergel et al., 2021; Tuckett et al., 2021), Roi Baudouin (Dell et al., 2022), Nivlisen (Dell et al., 2020) and Riiser-Larsen (Mahagaonkar et al., 2024) ice shelves. Supraglacial lakes are most prevalent in these regions of the Antarctic Peninsula and East Antarctica since their relatively low latitudes, ice-surface elevations and surface slopes, in conjunction with the warming effects of foehn or katabatic winds (Cape et al., 2015; Lenaerts et al., 2017), result in high enough temperatures to cause surface melting during the austral summer (Trusel et al., 2012) that is sufficient for firn saturation and pooling of excess runoff to occur (Munneke et al., 2014).

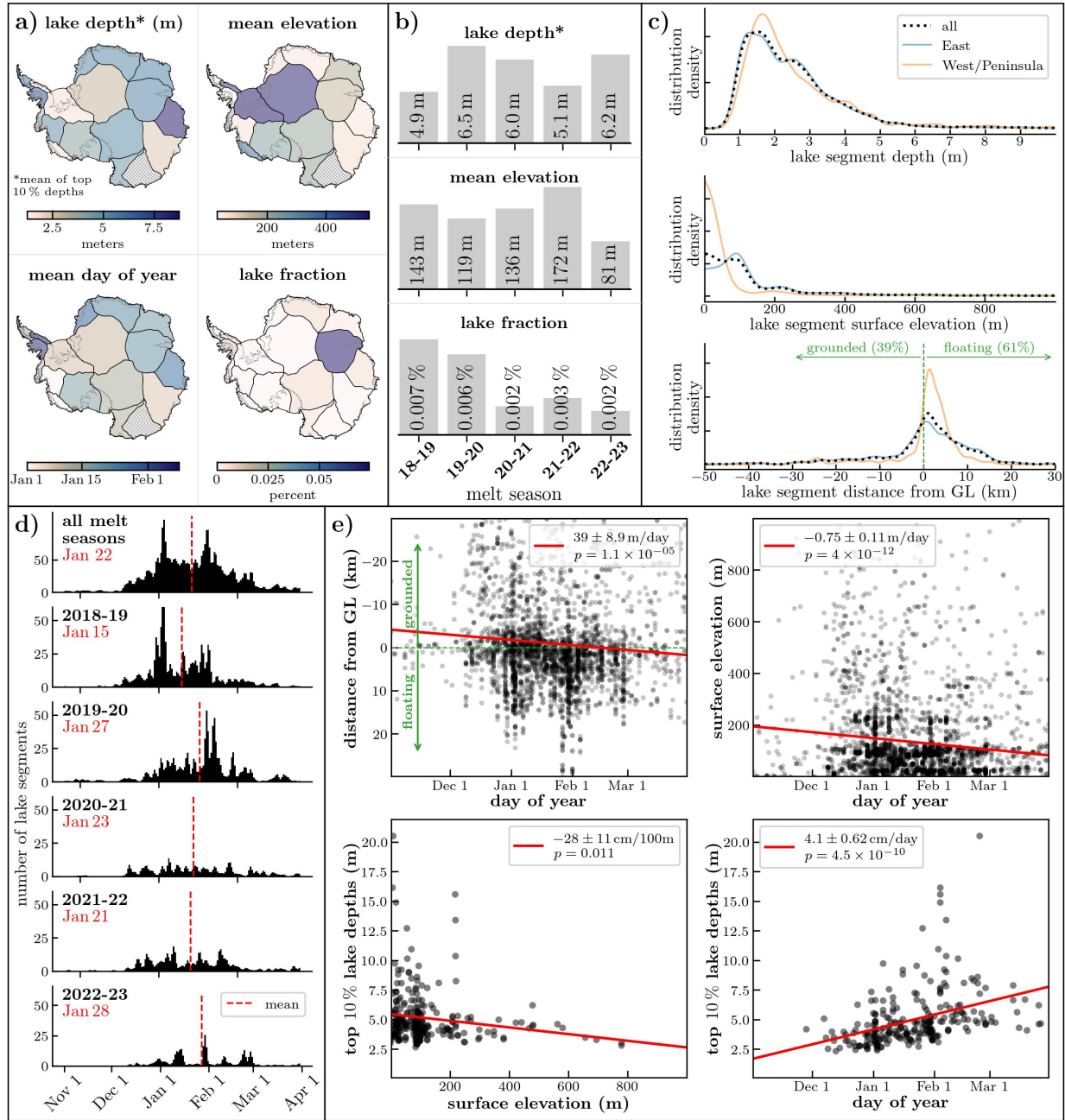
Melt lakes on grounded and floating ice: Lake segment locations cluster around the ice shelf grounding lines (as defined by the IMBIE basins), with 95 % of lake detections within a distance of 25 km or less. This is consistent with Tuckett (2023), who reported 91 % of meltwater extents in East Antarctica within 20 km of the grounding line. The highest density of lake segments is concentrated within approximately 5 km downstream of grounding line locations (Fig. 4.2,c). The strikingly dense clustering of supraglacial lakes in close proximity to the grounding line is likely driven by interactions between winds and the local topography of ice surfaces. Both foehn and katabatic winds warm and mix air as they flow downward over grounded ice towards the ice shelves, which efficiently increases surface temperatures and decreases relative humidity, thus inhibiting snow accumulation (Grazioli et al., 2017) and enhancing sublimation and surface melt upstream of the grounding zone (Hubbard et al., 2016; Lenaerts et al., 2017). These strong and persistent winds can also cause intense wind scouring (Das et al., 2013), which may expose bare ice and lead to the formation of low-albedo blue ice zones (Bintanja and Van Den Broeke, 1995), particularly in and upstream of the grounding zone (Tollenaar et al., 2024). This lower albedo leads to increased absorption of shortwave radiation and hence higher surface melt rates (Liston et al., 1999). When surface melt is initiated in blue ice zones upstream of the grounding

Table 4.1: Statistics for Antarctic ICESat-2 lake depth segments by melt season and individual study regions. The column labeled “Percent Depths” is the percentage of total analyzed ICESat-2 along-track distance where water is present and the lakebed is visible in the ATL03 data. Drainage basins D-Dp and H-Hp have no detected lake segments.

		Percent Depths	Mean of Top 10% Depths (m)	Mean Elevation (m)	Mean Day
melt season	total	0.0039	5.7	134	Jan 21
	2018-19	0.0069	4.9	143	Jan 11
	2019-20	0.0058	6.5	119	Jan 30
	2020-21	0.0021	6.0	136	Jan 20
	2021-22	0.0027	5.1	172	Jan 18
	2022-23	0.0018	6.2	81	Jan 29
region	East	0.0079	5.6	149	Jan 17
	Peninsula	0.0073	6.6	39	Feb 04
	West	0.0002	4.6	197	Jan 02
drainage basin	A-Ap	0.0071	5.3	56	Jan 21
	Ap-B	0.0025	5.5	163	Jan 18
	B-C	0.0743	5.5	138	Jan 19
	C-Cp	0.0059	8.7	54	Jan 26
	Cp-D	0.0004	2.4	71	Jan 07
	D-Dp	0.0000	—	—	—
	Dp-E	0.0048	4.6	208	Jan 11
	E-Ep	0.0072	5.1	198	Jan 12
	Jpp-K	0.0003	2.9	524	Jan 09
	K-A	0.0008	5.3	66	Jan 28
	Hp-I	0.0122	6.8	29	Feb 04
	I-Ipp	0.0030	5.6	57	Jan 13
	Ipp-J	0.0001	1.3	429	Feb 09
	Ep-F	0.0002	4.0	227	Jan 16
	F-G	0.0000	1.7	361	Jan 01
	G-H	0.0006	5.0	62	Jan 01
	H-Hp	0.0000	—	—	—
	J-Jpp	0.0000	1.8	547	Jan 08

Figure 4.2: Spatiotemporal variability and trends in the Antarctic-wide supraglacial lake depth dataset. a): Depth, elevation, timing and spatial density of supraglacial lakes by drainage basin. Reported values are statistics based on all ICESat-2 lake segments found in each basin. Lake depths are reported as the mean of the top 10 % of maximum along-track lake segment depths. b): Same statistics as in a), by melt season. c): Distributions of maximum along-track segment depths, surface elevations and planar distances from the grounding line, for the full dataset and by major Antarctic region. d): Histograms of the day of year for lake segment ICESat-2 overpasses, for the full dataset and by melt season. e): Estimates for the relationship between various parameters in the dataset. Upper left: lake segments' upstream/downstream distances from the grounding line versus the day of the year of each observation. Upper right: surface elevation of lake segments versus the day of the year. Lower left: top 10 % of the lake segment depths versus lake segment surface elevation. Lower right: top 10 % of the lake segment depths versus the day of the year. Values in the legends are the slopes of the linear fits (red line) to the data and uncertainties are standard errors of the slopes. Uncertainties and p-values were calculated in the standard way using `statsmodels.api.OLS` for linear model fitting, under the assumption of unbiased and uncorrelated sampling, with standard errors and p-values derived from the model fit.

4. Antarctic Ice Shelf Mass Balance Processes: High-Resolution 3D Satellite Observations



line, excess runoff is efficiently transported across the impermeable bare ice and downstream into the grounding zone and onto the ice shelf (Lenaerts et al., 2017). In this region, ice flow across the grounding line creates a break in surface slope where the ice begins to float, and the resulting ice shelf flexure leads to a distinct surface depression just downstream of the grounding line (Vaughan, 1994; Fricker and Padman, 2006), which further promotes the pooling of meltwater from upstream in supraglacial lakes. Surface melting and the presence of lakes then further lower albedo and therefore create a positive feedback that results in more localized surface melt in close proximity to the grounding line (Lüthje et al., 2006; Jakobs et al., 2019).

Overall, 60.8 % of lake segments are located on the floating ice shelves, and 39.2 % on grounded ice. In East Antarctica, the fraction of ICESat-2 lake segments on floating ice is 57.3 %, which is similar to the results of the imagery-based study by Stokes et al. (2019), who reported a fraction of 60.4 % on East Antarctic ice shelves. Across West Antarctica and the Peninsula, the fraction of ICESat-2 lake segments on floating ice is 77.1 %, compared to Corr et al. (2022), who reported that 72.7 % of lakes were either fully located on floating ice or intersected the grounding line in spatial extent. While the majority of previous studies on Antarctic supraglacial lakes have concentrated on those forming on ice shelves (Sect. 4.1.1), the significant number of lakes observed on grounded ice highlights the high potential for surface-to-bed hydraulic connections to exist and influence grounded ice dynamics around Antarctica, particularly given their existence in most other glaciated regions (e.g., Iken and Bindshadler, 1986; Zwally et al., 2002) and the growing evidence suggesting that surface meltwater influences grounded ice dynamics on the Antarctic Peninsula (Tuckett et al., 2019; Hodgson et al., 2022; Boxall et al., 2024). These findings emphasize the need for further investigation into the mass loss processes associated with supraglacial lakes on grounded ice in Antarctica, particularly in light of the projected “Greenlandification” of

the Antarctic Ice Sheet under future warming scenarios (Bell et al., 2018; Mottram et al., 2021).

Our dataset suggests that lakes become larger in spatial extent downstream of the grounding line. A linear regression of top 10 % along-track lake extents on downstream distance from the grounding line suggests that the horizontal length scale of largest lakes increases at a rate of 34 ± 4.5 m per kilometer in downstream direction. This is consistent with results from Stokes et al. (2019), who report that the ~ 60 % of lakes found downstream of the grounding line in East Antarctica contributed over 80 % of total lake area. The trend towards larger lakes downstream of the grounding line is likely because surface topography becomes significantly flatter downstream of the grounding line where the ice shelf is in hydrostatic equilibrium, allowing meltwater to spread out over a larger area.

Northern- and southernmost melt lakes: We recorded the northernmost supraglacial lake depths north of 64°S on the Antarctic Peninsula (basin I-Ipp). The southernmost ICESat-2-detected melt lake clusters are near the southeastern grounding line of the Ross Ice Shelf (both on grounded and floating ice) and in close proximity to the Transantarctic mountains. In this region, Scott and Amundsen Glaciers (basin E-Ep, East Antarctica), as well as Mercer Ice Stream (basin Ep-F, West Antarctica) feature multiple lake segments south of 85°S , with the southernmost lake at 85.94°S on Scott Glacier, at a distance of only 450 km from the South Pole. Occurrences of supraglacial lakes have not previously been documented further south than 85.2°S (Shackleton Glacier; Kingslake et al., 2017), and lakes detected by ICESat-2 data in these southernmost regions are missing from published pan-Antarctic inventories of supraglacial lake extents (e.g., Kingslake et al., 2017; Bell et al., 2018; Stokes et al., 2019; Arthur et al., 2020a; Corr et al., 2022; Tuckett et al., 2022). This is because past continent-wide studies mapping lake extent have relied on high-resolution passive optical imaging satellites (Landsat 8 or Sentinel-2), whose orbits only allow for ac-

quisition of imagery for latitudes up to approximately 83° N/S. While this means that we were unable to verify the location of the small (310 m long) southernmost lake in satellite imagery, some of the larger lakes in the Scott/Mercer region are distinguishable in MODIS imagery (e.g., Fig 4.1, l and m, 85.43° S and 85.32° S). This highlights that in addition to providing water depths, ICESat-2’s low-inclination orbit and high along-track resolution makes it possible to observe Antarctic surface melt in locations where no other satellites are able to and where supraglacial melt lakes not previously been reported.

4.1.4.2 Distribution of lake depths with elevation and distance from the grounding line

Most lake segments in our dataset are found at low elevations, with 80 % of observations below 200 m and 95 % below 500 m (Fig. 4.2, c). The drainage basins with the highest mean elevation of lake segments are J-Jpp and Jpp-K, where lakes form near the grounding lines of the Filchner and Ronne Ice Shelves (Fig 4.1, Table 4.1). The locations of ICESat-2 lake segments in the Filchner-Ronne area agree with those of meltwater features first reported at the eastern margin of the Filchner Ice Shelf (Jpp-K) by Corr et al. (2022) and at the western margin of the Ronne Ice Shelf (J-Jpp) by Tuckett (2023). Very few lake segments exist in these basins, however, and most observations of melt lakes at high elevations in the continent-wide ICESat-2 data cluster around outlet glaciers draining into the Ross Embayment from the Transantarctic mountains.

Our ICESat-2 dataset suggests that the deepest lakes are generally found at lower elevations. A linear regression of maximum 10 % lake depths on surface elevation residuals implies that maximum lake depths decrease with elevation ($p = 0.011$) at a rate of 28 ± 11 cm every 100 m of elevation gain, where the uncertainty for the slope is the standard error. A similar continent-wide inverse relationship between lake depths and elevations is also

observed in Greenland (Chapter 3). In Antarctica, the absence of comparatively deeper lakes at higher elevations is likely due to the efficient channelized surface drainage in blue ice zones (Sect. 4.1.4.1), combined with the continued meltwater input further downstream allowing for meltwater to fill deeper surface depressions in the grounding zone.

The Antarctica-wide inverse relationship between lakes' elevations and depths is opposite to the localized trend that we reported for the Amery catchment in Chapter 2, where lake depths increased with elevation for melt seasons 2018-19 and 2020-21. The previously reported trend for the Amery catchment, however, was not statistically significant, and the data were strongly dominated by the anomalously strong 2018-19 melt season in this particular region. We suggest that this allowed for anomalously deep lakes to form on portions of the higher-elevation grounded ice that do not usually experience significant surface melting. The narrow geometry and thick ($> 2,500$ m Wen et al., 2014) ice of the southern (upstream) part of the Amery Ice Shelf further allow meltwater to pool in deep surface depressions controlled by particularly prominent flow lines at elevations > 200 m. Since such deep surface depressions are absent further downstream on thinner ice and thus lower elevations, this could contribute to deeper lakes being more likely to form at higher elevations on the Amery Ice Shelf in particular.

While lakes across the continent expand in extent downstream from the grounding line (Sect. 4.1.4.1), we did not find a statistically significant relationship between lake depths and their downstream distances relative to the grounding line ($p = 0.92$). Here, the downstream distance refers to the measured distance from the grounding line, with upstream distances represented as negative values and downstream distances as positive values. Conversely, we found that maximum lake depths decrease with the absolute distance from the grounding line ($p = 3.2 \times 10^{-8}$) at a rate of 5.0 ± 0.9 cm/km, where the absolute distance represents the non-negative measure of distance from the grounding line, regardless

of direction. This implies that the deepest lakes typically form in close proximity to the grounding line, both in the upstream (grounded) and downstream (floating) directions. We suggest that this is because ice shelf flexure in the grounding zone leads to a local minimum in surface elevation (Vaughan, 1994; Fricker and Padman, 2006), which allows surface meltwater from upstream to be captured and to accumulate in a stationary location (i.e. not moving with the ice flow) over many consecutive melt seasons, thus deepening these lakebeds in the grounding zone over time. This is supported by the presence of lake ogives (Echelmeyer et al., 1991) downstream of often “teardrop-shaped” lakes straddling the grounding lines of Antarctic ice shelves, which are the surface expression of summer-season lakebed ablation combined with ice flow under a stationary lake (Darnell et al., 2013). The characteristic teardrop shape of these lakes is likely due to the downstream shoreline of these lake basins slowly being advected past the flexure-induced local minimum, thus preventing further pooling of water and lake bottom ablation in the same downstream location, followed by a gradual viscous creep that causes the remnant lakebed depression to become more narrow and shallow over time as it is advected further downstream.

