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Applications of CryoSat-2 swath radar altimetry over Icelandic ice caps and Patagonian ice fields

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THE UNIVERSITY of EDINBURGH

Thesis submitted in fulfilment of the requirements for the degree of
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to the
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I declare that this thesis has been composed solely by myself and that it has not been submitted, either in whole or in part, in any previous application for a degree. Except where otherwise acknowledged, the work presented is entirely my own.

Luca Foresta
May 2018
Abstract

Satellite altimetry has been traditionally used in the past few decades to measure elevation of land ice, quantify changes in ice topography and infer the mass balance of large and remote areas such as the Greenland and Antarctic ice sheets. Radar altimetry is particularly well suited to this task due to its all-weather year-round capability of observing the ice surface. However, monitoring of ice caps and ice fields - bodies of ice with areas typically smaller than $\sim 10,000 \text{ km}^2$ - has proven more challenging. The large footprint of a conventional radar altimeter and coarse ground track coverage are less suited to observing comparatively small regions with complex topography.

Since 2010, the European Space Agency’s CryoSat-2 satellite has been collecting ice elevation measurements over ice caps and ice fields with its novel radar altimeter. CryoSat-2’s smaller inter-track spacing provides higher density of observations compared to previous satellite altimeters. Additionally, it generates more accurate measurements because (i) the footprint size is reduced in the along-track direction by means of synthetic aperture radar processing and (ii) interferometry allows to precisely locate the across-track angle of arrival of a reflection from the surface. Furthermore, the interferometric capabilities of CryoSat-2 allow for the processing of the delayed surface reflections after the first echo. When applied over a sloping surface, this procedure generates a swath of elevations a few km wide compared to the conventional approach returning a single elevation.

In this thesis, swath processing of CryoSat-2 interferometric data is exploited to generate topographic data over ice caps and ice fields. The dense elevation field is then used to compute maps of elevation change rates at sub-kilometer resolution with the aim of quantifying ice volume change and mass balance. A number of algorithms have been developed in this work, partly or entirely, to form a complete processing chain from generating the elevation field to calculating volume and
mass change. These algorithms are discussed in detail before presenting the results obtained in two selected regions: Iceland and Patagonia.

Over Icelandic ice caps, the high-resolution mapping reveals complex surface elevation changes, related to climate, ice dynamics and sub-glacial, geothermal and magmatic processes. The mass balance of each of the six largest ice caps (90% of Iceland’s permanent ice cover) is calculated independently for the first time using spaceborne radar altimetry data. Between October 2010 and September 2015 Icelandic ice caps have lost a total of $5.8 \pm 0.7 \text{ Gt a}^{-1}$, contributing $0.016 \pm 0.002 \text{ mm a}^{-1}$ to eustatic sea level rise. This estimate indicates that over this period the mass balance was 40% less negative than the preceding 15 years, a fact which partly reflects the anomalous positive balance year across the Vatnajökull ice cap ($\sim 70\%$ of the glaciated area) in 2014/15. Furthermore, it is demonstrated how swath processing of CryoSat-2 interferometric data allows the monitoring of glaciological processes at the catchment scale. Comparison of the geodetic estimates of mass balance against those based on in situ data shows good agreement.

The thesis then investigates surface elevation change on the Northern and Southern Patagonian Ice Fields to quantify their mass balance. This area is characterized by some of the fastest flowing glaciers in the world, displaying complex interactions with the proglacial environments (including marine fjords and freshwater lakes) they often drain into. Field observations are sparse due to the inaccessibility of these ice fields and even remotely sensed data are limited, often tied to comparisons to the topography in 2000 as measured by the Shuttle Radar Topography Mission. Despite gaps in the spatial coverage, in particular due to the complex topography, CryoSat-2 swath radar altimetry provides insight into the patterns of change on the ice fields in the most recent period (2011 to 2017) and allows to independently calculate the mass balance of glaciers or catchments as small as 300 km². The northern part of the Southern Patagonian ice field displays the strongest losses due to a combination between ice dynamics and warming temperatures. In contrast Pio XI, the largest glacier on this ice field and in South America, is advancing and gaining mass. Between April 2011 and March 2017, the two ice fields combined have lost an average of
21.29±1.98 Gt a$^{-1}$ (equivalent to 0.059±0.005 mm a$^{-1}$ eustatic sea level rise), 24% and 42% more negative when compared to the periods 2000-2012/14 and 1975-2000. In particular the Northern Patagonian ice field, responsible for one third of the mass loss, is losing mass 70% faster compared to the first decade of the 21st century. These results confirm the overall strong mass loss of the Patagonian ice fields, second only to glaciers and ice caps in Alaska and the Canadian Arctic, and higher than High Mountain Asia, which all extend over areas ~5-8 times larger (excluding glaciers at the periphery of the Greenland and Antarctic ice sheets).
Lay Summary

With few exceptions, glaciers, ice fields and ice caps are thinning, retreating and losing ice to the ocean. Despite the fact that they contain only a small fraction of the total ice mass on Earth compared to the two large ice sheets of Greenland and Antarctica, their contribution to global sea level rise is significant and will remain so in the decades to come. Furthermore, glaciers are a source of freshwater which communities need for a number of reasons, such as drinking water, irrigation and hydro-power generation. It is thus vital to monitor these areas and quantify their changes in volume and mass. Given that glaciers are spread across all latitudes and that they are often located in remote areas, the only way to achieve global monitoring is through satellite remote sensing.

This thesis focuses on the exploitation of radar altimetry data. Radar altimeters are but one instrument that can be used to observe glaciers from space. They are particularly useful for this application since they do not depend on weather conditions or sunlight, which means they can collect data through thick cloud coverage as well as during periods of darkness. However the ‘footprint’ of spaceborne radar altimeters (i.e. the surface area illuminated by the instrument), up to several kilometres in diameter, has been a limiting factor for applications over ice fields and ice caps until the launch of the European Space Agency CryoSat-2 satellite in 2010. CryoSat-2, specifically designed for cryospheric applications, flies on a different orbital path than its predecessors, resulting in a higher density of observations compared to previous satellites. It also carries a novel altimeter which reduces the footprint size, providing more accurate measurements of ice elevation. More importantly it features a second antenna, activated in the receiving channel. It is thus possible to calculate the signal’s phase difference, which is directly related to the angle of the arrival of the surface reflections, or echoes. Therefore, the satellite is able to correctly localize the ground location of an echo, a fundamental improvement compared to previous radar
altimeters. This not only increases the precision of the elevation measurements, but the knowledge of the phase difference allows for the exploitation of data beyond the limit of conventional radar altimetry thereby generating a swath of heights, as opposed to one single elevation, for each signal emitted by the satellite. This technique, labelled swath radar altimetry, is at the core of the work in this thesis.

Swath radar altimetry is employed over glaciated regions of comparatively small size, when compared to the Greenland and Antarctic ice sheets, and with considerable topography such as the ice caps and ice fields of Iceland and southern Patagonia. The dense field of elevations is exploited to observe changes in surface elevation, which reveal complex patterns related to climate, ice dynamics and highly localized sub-glacial volcanic processes. This work shows how swath radar altimetry may be employed to observe glaciological processes at the catchment scale, a vast improvement compared to previous radar altimetry missions. This thesis finally quantifies the mass changes occurring over Icelandic ice caps and Patagonian ice fields. Both regions are thinning and losing mass considerably, and their meltwater contributes to global sea level rise. In Iceland, it is found that between 2010 and 2015 the rate of mass loss was about 40% less negative compared to the preceding 15 years, partly reflecting the fact that between 2014 and 2015 the largest ice cap in Iceland (70% of the glaciated area) had positive mass balance. However all Icelandic ice caps lost mass during the combined 5 years period. In Southern Patagonia, elevation and mass change is highly heterogeneous spatially, with some regions thinning very rapidly while others are more stable and one glacier is advancing and gaining mass. In total between 2011 and 2017 the Northern and Southern Patagonian ice fields combined have lost mass at a rate 24% and 42% more negative when compared to the periods 2000-2012/14 and 1975-2000. Excluding the ice sheets of Greenland and Antarctica, their mass loss is second only to glaciers and ice caps in Alaska and the Canadian Arctic, which extend over areas ~5-8 times larger. The Patagonian ice fields remain the highest contributor to sea level rise per unit area.
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Chapter 1

Introduction

This thesis is concerned with investigating the changes occurring at the surface of ice caps and ice fields. Specifically, it investigates how their surface topography changes through time. This information can be used to make inferences about the total volume change of an ice cap and convert that to an estimate of its mass change. Quantifying such changes is fundamental since meltwater from glaciers, ice fields and ice caps contributes significantly to sea level rise (SLR, Vaughan et al., 2013). Before describing in detail how measured elevation change can be used to infer volume and mass changes, as well as which assumptions are made, it is important to place the thesis’ topic in a broader perspective. The objective of this introductory Chapter is thus to provide information on the role that ice caps and ice fields play in the overall climate system, highlight their importance and summarise the state of knowledge regarding their net contribution to SLR at the global scale. Finally, the specific geographical areas on which this thesis has focussed are introduced.
Figure 1.1: Global distribution of the components of the Cryosphere. After Vaughan et al. (2013).
1.1 The climate system and the Cryosphere

The climate system can be thought of as the combination of five broad components, namely the atmosphere, hydrosphere, cryosphere, lithosphere and biosphere (Cubasch et al., 2013). Planton (2013) defines them as:

- atmosphere: the gaseous envelope surrounding the Earth.

- hydrosphere: the component of the climate system comprising liquid surface and subterranea water, such as oceans, seas, rivers, fresh water lakes, underground water, etc.

- cryosphere: all regions on and beneath the surface of the Earth and ocean where water is in solid form, including sea ice, lake ice, river ice, snow cover, glaciers and ice sheets, and frozen ground (which includes permafrost).

- lithosphere: The upper layer of the solid Earth, both continental and oceanic, which comprises all crustal rocks and the cold, mainly elastic part of the uppermost mantle. Volcanic activity, although part of the lithosphere, is not considered as part of the climate system, but acts as an external forcing factor.

- biosphere: the part of the Earth system comprising all ecosystems and living organisms, in the atmosphere, on land (terrestrial biosphere) or in the oceans (marine biosphere), including derived dead organic matter, such as litter, soil organic matter and oceanic detritus.

Despite this schematic division, climate is a single interconnected system. In fact, the definitions above clearly show the overlap between the domains. The cryosphere exists across a range of latitudes on Earth (Fig. 1.1). It crosses most other climate domains taking the form of solid precipitation within the atmosphere and of sea ice, river ice, lake ice and ice shelves within the hydrosphere. Within the lithosphere, it appears as seasonal snow cover and permafrost as well as land ice, namely permanent glaciers, ice fields, ice caps and ice sheets. Physically, elements of the cryosphere span a wide
range of spatial scales from meters to thousands of kilometers. Evolution and decay of land ice, specifically, may take between decades (mountain glaciers) up to about a million years for the oldest ice in the East Antarctic ice sheet.