4.1.4.3 Timing and trends in lake formation

Our dataset contains valuable information about the temporal variability of lake locations and water depths. Considering all five melt seasons, the average acquisition time of ICESat-2 lake segments suggests that Antarctic melt seasons typically peak around January 22 each year (Fig. 4.2, d). This is 182 days offset from the corresponding date for the Greenland Ice Sheet (Jul 23; Chapter 3), suggesting that the peak of the surface melt accumulation is reached approximately a month after solstice on both ice sheets.

Trends within the annual melt season: A linear regression of the day of year of ICESat-2 lake segment observations against surface elevation reveals a clear temporal

trend in supraglacial lake elevations within each Antarctic melt season: lakes generally appear at lower elevations as the season progresses ($p = 4 \times 10^{-12}$), with an average downward migration rate of 5.0 ± 0.3 m per day (Fig. 4.2, e). This corresponds to a continent-wide lateral shift in lake locations downstream, relative to the grounding line ($p = 1.1 \times 10^{-5}$) at an average rate of 39 ± 8.9 m per day. Summertime redistribution of surface meltwater onto and across Antarctic ice shelves, featuring lateral transport toward ice shelf fronts, has previously been documented as a widespread phenomenon across Antarctica (Kingslake et al., 2017), with notable examples on the Amery (Phillips, 1998; Spergel et al., 2021), Nivlisen (Dell et al., 2020) and Nansen (Bell et al., 2017) ice shelves. This observed downstream migration of supraglacial lake locations in Antarctica contrasts with the behavior on the Greenland Ice Sheet, where lakes typically appear at higher elevations as the season progresses and above-freezing temperatures reach higher elevations later in summer (Chapter 3).

We propose that this contrasting behavior arises primarily from differences in meltwater drainage processes and climatic conditions between the two ice sheets. In Antarctica, direct mass loss from supraglacial lake drainage to the bed is minimal (Van Wessem et al., 2018), and surface melt is largely driven by either brief, intermittent melting events (Trusel et al., 2013) or more persistent and localized melting in blue ice zones, whose locations are topographically controlled (Lenaerts et al., 2017). In contrast, the Greenland Ice Sheet experiences widespread lake drainage to the bed and sustained melt seasons, during which progressively higher elevations reach above-freezing temperatures (van den Broeke et al., 2023).

In Antarctica, surface melting is typically initiated in blue ice zones (Lenaerts et al., 2017), which form in regions of steepest surface slopes upstream of the grounding zones of ice shelves, where katabatic winds are strongest and thus snow scouring and adiabatic

warming are most intense (Van Den Broeke and Bintanja, 1995). The steep slopes facilitate efficient surface lake drainage through channelized systems (Kingslake et al., 2015), and the impermeable bare ice surface of blue ice zones prevents meltwater from percolating downward and lake drainage to the bed. As a result, over time, most available meltwater is transported efficiently across the ice surface downhill and toward the grounding zone (Kingslake et al., 2017). With continued meltwater transport from upstream, increasingly many surface depressions in the grounding zone and further downstream on the ice shelf can accumulate meltwater to form supraglacial lakes at lower elevations, while the significantly gentler surface slopes in these regions inhibit channelized drainage that completely empties existing lakes (Kingslake et al., 2015). At the same time, since most regions in Antarctica lack a prolonged melt season during which above-freezing temperatures are encountered at progressively higher elevations, the formation of new lakes at higher altitudes later in the summer is relatively rare (van den Broeke et al., 2023). The combination of (1) efficient downstream meltwater transport across the surface, (2) limited drainage and removal of low-elevation lakes, and (3) minimal formation of higher-elevation lakes results in the observed downstream migration of supraglacial lake locations over the course of each Antarctic melt season.

By contrast, the prolonged melt seasons in Greenland allow for surface melt to extend to progressively higher elevations as temperatures increase and the firn layer becomes saturated over time (Sundal et al., 2009). This leads to the formation of new supraglacial lakes at higher elevations later in the season, while lakes at lower elevations are often removed via drainage to the bed or the development of efficient supraglacial drainage networks (Sect. 3.3.1; Johansson et al., 2013; Smith et al., 2015; Stevens et al., 2016). The simultaneous addition of higher-elevation lakes and removal of lower-elevation lakes creates the observed upward migration of supraglacial lake locations in Greenland over the course

of each melt season.

Our ICESat-2 data indicate that the deepest supraglacial lakes in Antarctica deepen over the course of each melt season ($p = 4.5 \times 10^{-10}$), with an average rate of 4.1 ± 0.62 cm per day (Fig. 4.2, e). This behavior is consistent with our observations from Greenland, where we also found lakes to deepen as the melt season progresses (Chapter 3). On both ice sheets, this trend is likely driven primarily by continued meltwater input throughout the melt season, which enables deep surface depressions to fill to higher levels, but lake bottom ablation may also play a significant role in this process (Tedesco et al., 2012; Arthur et al., 2020b). Additionally, on Antarctica’s floating ice shelves, the surface loading caused by the filling of a supraglacial lake induces localized downward flexure of the ice shelf surface, further deepening the lake basin (Banwell and Macayeal, 2015).

Trends throughout the study period: The strongest melt season in our data was 2018-19, with a supraglacial lake density of 0.007 % as a fraction of all analyzed along-track data (Fig. 4.2, b). Based on the along-track fraction of depth measurements in our data, the last three melt seasons (2020-21 to 2022-23) all experienced less than half the amount of melt compared to the previous two melt seasons (Table 4.1). While the five-year period examined in this study is arguably not long enough to draw conclusions about long-term trends, our data reveals a statistically significant decreasing trend in the total along track meltwater extent across Antarctica ($p = 0.04$). This trend is dominated by a decrease in East Antarctic meltwater extent ($p = 0.02$), while the corresponding along-track meltwater extents across West Antarctica and the Peninsula show no significant trend (Fig. 4.3).

The decrease in East Antarctic meltwater in our data is opposite to the trend reported by Tuckett et al. (2022), whose imagery-based analysis of melt lake extents from 2006-07 to 2020-21 suggested a recent rise in East Antarctic surface meltwater. It has been shown that interannual variability in East Antarctica supraglacial lakes is large (Arthur

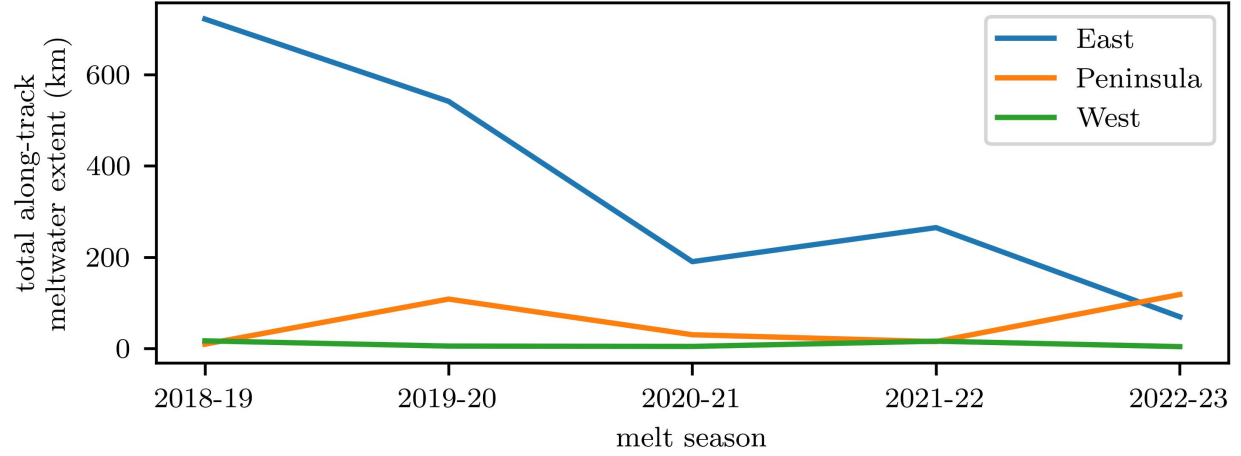


Figure 4.3: Regional interannual trends in meltwater extent in the ICESat-2 data.

et al., 2022), making it difficult to assess long-term trends using high-resolution satellite data, which has only been continuously available since Landsat 7 was launched in 1999 (Spergel et al., 2021). Our results suggest that making long-term predictions from the relatively short satellite record available for East Antarctic supraglacial lakes is difficult, making assessments of the future impact of a warming climate on East Antarctic meltwater uncertain.

4.1.5. Summary and future work

We have presented the first pan-Antarctic dataset of ICESat-2-derived supraglacial lake depth measurements, for five melt seasons from 2018-19 to 2022-23. The ICESat-2 data confirm previously reported overall patterns in spatial variability of supraglacial lake extent, but due to ICESat-2’s low-inclination orbit we were also able to map new high-latitude supraglacial lakes near the southeastern grounding line of the Ross Ice Shelf and in close proximity to the Transantarctic mountains at locations up to $> 95.9^{\circ}\text{C}$, which is significantly further south than where surface meltwater features have previously been reported. our data indicate that the average location of Antarctic supraglacial lakes shifts

downstream as the melt season progresses. Our data indicate that the average location of Antarctic supraglacial lakes shifts downstream as the melt season progresses, which is opposite of the upward migration of lake locations observed in Greenland (Chapter 3). We attribute this to surface meltwater being produced in blue ice zone upstream of the ice shelves' grounding lines (Lenaerts et al., 2017), and subsequently being efficiently transported downstream towards the ice shelves (Kingslake et al., 2017), where particularly deep supraglacial lakes can form near the slope break due to ice shelf flexure in the grounding zone (Vaughan, 1995; Trusel et al., 2022). Our findings also reveal that a substantial proportion ($\sim 40\%$) of supraglacial lakes in Antarctica occur on grounded ice. This underscores the potential for surface meltwater to influence ice dynamics via active surface-to-bed hydraulic connections in Antarctica (Boxall et al., 2024), similar to processes widely observed in Greenland (Zwally et al., 2002). These results highlight the urgent need for further research into the impact of supraglacial lakes on grounded ice dynamics, particularly given the projected "Greenlandification" of the Antarctic Ice Sheet under future warming scenarios (Bell et al., 2018; Mottram et al., 2021).

ICESat-2's unique capability to make direct measurements of water depths from space makes it possible for our data to provide new insights into patterns of supraglacial lake depth. Our results show that supraglacial lakes in Antarctica generally remain shallower than those on the Greenland Ice Sheet. This disparity is likely driven by lower overall surface meltwater production during Antarctica's shorter melt season (van den Broeke et al., 2023), efficient channelized surface drainage of meltwater in blue ice zones on grounded ice (Kingslake et al., 2017), and the absence of bedrock control on the formation of deep surface depressions on floating ice shelves (Macdonald et al., 2018; Ignéczi et al., 2016). The deepest lakes are found at low elevations late in the melt season, with maximum depths decreasing about 0.28 m every 100 m in altitude and increasing throughout the progression of the

annual melt season at a rate of about 4 cm/day. Deepest lakes likely form predominantly at low elevations since flexure in the grounding zone allows for meltwater to repeatedly form in deep depressions (Trusel et al., 2022), and since the flatter surface slopes of low-elevation ice shelves inhibit efficient channelized surface drainage (Kingslake et al., 2015), which allows for meltwater to accumulate in lake basins for longer. The progressive deepening of supraglacial lakes over the melt season is likely the result of a combination of continued meltwater input from upstream blue ice zones, lake bottom ablation, and localized ice shelf flexure caused by increasing of meltwater loading as lakes fill (Tedesco et al., 2012; Banwell and Macayeal, 2015; Lenaerts et al., 2017). During the five-year study period, East Antarctica experienced a significant decline in total supraglacial lake extent, which is opposite to previously reported trends (Tuckett et al., 2022), and therefore highlights the need for continued multi-modal high-resolution satellite monitoring of surface melt near the Antarctic Ice Sheet’s margin for constraining uncertainty in future projections.

The results presented for Greenland lake volume estimation in the previous chapter (Chapter 3), suggest that the Antarctic ICESat-2 depth data presented here (Chapter 4) could be used to improve estimates of supraglacial lake volumes in Antarctica in similar fashion to the methods used in Greenland: Fusion of the ICESat-2 lake depths with coincident passive optical satellite imagery would generate a training dataset that can be used to train machine learning models for continuously monitoring water depths. This will be addressed in future work.

4.2. Altimetry and stereophotogrammetry observations of doline formation can improve our mechanistic understanding of ice shelf collapse by hydrofracture

4.2.1. Antarctic surface melt and through-ice-shelf lake drainage

Many of Antarctica’s ice shelves experience significant surface melting each season (Stokes et al., 2019; Arthur et al., 2020b; Dirscherl et al., 2020; Dell et al., 2020; Halberstadt et al., 2020; Banwell et al., 2021; Spergel et al., 2021; Corr et al., 2022; Dell et al., 2024), and projections suggest that meltwater production will likely increase in the future (Trusel et al., 2015; Gilbert and Kittel, 2021). Yet, it is generally assumed that nearly all the produced meltwater re-freezes on the ice shelves rather than being lost as runoff. For example, in the regional climate model RACMO2.3 all produced meltwater is modelled to refreeze in the snow, so “surface melt has no influence on the SMB” (Surface Mass Balance) (Van Wessem et al., 2018). Individual events of direct surface meltwater loss to the ocean have been documented (Bell et al., 2017; Dunmire et al., 2020; Warner et al., 2021; Trusel et al., 2022), but were thought to be rare. One such mechanism, which exports meltwater off an ice shelf, is through-ice-shelf drainage of supraglacial lakes by meltwater-driven hydrofracture (Scambos et al., 2000). This process leaves behind an empty drainage basin, which is lifted up with respect to the surrounding ice shelf surface due to the ice shelf’s flexural response to the removal of the water load (Fig. 4.4). The resulting structure is referred to as an ice doline (Moore, 1993).

4.2.2. Early observations of ice doline features

Ice dolines were first observed in the 1930s on George VI Ice Shelf during the British Graham Land expedition (Fleming et al., 1938). Early Antarctic explorers described them as “crater-like formation[s]” (Stephenson and Fleming, 1940) up to a mile in diameter

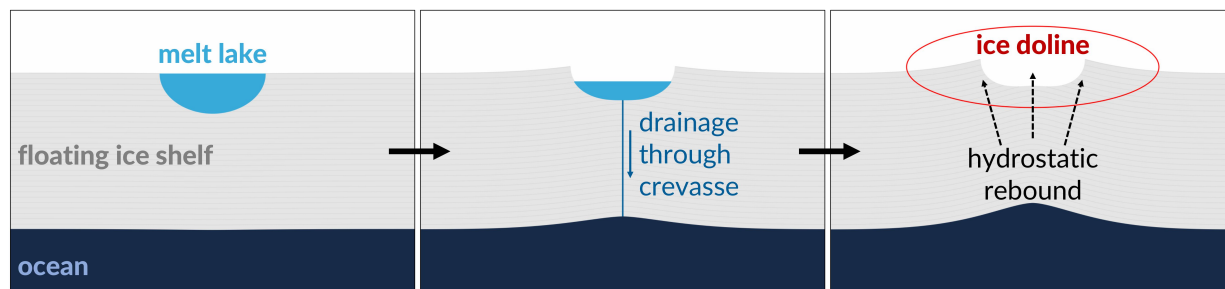


Figure 4.4: A schematic for the ice doline formation mechanism When a melt lake drains through an ice shelf, a large load is removed from the floating ice. The ice shelf compensates by flexing upwards.

and bordered by ice cliffs as high as a hundred feet, and initially referred to them as “ice calderas” (Rymill, 1938), or “ice volcanoes” (Byrd, 1947). Mellor (1960) suggested the term “ice dolines”, by analogy with depressions formed by collapse of subterranean cavities in karst landscapes, and to avoid inappropriate association with volcanism. Further examples of these surface features were later described on the Amery, Lazarev, Nivlisen and Larsen ice shelves (Mellor and McKinnon, 1960; Kruchinin, 1965; Swithinbank, 1988). While the existence of ice dolines on various ice shelves around Antarctica was well-established by the early 1990s, there was no generally agreed-upon explanation for the formation mechanism of ice dolines at the time, with explanations including explosions of trapped gas, impact craters and drainage of englacial water bodies (Byrd, 1947; Mellor and McKinnon, 1960; Moore, 1993). Moore (1993) presented evidence suggesting that dolines form when ice-covered supraglacial melt lakes drain through fractures in their base to the ocean beneath the ice shelf, causing the unsupported ice cover to collapse into the drained lake basin. Fricker et al. (2002) used an observation of an ice doline to support their argument that a part of the Amery Ice Shelf previously thought to be grounded was actually floating. Ice dolines were also observed on the Larsen B Ice Shelf prior to its disintegration in 2002 (Bindshadler et al., 2002). At this time, ice doline surface features had been described extensively in the scientific literature and the consensus was that they formed via lake

drainage. However, the process of ice doline formation had not been directly observed and its impact on SMB and ice shelf stability had not been evaluated.

4.2.3. Ice shelf collapse by hydrofracture

Hydrofracture in glaciers and ice shelves occurs when water infiltrates crevasses, filling them until the hydrostatic pressure at the crack tip surpasses the ice’s fracture toughness (Weertman, 1973; Alley et al., 2018). Melt lakes serve as significant surface reservoirs that can drain into these fractures, further increasing pressure and driving sustained fracture propagation (Krawczynski et al., 2009). When a melt lake on an ice shelf triggers hydrofracture that extends to the base, the lake drains into the sub-ice-shelf ocean cavity, directly reducing the ice shelf’s mass at the surface and forming an ice doline (Warner et al., 2021). The resulting local hydrostatic adjustment and the subsequent upward bending of the floating ice shelf introduces additional flexural stresses, potentially weakening the ice shelf further (Banwell and Macayeal, 2015).

The widespread presence of melt ponds before Larsen B’s disintegration suggests that lake drainage and ice doline formation initiated a chain reaction of multiple hydrofracture-driven supraglacial lake drainages, leading to the ice shelf’s collapse (Glasser and Scambos, 2008; Banwell et al., 2013). While doline formation through ice-shelf lake drainage represents a direct mass loss term in the ice shelf’s surface mass balance, the indirect impact of such events on long-term ice sheet mass balance and stability is potentially far more significant. After Larsen B’s collapse, Scambos et al. (2004) and Rignot et al. (2004) observed increased discharge of grounded ice into the ocean due to the loss of buttressing backstresses provided by the ice shelf, leading to accelerated loss of grounded ice and thus sea level rise.

Some modeling studies have explored the local effects of lake drainage and doline for-

mation on ice shelf stability (Banwell et al., 2013; MacAyeal and Sergienko, 2013; MacAyeal et al., 2015, 2021). However, most large-scale projections of Antarctic sea-level rise contributions still rely on simplistic parameterizations to evaluate the impacts of supraglacial lakes on ice shelves and their potential to cause collapse by hydrofracture (Seroussi et al., 2020; DeConto et al., 2021). Despite their potential impact on ice sheet stability, direct observations of doline formations were not reported in the literature until 2019, when a significant doline event on the Amery Ice Shelf was observed by the ICESat-2 and WorldView-3 satellites (Warner et al., 2021). Further observations on the Amery Ice Shelf were documented by Trusel et al. (2022) using similar satellite remote sensing techniques, indicating that tidal flexure can trigger doline formation in the grounding zone. The first in-situ observations of meltwater-induced flexure and ring fracture formation were reported by Banwell et al. (2024) for a doline on the George VI Ice Shelf.

However, there have been no continent-wide observational studies of doline formations across Antarctica. This lack of data highlights a critical observational gap in understanding how supraglacial hydrological systems on Antarctic ice shelves evolve to produce meltwater lakes capable of initiating hydrofracture and their potential effects on future ice sheet stability.

4.2.4. Direct observation of an ice doline formation on Amery Ice Shelf

In 2021, we presented the first satellite observations of a doline forming on Amery Ice Shelf, East Antarctica, under the lead of Roland Warner (Warner et al., 2021). These observations of ice shelf surface deformation were made possible through high-resolution satellite data from both ICESat-2, and WorldView stereo imagery, capturing the drainage of a deep (> 120 m), ice-covered supraglacial lake in midwinter (June 2019). This event, which we confirmed to have occurred over a span of two days or less, resulted in a an

uneven collapse basin covering approximately 11 km^2 (Fig. 4.5, c).

Elevation differences from repeats of four ICESat-2 ground tracks provided high-accuracy measurements of the surface elevation drop where the lake had drained, as well as the flexural uplift in the area surrounding the drained lake basin (Fig. 4.5, d-k). To map the full extent of surface deformation, we used two photogrammetry-based DEMs generated from in-track stereo pairs of WorldView satellite imagery (i.e. two images of the same area, taken from different angles while on the same orbit), pre- and post-drainage. We advected the pre-drainage DEM with the ice flow (from the NASA MEaSUREs ITS_LIVE project; Gardner et al., 2018, 2019) to match the post-drainage one, allowing us to evaluate the lagrangian elevation difference. This revealed that across the entire collapse basin, the surface dropped by up to 80 m, while adjacent regions experienced flexural uplift of up to 36 m due to the removal of the water load. Flexural modeling suggested that around 0.75 km^3 of meltwater drained through the ice shelf into the ocean beneath, representing a significant near-instantaneous mass loss from the ice shelf.

During the first melt season following the drainage event, we observed a new lake forming upstream of the doline due to flexural uplift (“rebound lake”; Fig. 4.6, a). The lake eventually spilled over into the collapse basin, rapidly incising a narrow meltwater channel and transiently refilling the deepest parts of the doline (Fig. 4.6, b-f). This suggests that doline formation nearly instantaneously affects meltwater routing and may play a key role in reshaping the surface hydrology of ice shelves in the long term, with implications for future ice shelf stability. Our observations provided the first detailed observational insights into the process of doline formation and highlighted that high-resolution 3-dimensional satellite observations of ice shelf change are crucial for resolving critical fine-scale processes that have potentially significant impacts on ice shelf mass balance.

Figure 4.5: ICESat-2 data for an ice dooline formation on Amery Ice Shelf. (a) Landsat 8 image over the southern Amery Ice Shelf on January 17, 2019; Landsat 8 images for (b) March, 31 and (c) September 14, 2019, with color-coded ICESat-2 ground tracks (GTs) overlaid; (d–k) ICESat-2 ATL06 data for repeats of GTs (from west to east) before and after dooline formation. Figure by Philipp Arndt, from Warner et al. (2021).

4. Antarctic Ice Shelf Mass Balance Processes: High-Resolution 3D Satellite Observations

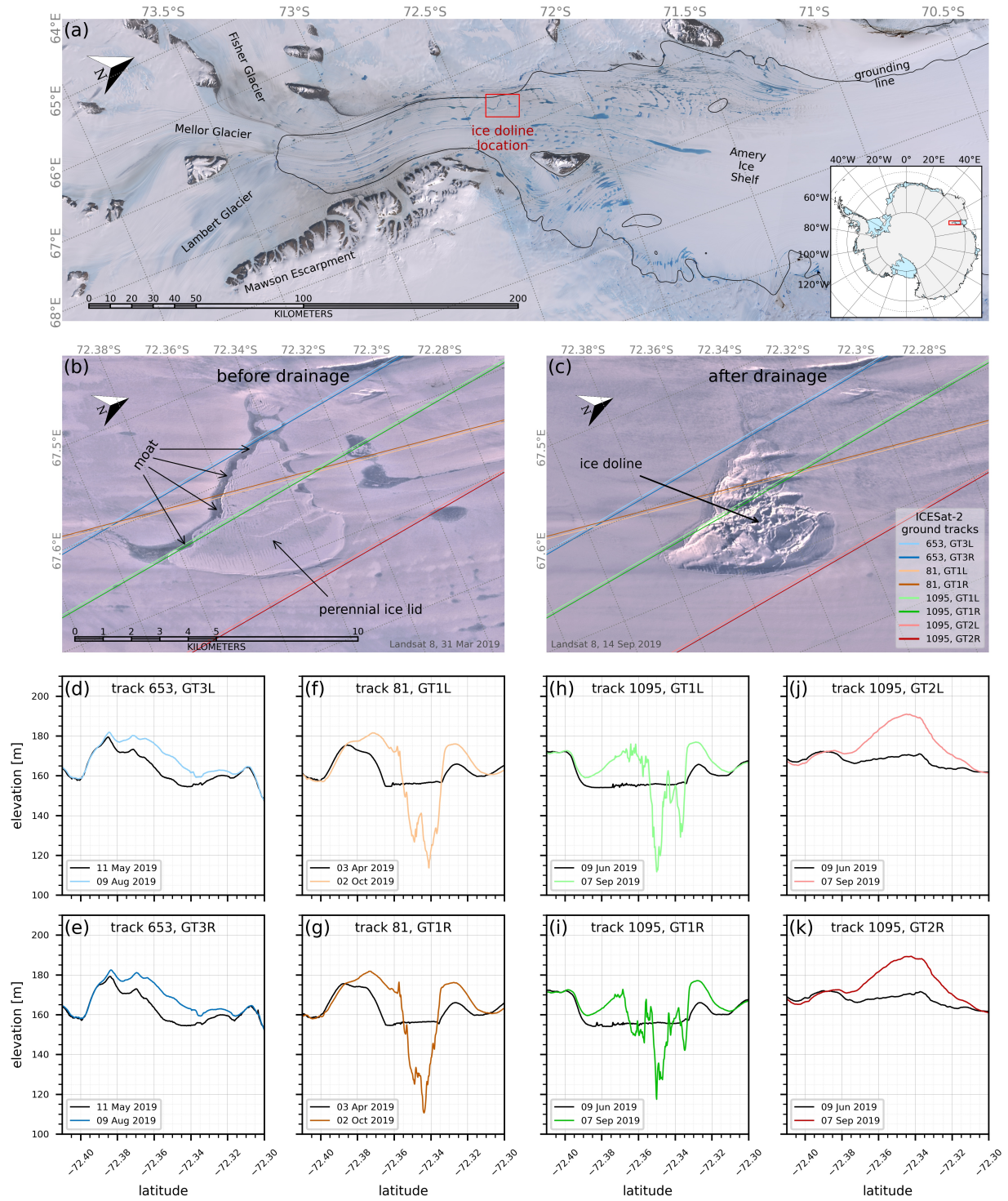
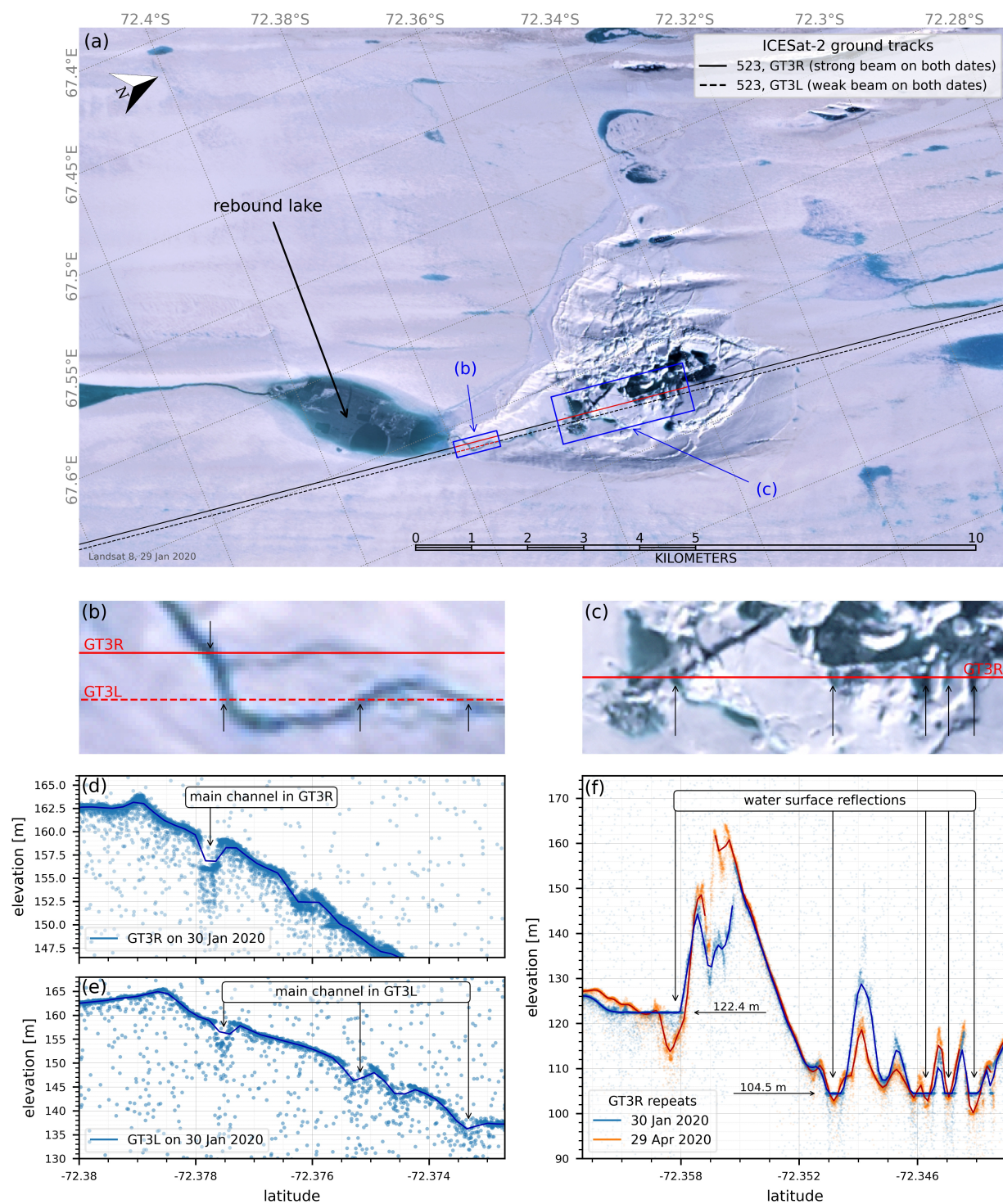


Figure 4.6: First melt season after the ice doeline formation on Amery (2019/2020). (a) Landsat 8 mosaic from January 29, 2020; ICESat-2 Tracks 523 GT3L and GT3R are shown; (b and c) zooms of Landsat 8 image; ICESat-2 ATL03 and ATL06 data (d and e) for Track 523 GT3L and GT3R across a drainage channel (at -72.378°) incised by meltwater flow from the rebound lake to the doeline; (f) for Track 0523 GT3R across the doeline in January and April 2020 showing the structure of the collapsed ice lid and meltwater surfaces at 122.4 and 104.5 m; the April track is displaced to align major features with the January profile. Figure by Philipp Arndt, from Warner et al. (2021).

4. Antarctic Ice Shelf Mass Balance Processes: High-Resolution 3D Satellite Observations



4.2.5. Continent-wide satellite observations of ice doline formations

We present an inventory of satellite observations of doline formations across Antarctica. Using this data, we describe where and when dolines form, and explore how high-resolution satellite observations of ice shelf deformation in response to doline formation can improve our understanding of ice shelf mechanics.

4.2.5.1 Compilation of the doline formation inventory

We examined various sources of satellite data in regions on the ice shelves where surface melt had been previously reported (e.g., Kingslake et al., 2017; Stokes et al., 2019). To identify areas where dolines have likely formed in the past we first browsed the REMA DEM (Howat et al., 2019) in these regions, manually looking for the characteristic “crater-like” (Stephenson and Fleming, 1940) surface expressions of ice dolines. We also created annual mosaics of surface elevation from individual REMA strip data (version 1) in Google Earth Engine (GEE) (Gorelick et al., 2017), and evaluated the elevation differences between consecutive years for the characteristic elevation change pattern for doline formation (elevation drop in the center of the collapse basin and surrounding uplift (Fig 4.10, a,d,g,j)). Since coverage and temporal resolution of REMA strips are limited, we generated bi-monthly mosaics of Landsat 7 and 8 imagery and visually searched for images showing dolines. In locations where we found the surface expression of an existing (or suspected) doline, we traced back the satellite imagery record (Landsat 1-5, 7, 8 and MODIS) for signs of previous lake drainage, and queried ICESat or ICESat-2 data when available. We further searched existing literature for mentions of dolines (e.g. Bindshadler et al., 2002; Fricker et al., 2002) and checked whether we could find pre-drainage satellite data of the corresponding lake. We also included an Interferometric Synthetic Aperture Radar (InSAR)-based observation of doline formation that occurred in December 2017 on Roi Baudouin Ice Shelf, which Li

et al. (2021c) described shortly after we published our observation of doline formation on the Amery Ice Shelf (Warner et al., 2021). To further constrain the time period during which lake drainage and doline formation occurred, we inspected Sentinel-1 Synthetic Aperture Radar (SAR) data for any significant increases in radar backscatter in the location of the lakebed, which can be a sign of doline formation due to a typical increase in surface roughness associated with collapse of the ice cover of frozen-over lakes. We compiled the locations of all resulting observations of doline formation, together with the lower and upper bounds on the timing of each event, as well as the sources of satellite data that were used to assess the existence, location and timing of each observation (Table 4.2). This research was carried out in 2021, so any potential doline formations after the 2020-21 Antarctic melt season are not included in the data. Since the compilation of this inventory relied largely on visual inspection of mosaics, the results are not necessarily comprehensive.