The role of the cryosphere in the climate system is critical since it has an impact on physical, biological and socio-economic environments over most of the Earth’s surface. Given its intrinsic dependency on temperature, the state of the cryosphere can be used to observe and assess climate variability. Specifically, land ice is an important indicator of climate change (Cubasch et al., 2013), primarily because of its high sensitivity to both temperature and precipitation (Key et al., 2007), and over short time scales. Valley glaciers, for example, have typical response times of only 20-50 years (Oerlemans, 1994).

1.2 Glaciers, ice fields and ice caps

The growth and decay of land ice impacts directly on global sea level. The ice stored in the two largest masses of ice, the Greenland and Antarctic Ice Sheets (GrIS and AIS), has the potential to raise sea level by about 7 m (Dowdeswell, 2006) and 57 m (Lythe et al., 2001) respectively, if it all melted. Estimates vary for the potential contribution of land ice stored in glaciers, ice caps and ice fields (GICs), as reviewed in Cogley (2012). Church et al. (2001) estimated that a 0.50 ± 0.10 m Sea Level Equivalent (SLE) is stored in GICs on Earth, including the ones at the periphery of the GrIS and AIS. This figure has been updated by a number of studies as part of the IPCC AR4 (Lemke et al., 2007), resulting in the range 0.15 to 0.37 m SLE (excluding GICs from the GrIS and AIS) or 0.72 ± 0.2 m in total. The latter was revisited by Radić and Hock (2010) to 0.60 ± 0.07 m. Finally, two recent studies indicate that land ice outside of the ice sheets (but including their peripheral GICs) stores 0.43 ± 0.06 m (Huss and Farinotti, 2012) and 0.35 ± 0.07 m (Grinsted, 2013) of SLE. Despite the wide range, even the highest SLE estimate for glaciers, ice fields and ice caps is one
order of magnitude smaller than the potential contribution from Greenland and about 1.2\% that of Antarctica.

While GICs represent a small proportion of all land ice on Earth, they have been retreating considerably throughout the 20th century and have additionally shown an acceleration in mass loss (Lemke et al., 2007). Their contribution to SLR is estimated to be $0.37 \pm 0.16$ mm a$^{-1}$ between 1960/61 and 1989/90, rising to $0.77 \pm 0.22$ mm a$^{-1}$ between 1992/93 and 2003/04 (Lemke et al., 2007). For the following decade (1995-2006) Meier et al. (2007) reported a \~{}30\% increase ($1.1 \pm 0.24$ mm a$^{-1}$). Between 1995 and 2006, GICs contributed 30\% of the total sea level rise and about 60\% of all land ice loss, i.e. more than the two ice sheets combined. More recently (2003-2009), the GICs’ mass loss has been comparable to that of the GrIS and AIS, reflecting the accelerated mass loss from the two global ice sheets (Gardner et al., 2013; Vaughan et al., 2013).

The loss from GICs will remain significant during the 21st century, but the impact of their retreat and shrinkage is not only important to global sea levels. At the local scale, GICs are a decreasing source of potable water as well as hydro-power generation. Furthermore, they may represent a geo-hazard to communities living downstream in the form of glacial lake outburst floods. It is therefore fundamental to monitor changes over glaciers, ice fields and ice caps worldwide and quantify their global and regional mass change. Studies until the IPCC AR4 (Lemke et al., 2007) relied mostly on modelled data and scaling laws to generate estimates of mass loss based on direct observations from a relatively small numbers of selected glaciers (e.g. Meier et al., 2007). In situ data of glacier mass balance are valuable because of their accuracy, but are extremely limited in space and often discontinuous in time. Given the large (\~{}170,000) number of glaciers on Earth, spanning an area of \~{}730,000 km$^2$ spread over all continents (Vaughan et al., 2013), the only feasible way to achieve continuous monitoring over such vaste and remote regions is through satellite remote sensing.
1.3 Monitoring GICs from space

Conceptually, there are two ways of measuring glacier mass balance based solely on satellite data. (i) Detecting the changes in the gravitational pull, which are directly related to the redistribution of mass at and near the Earth’s surface and (ii) inferring the elevation of a surface with a given area at different moments in time and calculating their rate of change; knowledge of the glacier area and assumptions on the snow, firn and ice density are used to convert that volume change to an estimate of mass change.

Gravity data from GRACE (Gravity Recovery and Climate Experiment; (Tapley et al., 2004) have been used to produce monthly time series of mass change (Fig. 1.2), from which rates of mass change of GICs at the regional scale can be inferred Jacob et al. (2012). However, GRACE is not designed to deliver information on the spatial patterns of surface elevation change given its nominal resolution of about 300-400 km at the ground (Tapley et al., 2004). Furthermore, GRACE data may incorporate changes unrelated to the cryosphere which need to be removed according to global models for hydrology and post-glacial isostatic rebound.

Methods within the second category can be further subdivided depending on the approach used to determine the glacier topography. Gridded Digital Elevation Models (DEMs) can be produced using for example radar or optical data. For a given area of interest, multiple DEMs from different times can be differenced to calculate elevation change which is then converted to mass change as specified above (e.g. Jaber et al., 2013; Melkonian et al., 2013, 2014, 2016; Willis et al., 2012a,b, ; Fig. 1.3). This technique produces by far the finest horizontal spatial resolution (30 m globally and p to 1-2 m regionally on selected locations). However, given the size of some ice caps, often data from one year or longer need to be combined together to provide full spatial coverage, particularly when based on optical data which are affected by cloud coverage. Furthermore, DEMs generated with optical and radar data are not straightforward to
Figure 1.2: Time series of mass loss for a variety of GICs based on GRACE gravimetry data. After Jacob et al. (2012).
1.3 Monitoring GICs from space

compare because of the different penetration of the signals into the glacier surface, which may bias the estimate of elevation change.

Ungridded glacier topography is commonly generated with satellite altimeters. An example is the GLAS (Geoscience Laser Altimeter System) instrument on board ICESat (Zwally et al., 2002), which operated between 2003 and 2009. Repeat ICESat laser altimetry data have been extensively used to calculate glacier surface elevation change and infer glacier mass balance between 2003 and 2009 both at the global scale (Gardner et al., 2013), over all Arctic ice caps (Nilsson et al., 2015a) and regionally for Svalbard ice caps (Moholdt et al., 2010b,a; Nuth et al., 2010), for Canadian ice caps (Gardner et al., 2011; Rinne et al., 2011a), in the Russian Arctic (Moholdt et al., 2012) and for the Flade Isblink ice cap (NE Greenland Rinne et al., 2011b), to name a few examples. However, the spatial coverage provided by ICESat was limited (Fig. 1.4) due to both its inability to penetrate clouds, a common phenomena over GICs, and its relatively coarse spacing between adjacent ground tracks. Additionally, it was only activated intermittently in time.

Altimeter systems may also employ radar frequencies, whose longer wavelengths are able to penetrate through clouds. Repeat radar altimetry (Chapter 2) has been used for decades to observe surface elevation, volume and mass change over the GrIS and AIS
CHAPTER 1. Introduction

(a) After Moholdt et al. (2010b) (b) After Moholdt et al. (2012)

Figure 1.4: Rates of elevation change based on repeat ICESat laser altimetry data (a) over Svalbard GICs between 2003 and 2008 and (b) in the Russian Arctic between 2003 and 2009.

(e.g. Wingham et al., 2006b; Flament and Rémy, 2012; Shepherd et al., 2012; Helm et al., 2014; McMillan et al., 2014b, 2016). However, applications over comparatively smaller regions, which are often characterized by complex topography and steep margins, have been sparse. Rinne et al. (2011a) and Rinne et al. (2011b) first tested the use of this technique over GICs, exploiting data from the RA-2 instrument on board Envisat to produce rates of surface elevation change at 10 km spatial resolution (Fig. 1.5). Applications over the Devon and Flade Isblink ice caps, in northern Canada and northeast Greenland respectively, showed good agreement compared to similar maps produced with ICESat laser altimetry (Rinne et al., 2011a,b). More recently, the launch of CryoSat-2 (Wingham et al., 2006a) allowed observations of elevation changes at the increased spatial resolution of 2 km over the Austfonna ice cap, Svalbard (Fig. 1.6; McMillan et al., 2014a) as well as the generation of yearly and monthly time series of elevation change for a number of Arctic ice caps (Gray et al., 2015).

This thesis is focussed on the exploitation of radar altimetry data, specifically from CryoSat-2, over the ice caps of Iceland and the ice fields of Patagonia. These two geographic regions are briefly introduced in the following section and discussed in detail in Chapters 4 and 5, respectively. Given the importance of the technique, the Chapter
1.3 Monitoring GICs from space

**Figure 1.5:** Rates of surface elevation change between 2004 and 2008 over the Flade Isblink ice cap (northeast Greenland), based on Envisat RA-2 radar altimetry data gridded at 10 km spatial resolution. After Rinne et al. (2011b).

**Figure 1.6:** Rates of surface elevation change between 2010 and 2014 over the Austfonna ice cap (Svalbard), based on CryoSat-2 radar altimetry data gridded at 2 km spatial resolution. After McMillan et al. (2014b).
introduces the principles of radar altimetry and further describes how CryoSat-2’s state-of-the-art altimeter improves upon previous missions, with a particular emphasis on GICs applications.

1.4 Icelandic ice caps

Located just south of the polar circle, Iceland is wrapped to the east and west by the cold southward East Icelandic and East Greenland oceanic currents, respectively, and to the south from the warm northward Irminger current (Fig. 1.7). Additionally, it lies roughly at the boundary between the polar and mid-latitude atmospheric cells. These characteristics contribute to its high sensitivity to climatic shifts (Björnsson et al., 2013, see Chapter 4). About 11% of the land is covered in ice, most of which exist in the form of large ice caps (Fig. 1.7), including Vatnajökull, the largest ice cap in Europe by volume with an area and volume of \(~8,100 \text{ km}^2\) and \(~3,100 \text{ km}^3\), respectively (Björnsson and Pálsson, 2008). There are numerous surge-type glacier outlets on all the ice caps, including 75% of the surface of Vatnajökull (Björnsson et al., 2003). Icelandic ice caps have been losing mass since the mid-1990s (Björnsson et al., 2013).
1.5 The Patagonian ice fields

Excluding Antarctica, the Patagonian ice fields are the largest masses of ice in the southern hemisphere (Fig. 1.8). They lie on top of the steep and narrow Andean mountain range and span an area of $\sim 17,200 \text{ km}^2$. The volume of the ice fields is not known, but it is estimated to be $\sim 5,400 \text{ km}^3$ (Carrivick et al., 2016). They host some of the fastest glaciers in the world, with velocities of up to 10,000 m a$^{-1}$ (Mouginot and Rignot, 2015). Dynamic changes and warming temperatures combined are driving rapid wastage of the ice fields which are currently the highest contributor to sea level rise per unit area (Gardner et al., 2013; Carrivick et al., 2016). Despite their importance, they remain comparatively unmonitored due to their remoteness, harsh climate and complex topography. The ice fields range in elevation between sea level and above 3,000 m over distances of less than 30 km and they are often covered with clouds. Such characteristics make it challenging to monitor their glaciers, both with optical data as well as conventional radar altimeters.
Figure 1.8: Little ice age and current extent of the Patagonian ice fields. After Glasser et al. (2011)
1.6 Conclusion