4.2.5.2 Spatiotemporal distribution and typical characteristics of doline observations

Across Antarctica, our search for dolines yielded a total of 47 instances where satellites observed melt lake basins both before and after they drained through an ice shelf, distributed across all major Antarctic regions (in the East, West and on the Peninsula; Fig. 4.7). This suggests that while doline formation is a relatively rarely observed phenomenon, it is more widespread across Antarctica than previously thought. More than half (25) of the doline formation events that we observed occurred on the Amery Ice Shelf. George VI featured seven satellite-observed doline formations, while all remaining ice shelves had only three or less (Table 4.2). While the overall number of observations is small, the general spatial distribution of doline formations is similar to the distribution of regions with extensive surface melt and deep lakes across Antarctica (Sect. 4.1.4.1, Fig. 4.1), suggesting that dolines can form on most ice shelves where meltwater ponding is prevalent.

4.2. Observations of ice doline formation

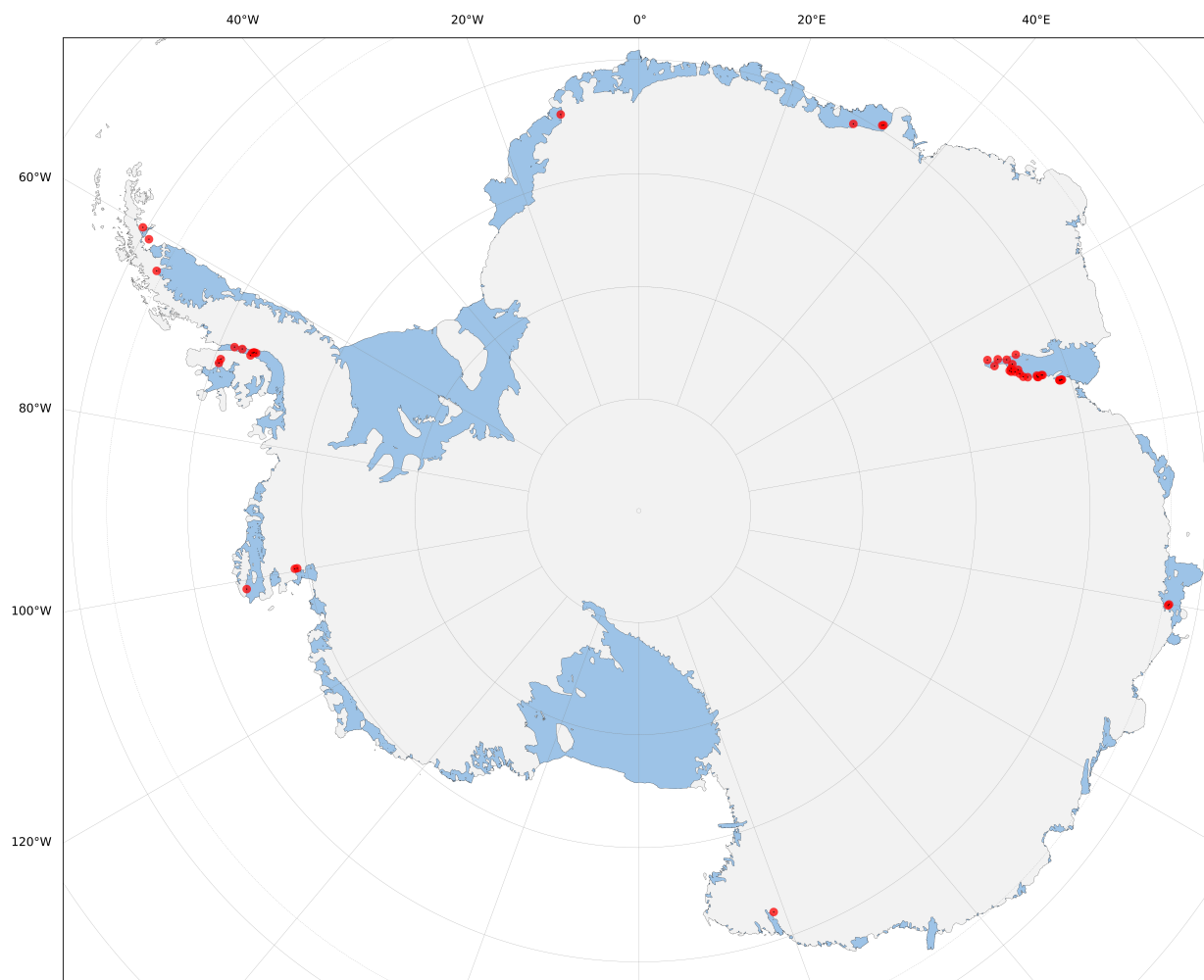


Figure 4.7: Locations of doline formation events observed by satellites.

On the Amery Ice Shelf, the majority of doline observations were found for lakes straddling the grounding line. The lake basins of these particular lakes often have a characteristic “teardrop”-shape (e.g., Fig 4.8, a and b), in contrast to lakes on fully floating ice that are typically more round or oval-shaped (e.g., Fig 4.10, d-f). Where full spatial extents of surface deformation were available from the REMA strip data, the elevation change data for lakes straddling the grounding line showed a flexural uplift that was limited to the downstream (floating) direction (e.g., Fig. 4.10, g). The dolines on the Amery Ice Shelf grounding line were also the only locations in which we observed repeated filling

and drainage of the same lake basin / doline. Across all other ice shelves, the majority of doline formations were recorded at a distance further downstream of the grounding line, with no observations of repeated filling and draining.

The depths of the doline collapse basins varied from a few meters to over a hundred meters, with dolines on thinner ice shelves typically being less deep. Across all doline formation observations, the one with the deepest collapse basin and the largest spatial extent, was the Amery doline that we described in Warner et al. (2021); however the doline with the largest elevation difference between the collapse basin and the lifted fringe measured in ICESat-2 data was obtained for a teardrop-shaped lake on the grounding line of Amery in winter 2019 (Fig. 4.8, a-d).

Tracking surface lakes that eventually drained back in time in satellite imagery revealed that prior to doline formation meltwater can accumulate in lakes, which are often covered by an ice lid, for multiple decades. We observed doline formation events year-round, with no clearly distinguishable seasonal pattern.

4.2.6. Observational data of ice shelf flexure

As we demonstrated in Warner et al. (2021), the surface elevation changes that occur as a result of doline formation can be monitored using high-resolution satellite remote sensing data, in particular from elevation differences of ICESat-2 repeat-tracks and lagrangian differencing of DEMs. These data can help us better understand the mechanical properties of ice shelves and can be used to validate or improve models of ice shelf flexure (e.g., Banwell and Macayeal, 2015; MacAyeal et al., 2015). Through-ice-shelf lake drainage is often near-instantaneous, which means that repeat measurement of surface elevation just before and after drainage can provide an estimate of the initial elastic response of the ice shelf to unloading. When the time span over which elevation change is assessed is longer (i.e., the

Table 4.2: Satellite observations of doline formation events across Antarctica. Columns “before” and “after” denote the date of the closest satellite data acquisition before and after the event. Abbreviated satellite data sources are as follows: IS2: ICESat-2, L: Landsat, S1: Sentinel-1, WV: WorldView. Ice shelf names are as in the IMBIE dataset (Mouginot et al., 2017).

4. Antarctic Ice Shelf Mass Balance Processes: High-Resolution 3D Satellite Observations

lon	lat	before	after	ice shelf	sources
-60.2567	-64.8252	1979-01-01	1986-12-31	LarsenA	L1-5
67.8588	-72.9398	1988-03-15	1989-02-14	Amery	L1-5
-99.5602	-74.5809	1997-01-01	1999-12-31	Pine_Island	L1-5
-61.0000	-65.3000	2000-02-21	2000-10-05	LarsenB	L7, IKONOS
69.0791	-72.3006	2006-03-09	2006-03-10	Amery	L7, MODIS
28.9977	-70.3841	2008-01-01	2008-12-31	Baudouin	L7
100.0231	-66.2391	2010-02-24	2010-11-07	Shackleton	L7, MODIS
32.2558	-69.8031	2011-02-08	2010-12-22	Baudouin	L7
161.4302	-71.2137	2011-12-30	2012-01-31	Rennick	L8
70.2133	-72.0280	2014-01-25	2014-02-03	Amery	L8
-11.1684	-72.0619	2014-02-25	2014-09-19	Riiser-Larsen	REMA, L8
66.6099	-73.1228	2014-03-17	2014-09-14	Amery	L8
71.2393	-71.3486	2014-04-01	2014-09-24	Amery	L8
72.7879	-70.3618	2014-04-08	2014-09-22	Amery	L8
72.7276	-70.3879	2014-04-08	2014-09-22	Amery	L8
71.0386	-71.7470	2014-10-03	2014-10-18	Amery	REMA, L8
67.4930	-71.8871	2014-10-18	2014-10-23	Amery	L8
71.3684	-71.1527	2014-12-22	2014-12-27	Amery	L8
-67.5953	-71.6175	2014-12-29	2015-12-11	George_VI	REMA
-68.2052	-71.4341	2014-12-29	2015-12-10	George_VI	L8
69.5881	-72.0370	2015-03-28	2015-04-02	Amery	REMA, L8
72.8028	-70.4273	2015-04-04	2015-10-04	Amery	L8
71.4144	-71.1052	2015-09-25	2015-10-04	Amery	L8
-67.6991	-71.5116	2016-01-12	2016-02-09	George_VI	REMA, L8
-70.6201	-70.2585	2016-02-14	2017-02-25	Wilkins	L8
-63.5585	-66.2224	2016-04-18	2016-08-24	LarsenC	L8
67.1147	-72.6937	2017-03-14	2017-09-08	Amery	L8
32.3908	-69.7595	2017-12-01	2017-12-19	Baudouin	S1_InSAR, L8
100.1537	-66.2706	2017-12-20	2017-12-27	Shackleton	L8
-67.7892	-71.4591	2018-02-07	2018-03-02	George_VI	L8
-67.9697	-70.6518	2019-01-01	2021-12-31	George_VI	L8
69.7134	-72.1944	2019-02-19	2019-03-12	Amery	L8
71.4488	-71.3453	2019-03-21	2019-03-30	Amery	L8
71.5013	-71.3082	2019-05-15	2019-09-04	Amery	IS2, L8
67.6697	-72.3378	2019-06-09	2019-06-11	Amery	L8, S1, IS2, WV
69.2934	-72.3961	2019-07-24	2019-09-18	Amery	L8, IS2
-101.2930	-72.2344	2019-11-19	2020-12-31	Abbot	L8
-99.5764	-74.4735	2019-12-23	2019-12-25	Pine_Island	L8
-67.8059	-70.9986	2020-01-02	2020-03-23	George_VI	L8, IS2
-70.0616	-70.2791	2020-01-24	2020-01-31	Wilkins	L8
72.7514	-70.4752	2020-02-13	2020-02-20	Amery	L8
72.7463	-70.4753	2020-02-14	2020-02-21	Amery	L8
70.7840	-71.9256	2020-04-02	2020-09-18	Amery	L8
68.5589	-72.1843	2020-04-02	2020-09-14	Amery	L8
69.5140	-72.3457	2020-12-14	2020-12-21	Amery	L8, IS2
72.7924	-70.4625	2021-01-30	2021-02-24	Amery	L8
-67.6252	-71.5277	2021-02-15	2021-03-10	George_VI	L8

post-drainage elevation measurement of the doline is obtained months or years after doline formation), such measurements of elevation change represent the combined effect of the elastic response to unloading and continuing viscous deformation of the ice shelf (Warner et al., 2021).

ICESat-2 elevation change: Due to ICESat-2’s coarse track spacing across most of Antarctica’s ice shelves, only five of the 47 dolines in our inventory had elevation change data from ICESat-2. We present results for the doline with the largest signal in ICESat-2 data, which formed on the eastern grounding line of the Amery Ice Shelf in winter 2019 (Fig. 4.8). ICESat-2 track 721 GT2R recorded the pre-drainage elevation of the ice-covered lake surface on May 15, 2019. Approximately six months later (November 13, 2019), a repeat elevation measurement along this ground track revealed a doline collapse basin > 80 m deep and a flexural uplift of the surrounding ice shelf creating a “lake sill” of about 9 m height (Fig. 4.8, c). A further repeat on November 5, 2021 revealed a continued uplift at the fringe of the collapse basin that increased the height of the lake sill to about 16 m, combined with a decrease in the maximum depth of the collapse basin to about 45 m (Fig. 4.8, d). The center of the collapse basin also appeared to have experienced further uplift, thus developing a mound inside the basin, with a local elevation maximum near the center. Such mounds at the center of dolines were first observed by Fleming et al. (1938), who described them as “slabs of radially cracked ice tilted upwards to meet in a point”.

The patterns of continued elevation change observed by ICESat-2 are qualitatively consistent with results presented in Banwell and Macayeal (2015), who modeled the viscoelastic ice shelf deformation in response to lake drainage of a shallower, idealized cylindrical lake (Fig. 4.8, e). While the spatial extent, shape and depth of the doline modeled by Banwell and Macayeal (2015) are different from those of the doline observed by ICESat-2, their model results also suggest a continued growth of the lake sill due to the long-term

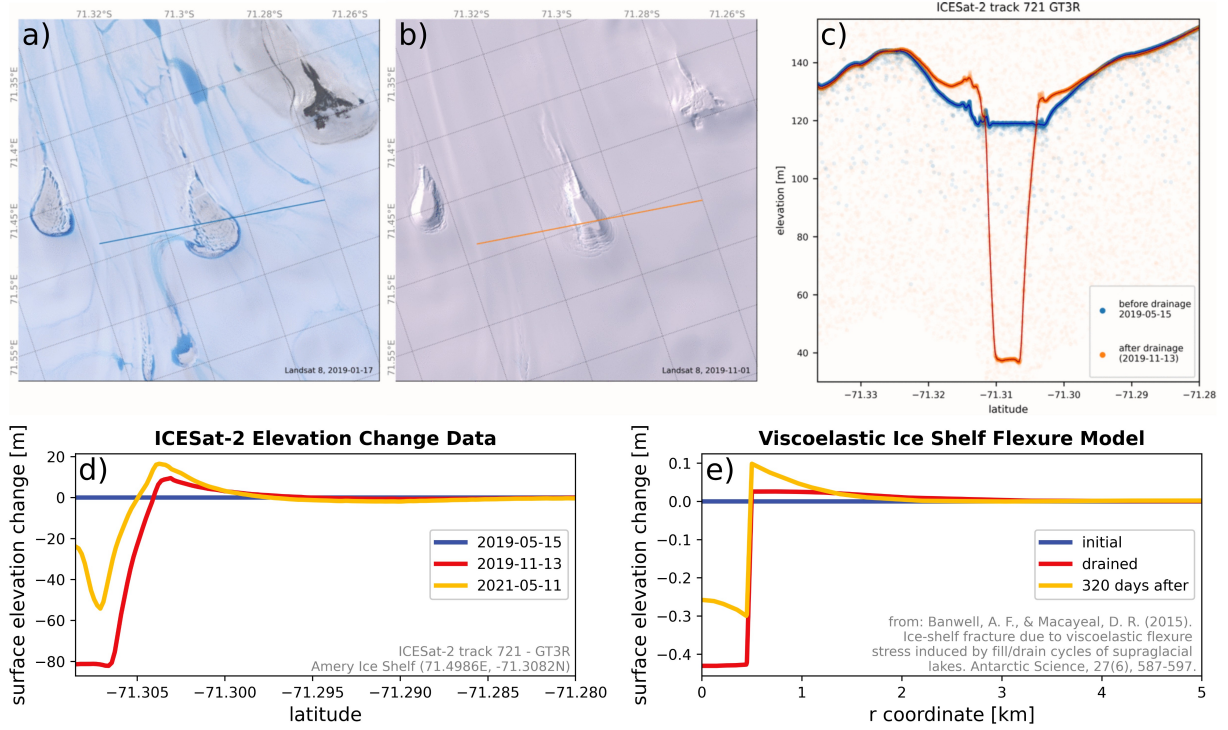


Figure 4.8: Comparison between ICESat-2 data over a doline and modeled ice shelf flexure. a) Landsat 8 imagery from before lake drainage (Jan 17, 2019). b) Landsat 8 imagery from after lake drainage (Nov 1, 2019). c) ICESat-2 elevations from before and after drainage. Lines are ATL06 elevations and scatterpoints are ATL03 photons. d) Repeat-track elevation changes from ICESat-2. e) Modeled elevation changes for lake drainage from Banwell and Macayeal (2015)). Note that the axis and time scales in d and e are different; the data is presented in a visually similar style for qualitative comparison of the modeled and observed evolution of doline shape only.

viscous response of the ice shelf and also show the formation of a mound at the center of the collapse basin, similar to the one observed by ICESat-2.