Glaciers, ice fields and ice caps are key components of the climate system and they may impact significantly on it, as well as on human society, at the regional as well as global scale. Given that GICs are shrinking and retreating rapidly, it is crucial to continue monitoring and quantifying their changes. The unique features of CryoSat-2 (sections 2.2 and 2.3) offers great potential for determining elevation and mass changes in the most recent period (2010 onward) with greater accuracy than it could be achieved with previous satellite altimeters.
Chapter 2

Mapping ice topography with radar altimeters

Artistic representation of CryoSat-2 (ESA)
2.1 Principles of radar altimetry

An altimeter is an instrument which infers the elevation of the Earth’s surface. The working principle is simple: the instrument (source point) emits a signal and measures the two-way travel time $\Delta t$ to a target point. Assuming that the velocity of the signal is known, and that the motion of source/target points is negligible, this measurement can be converted to a distance or range:

$$r = \frac{v \Delta t}{2}. \quad (2.1)$$

Assuming that the source point is airborne or spaceborne and the instrument points at the surface directly at nadir, if the altitude $H$ of the source point is known the elevation $h$ of the target can be inferred (Fig. 2.1):

$$h = H - r. \quad (2.2)$$

The type of signal defines the type of altimeter. For the purposes of this work, the two most common types of altimeters use an electromagnetic signal. Laser altimetry uses wavelengths in the visible range (e.g. GLAS on board ICESat), while radar altimetry employs longer wavelengths corresponding to radio frequencies (for oceanographic and glaciological applications, most often in the 12-18 GHz Ku band). The wavelength defines an important property of the altimeter, namely the ability of the signal to pass through different media. In particular, laser wavelengths can not pass through thick clouds, which are however transparent to radar altimeters. This property makes radar altimeters weather independent, a key factor in achieving continuous monitoring. Another important property is the size of the footprint, that is, the surface area illuminated by the instrument. Typically, laser altimeters illuminate a surface area a few tens of meters in diameter as compared to kilometers for their radar counterparts.
Figure 2.1: Principles of radar altimetry.

Despite the underlying simplicity of the method, achieving accurate measurements (\(<10\) cm) poses considerable challenges. The location of the emitting source (the satellite’s antenna) must be known precisely, as well as its orientation in space (attitude). Most modern satellites use GPS (Global Positioning System) and DORIS (Doppler Orbitography and Radiopositioning; Tavernier et al. (2003)) systems, coupled to laser ranging from the ground to precisely identify their location. The attitude of the satellite is provided by one or more star trackers. These instruments compare the stars in the camera field of view with an onboard catalogue to determine the yaw, roll and pitch angles. In addition to the location of the source point, one must have knowledge of the processes potentially affecting the signal’s velocity in air, as well as whether the location of the target point is stable in time or oscillates around a mean value (for example due to the combined gravity pull from the sun and moon, which changes periodically). These geo-physical corrections are discussed in section 2.1.1.

A short time after the signal is emitted, the altimeter will start recording the echo
2.1 Principles of radar altimetry

Figure 2.2: Example waveform acquired by a radar altimeter. The highlighted point is the Point Of Closest Approach, i.e. the point at the surface closest to the satellite. Credit: Nilsson et al. (2015b)\(^1\).

Reflections. The output is a waveform, i.e. the power received by the instrument as a function of time (Fig. 2.2). A radar altimeter provides a waveform every few hundred meters along the flight track (Fig. 2.3). The power is recorded at a specific frequency (set by the satellite’s characteristics) for a fixed number of tracking gates, also called range bins. Therefore each waveform in Fig. 2.3 should be thought of as composed of \(N\) samples of power, each a specific \(\delta r\) further away from the satellite. During its orbit around the Earth, the distance between the satellite and the surface may vary by kilometers (between sea level and mountain ranges), yet the instrument can only record reflections within a pre-set range window. A satellite altimeter uses a waveform tracker to adjust this window to ensure that the instrument is recording surface echo reflections when they reach the satellite. If this fails, the satellite has lost track of the surface, a phenomenon called loss-of-lock.

As seen in Fig. 2.2, initially the satellite is only recording thermal noise from its own instruments; in other words the echo reflections have not yet reached the satellite. Afterwards, there is an increase in power until a peak is reached. Finally, the satellite

\(^1\)http://onlinelibrary.wiley.com/store/10.1002/2015GL063296/asset/supinfo/grl52899-sup-0002-documentS2.png?v=1s=c918b319d278f32a99a957b3a8e8b03ed147495c
is still recording a considerable power, which is now decreasing in time. In an ideal case, for example a perfectly flat and reflective surface, the radar return curve (Fig. 2.2) would have a single peak of very narrow width, in which case the range to the surface would be straightforward to identify. In reality, finding the range to the so-called Point Of Closest Approach (POCA), i.e. the point at the surface closest to the satellite, is a complex procedure generally termed retracking. Numerous retrackers have been developed and the choice affects the resulting elevation. Retrackers are designed for specific types of surfaces, such as oceans, ice and sea-ice. Retrackers are not discussed in detail here because they are not used in this work (see Chapter 3).

2.1.1 Geo-physical corrections

As mentioned above, a number of geophysical corrections need to be applied to the range to account for the properties of the atmosphere the signal is travelling through as well as to correct for periodic oscillations of the surface due to tidal effects. The types of corrections needed for land ice applications, together with their order of magnitude, are given in Table 2.1.

[2]https://earth.esa.int/web/sentinel/user-guides/sentinel-3-altimetry/applications/coastal-zones
Table 2.1: Geo-physical corrections that are applied to the range for land ice applications (Bouzinac, 2012).

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<thead>
<tr>
<th>Correction type</th>
<th>Correction to range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ionosphere electron content</td>
<td>0.06 to 0.12 m</td>
</tr>
<tr>
<td>Dry troposphere</td>
<td>1.7 to 2.5 m</td>
</tr>
<tr>
<td>Wet troposphere</td>
<td>0 to 0.5 m</td>
</tr>
<tr>
<td>Ocean loading tide</td>
<td>-0.02 to 0.02 m</td>
</tr>
<tr>
<td>Solid Earth tide</td>
<td>-0.3 to 0.3 m</td>
</tr>
<tr>
<td>Geocentric polar tide</td>
<td>-0.02 to 0.02 m</td>
</tr>
</tbody>
</table>

In the atmosphere, the radar signal travels through the ionosphere and troposphere. The total electron content in the ionosphere introduces a range bias which can be estimated from the Global Ionospheric Map\(^3\) or the Bent model\(^4\). The dry and wet tropospheric corrections take into account the path delay introduced, respectively, by dry gases (e.g. oxygen and nitrogen) and liquid water in the atmosphere. They depend on atmospheric temperature and pressure, provided for the CryoSat-2 mission by Meteo France CNES SSALTO system. Additionally, the Earth’s crust is deformed by three tidal phenomena. The ocean loading tide correction removes the deformation bias due to the weight of the overlying ocean tides. Such correction is derived using the Finite Element Solution Tide model, FES2004\(^5\). The solid Earth tide correction takes into account the deformation induced by the sun and moon’s combined gravitational pull, estimated from the Cartwright model. Finally, the geocentric polar tide correction is applied to remove a long period distortion of the Earth’s crust, which is caused by variations in centrifugal force as the Earths rotational axis moves its geographic location. The correction is derived from historical pole locations data provided by Meteo France CNES SSALTO system.

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\(^3\)https://iono.jpl.nasa.gov/gim.html  
\(^4\)http://modelweb.gsfc.nasa.gov/ions/bent.html  
2.1.2 Radar penetration into the glacier surface

Figure 2.4: (a) Surface elevation differences between the May-June and August-September 2012 CryoSat-2 L2i data. The differences in surface elevation shows a clear positive increase in the dry-snow zone and ablation in the coastal regions. Black lines indicate the 2000 and 3000 m elevation contours. (b, c) Histograms (regional analysis) and time series (local analysis) of the changes in surface elevation around NEEM estimated from the re-analysed CS-2 L1b data presented in this study. The 2012 elevation change is indicated in red. After Nilsson et al. (2015a).

Depending on the conditions of the snow pack at the near-surface, the radar signal may penetrate at depth. Under cold and dry conditions the signal will scatter from a number of internal layers below the surface (volume scattering) and may reach several meters deep. Conversely, when the snow is wet, the signal’s horizon will be the snow-air interface, i.e. the glacier surface (near-surface scattering). The depth of the radar horizon changes spatially as well as temporally, with the signal typically reaching deeper into the snow pack in winter when the surface is comparatively dry. Therefore, changes in air temperature and surface water content may bias the elevation measurement acquired from a radar altimeter at a given location. One approach to
minimize the impact of radar penetration on elevation change $dH$ is to adjust $dH$ estimates for changes in backscattered power (e.g. Wingham et al., 1998; Davis and Ferguson, 2004). If surface conditions change in time and this correction is not applied, artificial thinning or thickening patterns may arise at a regional scale. For example, Nilsson et al. (2015b) reported an apparent thickening of the interior of the Greenland Ice Sheet during the summer of 2012 (Fig. 2.4-a,c). However, this pattern was an artifact induced by a change in scattering regime, from volume to surface, in an area typically characterised by comparatively cold temperatures and dry snow (Nilsson et al., 2015b).

The correction is not needed if the glacier surface is known to be wet, so that surface scattering prevails. For example, to minimize the variation of radar penetration, Rinne et al. (2011b) used only altimetry data acquired between late summer and early fall of 2002 to 2009 when quantifying surface elevation changes over the Flade Isblink Ice Cap in North East Greenland. In this work, no penetration correction was applied to CS-2 altimetry data. The choice was justified by the fact that Icelandic ice caps and Patagonian ice fields receive abundant liquid precipitation (see Sections 4.2 and 5.2), including in winter time. Furthermore, time series of elevation change show an absence of artifacts similar to that reported by Nilsson et al. (2015a), as reported in Chapters 4 and 5. Finally, seasonality biases are avoided given the regular flight path followed by CS-2, which ensures that data at a given location are acquired at the same epochs (within a few days) in each year.

### 2.1.3 Surface slope

Before the launch of CryoSat-2 (section 2.2), inferring land ice topography with radar altimeters has been a secondary application of altimetric missions. Radar altimeters, whose historic (and current) application is to map sea surface height (e.g. Resti et al., 1999), are all nadir looking and implicitly assume that the surface slope is negligible, so
that the POCA will be located directly below the satellite. This assumption by contrast is not generally met over land ice. Thus, it is necessary to correct for slope-induced errors in the geolocation of the radar echo (Brenner et al., 1983). Given the typical altitude and bandwidth, which define the size of the footprint, there may be horizontal displacements of several kilometres and tens of metres, respectively, for slopes between 0.5 and 1 degrees. The radar echo can be relocated based on the slope extracted from a DEM, if available. The accuracy of the DEM, as well as its spatial resolution, directly impacts the precision of the resulting correction (Levinsen et al., 2016).