While the modeling approach makes it possible to estimate the shape of the doline directly after lake drainage, it is likely that ICESat-2 only observed the collapse basin after some time had passed. This means that the post-drainage ICESat-2 elevation change observation from November 13 already represents a combined effect of elastic flexure and some viscous effects. This highlights that the 3-month return period of ICESat-2 limits our ability to disentangle the instantaneous elastic response to ice shelf unloading and the long-

term viscous deformation due to ice creep. However, with ICESat-2 continuing to operate, it is possible that observational data of ice shelf flexure shortly after doline formation will become available in the future. In future work, continued ICESat-2 observations of the long-term deformation of ice dolines could provide further insights into the viscous ice shelf response to doline collapse basins, and could be used to quantitatively validate viscoelastic models of ice shelves. Such data could better constrain mechanical parameters in ice shelf models and provide more accurate estimates of the volume of water that drained through the ice shelf during each doline formation event.

Lagrangian DEM elevation change: In addition to the WorldView DEM model of surface elevation change of the doline presented in (Warner et al., 2021, Fig. 4.10, a), we evaluated lagrangian elevation change for those doline in our dataset where REMA DEM strips (version 1) were available before and after drainage (Fig. 4.10, a, d, g and j). Since the temporal resolution of version 1 REMA strips is coarse (often over a year between strips in the same location), these elevation change maps typically show the combined effect of the instantaneous elastic rebound and long-term viscous deformation. Most maps of lagrangian elevation change show the characteristic surface drop where the collapse basin formed, with an uplift around its edges; however, for dolines that form on the grounding line, the flexural uplift is largely constrained to the downstream, floating portion of the ice (e.g., Fig. 4.10, g). Such observations could provide further insights into ice shelf flexure in the grounding zone, which has previously been observed due to tidal forcing (e.g., Vaughan, 1995; Fricker and Padman, 2006; Freer et al., 2023). Some of the observations also show evidence of a mound at the center of the dolines (e.g., Fig. 4.10, d/e and j/l). In the future, the greatly improved coverage and temporal resolution of REMA DEM strips in the recently published second version of the dataset (Howat et al., 2022b) should make it possible to not only produce more maps of lagrangian elevation difference before and after lake drainage, but

also to assess the long-term deformation of the ice shelf analogous to the example presented for ICESat-2.

4.2.7. Implications for ice shelf stability

The surface elevation changes characteristic for doline formation have the potential to significantly change the surrounding ice shelf surface hydrology, leading to two different processes with opposing effects on ice shelf stability (Fig. 4.9).

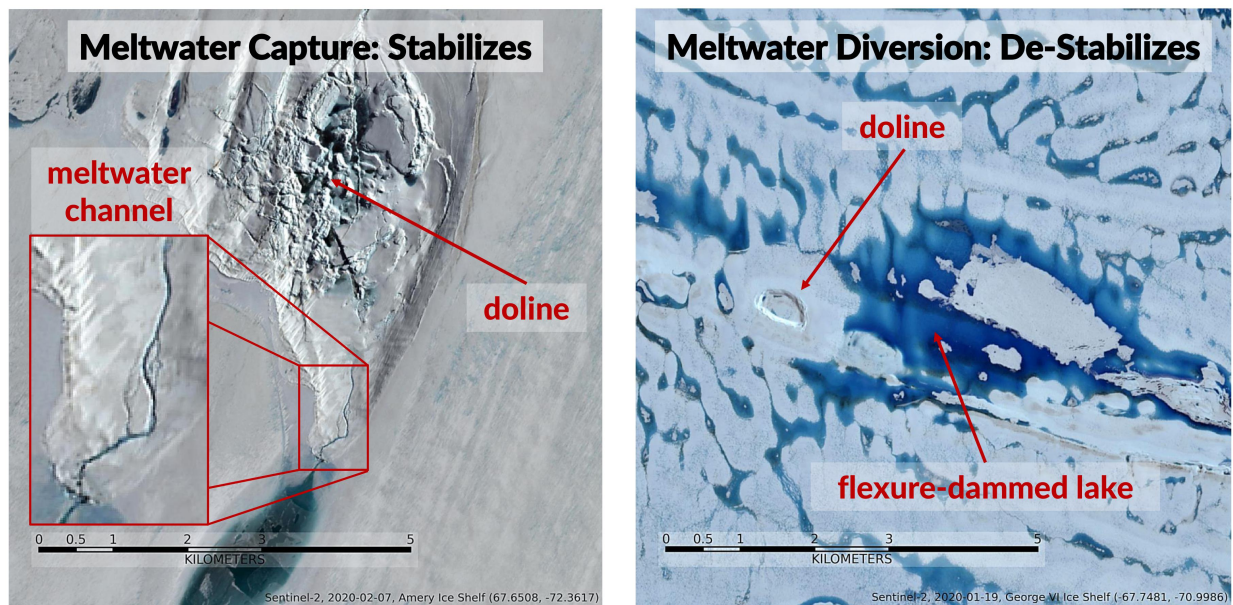
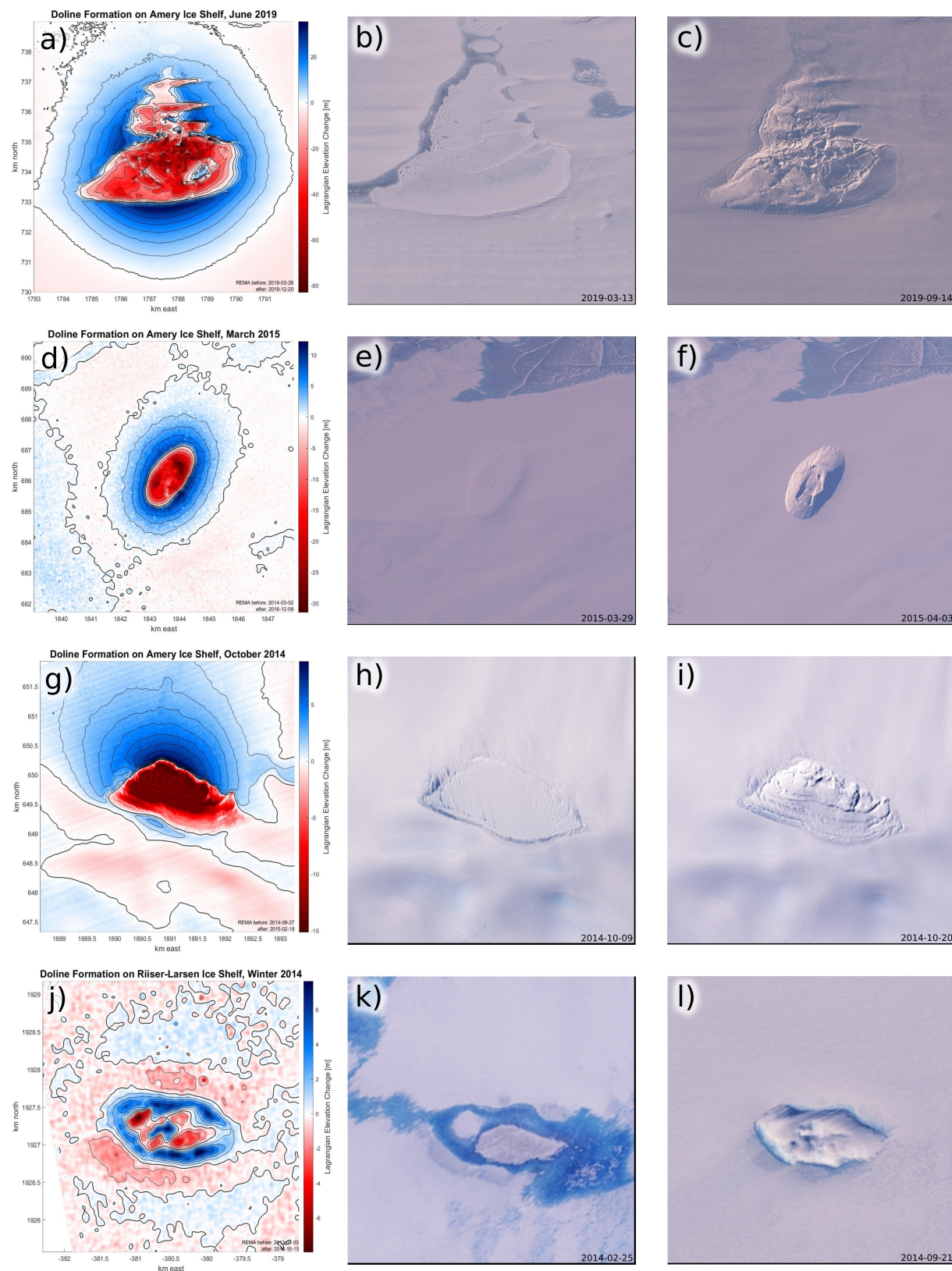


Figure 4.9: Doline Formation can lead to two possible surface meltwater routing mechanisms, with opposing effects on ice shelf stability. Left: Meltwater capture stabilizes the ice shelf. The drainage crevasse provides a pathway to remove water from the surface, preventing future hydrofracture. Right: Meltwater diversion de-stabilizes the ice shelf. The flexural uplift can prevent future meltwater from entering the collapse basin and instead re-route it to regions further downstream that are more vulnerable to hydrofracture.

Meltwater capture stabilizes the ice shelf: If the surface depression formed by the former lake bed acts to capture meltwater and channels it straight down to the ocean via the newly-created drainage pathway, this process could effectively remove new meltwater from the ice shelf surface. This would halt supraglacial meltwater system growth

Figure 4.10: Lagrangian elevation change measurements for four doline formation events, from WorldView Stereophotogrammetry. Left: Lagrangian elevation change. Center: Landsat 8 images of the melt lakes before they drained. Right: Landsat 8 images after doline formation.

4. Antarctic Ice Shelf Mass Balance Processes: High-Resolution 3D Satellite Observations



and thus prevent meltwater from reaching areas more vulnerable to hydrofracture (Trusel et al., 2022), thus stabilizing the ice shelf.

Meltwater diversion de-stabilizes the ice shelf: If flexural uplift around the margins of the collapse basin is prominent enough to prevent new meltwater from entering it, instead diverting flow around the doline, more meltwater is able to reach downstream areas on the ice shelf surface that are typically more vulnerable to hydrofracture (Dow et al., 2018; Lai et al., 2020). This can facilitate repeated hydrofracture in multiple locations and thus act to destabilize the ice shelf.

Which of these mechanisms dominates over time on each ice shelf may ultimately be crucial for its long-term resilience in a warming climate.

4.2.8. Summary and future work

Our observations of widespread through-ice lake drainage suggest that Antarctic ice shelf mass loss through direct loss of surface meltwater (i.e., runoff) may be larger than previously thought. We have demonstrated that high-resolution satellite observations of surface elevation change resulting from lake drainage can provide new insights about the mechanical properties of ice shelves and about the potential implications of surface melt lake drainage and doline formation on ice shelf stability in a warming climate. This suggests that that doline formation is an ice shelf process that should be considered when modeling future ice shelf hydrology and assessing its impacts on mass loss and stability. To obtain a better understanding of the conditions under which dolines form and the consequences that these events have on the ice shelves, it would be helpful to identify as many drainage observations as possible using a continent-wide automated approach for detecting them in multi-sensor satellite data. A better understanding of this process could help improve ice sheet models and thus increase confidence in future sea-level rise projections.

4.3. ICESat-2 bathymetry measurements at ice shelves' calving fronts can help constrain models of buoyancy-driven ice shelf flexure and calving

4.3.1. Introduction: buoyancy-driven ice shelf flexure and calving

Calving is a critical process contributing to the mass balance of ice shelves, where large volumes of ice are lost to the ocean when icebergs break off. Recent studies have highlighted that calving loss in Antarctica can rival ice-shelf thinning as a key factor in ice mass balance (Greene et al., 2022). While large tabular iceberg calving events often receive significant attention, smaller-scale calving events can also play a crucial role in the overall mass loss from ice shelves. It has been shown that smaller calving events in particular have been increasing in regions where calving results in a reduction in ice shelf buttressing, accelerating the rate of mass loss (Greene et al., 2022).

One suggested mechanism for sustained, small-scale calving at the ice front involves wave erosion, which acts primarily at the waterline. Over time, this erosion creates a notch, or wavecut, in the ice above the waterline. As the notch deepens, sections of the unsupported ice shelf above it eventually break off, leaving behind a submerged fringe of ice known as a "foot" (Wagner et al., 2014) or "bench" (Becker et al., 2021). This submerged bench is buoyant, exerting an upward force on the remaining ice shelf, which causes the front to flex upward. This flexure generates stress in the ice shelf, leading to the formation of basal crevasses that can ultimately drive further calving of small icebergs, a process known as the "footloose" mechanism (Wagner et al., 2014). This buoyancy-driven flexure has been linked to the development of characteristic "rampart-moat" surface profiles at the ice shelf front, where a raised ridge (rampart) forms at the edge of the shelf, followed by a depression (moat) just behind it (Scambos et al., 2005; Mosbeux et al., 2020). These

features have been observed on several ice shelves, including the Ross Ice Shelf, where ICESat-2 data revealed horizontal offsets between the rampart and moat of a few hundred meters, with elevation differences ranging from 5 to 10 m (Becker et al., 2021).

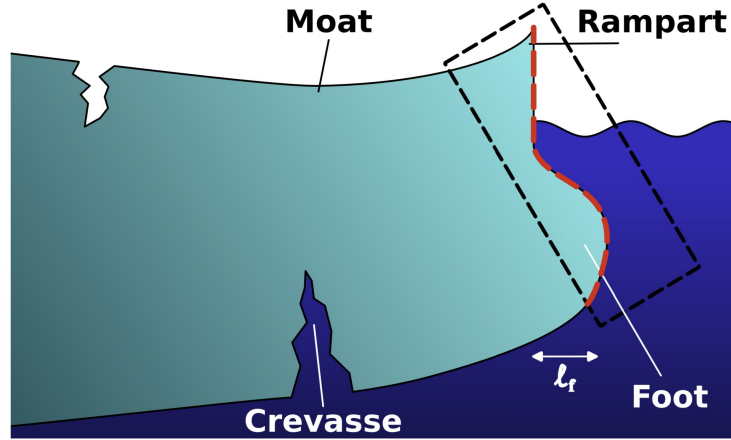


Figure 4.11: Schematic of buoyancy-driven ice shelf flexure at a calving front with a submerged bench. Wave erosion at the ice shelf front causes the presence of a positively buoyant submerged bench (or “foot”). This results in upward bending of the ice shelf front, causing characteristic rampart-moat profiles. The flexure-driven stress at the base of the ice shelf can cause basal crevasses and ultimately lead to small-scale calving events. From Sartore et al. (2024).

Although the process of buoyancy-driven flexure and its influence on calving has been widely hypothesized, direct observations of submerged benches at Antarctic ice shelf fronts have remained elusive. Previous studies of ice shelves have inferred the presence of a bench through surface topography, indirect measurements, or modeling approaches (e.g., Sartore et al., 2024; Buck, 2024). Direct observational evidence of submerged benches has previously been limited to icebergs, including multibeam sonar observations of the underwater geometry of an iceberg in Baffin Bay, East Canada (Wagner et al., 2014), as well as in-situ photographs and satellite imagery showing evidence of bench-like features on icebergs in the Southern Ocean (e.g., Scambos et al., 2008; Sartore et al., 2024). Here, we present the first direct observations of submerged benches at Antarctic ice shelf calving

fronts, derived from bathymetric return signals in ICESat-2 ATL03 photon data. These observations provide critical constraints on the geometry and depth of the bench, offering new insights into its role in driving ice shelf flexure and calving.

4.3.2. Data and methods

The initial discovery of submerged ice shelf benches in ICESat-2 data was made while using the FLUID/SuRRF algorithm for extracting supraglacial lake depths across Antarctica (Sect. 4.1). Some of these lake detections, however, were found to be false positives, where the ice mask used in FLUID/SuRRF extended beyond the ice shelf calving front, allowing the algorithm to pick up bathymetric signals from submerged benches in the ocean instead of lakes on the ice surface (Arndt and Fricker, 2024d).

Following the discovery of these ICESat-2-observed ice shelf benches, we investigated the regions where FLUID/SuRRF had flagged potential lakes that were, in fact, submerged benches. Using OpenAltimetry (Khalsa et al., 2022), we explored ICESat-2 ATL03 photon data to look for further evidence of these benches along the calving fronts. Where possible, we corroborated the presence of these benches using Sentinel-2 satellite imagery.

4.3.3. Results and discussion

Our manual search for ICESat-2 profiles of ice shelf benches yielded 18 observations, both in West and East Antarctica (e.g., Fig. 4.12). This is not a comprehensive collection, because initial bench detection depended on parameters for supraglacial lake detection in FLUID, and was only possible in regions where the ice mask used for implementing FLUID/SuRRF erroneously extended past the ice shelf front. This suggests that more direct observational data of ice shelf benches likely exist in the ICESat-2 ATL03 data, and that extracting them would be possible in future studies by applying the FLUID/SuRRF algorithms (with minor modifications) to a mask that includes all Antarctic ice shelf calving

fronts. We here limit ourselves to briefly describe our observations in a predominantly qualitative way, noting that the existence of direct ICESat-2 observations of ice shelf benches presents an exciting opportunity for more detailed observational studies in the future.

Theoretical studies suggest that there exists a maximum length to which the bench can grow, at which the flexure-induced stress at the base of the ice shelf is believed to reach a critical threshold (the yield strength of the ice) and cause the ice shelf to fracture and calve (Wagner et al., 2014). Sartore et al. (2024) calculated critical lengths between 0 and 39 m for a ~ 200 m thick ice shelf, depending on model parameters and observed surface structure. However, our data show multiple submerged benches exceeding 100 m in length (in orthogonal direction with respect to the ice shelf front) for ice shelves of similar ice thickness (Fig. 4.12). This suggests that ICESat-2 observations of ice shelf benches could be used to better constrain models of calving (e.g., Mosbeux et al., 2020).

Most benches show bathymetric signals up to approximately 15 m below the surface. Observations of benches where the bathymetric signal is clear in the ICESat-2 data appear to show a subsurface rampart-moat structure that mirrors the shape of the above-water rampart-moat. In many cases, this subsurface rampart-moat is also visible in coincident satellite imagery, with the subsurface moat evident as a darker band between the calving front and the brighter subsurface rampart (Fig. 4.12, left images). In cases where the bench is clearly visible in ICESat-2 data and exhibits a subsurface rampart-moat geometry, the bathymetric signal typically drops off sharply at a depth shallower than the maximum measured water depth at the subsurface moat. This suggests that the end of the submerged bench likely coincides with this sharp bathymetric drop-off, rather than ICESat-2 merely losing the signal at a certain depth. These findings are consistent with the hypothesized mechanism of rampart-moat development and the growth of submerged benches due to wave erosion at the ice shelf front. As continued wave erosion at the calving front causes

the bench to grow, the ice shelf front progressively flexes further upward, causing wave erosion at sea level to occur at progressively larger vertical distances from the increasing rampart elevation. Meanwhile the submerged bench flexes upward with the rest of the ice shelf, eventually causing the subsurface geometry of the bench to mirror the shape of the above-water rampart-moat. The presence of these features in both the bathymetric and surface elevation data supports the idea that submerged benches play a significant role in the mechanical behavior of ice shelves and their eventual calving.

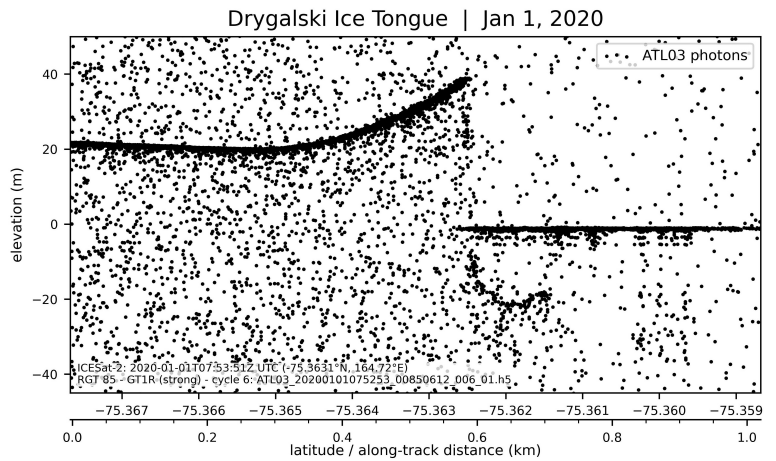
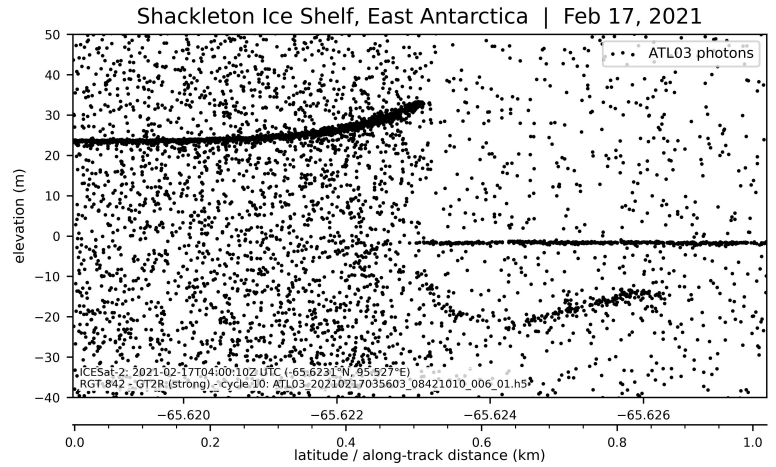
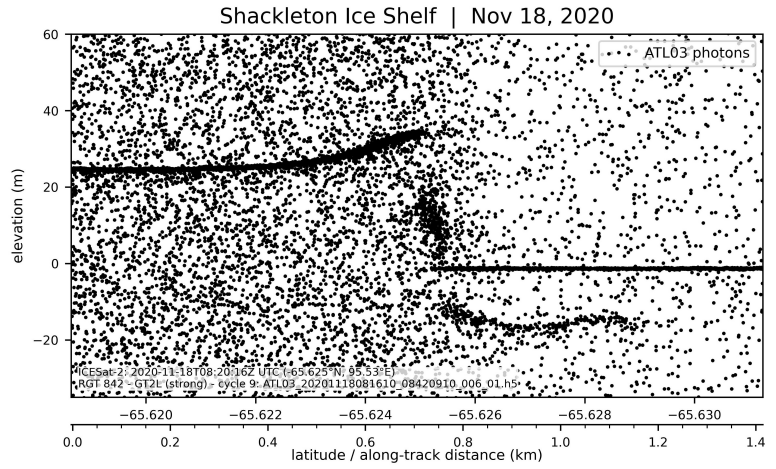
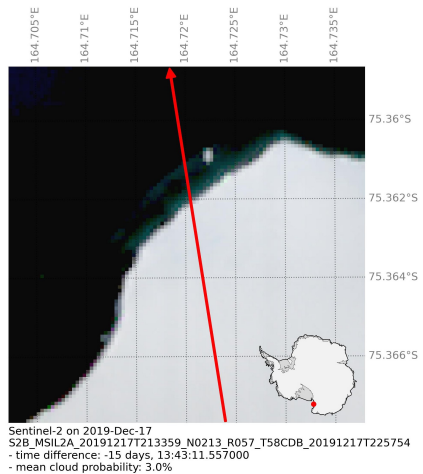
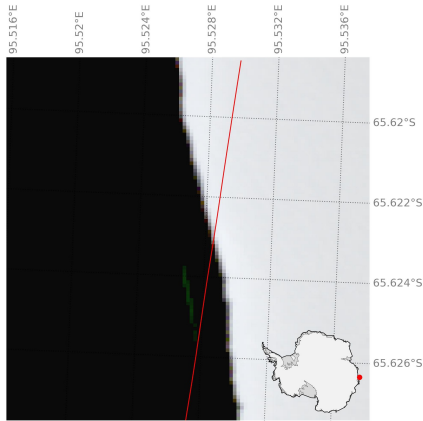
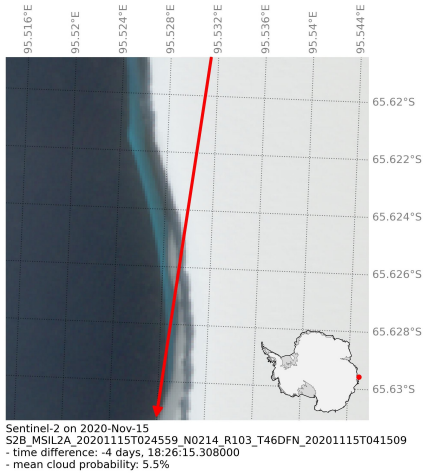
4.3.4. Summary and future outlook

We presented the first observational evidence of submerged benches at the front of Antarctic ice shelves, which reveal their geometry below the ocean surface. These features are clearly visible ICESat-2 photon data in various locations across Antarctica. We demonstrated, that it is possible to infer their characteristic shape, as well as their length and depth in examples where ICESat-2 data quality is high. The observations we presented are consistent with previously suggested mechanisms for wave erosion, buoyancy-driven flexure and calving.

A comprehensive dataset of ICESat-2 ice shelf bench observations could be generated using methods similar to FLUID/SuRRF for detection of a bathymetric signal near the calving front. This would make it possible to relate rampart-moat parameters (such as the ones from Becker et al. (2021)) to the observed morphology of benches, and observed calving events, to obtain a better understanding of this ice shelf calving process. This suggests that ICESat-2 observations of ice shelf benches could constrain parameters in models of this mode of ice front calving and ice shelf mass loss.

Figure 4.12: Three examples of ICESat-2 observations of ice shelf benches in East Antarctica. The images on the left are Sentinel-2 scenes. ICESat-2 ground tracks are overlain as red arrows. The bench is visible extending up to a length of approximately 110 m past the ice shelf calving front in all Sentinel-2 images, based on visual inspection and manual measurements on the georeferenced imagery. The ATL03 photon elevations in the plots on the right are geoid-corrected, so that the ocean surface is approximately at 0 m.

4. Antarctic Ice Shelf Mass Balance Processes: High-Resolution 3D Satellite Observations



4.4. Acknowledgements

Section 4.1, in full, is currently being prepared by Arndt, P.S. and Fricker, H.A. for submission for publication of the material. Sections 4.2 and 4.3 were prepared for this dissertation. Subsection 4.2.4 is a summary of the material in: Warner, R.C., Fricker, H.A., Adusumilli, S., Arndt, P.S., Kingslake, J. and Spergel, J.J. (2021). “Rapid formation of an ice doline on Amery Ice Shelf, East Antarctica.” *Geophysical Research Letters*, 48(14). DOI: 10.1029/2020GL091095. The dissertation author was a coauthor on this publication, and created all figures reproduced in subsection 4.2.4. The dissertation author was the author of the material in chapter 4 and the primary investigator of all contents except the paper summarized in subsection 4.2.4.

CHAPTER 5: SUMMARY AND CONCLUSIONS

The objective of the research described in this dissertation was to provide improved observations of critical ice sheet mass loss processes that are not yet understood well enough to be adequately represented in models of future ice sheet change, with a focus on processes driven by surface meltwater pooling in supraglacial hydrological systems. Through the use of high-resolution satellite data, our research has developed new tools and datasets that are essential for understanding the future stability of the ice sheets and ultimately their contribution to sea level rise. These advancements represent crucial steps toward more accurate predictions of ice sheet behavior and sea level rise in a warming climate.

5.1. Summary

In **Chapter 2**, we demonstrated that ICESat-2 can measure the depth of pooled surface meltwater from space, and presented a framework that allows for automatic detection and depth determination of supraglacial melt lakes across both the Greenland and Antarctic ice sheets. This chapter introduced the FLUID/SuRRF framework, a novel, automated method for extracting lake depth information from ICESat-2’s photon-level laser altimetry data. ICESat-2’s capability to measure meltwater depths from space is a significant improvement in our observational capabilities, as it provides direct, high-accuracy depth measurements over vast and previously under-sampled regions. This framework addresses a major gap in our ability to quantify meltwater volumes, which are critical for understanding processes that could potentially have significant impacts on ice dynamics

and mass loss. By offering a scalable and automated satellite-based solution, this research lays the foundation for routine, large-scale monitoring of meltwater volumes across the ice sheets, improving the observational data that can be used to inform ice sheet models.

In **Chapter 3**, we applied the FLUID/SuRRF framework to generate the first comprehensive, pan-Greenland dataset of supraglacial melt lake depths from ICESat-2 observations, covering the period from 2019 to 2023. This dataset provided novel insights into the spatial and temporal variability of melt lake depths across the Greenland Ice Sheet. We discovered distinct patterns in lake formation and depth variability, with deepest lakes found at low elevations and lakes typically migrating to higher elevations and deepening over the course of the annual melt season. This information is vital because it highlights the dynamic nature of meltwater accumulation and drainage, processes that are poorly understood but critical for predicting the response of the Greenland Ice Sheet to future climate warming. Furthermore, by integrating our ICESat-2 lake depth data with passive optical imagery, we demonstrated that using data fusion and machine learning approaches can significantly improve estimates of meltwater volumes, reducing errors by over 60% compared to traditional methods. This chapter emphasizes the importance of combining different types of satellite data to refine estimates of meltwater contributions to ice sheet mass balance, offering a path toward more comprehensive and accurate monitoring.

In **Chapter 4**, we extended our analysis to the Antarctic Ice Sheet, presenting the first pan-Antarctic dataset of supraglacial lake depths from ICESat-2 data. This is important because Antarctic surface melt is less well-studied and understood than that of Greenland, yet its potential to destabilize ice shelves through meltwater-induced hydrofracture could lead to catastrophic ice shelf collapse. Our research revealed that, unlike in Greenland, melt lakes in Antarctica migrate downstream and toward the floating ice shelves through the melt season, a phenomenon that has not been quantified before. More-

over, combining ICESat-2 data with various other high-resolution satellite data products provided evidence of previously unobserved processes and features, such as doline formation — where surface lakes drain through ice shelves and trigger a flexural rebound in response to the loss of water from the ice shelf surface — and flexure of ice shelf fronts due to a submerged ice shelf bench created by wave erosion, which impacts calving dynamics. These findings contribute to a deeper understanding of processes having potentially large impacts on ice shelf stability, an essential factor in predicting future Antarctic contributions to sea level rise. By using ICESat-2’s unique capabilities and merging ICESat-2 data with other satellite remote sensing observations, this research highlights the transformative potential of high-resolution, three-dimensional satellite data to uncover new processes that may ultimately have far-reaching implications for global sea level rise.

5.2. Methodological and observational advancements

This thesis predominately focused on developing novel methodologies that harness ICESat-2’s unique observational capabilities (Sect. 2.3.1) to create a new, comprehensive dataset of accurate supraglacial lake depth measurements spanning both the Greenland and Antarctic Ice Sheets across multiple melt seasons, with the ultimate goal of facilitating more accurate and high-resolution estimates of ice-sheet-wide surface meltwater volumes, which can improve our understanding of ice sheet mass loss processes and their implementation in models of future ice sheet evolution.

5.2.1. Leverage of ICESat-2’s unique bathymetric capabilities

ICESat-2 represents a breakthrough in satellite laser altimetry as the first and only satellite mission capable of directly measuring shallow water bathymetry from space (Sect. 2.3.1). Unlike past missions such as ICESat (Schutz et al., 2005), present missions like Global Ecosystem Dynamics Investigation (GEDI; Dubayah et al., 2020), or proposed mis-

sions such as Earth Dynamics Geodetic Explorer (EDGE) (EDGE; Helen A. Fricker, personal communication, November 2024), which use near-infrared wavelength lasers unable to penetrate water, ICESat-2 employs a green (532 nm) laser capable of measuring water depths exceeding 40 m (Markus et al., 2017; Dietrich et al., 2024). ICESat-2 therefore offers an unprecedented and unparalleled opportunity to directly observe the three-dimensional structure of supraglacial hydrological systems from space—a capability that no other satellite mission can match and is unlikely to be replicated in the foreseeable future.

The FLUID/SuRRF framework for automated detection and depth determination of supraglacial lakes in ICESat-2 data, presented in Chapter 2, is a critical step towards leveraging this capability and providing scientifically useful measurements of surface meltwater depths. We demonstrated that this framework makes it possible to extract supraglacial lake depths at ice-sheet-scale, while also presenting more broadly applicable methodological improvements, such as an improved treatment of ICESat-2 afterpulsing artifacts (Sect. 2.3.2.2) and improved signal photon density estimation and noise filtering in ATL03 photon data (Sect. 2.3.2.3). We further demonstrated that ICESat-2’s direct measurements of supraglacial lake depths are significantly more accurate than any alternative indirectly inferred depths from other satellite remote sensing products (Sect. 2.4.2.2), highlighting ICESat-2’s transformative potential for improving surface meltwater volume estimates.