### 2.2 ESA Explorer CryoSat-2

Recognizing the need for a radar altimetry mission specific for ice applications, the European Space Agency (ESA) launched CryoSat-2 (CS-2) in 2010. This mission is the first of the ESA Earth Explorers which form the science and research element of ESA’s Living Planet Programme. The focus of the Explorers is to provide knowledge on natural Earth processes and the influence that human activity is having on them. CS-2’s mission goal is to map temporal variations in the thickness of sea ice as well as to monitor topographic changes over land ice. To achieve this objective, CS-2 carries a state-of-the-art radar altimeter called SIRAL: Synthetic Aperture Radar (SAR) Interferometric Radar Altimeter. While based on heritage from previous altimeters such as those on board Envisat or ERS-1,2, SIRAL features two key improvements: SAR processing along-track and interferometric processing across-track (Wingham et al., 2006a). SAR and interferometric processing are activated in specific geographic areas (Fig. 2.5). Over the oceans and ice sheets’ interior (Fig. 2.5, red), CS-2 works as a conventional pulse limited radar altimeter (Low Resolution Mode, LRM). Considering CS-2 altitude and antenna beamwidth, the beam- and pulse- limited footprints have a diameter of about 14 and 1.65 km, respectively (Fig. 2.6-a,b). Over sea ice and key selected regions (Fig. 2.5, green), SAR processing along-track (SAR mode) exploits
the Doppler history of the coherent signals to reduce the footprint size in the along-track direction to about 305 m (Fig. 2.6-c). Finally, over regions with considerable topography (Fig. 2.5, purple), a second antenna is activated in the receiving channel allowing for across-track interferometry (SARIn mode). In this case, the two antennae which form an interferometer perpendicular to the line of flight, record the surface reflections at slightly different times. Their phase difference is used to calculate the across-track angle of arrival\(^6\) of the echo reflection (Eq. 3.2). Therefore, while operating in SARIn mode, CS-2 improves upon previous missions by providing a smaller footprint as well as by measuring precisely the location of the POCA. For this reason, CS-2 SARIn data do not need a slope relocation correction such as conventional pulse limited altimeters (section 2.1.3).

\(^6\)The angle of arrival is the angle between the nadir and the scattering surface.
In addition to the improvements on the radar altimeter, CS-2 flies in a non sun-synchronous orbit at 92° inclination (0.0014 eccentricity) with a repeat period of 369 days (5344 revolutions) and a sub-repeat period of 30 days. The inter-track spacing at the equator is 7.5 km (2.5 km at 70°; 4 km at 60°), half that of ICESat (Zwally et al., 2002) and one order of magnitude smaller than that of Envisat and ERS-1,2. Such narrow spacing provides a much higher density of observations than previously available. Furthermore, the orbit reaches closer to the pole and thus further inland in Antarctica than previous missions (81.5° and 86° for Envisat/ERS-1,2 and ICESat, respectively) and therefore offers better coverage of the Arctic sea and Antarctic continent.
2.3 Radar echoes beyond the POCA

As discussed in the previous section, the interferometric capabilities of CryoSat-2 allow it to locate the across-track angle of arrival of the surface reflection. Similarly, the same information is measured for the time-delayed reflections reaching the satellite after the POCA. The analysis and exploitation of this data provides the basis for the results presented in this thesis and the methodology used to derive and analyse this data is presented in Chapter 3.
Chapter 3

Methods development and testing

Figure 3.1: Chart presenting the logical work flow followed in this thesis. Each box corresponds to a major program which was developed, partly or entirely, for this thesis. CryoSat-2 POCA data were downloaded from the ESA CroSat-2 ftp server. Blocks in blue can run on a local server as well as on the University of Edinburgh supercomputing cluster.
The objective of this work is to quantify changes in elevation, volume and mass over large and remote glacier areas by means of radar altimetry data delivered by CryoSat-2. For this reason, the development, testing and deployment of several algorithms has been a major and ongoing part of this PhD. The code also had to scale properly with increasing amount of input data (longer time series) and perform well over geographical areas with large spatial extent. In fact, despite regions where the methods were applied in this thesis were relatively small, the same programs were used for larger regions at the periphery of the Greenland and Antarctic ice sheets.

The work flow is shown in Figure 3.1. The first stage is to generate the elevation field from CS-2 SARIn interferometric data, labelled SwSARIn (Figure 3.1-A). The scientific property of this program lies with Dr. N. Gourmelen and all the partners\(^1\) to the ESA funded STSE\(^2\) CryoTop project\(^3\) and is based on earlier work from Hawley et al. (2009) and Gray et al. (2013). It is described in detail in section 3.1 since it is the foundation of the results presented in this thesis. Additionally, my contribution during the first 12-18 months of the PhD has been instrumental in developing and testing an operational product which could be used to generate swath processed elevations over large regions in a timely manner. This included deployment of the code on the University of Edinburgh supercomputing cluster eddie2, and its successor eddie3. Such work enabled not only the results presented in Chapters 4 (Icelandic ice caps) and 5 (Patagonian Ice Fields), but also over areas in Greenland and Antarctica. The latter results, together with the details on the CryoTop algorithm, are published in Gourmelen et al. (2017a), which I am a co-author of. Furthermore, during the same initial period I also contributed to validating SwSARIn elevations (Figure 3.1-E), results of which

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\(^1\)In alphabetical order: Dr. S. Baker (University College London), Dr. K. Briggs (Centre for Polar Observation and Modelling, University of Leeds), Dr. M. Drinkwater (European Space Agency), Dr. M.J. Escorihuela (isardSAT), Dr. N. Gourmelen (School of GeoSciences, University of Edinburgh), Dr. A. Muir (University College London), Dr. M. Roca (isardSAT), Prof. A. Shepherd (Centre for Polar Observation and Modelling, University of Leeds)

\(^2\)Support To Science Element

\(^3\)www.stse-cryotop.org
are published in Gourmelen et al. (2017a) and briefly presented in section 3.1.7. For completeness, this publication is included in Appendix B. The second stage is to calculate mean rates of elevation change using either SwSARIn or POCA observations (Figure 3.1-B). A number of approaches has been published in the literature and is briefly discussed in section 3.2.1, before presenting and justifying the algorithm used in this thesis (section 3.2.2), which is a modification of, e.g., McMillan et al. (2014a). The dense field of SwSARIn observations allows generating maps of surface elevation change rates at sub-kilometer scale, a spatial resolution up to one order of magnitude finer than previously achievable. However, the data do not cover the entire glacier surface and some gaps may be considerable in size, depending on the local topography.

As part of the module which produces an estimate of total volume change (Figure 3.1-C), a model was constructed using the relationship between elevation and elevation change (section 3.3.2). This modelling approach, named hypsometric averaging, follows from, e.g., Moholdt et al. (2010b) and Nilsson et al. (2015a). Assumptions on the ice/snow density are then employed to convert this value into a rate of mass change (section 3.3.2). Finally, the propagation of uncertainties and the quantification of the overall error budget on the mass change of an ice cap are presented in section 3.4.

Given the density of SwSARIn data, time series of elevation change (Figure 3.1-D) can be produced at the scale of an ice cap or even of a single catchment. The methodology, similar to Gray et al. (2015), is introduced in section 3.5.

Algorithms to generate rates of elevation, volume and mass change, as well as time series of elevation change, are already published. However, the source code is not made available to users. As part of this PhD, a complete workflow was set up so to streamline processing of any geographical area where CS-2 SARIn data are available, from automatic download and processing of CS-2 SarIn data to the generation of maps of surface elevation change at a given spatial resolution, to the computation of the overall volume and mass change of a given region. Furthermore, the programs
3.1 The elevation field: swath processing of CryoSat-2 interferometric data

calculating elevation, volume and mass change are not bound specifically to CS-2 data but can be used with other datasets. This has been a combined effort with a few other developers (in particular Dr. Gourmelen and Dr. Weissgerber, University of Edinburgh), but I was the main developer of parts B, C, D (Figure 3.1) and my (technical) contribution has been substantial for parts A and E (Figure 3.1) in the way stated above. Furthermore, as code development has been ongoing throughout this project, important updates were introduced in the processing chain after publishing the results presented in Chapter 4. These changes are discussed in the relevant sections of the current chapter.

3.1 The elevation field: swath processing of CryoSat-2 interferometric data

Figure 3.2: Swath processing of ASIRAS (a) and CS-2 SARIn (b) data successfully retrieved the topography of the Austfonna (Svalbard) and Devon (Canada) ice caps, respectively.

Swath processing of interferometric radar altimetry data consists in exploiting the delayed returns after the POCA over sloping glacial terrain. The concept was successfully demonstrated by Hawley et al. (2009) before the launch of CryoSat-2, using data from

(a) After Hawley et al. (2009).
(b) After Gray et al. (2013).
the Airborne SAR/Interferometric Radar Altimeter System (ASIRAS) over the Austfonna ice cap (Svalbard). The presence of a slope is important, because over flat terrain, reflected echoes will simultaneously reach the instrument’s antennae from both sides of POCA across-track, contributing to the same sample of power, phase difference and coherence. Under this scenario, it is impossible to determine the (across-track) surface location of the reflection (Hawley et al., 2009). However, over sloping terrain the POCA may be at the edge or outside of the antenna beam. In this case, contribution of the echoes outside of the beam will be negligible and the phase signal measured at the antennae can be used to geo-locate the samples and calculate their elevation (Figure 3.2a). Using this technique, Hawley et al. (2009) report a 75 fold increase in the number of observations with comparable quality to POCA data when compared to an independent dataset. Exploiting the same concept, Gray et al. (2013) generated DEMs
of the Devon ice cap (Canada), using CryoSat-2 SARIn data acquired between February 2011 and January 2012 (Figure 3.2b).

The swath processing scheme used in this thesis follows from Gourmelen et al. (2017a) and is shown in Figure 3.3. Each surface reflection can be geo-coded by having information on the slant range from the satellite to the surface, as well as on the look angle (the across-track angle between nadir and the point of reflection at the surface). The key equations for the determination of the location and elevation of each given echo are given in section 3.1.4. In particular, the look angle equation (Eq. 3.2) depends on the phase information retrieved by the satellite. Therefore, a number of steps are performed before computing Eq. 3.2 to ensure that as little noise as possible is propagated to the calculation of the look angle, which would affect both the location and elevation of the geocoded echo.

### 3.1.1 Input and auxiliary data

The input to the algorithm are CS-2 intermediately processed L1b baselineC files acquired in SARIn mode (section 2.2). Each SARIn file represents a satellite track containing a number of waveforms separated by about 400 m along-track. Figure 3.4 (panel a) shows one ascending and descending track over the Vatnajökull ice cap (Iceland), acquired on 24-09-2012 and 21-09-2012, respectively. Power, coherence and phase difference data from a section of the descending track (red section in panel a) are displayed in panels b, c and d. Each waveform record is composed by 1,024 samples of these three fields (e.g. panels e, f and g for waveform 677 of the descending track). The power in each record is rescaled so that values span the dimensionless range 0 to 65,535 (Bouzinac, 2012). The samples span 240 m in slant range, which translates to a few km in ground range. At this stage, multi-look averaging has been already applied as part of the SAR algorithm (section 2.2).
Figure 3.4: (a) CS-2 tracks acquired on 24-09-2012 (ascending) and 21-09-2012 (descending) over the Vatnajökull ice cap, Iceland. (b-d) Power, coherence and phase difference for a section of the descending track. (e-g) Power, coherence and phase difference for an individual waveform in this section. Background map from Google Earth.
3.1 The elevation field: swath processing of CryoSat-2 interferometric data

3.1.2 Smoothing and masking waveforms

To reduce instrument noise, the phase and amplitude are filtered by recreating the interferogram, filtering its real and imaginary components with a low pass filter and retrieving the phase from the smoothed interferogram (Gray et al., 2013). Each waveform is smoothed independently, with a filter size equal to 3 bins so to limit the loss of spatial resolution (Figure 3.5, black dots). Furthermore, the phase signal is masked according to thresholds on coherence and power. This is to ensure that noisy data is not further processed and to minimize phase unwrapping errors.

3.1.3 Local phase unwrapping

The phase difference between the receiving antennas can only be within the \([-\pi, \pi]\) interval. A phase ambiguity will be present when surface slope exceeds about half
a degree, identified as a sharp jump in the values which are otherwise varying more smoothly according to the surface slope (Figure 3.5). Since an error in the phase difference will translate in an error in the satellite’s look angle and eventually in the echo geolocation (see following sections), a phase unwrapping procedure is applied to each waveform. In this step, a value of $2\pi$ is either added or subtracted when the absolute phase change between 2 consecutive bins exceeds $\pi$. The smoothed, masked, unwrapped phase difference field is shown in Figure 3.5 (red dots).

### 3.1.4 Computation of echo geolocation and elevation

Following Bouzinac (2012), the slant range of each waveform’s sample to the satellite is given by:

$$ R(n) = \frac{c}{8} \left( 4T - \frac{1}{B} (N + 2n) \right) [m] $$ \hspace{1cm} (3.1)

where $n$ is the sample number within the waveform (0 to 1,023), $T$ is the window delay in seconds, $N$ is the total number of waveform samples (1,024), $B$ is the instrument bandwidth (320 MHz) and $c$ is the speed of light. Units are provided in squared brackets after the equation. Relevant geo-corrections (section 2.1.1) to the range are extracted from CS-2 L1b SARIn files and applied to the sample ranges calculated in Eq. 3.1.

The across-track look angle of each sample is given by:

$$ \theta(n) = \arcsin \left( \frac{\lambda}{2\pi} \frac{\delta \phi(n)}{b} \right) - \beta \ [rad] $$ \hspace{1cm} (3.2)

where $\lambda$ is the signal’s wavelength, $\delta \phi$ the phase difference, $b$ the interferometer baseline (distance between the two antennas) and $\beta$ the satellite’s roll angle.

Information on CS-2 location ($lon_0, lat_0$), elevation $z_0$ w.r.t. the WGS84 ellipsoid and orientation in space (yaw, pitch, roll angles) is contained in the L1b SARIn files. The heading completes the set of details needed to localize CS-2 in a 3D space. This field
3.1 The elevation field: swath processing of CryoSat-2 interferometric data

Figure 3.6: Phase ambiguity may cause errors of the order of tens of meters in elevation and kilometres in geo-location for a ∼0.54° surface slope. Credit: Dr. Gourmelen.

can be calculated from the dot product between the satellite’s velocity vector and the normal to the plane spanning the along-track and vertical directions. By referencing the sample’s range \( R(n) \) and look angle \( \delta \phi(n) \) to the satellite position, the individual reflections are geocoded into (longitude, latitude, elevation) values with respect to the WGS84 ellipsoid.

3.1.5 Global phase unwrapping

Finally, an iterative step is introduced to account for potential ‘global’ phase ambiguities. In this case, no sharp jump is visible in the phase difference field. Rather, the entire waveform is affected by a phase shift and the conventional phase unwrapping procedure described above is ineffective. This may happen for echoes whose across-track angle is above ∼0.54° for all or part of the beam limited footprint (see Figure 2.6-a) and affects swath and POCA altimetry in the same way. In this case, a phase ambiguity may result in errors of the order of tens of meters in elevation and kilometres in geo-location (Figure 3.6). Thus, for each waveform, a number of positive/negative \( 2\pi \) multiples is added to the phase difference, producing a set of geocoded elevations, one set for each \( 2\pi \) multiple tested. Each set is evaluated against a reference DEM (section
Figure 3.7: (a) Correction applied to the phase difference (colors) for a descending track acquired on 21-09-2012 (black line). A group of waveforms would be mislocated without the global unwrapping procedure (black circles). The geo-location of one waveform in that group for all seven $2\pi$ corrections is shown in red. (b) Elevation of the same waveform (black) and corresponding elevation of the LMI DEM (grey). (c) Mean and maximum elevation difference (black, red) for each $2\pi$ multiple as well their mean absolute deviation (green) multiplied by ten to fit the scale. Background map from Google Earth.
3.1 The elevation field: swath processing of CryoSat-2 interferometric data

3.1.8):

$$\delta z_k = |z_k - z_k^*| \quad k \in [1, K]$$

where $k$ identifies the $2\pi$ multiple tested, $z_k$ are the geocoded elevations within the waveform and $z_k^*$ are the corresponding elevations from the DEM. The correct $2\pi$ ambiguity is chosen by minimizing the mean of the elevation differences in Eq. 3.3 between the possibilities.

An example is provided in Figure 3.7 to illustrate the procedure. The scatter plot (Figure 3.7-a) shows the $2\pi$ multiple selected for each waveform of a descending track acquired on 21-09-2012. In most cases, no correction is needed (green). However without this procedure, a block of waveforms above 64.6° N would be mis-located (black). The geo-location of the seven set of measurements for the northernmost waveform in this block are shown in red. Their elevations, together with the corresponding values from the DEM, are displayed in Figure 3.7-b. There is a clear match when applying a -2\pi correction to the phase difference (Figure 3.7-c). Given the magnitude of the mis-location as well as elevation shift induced by a $2\pi$ correction (Figure 3.7-a,c), the DEM needs not be extremely accurate. The DEMs of Iceland and southern Patagonia used in this thesis are introduced in section 3.1.8.

3.1.6 Alternative selection of waveform samples

Selecting waveform samples based on fixed thresholds on coherence and power is an empirical approach which has been applied successfully to infer glacial topography and higher products based on it such as topography changes (Gray et al., 2013; Christie et al., 2016; Ignáczi et al., 2016; Foresta et al., 2016; Gourmelen et al., 2017a). However a different procedure was developed by Dr. F. Weissgerber (University of Edinburgh), which relies entirely on the phase difference field. This method, first developed for InSAR images (Weissgerber, 2016) and updated for CS-2 SARIn data (Weissgerber et al., 2017), was shown to further increase the density of the swath
elevation field and to improve the spatial coverage of the Jakobshavn glacier, Greenland (Weissgerber and Gourmelen, 2017). The original phase difference (Figure 3.8-a) is divided into overlapping segments (Figure 3.8-b). Their length and overlap is set by the user; for this work, each segment is 64 samples long and the overlap is half the length. The slope of the phase difference is then calculated independently in each segment. Instead of applying a linear regression, the algorithm applies a Fourier transform on the normalized complex coherence $e^{i\delta\phi}$, where $\delta\phi$ is the phase difference field. Compared to linear regression, this approach is both more efficient computationally\(^4\) as well as independent on phase wrapping. The Fourier transform enables to testing a large number of possible slopes and the one with the highest correlation $\hat{R}$ with the input data is selected. The signal is oversampled by a factor set by the user to take into account that the slope of CS-2’s phase difference can represent non integer frequencies. Thus, each overlapping section has two possible slopes (Figure 3.8-b). A correlation is applied again to the data in each overlapping section, this time using only its two estimated slope values (Figure 3.8-c). Sections whose correlation is below a set threshold (for this work, 0.95) are considered noisy and discarded. Finally, the remaining segments are used to unwrap the phase difference (Figure 3.8-d). With this procedure, no smoothing is applied to the phase difference and no threshold is set on the power or coherence. It replaces sections 3.1.2 and 3.1.3 (Figure 3.3).

This approach has the advantage of generating a denser field of valid observations of ice topography. This is extremely valuable over mountainous areas where CS-2 may lose track of the surface (loss-of-lock, see section 2.1) because of abrupt height changes in short distances along the flight line (Dehecq et al., 2013). Although swath altimetry is affected by loss-of-lock as much as POCA, enhanced spatial coverage is achieved because a swath of heights, rather than one single elevation, is acquired when the on board tracker correctly sets the range window, therefore maximising the number

\(^4\)Highly optimized Fourier transform algorithms are available to the scientific community.
3.1 The elevation field: swath processing of CryoSat-2 interferometric data

Figure 3.8: After Weissgerber et al. (2017).
CHAPTER 3. Methods development and testing

3.1.7 Validation of the elevation field

As part of the ESA STSE CryoTop project, the swath processing algorithm was validated against an independent dataset, results of which are published in (Gourmelen et al., 2017a). The SwSARIn elevation field is compared against laser altimetry data in Greenland (Jakobshavn and Petermann glaciers) and in the Amundsen Sea Sector of Antarctica (Pine Island and Thwaites glaciers) in the period April to May and October-November, respectively (Gourmelen et al., 2017a). This choice excludes periods of rapid melting and large precipitation. Data from Operation Ice Bridge (OIB) Airborne

Figure 3.9: Location of the validation sites: Petermann (North West Greenland), Jakobshavn (West Greenland), Pine Island and Thwaites (Amundsen Sea Sector, Antarctica). The background map shows surface elevation change rates in the period 2011-2014 (Greenland) and 2010-2013 (Antarctica) based on CS-2 POCA data (McMillan et al., 2014b, 2016).

of observations in regions with challenging topography. This approach was used to generate results over the Patagonian Ice Fields presented in Chapter 5.
Table 3.1: Median difference between CS-2 SwSARIn/POCA and OIB ATM elevations. The number of observations for each comparison is given in parenthesis. Pine Island and Thwaites glaciers are grouped together as Amundsen Sea Sector.
Table extracted from Gourmelen et al. (2017a).