5.2.2. **Generation of large-scale data products**

Our results in Chapters 3 and 4 indicate that overall coverage of ice sheet surface with supraglacial lakes is low, with only 0.033 % of ICESat-2 along-track distance corresponding to visible supraglacial lakebeds in Greenland (Sect. 3.3.1) and an even lower corresponding fraction of 0.0039 % over the Antarctic Ice Sheet (Sect. 4.1.4). The relatively low proportion of usable ICESat-2 supraglacial bathymetry measurements compared to the

total processed ATL03 data highlights the difficulty of processing ICESat-2 bathymetric data of supraglacial lakes at scale and underscores that scalable, automated methods such as FLUID/SuRRF are needed to detect and extract ICESat-2 supraglacial lake segments across the ice sheets. Our implementation of FLUID/SuRRF on the OSG Open Science Pool for distributed High-Throughput Computing (Sect. 2.3.4) provided an efficient, reproducible and low-cost method to generate a comprehensive dataset of supraglacial lake depths from ICESat-2 photon data. We used this method to generate a comprehensive cross-ice-sheet data product of supraglacial lakes depths from 2018 to 2023 (Sect. 3.3.1 and 4.1.4), which provided key insights into surface hydrological processes on both the Greenland and Antarctic ice sheets, revealing important differences and commonalities between surface-meltwater-driven processes on both ice sheets (Sect. 5.3). Although processing and analyzing multi-source high-resolution satellite data at the scale of entire ice sheets over extended time periods – while also capturing the fine-scale details necessary to observe critical small-scale processes – can be highly challenging, our successful generation of a comprehensive five-year dataset of accurate supraglacial lake depths across both ice sheets demonstrates the significant value of such efforts.

5.2.3. Expansion of surface meltwater observations to high latitudes

While ICESat-2’s ability to measure water depths from space was the main motivation of our research, its high-inclination orbit provides another notable observational capability that distinguishes it from other satellite missions. This is because previous “inventory-style” studies mapping supraglacial lake extents across Antarctica (e.g., Stokes et al., 2019; Dirscherl et al., 2021; Corr et al., 2022; Arthur et al., 2022; Tuckett, 2023) have relied on high-resolution passive optical imaging satellites, such as Landsat or Sentinel-2, or Synthetic Aperture Radar (SAR) missions, such as Sentinel-1. These missions have lower-inclination orbits and so are limited to acquiring imagery between latitudes 83°N

and 83°S. Observations of supraglacial meltwater features at higher latitudes have, therefore, been limited to sparse aerial or ground photography collected during field campaigns, with no such features reported beyond 85.2°S (Kingslake et al., 2017; Bell et al., 2018). Since ICESat-2’s measurements extend up to 88°N/S, we were able to map the extent and depths of Antarctic supraglacial lakes at high latitudes, where surface meltwater features had not previously been reported. This included lakes near the southernmost section of the Ross Ice Shelf grounding line and close to the Transantarctic Mountains, at latitudes higher than 85.9°S and within just 450 km of the South Pole. (Sect. 4.1.4.1).

5.2.4. **Data fusion and machine learning for meltwater volume estimates**

While ICESat-2 provides accurate measurements of surface meltwater depths, its limited temporal resolution and spatial coverage along discrete ground tracks necessitate complementary approaches to scale observations more broadly in space and time (Sect. 2.4.4). To address this, we developed an approach that integrates ICESat-2 depth measurements with spectral reflectances from passive optical imagery and improves lake volume estimates (Sect. 3.2). We presented a method to extract Sentinel-2 data along ICESat-2 supraglacial lake segments detected by FLUID/SuRRF and applied it to all available data over the Greenland Ice Sheet (Sect. 3.2.5), resulting in a ice-sheet-wide training data set that connects ICESat-2-measured water depths to Sentinel-2 spectral reflectances and can therefore be used to calibrate existing methods or to train new models for predicting water depth from optical imagery.

We used this training data to fit a random forest model for predicting meltwater depths and volumes from Sentinel-2 (Sect. 3.2.6). We demonstrated that our model is able to estimate supraglacial lake depth from Sentinel-2 imagery with an accuracy of approximately 0.5 m (Sect. 3.3.2.1), which we successfully validated against independent *in*

situ sonar observations (Sect. 3.3.2.2). We further showed that our random forest model significantly outperforms both traditional (RTE-based) methods that are independent of the ICESat-2 data (Sect. 3.3.2.4), as well as previously employed empirical methods for fitting the data, such as the band-ratio method (Sect. 3.3.2.3), reducing overall mean errors by over 60 % in all cases.

We conclude that our combined ICESat-2 and Sentinel-2 training data set can be used to significantly improve high-resolution meltwater depth and volume estimates from optical imagery, but that achieving such improvements at ice-sheet-wide scales requires more sophisticated methods than the empirical methods that have been previously employed for this task. Our findings indicate that machine learning methods, particularly those capable of capturing multiple non-linear relationships, are well-suited for this purpose. By leveraging such methods, our training data offers the potential for generating accurate, ice-sheet-wide surface meltwater depth and volume products in the future. This indicates that combining both data fusion and machine learning approaches has great potential to provide further ice sheet-wide observational insights into processes that have a potentially large future impact on ice sheet mass balance and sea level rise, but are currently not understood well enough to be adequately represented in long-term future projections.

5.2.5. Observational strategies for Surface Topography and Vegetation

The methods and observations presented in this thesis improve estimates of supraglacial meltwater depths and volumes across both ice sheets and provide valuable insights into where, when, and how surface melt on the ice sheets can have an impact on ice dynamical and mass balance processes. More broadly, the techniques described will aid the continued development of key observational datasets at ice sheet-wide scales. Together, these studies demonstrate how multi-modal studies fusing high-resolution three-dimensional

satellite measurements with optical imagery can provide valuable Earth-observational insights that may extend well beyond ice sheet hydrology. We suggest that combining multi-sensor satellite observations with machine learning methods is an effective strategy for accurate and continuous large-scale monitoring in the broader context of global Surface Topography and Vegetation (STV; Donnellan et al., 2024), but can be especially effective in challenging environments such as the remote and rapidly evolving supraglacial hydrological networks on the ice sheets.

5.3. Insights into the geographical distribution, depths and temporal evolution of supraglacial lakes on both ice sheets

In addition to the methodological and observational advancement presented in this dissertation, we provide a comprehensive analysis of ice sheet surface hydrological processes on both the Greenland and Antarctic Ice Sheets, leveraging the first pan-ice-sheet dataset of supraglacial lake depths produced from ICESat-2 data. Our findings highlight critical distinctions and commonalities between the two ice sheets, offering new perspectives on the underlying processes and potential drivers affecting their behavior in a warming climate.

Our data indicate that on both ice sheets, peak melt occurs approximately one month after summer solstice (Sect. 3.3.1.4 and 4.1.4.3), underscoring an overall strong control of summertime warming on the formation of supraglacial lakes, with maximum meltwater coverage occurring in late summer due to the cumulative effects of gradual firn saturation and pooling of excess runoff at the surface as the melt season progresses.

While the highest density of supraglacial lakes on the Greenland Ice Sheet is encountered at elevations between 750 m and 1700 m (Sect. 3.3.1.3), supraglacial lakes on the Antarctic Ice Sheet predominately form at lower elevations < 200 m, on and near the floating ice shelves (Sect. 4.1.4.2). This is driven by Greenland’s overall warmer climatic

setting, allowing above freezing temperature to reach higher elevations on the ice sheet (van den Broeke et al., 2023).

Our data further reveal that supraglacial lakes across Greenland typically grow deeper than those in Antarctica (Sect. 3.3.1.2 and 4.1.4). This is primarily due to higher meltwater production driven by Greenland’s warmer climate (van den Broeke et al., 2023), and the strong influence of fast ice flow and high basal slip ratios over rough bedrock topography on forming deep surface depressions on the grounded ice in Greenland’s ablation and percolation zones (Ignéczi et al., 2018). In contrast, the tendency of Antarctic supraglacial lakes to remain shallower can be attributed to lower overall surface meltwater production during Antarctica’s colder and shorter melt season (Trusel et al., 2013), efficient channelized surface drainage of meltwater in blue ice zones on grounded ice (Kingslake et al., 2017), and the absence of bedrock control on the formation of deep surface depressions on the floating ice shelves (Macdonald et al., 2018).

5.3.1. Controls on geographical distribution of lakes

To first order, the spatial distribution of supraglacial lakes around both the Greenland and Antarctic ice sheets appears similar: lakes cluster around the fringes of both ice sheets in regions where low elevations result in sufficiently high temperatures for significant surface melt to occur.

In Greenland, an abundance of supraglacial lakes in the Southwest and Central West and a striking scarcity in the Southeast (Sect. 3.3.1.1) reflect the complex interplay of competing atmospheric, radiative, surface hydrological, firn, subglacial and ice dynamical processes that can either favor or inhibit the pooling of water in surface depressions. In the Southwest and Central West, particularly extensive low-albedo bare-ice ablation zones (Ryan et al., 2019), prolonged above-freezing temperatures (Mernild et al., 2011), high rates

of summer ice thinning (Slater et al., 2021), high rainfall amounts (Box et al., 2023), and relatively low surface slopes with moderate topographic relief (Ignéczi et al., 2018) favor the development of widespread supraglacial lake coverage. In contrast, in the Southeast, steep surface slopes, abundant crevassing, and thick, permeable firn surfaces sustained by high snow accumulation rates (Sundal et al., 2009; Poinar et al., 2017; Gallagher et al., 2022) inhibit the formation of supraglacial lakes.

In Antarctica, a striking clustering of supraglacial lakes near the grounding lines of ice shelves (Sect. 4.1.4.1) suggests that the spatial distribution of lakes is largely driven by interactions between katabatic and foehn winds and surface topography to form low-albedo blue ice zones upstream of grounding zones (Tollenaar et al., 2024), in conjunction with ice shelf flexure at the slope break in the grounding zone (Vaughan, 1995). Surface melting is initiated in the blue ice zones (Bintanja and Van Den Broeke, 1995; Lenaerts et al., 2017) and then meltwater is efficiently transported across the ice surface downstream and towards the grounding zone (Kingslake et al., 2015, 2017), where ice shelf flexure creates surface depressions that favor the pooling of meltwater in supraglacial lakes (Trusel et al., 2022). In Antarctica, ICESat-2 was also able to detect the highest-latitude supraglacial lakes reported to date at up to $> 85.9^{\circ}\text{S}$ near the southernmost part of the Ross Ice Shelf grounding line and in close proximity to the Transantarctic mountains (Sect. 4.1.4.1), which confirms previous reports of supraglacial lake formation being possible at extreme elevations and latitudes in blue ice zones in combination with warm and dry winds, and particularly in close proximity to exposed bedrock (Kingslake et al., 2017; Bell et al., 2018).

5.3.2. Controls on maximum lake depths

Our data indicate that the deepest supraglacial lakes on both the Greenland and Antarctic ice sheets are typically found at lower elevations and late in the melt season (Sect.

3.3.1.3 and 4.1.4.2). This trend is likely predominately driven by continuous meltwater input from upstream sources throughout the melt season, enabling deep surface depressions to fill to higher levels. Additionally, lake bottom ablation may contribute to this process (Tedesco et al., 2012; Arthur et al., 2020b). On Antarctic ice shelves, the filling of supraglacial lakes further deepens their basins through localized downward flexure of the ice shelf surface caused by surface loading (Banwell and Macayeal, 2015).

The geographic distribution of the deepest lakes on the two ice sheets is shaped by factors that govern the formation of deep, closed surface depressions in which meltwater can pool to form lakes; however, these controls differ significantly between Greenland and Antarctica. In Greenland, where most lakes are located on thick grounded ice, the formation of deep lakes is primarily influenced by the interaction of bedrock roughness, thermal state, and ice velocity (Sect. 3.3.1.2). For example, our dataset reveals that the deepest lakes are concentrated in the Northwest drainage basin, a region whose margin is characterized by rough basal topography and fast-flowing ice (Rippin, 2013). High basal meltwater production (Karlsson et al., 2021), coupled with spatial variability in basal slip ratios (Bons et al., 2018; MacGregor et al., 2022), facilitates the transfer of long basal wavelengths to the ice surface through thick ice (Sergienko, 2013; Ignéczi et al., 2018). This process creates large and deep surface depressions capable of retaining substantial meltwater, leading to the formation of particularly deep lakes. Conversely, supraglacial lakes in Southwest Greenland tend to remain shallower, likely due to smoother basal topography, lower ice velocities, and reduced basal meltwater production, which collectively result in a weaker influence of bedrock undulations on surface topography and meltwater routing (Ignéczi et al., 2016; Fan et al., 2024).

In Antarctica, where most lakes form on or near the floating ice shelves, the formation of deep surface depressions is predominantly driven by ice shelf flexure near the

grounding zone (Sect. 4.1.4.2). The transition from grounded ice to floating ice creates a slope break that results in a local minimum in surface elevation downstream of the grounding line (Vaughan, 1994; Fricker and Padman, 2006). Meltwater from upstream is funneled into these depressions, where it accumulates over consecutive melt seasons, progressively deepening the depressions and forming deep lakes in the grounding zone (Trusel et al., 2022). Further upstream, efficient channelized surface drainage and downstream meltwater transport across the steep surfaces of blue ice zones likely inhibit the formation of deep lakes (Kingslake et al., 2015, 2017; Lenaerts et al., 2017).

These findings demonstrate that a range of factors – including basal topography, subglacial hydrology, ice flow dynamics, channelized surface drainage, and ice shelf flexure – jointly regulate the depths to which supraglacial lakes can grow. Future projections of supraglacial hydrology and its impact on ice sheets should account for these interconnected processes to better understand and predict the role of supraglacial lakes on mass loss processes.

5.3.3. Intra-seasonal evolution of supraglacial hydrology

Our data show that within each melt season in Greenland the region of highest supraglacial lake density migrates to higher elevations over time (Sect. 3.3.1.4), which is opposite to Antarctica, where the average location of supraglacial lakes shifts downstream as the melt season progresses (Sect. 4.1.4.3).

We attribute the upward migration of supraglacial lake locations in Greenland to its prolonged melt season, which allows for surface melt to extend to progressively higher elevations as temperatures increase and the surface firn layer becomes saturated over time (Sundal et al., 2009). This leads to the formation of new supraglacial lakes at higher elevations later in the season, while lakes at lower elevations are often removed via drainage

to the bed or the development of efficient supraglacial drainage networks (Sect. 3.3.1; Johansson et al., 2013; Smith et al., 2015; Stevens et al., 2016). The simultaneous addition of higher-elevation lakes and removal of lower-elevation lakes creates the observed upward migration of supraglacial lake locations in Greenland over the course of each melt season.

In contrast, Antarctic surface melt is initiated in higher-elevation blue ice zones upstream of the ice shelves’ grounding lines (Lenaerts et al., 2017), and the majority of surface meltwater is subsequently efficiently transported across the ice surface downstream towards the ice shelves (Kingslake et al., 2017), where particularly deep supraglacial lakes can form near the slope break due to ice shelf flexure in the grounding zone (Vaughan, 1995; Trusel et al., 2022). Due to the orographically controlled and thus limited spatial extent of surface melting in blue ice zones (Van Den Broeke and Bintanja, 1995), and the lack of a prolonged melt season during which above-freezing temperatures are encountered at progressively higher elevations (Trusel et al., 2013), the formation of new lakes at higher altitudes later in the summer is relatively rare. The combination of efficient downstream meltwater transport across the surface, absence of removal of low-elevation lakes by drainage, and limited formation of new lakes at higher elevations results in the observed downstream migration of supraglacial lake locations over the course of each Antarctic melt season.

This striking difference between the observed intra-seasonal evolution of supraglacial hydrology on the Greenland and Antarctic ice sheets highlights the different roles that supraglacial lakes have on each ice sheet, but also suggests that the impact of meltwater on Antarctic Ice Sheet processes may drastically change with the projected Greenlandification of Antarctica (Bell et al., 2018; Mottram et al., 2021) – a factor that needs to be considered in models of the future evolution of the Antarctic Ice Sheet.

5.3.4. Greenlandification: insights from present-day Greenland for the future of Antarctica

Our findings demonstrate that deep supraglacial lakes are widespread on grounded ice near the grounding zones of Antarctic ice shelves (Sect. 4.1.4.1). These lakes have the potential to drain to the bed and drive both short-term (Tuckett et al., 2019) and seasonal (Boxall et al., 2022) increases in ice flow, mirroring processes frequently observed in Greenland’s ablation and percolation zones (Zwally et al., 2002). With intensifying surface melting, the formation of surface-to-bed hydraulic connections on grounded ice in Antarctica is expected to become more frequent (Bell et al., 2018), potentially leading to a future Antarctic ice flow regime that is increasingly influenced by seasonal surface meltwater input (Tuckett et al., 2019). This potential transition is referred to as the “Greenlandification” of the Antarctic Ice Sheet (Mottram et al., 2021).