<table>
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<th></th>
<th>SwSARIn</th>
<th>POCA</th>
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<td>Petermann</td>
<td>-1.3 ± 1.2 m (44,900)</td>
<td>-1.1 ± 0.8 m (1,400)</td>
</tr>
<tr>
<td>Jakobshavn</td>
<td>-1.2 ± 2.0 m (99,900)</td>
<td>-0.6 ± 1.4 m (1,000)</td>
</tr>
<tr>
<td>Amundsen Sea Sector</td>
<td>-2.0 ± 2.0 m (199,300)</td>
<td>-1.1 ± 1.3 m (3,300)</td>
</tr>
</tbody>
</table>

Topographic Mapper (ATM) campaigns (Krabill, 2015, 2016) are used as validation dataset. ATM data have virtually no penetration in snow and ice as well as high accuracy (74 cm horizontal, 6.6 cm vertical) and 3 cm vertical precision (Martin et al., 2012). SwSARIn and ATM data are matched according to their distance in space and time. Pair of observations acquired within 10 days and located less than 50 m apart are selected and their elevation difference is computed. The median elevation difference is taken as the representative average elevation difference between the two datasets and their uncertainty is assigned by calculating the median absolute deviation. The validation is based on about 344 thousands co-located elevations between the two ice sheets, acquired between 2011 and 2014. Results are listed in Table 3.1. On average, the difference between the airborne and CS-2 SwSARIn elevations is -1.5 ± 1.73 m. The bias reflects the greater penetration of Ku-band radar (CS-2) into the snow and firn compared to the ATM laser data. For comparison, the difference between the airborne and CS-2 POCA is -0.93 ± 1.17 m (Gourmelen et al., 2017a).
As described in section 3.1.5, the swath processing algorithm benefits from the use of an external DEM. The current section introduces the two DEMs used for the areas of interest of this thesis, namely Iceland and Patagonia.

The National Land Survey of Iceland (Landmælingar Íslands, LMI; www.lmi.is) provides access to a free, continuously updated, DEM of the island. The version used in this thesis was downloaded in 2014. The LMI DEM is presented in conical Lambert projection (ISN93) at 20 m spatial resolution and the elevation field is referenced to the EGM96 geoid (Figure 3.10).

The Shuttle Radar Topography Mission (SRTM) DEM (Farr et al., 2007) was acquired during a 11-day mission in February 2000, whose aim was to generate the first global

\footnote{Specifically, the OIB ATM L2 Icessn Elevation, Slope, and Roughness product, Version 1.}
3.1 The elevation field: swath processing of CryoSat-2 interferometric data

Figure 3.11: Shuttle Radar Topography Mission C-band DEM (Farr et al., 2007) over the Southern Patagonian Ice Field, Patagonia. Glacier outlines (black) are taken from the Randolph Glacier Inventory version 6.0 (RGI Consortium, 2017). The white box shows the area displayed in Figure 3.12.
DEM at 1 arcsec (∼ 30 m) and 3 arcsec (∼ 90 m) resolution. The mission covered about 80% of the Earth’s land surface between 60° north and 56° south. Two radar bands were employed, namely C and X bands (5.6 cm and 3.1 cm wavelengths, respectively). The two DEMs are provided in geographic coordinates and elevation is referenced to the EGM96 geoid. For this thesis, the SRTM C-band DEM at 1 arcsec was downloaded between 66-75 degrees West and 45-56 degrees South. Figure 3.11 displays the DEM over the Southern Patagonian Ice Field.

Both the LMI and SRTM DEMs are converted to the WGS84 ellipsoid, the same vertical datum that CS-2 SwSARIn/POCA use. Additionally, the LMI DEM is converted from its native projection to geographic coordinates. Furthermore, the DEMs are down-sampled to 300 m spatial resolution. The rationale for this step is to use the DEMs at a spatial resolution comparable to the beam-limited along-track footprint of CryoSat-2.

An additional step is required before using the SRTM DEM. Its topography represents the surface in 2000, more than 10 years before the first CS-2 acquisition (∼ July 2010). Over some fast changing glaciers (Jorge Montt and Upsala, Southern Patagonia Ice Field), thinning rates exceeded 10 m a$^{-1}$ between 2000 and 2011/12 (Willis et al., 2012b; Jaber et al., 2013). The SRTM DEM topography is thus outdated over these regions and the total change is in the order of 80-120 m, which may affect the choice of the $2\pi$ multiple during the global phase unwrapping procedure (section 3.1.5). Other freely available DEMs covering Southern Patagonia are the (i) GTOPO30 (Global Topography), (ii) SRTM X band (Farr et al., 2007), (iii) ASTER v2 (Advanced Spaceborne Thermal Emission and Reflection Radiometer, Tachikawa et al. (2011)), and (iv) AW3D30 v1.1 (ALOS, Advanced Land Observing Satellite, (Tadono et al., 2014; Takaku et al., 2014; Tadono et al., 2016; Takaku et al., 2016)). However, these options are not suitable for different reasons. GTOPO30 and the SRTM X band DEMs are also outdated, the former dating to 1996 and the latter being generated coincidentally to the SRTM C band. Additionally, GTOPO30 has coarse spatial
resolution (1 km) and the SRTM X band has large gaps over the ice fields (not shown) due to the narrow strip width of the instrument (Figure 3.13, left panel). The ASTER DEM v2 and the AW3D30 v1.1 were released in 2011 and 2017, respectively. However, the first version of ASTER was known to be affected by large artefacts (Arefi and Reinartz, 2011) and, despite large overall improvements, v2 still has high frequency noise, particularly over glacial terrain (Meyer et al., 2011). Visual comparison of the SRTM C band and ASTER DEMs, both down-sampled to 300 m spatial resolution and referenced to the WGS84 vertical datum, shows evident noise in the latter (Figure 3.12), particularly at high altitude. Differences are at times in the order of tens of meters between neighbouring pixels. Finally, the AW3D30 v1.1 DEM, originally produced at 5 m spatial resolution and provided free of charge at 30 m posting, has large gaps over the SPI, including the ablation area of the Upsala glacier. The gaps are filled using data from the SRTM C band DEM (Figure 3.13, right panel). Thus, it would still be required to correct parts of it.

For this reason, it was decided to correct the SRTM C band DEM. The correction is extracted from Willis et al. (2012b), whose map of elevation change rates was digitized and referenced to geographic coordinates (Figure 3.14). In the reminder of the thesis, the modified SRTM DEM is simply referred to as the SRTM DEM.
Figure 3.12: SRTM and ASTER topography in a selected region of the Southern Patagonian Ice Field (white box in Figure 3.11), down-sampled to 300 m spatial resolution and referenced to the WGS84 vertical datum. Artefacts are evident in the ASTER DEM.

Figure 3.13: (left) SRTM X band topography. The large gaps are due to the narrow strip width of the instrument. (right) Voids in the AW3D30 DEM (red areas) are filled with the SRTM C band DEM. The voids include the Upsala glacier, which has thinned by more than 80 m since 2000.
3.2 Surface elevation change

3.2.1 Cross track and repeat track algorithms

The first algorithm used to calculate rates of elevation change from spaceborne radar altimetry data uses a simple approach, the crossing of two satellite tracks (Zwally et al., 1989). Since the measurements’ location of individual crossing tracks do not match, the elevation at the crossover is linearly interpolated from the two closest observations, typically within a threshold distance (e.g. Moholdt et al., 2010a,b) (Figure 3.15-a). This approach has high precision and can additionally be used to gauge the accuracy of the elevation estimates when used with acquisitions from the same month/season (Moholdt
3.2.2 The plane-fit algorithm

In order to avoid the input of a DEM when calculating elevation change, least-squares regression can be applied to a set of neighbouring observations and fit a predefined surface. For example, Moholdt et al. (2010b) grouped different tracks of data in overlapping rectangular planes and fit a surface linear in space and time to the observations (Figure 3.15-c). This approach automatically solves for the spatial and temporal components on elevation change.
3.2 Surface elevation change

In contrast to previous missions, the long repeat cycle (369 days) of CS-2 generates a denser network of ground tracks (section 2.2) and a higher number of observations. McMillan et al. (2014b) proposed a different method to calculate elevation changes, which is better suited to the acquisition pattern of CS-2. Their approach is similar to methods applied to ICESat laser altimetry data (e.g. Pritchard et al., 2009; Moholdt et al., 2010b; Flament and Rémy, 2012) and is based on near repeat observations. The method used in this thesis is similar to that developed by McMillan et al. (2014b) and exploits the dense spatial sampling offered by swath-processed CS-2 SARIn acquisitions. It consists of grouping elevations into grid cells of given radius and fit a time-dependent model to the observations. To illustrate the procedure, Figure 3.16 shows an example over one of the largest catchments of the Vatnajökull ice cap (Iceland): Brúarjökull. A uniform grid is generated at the desired spatial posting (grey dots) and observations (cyan dots) are grouped according to a specified search radius. Both these parameters are set to 500 m in the example so that grid cells partially overlap (Figure 3.16, inset). Elevation in each grid cell is modelled as a bi-linear function of
surface terrain \((x, y)\) and a linear function of time \((t)\), plus a constant term:

\[
z(x, y, t) = \beta_1 x + \beta_2 y + \beta_3 t + \beta_4 \text{ const}
\]  

(3.4)

where \(z\) is the elevation field (SwSARIn or POCA), \(x\) and \(y\) are the easting and northing coordinates and \(t\) is the time of data acquisition. The time-dependent coefficient \(\beta_3\) retrieved from the model fit is the linear rate of surface elevation change. Each observation is assigned a weight, generated according to the power field in the following way:

\[
w = \frac{P^i}{\max(P^i)}
\]  

(3.5)

where \(P\) are the scaled smoothed power values described in section 3.1. For POCA observations, all the weights are set equal to one. The best set of coefficients \(\beta\) (in a least squares sense) is then determined by:

\[
\beta = \left[\left(G^T w_D G\right)^{-1} G^T w_D \right] G^+ z
\]  

(3.6)

where \(G = [x \ y \ t \ \text{const}]\) is the model matrix, \(G^T\) is its transpose, \(G^+\) the pseudo-inverse and \(w_D\) is a matrix with diagonal elements equal to the weights \(w\) and null elsewhere. The chosen approach simultaneously solves for the spatial and temporal elevation change components.

To minimize the impact of outliers, a number of data editing steps is undertaken before the model fit. At the dataset level, observations are discarded if the median absolute deviation in their waveform is higher than 10 m or if their individual elevation differs by more than 100 m compared to the reference DEM. At the pixel level, elevations which deviate more than 3 standard deviations from the median elevation in the cell are also discarded. The model is then iteratively fitted to the data using a 3\(\sigma\) clip until no more outliers are detected.
3.2.3 Uncertainties on the rates of elevation change

The pseudo-inverse $G^+$ calculated in Eq. 3.6 is useful to construct the model covariance matrix $\text{cov}(\beta)$, from which the uncertainty on the rate of elevation change $\beta_3$, as well as on the other model parameters, is extracted. The model covariance matrix is defined as:

$$
cov(\beta) = G^+ \text{cov}(z) [G^+]^T.
$$

(3.7)

The square root of the diagonal elements of $\text{cov}(\beta)$ are the standard deviations of the model parameters $\beta$. As it is traditionally challenging to estimate uncertainties on the single elevations, the data covariance matrix $\text{cov}(z)$ was initially set equal to the identity matrix $I$ (Chapter 4), i.e. the error on the model parameters was independent from uncertainties on the data. This approach was later updated so that $\text{cov}(z)$ is now equal to the variance matrix whose diagonal elements are the squared elevation differences between the observed and modelled estimates $(z - z')^2$ (Chapter 5).

Uncertainties on the rates of elevation change over the Vatnajökull ice cap (Iceland) and over the Southern Patagonian Ice Field are shown in Figure 3.17 and 3.18, respectively.

3.2.4 Influence of the weights on rates of elevation change

Weighting the individual observations according to their power (Eq. 3.5) is an empirical approach which was implemented early in the processing chain. The rationale behind it is that a high power, coupled with high coherence, indicates a strong echo return and gives some confidence on the quality of the measurement. Visually, a notable improvement was noted when comparing SwSARIn maps of elevation change rates calculated with and without the use of weights. Their application generally reduces noise. However, occasionally it also introduces artefacts. Both phenomena are illustrated in Figure 3.19. The left panel shows the ‘conventional’ map of elevation
change, with rates calculated using the weights as defined in Eq. 3.5. A localized thickening pattern of order 5 m a\(^{-1}\) is visible in the ablation area of San Quintin (Figure 3.19-a, red box). Physically, such pattern may be the result of dynamic adjustment possibly related to, e.g., a surge event. However, inspection of the data in the area (Figure 3.20-a) reveals that the elevation, generally, is decreasing in time. The thickening pattern in this case is induced by the weights (Figure 3.20-b) which are by far at the highest in 2012, a year in which the average elevation in the given pixel is markedly lower than in other years. Whether this elevation decrease - and subsequent increase - is a physical process is difficult to assess without other data for comparison. In any case, the combination of the two factors results in the estimated thickening pattern.

The same map of elevation change was also reprocessed assigning the weight of each individual observation equal to its coherence value (Figure 3.19-b). Compared to the definition in Eq. 3.5, this formulation is comparable to not applying any weighting since the spread of their values is much lower. With this approach, the elevation change rate in the same area is now close to zero (Figure 3.19-b, red box). Additionally, it generates a smoother thinning pattern overall in the ablation area of San Quintin.
Figure 3.18: Uncertainties on the rates of elevation change over the Southern Patagonian Ice Field. The colormap is logarithmic. The errors are calculated with Eq. 3.7, where $\text{cov}(z)$ is equal to $(z - z')^2$ (see text). 82% of errors are below 1 m a$^{-1}$ (inset).
and improves on the spatial coverage. On the other hand, numerous artefacts are now obvious elsewhere on the ice cap. The scale is set between -10 and 10 m a\(^{-1}\) to display the magnitude of such artefacts in Figure 3.19-b. Noise in the two maps has been removed with the same procedure (section 3.3.2, 'Filtering noise').

It is important to note that SwSARIn elevations over Patagonia were generated using the updated processing described in section 3.1.6, which does not use thresholds on the power or coherence. The observations in Figure 3.19-a (red box) all have extremely low power and would be discarded by the processing used over Iceland. Despite this local artefact, the updated processing improves the number of valid observations and hence the spatial coverage over the Patagonian Ice Fields, which is extremely important given the complex topography of the region. A combination of the two approaches may improve further the results, but has not been tested as part of this work.
3.3 Estimating volume change and mass balance

3.3.1 Spatial coverage and data gaps

As mentioned in section 2.1, radar altimeters measure the distance from the satellite’s antenna to the point at the ground closest to the satellite on a straight line. One key implication of this fact in region of complex topography is that a uniform network of ground tracks does not automatically imply a uniform elevation field. Figure 3.21 shows the ~ 80 tracks which make a repeat cycle (369 days) over Vatnajökull (Iceland). Inter-track spacing at this latitude is about 4 km and the ice cap is spanned uniformly. However, the corresponding map of POCA sampled elevations is highly heterogeneous in space, covering only 38% of the ice cap (Figure 3.22-a). Swath processing improves coverage by a factor two since it provides up to two orders of magnitude more observations than POCA (Figure 3.22-b). However some gaps remain,
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Figure 3.22: Density of valid observations over the Vatnajökull ice cap (Iceland) at 500 m spatial resolution for the POCA (a) and SwSARIn (b) datasets. Note the two orders of magnitude difference in the scale. The average amount of elevations in each grid cell is 13 (POCA) and 1,150 (SwSARIn) and the total spatial coverage is 38% and 80% for POCA and SwSARIn, respectively. Grey cells have no observations.

often at the marginal areas, and they may be relatively large in size particularly over smaller ice caps or individual glaciers (e.g. Figure 5.1).

Before being able to quantify the volume change of a glacier, estimates of elevation change rates must be modelled over the entire region of interest (e.g. an ice cap), a processed which is referred to as regionalization (e.g. Nuth et al., 2010; Nilsson et al., 2015a). Broadly, there are three families of methods: (i) rescaling by area, (ii) spatial and (iii) hypsometric models. The first method is the simplest and can be used only if the voids are small (i.e. a few percent of the total glacier area). Ideally the gaps are also not clustered (e.g. at the front of the glacier) but dispersed on the glacier surface. The second method interpolates/extrapolates values in two dimensions according to the neighbouring rates. This approach is unsuitable if the gaps are relatively large and if they are located at the margins where artefacts may arise due to the extrapolation out of the data hull. Finally, the third approach exploits the relationship between elevation and elevation change, i.e. the hypsometric method, discussed in detail in the following section.
3.3.2 Regionalization: the hypsometric model

A common approach to regionalize observed elevation change $h$ to the entire glacier surface is based on generating a polynomial model of $h$ as a function of elevation using a reference DEM (e.g. Nuth et al., 2010; Moholdt et al., 2010a,b, 2012; Gardner et al., 2011; Nilsson et al., 2015a; Foresta et al., 2016). The order of the polynomial depends on the pattern of elevation change for any given region or sub-region. Nuth et al. (2010) allows polynomials of order up to 6, while more commonly the maximum order used is up to 3 (Moholdt et al., 2010a,b; Gardner et al., 2011; Moholdt et al., 2012; Nilsson et al., 2015a; Foresta et al., 2016). The polynomial is then evaluated at given elevations in the glacier elevation range, typically at 50 m steps in elevation. Examples of this approach are shown in Figure 3.23-a (Moholdt et al., 2010b) and Figure 3.23-b (Nuth et al., 2010) for Svalbard glaciers. Modelled estimates are multiplied to the surface area of the corresponding elevation band (extracted from a reference DEM) to obtain volume change rates. Conversion to mass change is typically done assuming that all the material has the density of glacial ice (Nuth et al., 2010; Gardner et al., 2011; Moholdt et al., 2012; Nilsson et al., 2015a; Foresta et al., 2016), although some studies have proposed (Moholdt et al., 2010a,b) or tested (Foresta et al., 2016) multiple density scenarios.

Most studies of recent elevation change over ice caps were undertaken using ICESat data (2003-2009). The small 70 m footprint makes for precise measurements but, together with a comparatively large inter-track spacing, provides limited density of observations. Particularly relevant to this thesis is the example of Iceland, where all ice caps except Vatnajökull have surface areas below 1000 km$^2$. In a period of six years between 2003 and 2009, ICESat provides 851 observations of elevation change over all Icelandic ice caps together (Figure 3.24, top right; Nilsson et al. (2015a)), largely from Vatnajökull itself. Data from different ice caps must be grouped together (Figure 3.24, top left) to generate a combined polynomial model. This may leads
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Figure 3.23: (a) Third-order polynomial fits to elevation change data over Svalbard glaciers in the period 2003-2008 (after Moholdt et al., 2010b). (b) Polynomial fits of order 2-6 to elevation change data over Svalbard glaciers in a variable period between 1966/1990 to 2005 (after Nuth et al., 2010).

Figure 3.24: Observed (top right) elevation change rates based on ICESat data (2003-2009). Data from all ice caps must be combined (top left) to generate the polynomial model used to fill the gaps (bottom). Modified, after Nilsson et al. (2015a).
to artefacts in the regionalized maps of elevation change rates. A clear example is Drangajökull (north-west Iceland), the fifth largest ice cap in Iceland. There is no data here to constrain results, but the modelled $h$ shows the strongest thickening amongst all ice caps in the region (Figure 3.24, bottom right). This output is simply driven by the fact that Drangajökull’s maximum elevation ($<900$ m) lies at low altitude compared to other ice caps in Iceland. The hypsometric model thus generates an artificially strong thinning over its entire surface.

Given the amount of data provided by CS-2, hypsometric averaging in this thesis is applied at the ice cap scale (Chapter 4), so that a more accurate model can be constructed to generate estimates of elevation change rates. Furthermore, the density of observations achieved through swath processing allows to going one step further and analyse single catchments. This was first tested over the Brúarjökull basin of the Vatnajökull ice cap (Iceland, Chapter 4) and then applied over a number of large glaciers on the Southern Patagonian Ice Field (Chapter 5). This is particularly useful as even neighbouring catchments may display significantly different patterns of change, especially in regions where dynamic changes are significant (Chapter 5). Thus being able to model their gaps individually improves the precision on the estimates of mass balance.

**The hypsometric model step by step**

The rest of this section describes in detail all the steps used in this work to interpolate/extrapolate rates of elevation change over the gaps, including filtering noise and automatically selecting the best polynomial fit, and to convert that into an estimate of glacier volume change and mass balance. The Vatnajökull ice cap (Iceland) is used as an example to graphically illustrate each step. The propagation of elevation change uncertainties and the quantification of the overall error budget on the mass balance estimate are discussed in section 3.4.
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Filtering noise from $\dot{h}$ maps

Once the rates of elevation change $\dot{h}$ are calculated (section 3.2), the first step is to filter the noise. Despite its importance, few studies explain in detail what procedure they apply. Nilsson et al. (2015a) removes $\dot{h}$ data according to the standard deviation of the regression used to calculate elevation change. They additionally mask observations according to a 10-point moving Hampel filter and finally compute a smoothed $\dot{h}$ field using an along-track filter over a distance of 2.5 km. Nuth et al. (2010) use an iterative $3\sigma$ filter on $h$ data binned at 50 m in elevation until the improvement on the standard deviation within the elevation band converges ($< 2\%$ threshold).
3.3 Estimating volume change and mass balance

For this work, it was decided not to apply any smoothing to the maps of elevation change rates. This approach preserves the physically-based variability between neighbouring catchments. However it poses a challenge when filtering noise, in particular given the high spatial resolution (500x500 m$^2$) achieved with SwSARIn data. Figure 3.25-a shows the original map of elevation change over Vatnajökull (Iceland). For comparison, the equivalent map computed with POCA data is shown in Figure 3.26. Noise was removed according to thresholds on the rates of elevation change, their estimated error and their temporal span. The thresholds are as follows:

- $\dot{h} < -20$ m a$^{-1}$ OR $\dot{h} > +5$ m a$^{-1}$
- $\epsilon_{\dot{h}} < 10$ m a$^{-1}$
- pixel time span $> 2$ a

where $\epsilon_{\dot{h}}$ are the rates’ errors calculated in Eq. 3.7, with $\text{cov}(z)$ equal to the identity matrix $I$. Additionally, a median smoothed map $\dot{h}'$ was computed and pixels differing from $\dot{h}'$ more than three times the mean absolute deviation between the original rates $\dot{h}$ and their smoothed values $\dot{h}'$ were discarded. The choice of the threshold is somewhat subjective and is justified by the need to filter as much noise as possible without removing quality data. The final output, for SwSARIn data, is shown in Figure 3.25-b.