The high prevalence of deep lakes on grounded ice just upstream of Antarctic ice shelf grounding zones underscores the high potential of lake drainage through surface-to-bed hydraulic connections impacting Antarctic ice dynamics, as has been directly observed in most other glaciated regions of the world (e.g., Iken and Bindshadler, 1986; Zwally et al., 2002) and indirectly inferred on the Antarctic Peninsula (Tuckett et al., 2019; Hodgson et al., 2022; Boxall et al., 2024). Due to the crucial impact of supraglacial lakes on the stability and potential collapse of Antarctica’s floating ice shelves (e.g., Glasser and Scambos, 2008; Banwell et al., 2013; Leeson et al., 2020), lakes on grounded ice in Antarctica have historically received comparatively little attention. This raises the possibility that Greenlandification may already be in its infancy in Antarctica, though largely unnoticed due to a lack of focused observational studies. Our observations highlight the urgent need for further investigation into the role of supraglacial lakes on grounded ice in Antarctic mass loss processes. In general, comparative studies between Greenland and Antarctica

will also be crucial to evaluate how well insights from present-day Greenland processes can inform predictions of Antarctic ice sheet behavior under future warming scenarios.

In summary, the unique ICESat-2-derived dataset of supraglacial lakes across the Greenland and Antarctic ice sheets presented in this thesis has provided key insights into ice sheet surface hydrological processes and their potential drivers, with a focus on existing observational and knowledge gaps regarding the depths of supraglacial melt features. By examining both ice sheets, it provides a comparative framework that reveals fundamental differences and shared mechanisms driving patterns in ice sheet surface hydrology. In the light of the projected Greenlandification of the Antarctic ice sheet, these insights underscore the importance of cross-ice-sheet comparative studies to anticipate the future evolution of ice sheet hydrological systems in a warming world. Such process-level understanding is essential for reducing uncertainties in sea-level rise projections and developing robust models of future ice sheet behavior.

5.4. Future work

Future work in this area of research should ideally focus on integrating a wide range of multi-sensor historical, current, and future satellite observations to extend the findings presented here, and to potentially discover new, previously unobserved ice sheet processes. Insights provided from such satellite remote sensing data can then be further used to identify targets for focused regional studies, process-oriented modeling efforts, or field campaigns that can provide valuable data for validation or observations of processes that cannot be made from space. Expanding the spatial coverage and temporal range of the satellite-derived data products presented here would allow for the detection of long-term trends and provide further insights into the processes driving ice sheet change. These data could then be used to further validate and assimilate models. They may also be used to inform new,

critical processes to be included in future projections of long-term ice sheet evolution. The ultimate goal of these efforts is to provide models that accurately represent the underlying physical processes, and therefore inspire confidence in their ability to accurately predict the long-term responses of the ice sheets to future warming. This is important because policymakers and local planners in coastal regions need actionable future projections of climate change and sea level rise to be able to develop effective and efficient mitigation and adaptation strategies.

5.4.1. Cross-ice-sheet data products and studies

More cross-ice sheet comparative studies of the climatic, geologic and dynamic controls on the formation and behavior of supraglacial hydrological systems and their impacts on both ice sheets are needed in order to identify crucial differences and commonalities between both ice sheets, which may reveal fundamental insights into how ice sheet behavior may change in a warming climate.

In the context of this thesis, the first and most obvious step would be to use the methods described in Chapter 3 to produce a comprehensive, cross-ice-sheet training data set combining FLUID/SuRRF meltwater depth measurements from ICESat-2 for both Greenland and Antarctica with reflectances from multiple passive optical imaging missions such as Sentinel-2 and the Landsat missions. Using machine learning methods similar to our random forest model presented for Greenland in Sect. 3.3.2, this training data set could be used to develop a unified efficient and accurate model for predicting supraglacial meltwater depths and volumes at high spatial and temporal resolutions across both ice sheets. Applying this model to all available optical imagery over the ice sheets would make it possible to create a comprehensive cross-ice-sheet data product mapping the distribution, depths and volumes of supraglacial lakes with unprecedented coverage and accuracy at high

spatiotemporal resolution.

Due to the critical role of rapid lake drainage on both grounded ice and the floating ice shelves, this data should also be used to detect lake drainages across both ice sheets with a focus on where and when supraglacial lakes drain and quantify the volumes of meltwater that are lost. Further advances aimed at minimizing the various biases and correlations inherent to data sets created from satellite imagery (Sect. 3.2.4) could build on the work by Tuckett et al. (2021), thus allowing for more robust statistical analyses aimed at identifying patterns in – and potential drivers of – supraglacial lake formation, meltwater transport across the surface and rapid lake drainages to the underlying bed or ocean. Based the potential controls on supraglacial lake formation and surface hydrological behavior in this thesis, such efforts should include a wide array of data that is available for both ice sheets, such as outputs from regional climate and firn densification models, surface topographical data from digital elevation models, maps of exposed bedrock, ice flow velocities, as well as estimates of basal topography and basal slip ratios.

In general, a higher level of collaboration between the Greenland and Antarctic Ice Sheet research communities would likely lead to better standardization of methodologies and data products across both ice sheets, thus making it easier to identify important conceptual cross-ice-sheet commonalities that may lead to fundamental insights into ice sheet behavior that are independent of the two ice sheets’ present-day climatic settings. This is particularly important in light of the potential “Greenlandification” of the Antarctic Ice Sheet, as it would aid the development of models that can predict the long-term future response of both ice sheets to a warming climate more confidently, even as the processes driving their observed behaviors may change significantly under significant climate change.

5.4.2. Regionally-focused and process-scale studies

The findings presented in this thesis highlight significant regional variability in supraglacial lake behavior, providing critical insights into the drivers of meltwater processes and their impacts on ice sheet dynamics. However, further regionally focused and process-scale studies are necessary to refine our understanding of these processes and their implications for ice sheet mass balance.

5.4.2.1 Regional drivers of lake formation and depth in Greenland

Our data reveal that the deepest supraglacial lakes in Greenland are concentrated in the Northwest, where they are significantly deeper than lakes in other regions (Sect. 3.3.1.2). This region's rough basal topography, fast ice flow, and spatially variable basal slip ratios likely contribute to the formation of large surface depressions capable of retaining significant meltwater volumes. Further investigations into these lakes could elucidate the interplay of surface and basal processes controlling lake depth on grounded ice, providing insights into the mechanisms that drive regional variability in supraglacial lake depths on grounded ice.

In Northeast Greenland, the combination of rough basal topography and fast-flowing ice over a thawed bed far inland supports the formation of surface depressions suitable for meltwater pooling beyond the current extent of runoff (Ignéczi et al., 2016). Regional studies here could explore the potential for future upstream expansion of supraglacial lake coverage under a warming climate. These studies could also evaluate the implications of expanding lake coverage for ice dynamics and long-term mass loss, particularly in regions with complex interactions between surface and subglacial hydrology.

Although rapid lake drainage to the bed is well-documented as a driver of transient ice flow accelerations (e.g., Zwally et al., 2002; Das et al., 2008; Maier et al., 2023), its

long-term effects on ice sheet mass loss remain poorly understood (e.g., Sundal et al., 2011; Hoffman et al., 2011; Nienow et al., 2017). Regional studies in Greenland could focus on the temporal evolution of lake drainage impacts, investigating whether repeated drainage events amplify long-term mass loss or whether transient accelerations are offset by subsequent stabilization of ice flow.

5.4.2.2 Hydrological processes on grounded ice in Antarctica

Our data demonstrate the widespread presence of supraglacial lakes on grounded ice above the grounding zones of Antarctic ice shelves (Sect. 3.3.1.1). Since evidence of summertime surface meltwater influencing ice flow on the Antarctic Peninsula is growing (Tuckett et al., 2019; Boxall et al., 2022), future studies should prioritize determining whether lake drainages to the bed are already occurring in Antarctica and assess their potential impacts on ice dynamics. While the Antarctic Peninsula is a logical starting point for such studies, regional investigations in East Antarctica, where supraglacial lakes are abundant upstream of many grounding lines, could explore whether similar processes are occurring in this colder region. These studies would provide key insights into the potential onset of “Greenlandification” in Antarctica (Bell et al., 2018; Mottram et al., 2021) and how surface hydrology-driven ice dynamics may differ between the two ice sheets.

5.4.2.3 Meltwater routing and ice shelf stability

On Antarctic ice shelves, the preferential pooling of meltwater and formation of deep supraglacial lakes in the grounding zone (Sect. 4.1.4.2) plays a critical role in meltwater routing and ice shelf stability. The Amery Ice Shelf, where deep lakes repeatedly fill and drain at the grounding line (Trusel et al., 2022), offers an ideal site for studying these processes. Future work could focus on how grounding zone lakes influence downstream meltwater transport and whether their repeated filling and drainage has significant long-

term impacts on grounding zone dynamics.

Ice doline formation on the free-floating sections of ice shelves is another important process affecting meltwater routing and ice shelf stability. Dolines are most commonly observed on the Amery and George VI ice shelves (Sect. 4.2.5.2). Regional studies on these ice shelves could investigate the conditions under which doline formation destabilizes ice shelves by routing meltwater flow to areas further downstream, and identify potential thresholds for this process to trigger large-scale ice shelf disintegration.

5.4.2.4 Potential links between buoyancy-driven calving and hydrofracture

In regions where surface meltwater extends to the calving fronts of ice shelves, buoyancy-driven flexure (Sect. 4.3) could concentrate large quantities of meltwater in moats near the ice shelf front. This process has the potential to accelerate buoyancy-driven calving or even initiate hydrofracture-driven ice shelf collapse. While many Antarctic ice shelves currently lack significant surface melt at their calving fronts, studies of past events on the Antarctic Peninsula’s Larsen B and Wilkins ice shelves – both of which have experienced large-scale disintegration – could provide valuable insights into the conditions under which this hypothesized mechanism could operate.

In summary, future regionally focused and process-scale studies should aim to build on the findings of this thesis, targeting key regions and processes that have the potential to significantly influence the long-term evolution of ice sheets. By combining high-resolution observations with process-oriented modeling and field validation, such studies can provide a more comprehensive understanding of how surface hydrology interacts with ice dynamics and stability across diverse regions of the Greenland and Antarctic ice sheets.

5.4.3. Recommendations for field measurements

Strategic field measurements continue to be crucial for further validation of any satellite-derived datasets presented here and those developed in the future. These measurements should target specific regions and processes to complement satellite remote sensing data, with a focus on improving the accuracy of meltwater depth and volume estimates and gaining a better understanding of the impacts that lake drainage has on dynamics and stability. Below, we outline recommendations for field campaigns in Greenland and Antarctica, tailored to the unique roles of surface meltwater and logistical challenges in each region.

5.4.3.1 Field campaigns in Greenland: focus on ICESat-2 validation

Greenland provides an ideal environment for calibrating and validating ICESat-2 measurements of supraglacial lake depths. This is important, since no direct ground truth validation data for ICESat-2 measurements of supraglacial bathymetry exist, and because our results from Sect. 2.4.2.2 indicate that most methods for locating the lakebed in ATL03 point clouds could potentially be biased towards overestimating lake depths. As the only satellite capable of directly measuring supraglacial lake depths from space, and with no successor mission with the same capability currently planned, it is critical to collect in situ validation data while ICESat-2 remains operational.

- **Established methods:** Field campaigns should employ established methods for acquiring in situ sonar measurements using remote-controlled boats or rafts. These methods have proven effective, as demonstrated by Lutz et al. (2024), whose data was indispensable for independently validating our water depth predictions from optical imagery (Sect. 3.3.2.2). Remote-controlled equipment is particularly important in this setting to mitigate the risks associated with rapid lake drainage.

- **Target locations:** Efforts should focus on regions where deep lakes form consistently in predictable locations, lake density is high, ICESat-2 ground tracks are densely spaced, and passive optical imagery revisit times are frequent. These criteria make the fast moving, marine-terminating outlet glaciers North and Northeast Greenland particularly suitable targets.
- **Timing and flexibility:** Aligning field measurements with ICESat-2 overpasses is logistically challenging due to the ephemeral nature of melt lakes and the effects of clouds and ice cover. A robust field plan should identify multiple candidate lakes, allowing flexibility to adapt based on meteorological conditions and lake status during the campaign. The ICESat-2 data presented in Chapter 3 can guide the selection of lakes most likely to yield bathymetric measurements during overpasses.

5.4.3.2 Field campaigns in Antarctica: focus on the impacts of lake drainage

Field studies in Antarctica should prioritize understanding the effects that supraglacial lake drainage on ice shelves has on meltwater routing and stability, as well as the potential for grounded-ice lake drainage to influence ice dynamics.

Targeted studies on ice shelves: Field campaigns on the Antarctic Peninsula can offer insights into the impact of meltwater on ice shelves currently experiencing the warmest temperatures. Observations in this region can provide a valuable preview of how the rest of Antarctica might respond to future warming. Studies of the effect lake drainage on the fully floating portions of the ice shelves on meltwater routing should focus on dolines that have been observed to repeatedly fill and drain, such as those on the George VI Ice Shelf (Banwell et al., 2024). Campaigns exploring the effect of lake drainage in the grounding zone could target the Amery Ice Shelf, where repeated filling and draining of lakes in the grounding zone has been reported (Trusel et al., 2022). These studies would offer an opportunity to

make measurements that could reveal potential links between grounding zone flexure and dynamics, and the fill/drain cycles of these deep lakes.

Impact on ice dynamics: The ICESat-2 data presented in this thesis indicate that a significant fraction of deep Antarctic supraglacial lakes are found on grounded ice upstream of the grounding zone (Sect. 4.1.4.2), which have the potential to influence ice dynamics via surface-to-bed hydraulic connections. Initial field studies of such lakes should target the Antarctic Peninsula, where evidence of surface meltwater input leading to short-term and seasonal ice flow accelerations is emerging (Tuckett et al., 2019; Boxall et al., 2022). Such studies could use Seismometers to detect the tremors associated with drainage of supraglacial lakes to the bed (Röösli et al., 2014) in combination with GPS stations that can detect ice deformation and accelerations in ice flow in response to meltwater injection to the bed (Tedesco et al., 2013). Regionally focused satellite studies would first need to identify potential field sites where lake drainage events have occurred and are likely to occur again.

Field measurements are indispensable for advancing our understanding of supraglacial hydrology and its impacts on ice sheet dynamics. By strategically targeting key regions and processes, future campaigns can provide crucial validation for satellite observations, improve predictive models, and deepen our understanding of the mechanisms driving ice sheet change.

5.4.4. Enabling data-driven polar exploration

A lot has changed since the first polar explorers set foot on the ice sheets. Today, groundbreaking polar discoveries are often made not by those braving the unforgiving cold climates of Greenland and Antarctica but by researchers analyzing immense datasets collected by satellites. While direct fieldwork remains vital for validation and specific

localized studies, the increasing availability of remotely sensed data has transformed polar science into a data-driven discipline. However, this shift has introduced new challenges and demands new skills.

Developing ice-sheet-wide datasets from multi-sensor high-resolution satellite remote sensing data requires effective software development, large-scale computation, and data management. Recent advancements in cloud-based computing and data storage enable more accessible and collaborative studies that are easier to reproduce and build upon. However, to be able to take full advantage of the increasingly vast and complex datasets produced by modern satellites, the academic researchers involved in large-scale satellite remote sensing studies of the ice sheets need improved training in these relatively new methods, which have quickly become some of the most important aspects of conducting polar satellite remote sensing research. This effort will require close collaboration between educational and research institutions, data and computing centers, cloud computing and data storage providers, and the space agencies and private companies who plan and operate satellite missions and distribute the resulting data. Data science has become an integral part of modern-day polar exploration, but there is much work left in improving our tools and learning how to use them to push forward on this new frontier.

To ensure continuous records of meltwater and other key ice sheet processes, more funding is needed not only for the continued operation and development of satellite missions but also for supporting the researchers who carry out the essential analytical work. This includes funding for computational resources, data storage, and collaborative infrastructure, all of which are required for processing the vast amounts of data generated by modern satellite missions. Investment in these areas is critical for enabling the data-driven discoveries that are essential for understanding the future of the ice sheets and for informing policy decisions related to climate change mitigation and adaptation.

5.5. Conclusion

In this thesis, I have contributed to advancing our understanding of ice sheet surface hydrology by leveraging high-resolution satellite observations to uncover critical insights into the processes driving surface meltwater formation, distribution and depths of supraglacial lakes, and their impacts on ice sheet stability. These findings, spanning both the Greenland and Antarctic Ice Sheets, highlight the dynamic interplay between climatic, topographic, and hydrological factors that govern ice sheet behavior. By developing new methods and datasets, this research lays the foundation for more accurate predictions of ice sheet contributions to sea level rise. Looking ahead, continued collaboration between satellite missions, field campaigns, and data science innovations offers a promising pathway to uncover even deeper insights, ultimately equipping us with the tools to better anticipate and adapt to our changing planet.

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