Figure 3.26: Original map of elevation change rates over Vatnajökull based on POCA elevations gridded at 500 m spatial resolution.
Following the improvement on the rates’ uncertainty calculation discussed in section 3.2.3, maps of elevation change rates over the Patagonian Ice Fields (Chapter 5) were filtered using more stringent thresholds on the rate error, one for each sub-region analysed. For most regions the threshold ranges between 1 and 3 m a\(^{-1}\) and was never above 6 m a\(^{-1}\). Cells with unreasonably high rates of elevation change (\(|\dot{h}| > 30\) m a\(^{-1}\)) were also removed. Finally, the median smoothed map was again applied as for Iceland.

**Automatic selection of the best polynomial fit**

After filtering the original data, the altitude of each pixel is extracted from a reference DEM (section 3.1.7). The rates of elevation change are thus plotted versus elevation and polynomials of increasing order \(P^n\) are fitted to the data (Figure 3.27), where \(n\) ranges from one to three. An iterative procedure was set up to automatically find the model which best explains the observed variability in the data, statistically. In fact, since polynomial models are nested, \(P^{n+1}\) always fits better the data with respect to
3.3 Estimating volume change and mass balance

$P^n$. However, this might be due to over fitting. Previous work (e.g. Moholdt et al., 2010b; Nilsson et al., 2015a) has used the convergence of the $R^2$ statistics to select the polynomial. However, it is somewhat subjective to decide when convergence has been achieved. In this thesis, the f-test is used to evaluate if the improvement of the additional parameter in $P^{n+1}$ is statistically significant at the 99% confidence level. The f-test is defined as:

$$f = \frac{(\text{RSS}_{n-1} - \text{RSS}_n)}{\left(\frac{\text{RSS}_n}{N - p_n}\right)}$$

(3.8)

where the n and p subscripts indicate, respectively, the polynomial order and its number of parameters ($p = n+1$) and N is the number of observations used to generate the two models. The residual sum of squares, $\text{RSS}$, is given by:

$$\text{RSS} = \sum_{k=1}^{N} (\dot{h}_{\text{obs}} - \dot{h}_{\text{mod}})^2$$

(3.9)

The selected polynomial is used to model rates of elevation change over the gaps, individually for each pixel. The resulting estimates versus elevation are shown in Figure 3.28 (black dots); their spatial representation is displayed in Figure 3.25-c. This is slightly different than in previous work (e.g. Nuth et al., 2010; Moholdt et al., 2010a,b, 2012; Gardner et al., 2011; Nilsson et al., 2015a), where the fitted polynomial was used to model $\dot{h}$ at prescribed elevations.

Rate of volume and mass change

Combining observed and modelled rates of elevation change, the spatial coverage is complete and the simplest way to calculate volume change is to integrate the rates over the ice cap and multiply by the selected spatial resolution (500x500 m in the given example). Another approach (Nuth et al., 2010; Moholdt et al., 2010a,b, 2012; Gardner et al., 2011; Nilsson et al., 2015a; Foresta et al., 2016) is to separately calculate the average rate of elevation change in each 50 m elevation band k, $< \dot{h} >_k$ (Figure
Figure 3.28: Observed and modelled rates of elevation change (black dots) against elevation. The median value in each elevation band $k$ is shown in green. The area distribution of the LMI DEM is displayed in blue.

Figure 3.29: Volume change in each elevation band against elevation. The vertical dashed line displays the average ELA over the Vatnajökull ice cap (1,200 m).
Since variability within some elevation bands is relatively high, the median is taken as the average rate of elevation change. This statistics is more robust and reduces the influence of few potential outliers. The spatial representation of the averaged elevation change is shown in Figure 3.25-d.

The glacier’s surface area within each band $A_k$ is extracted from the reference DEM (Figure 3.28, blue line). The product $<\dot{h}>_k A_k$, integrated over all elevation bands, gives the total rate of volume change for the ice cap (Figure 3.29):

$$
\dot{V} = K \sum_{k=1}^{K} (<\dot{h}>_k A_k)
$$

The ice cap’s rate of mass change is then estimated by multiplying the rate of volume change $\dot{V}$ by a constant density of glacial ice ($\rho_{\text{ice}} = 900 \text{ kg m}^{-3}$). As this assumption may be over simplistic, a dual-density scenario was additionally tested in Iceland to quantify its impact on the rate of mass change (Figure 3.29 and Chapter 4). In this case, the density of glacial ice was applied to the ablation area, while for the accumulation area a firm density equal to $\rho_{\text{firn}} = 650 \text{ kg m}^{-3}$ was used.

### 3.3.3 Regional, ice cap and catchment scale

The map of elevation change rates provided by SwSARIn data over the Vatnajökull ice cap (3.25-b) gives great detail on the variability between different catchments (discussed in depth in Chapter 4). Such complexity in the spatial patterns of elevation change is smoothed when applying the hypsometric model at the ice cap scale (Figure 3.25-d), somewhat similar to applying this approach over a number of ice caps together as mentioned earlier in this section. The limitation of using a combined polynomial model for Vatnajökull as a whole is shown in Figure 3.30. Modelled rates of elevation change at the termini of Dyngjujökull and Skeiðarárjökull differ by about 1-2 m a$^{-1}$ despite their observed rates are comparable (about 4 m a$^{-1}$). Since the terminus of
Dyngjújökull lies at about 1000 m altitude, its modelled thinning rate is lower than Skeiðarárjökull, whose front is almost at sea level.

If one’s aim is to calculate the average mass change over the entire ice cap, these differences may be ignored to a first order calculation. However, this example also shows the potential of SwSARIn data to be used at the catchment scale for basins showing distinctive patterns of change. The observed rates of elevation change for the Brúarjökull and Skeiðarárjökull basins, together with their median rates within each 50 m elevation band, are shown in Figure 3.31-a. The southern basin (red) is thinning at any elevation, while the northern one (blue) is thickening in the accumulation area above 1,200 m altitude and thinning at lower elevation. The ice cap model (black) significantly deviates from the former at high elevation and from the latter at low elevation. In this case, there is enough data in both catchments to independently apply the hypsometric averaging and calculate their mass change.

This example shows the potential of CS-2 SwSARIn data to observe glacial processes at the catchment scale. This has been tested over the Brúarjökull catchment in Iceland (Chapter 4) and for a number of large glaciers in Patagonia (Chapter 5).
3.4 The error budget

When generating maps of elevation change rates $\dot{h}$, each individual pixel is assigned an uncertainty $\epsilon_{\dot{h}}$. Such value is extracted from the model covariance matrix (Eq. 3.7) introduced in section 3.2.3. These errors are propagated when applying the hypsometric averaging method (section 3.3.2), as illustrated here.

As shown in Figure 3.28 (green line), an average rate of elevation change $<\dot{h}>_k$ is calculated for each altitude band k. The uncertainties $\epsilon_{\dot{h}}$ on the observed $\dot{h}$ in the given band k are propagated to estimate the error on $<\dot{h}>_k$. The calculation is as follows:

$$E^k_{\dot{h}} = \frac{1}{N_k} \sqrt{\sum_{j=1}^{N_k} (\epsilon^j_{\dot{h}})^2}.$$  \hspace{1cm} (3.11)

where $N^k$ and $\epsilon^k_{\dot{h}}$ are, respectively, the number of observed rates in elevation band k and their associated uncertainties. Continuing the example from the previous section, the Vatnajökull’s errors $E^k_{\dot{h}}$ versus elevation are shown in Figure 3.32.

Rarely, over smaller ice caps or individual glaciers (e.g. Jorge Montt, SPI), there may be no valid observations of elevation change rates in a given elevation band and thus no error on the average elevation change rate can be calculated. In this case, gaps are filled

---

**Figure 3.31:** (a) Observed (dots) and median (lines) rates of elevation change for the Brúarjökull (blue) and Skeiðarárjökull (red) catchments (Vatnajökull, Iceland). (b) Observed median rates for the two models (colors) compared to the one at the ice cap scale (black).
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Figure 3.32: Error on the average rate of elevation change versus elevation for the Vatnajökull ice cap (Iceland).

Figure 3.33: Errors on the median rates of elevation change versus elevation for the Mýrdalsjökull plus Eyjafjallajökull ice caps (Iceland) as well as for Jorge Montt glacier (Southern Patagonian Ice Field). Errors based on observed data are shown in black. The two-term exponential fit to the data (black line) is used to model the missing errors (red).
by fitting a two-term exponential \( y = e^{bx} + ce^{dx} \) to the data (Figure 3.33, black line). The choice of fit is justified by its flexibility. Generally, the errors \( E^h_k \) show a decreasing trend with increasing elevation (Figure 3.32 and 3.33-a). However the fitting function is flexible enough for cases where this relationship is more complex (Figure 3.33-b).

In the examples in Figure 3.33, the first elevation band (at the lowest altitude) does not have any observations. In such case, the two-term exponential would be unbound and may produce an extremely high error estimate. There is no clear general approach to deal with this issue. Conservatively, the first error is set equal to twice the highest observed error before calculating the fit (Figure 3.33).

Average elevation change errors \( E^h_k \) are then converted to volume errors \( E^V_k \) simply by multiplying them to the glacier’s surface area \( A^k \) in the given elevation band \( k \). Assuming that errors may be correlated in elevation, the total volume change error is taken as the sum across all elevation bands:

\[
E^V_{\text{tot}} = \sum_{k=1}^{K} E^V_k = \sum_{k=1}^{K} \left( E^h_k A^k \right).
\tag{3.12}
\]

With this method, the total volume error is based on propagation of uncertainties on the observed rates of elevation change. However, it does not account for the incomplete spatial coverage of the \( h \) dataset. In order to correct for this, \( E^V_{\text{tot}} \) is rescaled according to the fraction of unobserved glacier area in the following way:

\[
E^V_{\text{scaled}} = E^V_{\text{tot}} f.
\tag{3.13}
\]

The scaling factor \( f \) is the inverse of the mean coverage in the ablation and accumulation areas or the inverse of the total coverage \( \chi \) if the glacier’s ELA is not known:

\[
f = \frac{1}{(\chi_{abl} + \chi_{acc})/2}
\]

\[
f = \frac{1}{\chi}
\tag{3.14}
\]
This procedure generates a rather conservative error estimate since it assumes that the lack in data coverage has a direct impact on the total error estimate, which does not hold if the sampling is sufficiently uniform.

Finally, when converting volume to mass change, the uncertainty on the density is prescribed as in Nilsson et al. (2015a) and Moholdt et al. (2010a), namely:

$$\epsilon_\rho = \frac{1}{2} \left( \rho_{\text{ice}} + \rho_{\text{firn}} \right).$$  \hspace{1cm} (3.15)

Following uncertainty propagation rules, the final error on the mass balance is:

$$E_\dot{M} = |\dot{M}| \sqrt{\left( \frac{E_{\text{scaled}}}{V} \right)^2 + \left( \frac{\epsilon_\rho}{\rho_{\text{ice}}} \right)^2}.$$  \hspace{1cm} (3.16)

### 3.5 Time series of elevation change

CS-2 produces enough data to allow computing time series of average elevation change, as demonstrated by Gray et al. (2015) for a number of Arctic ice caps. The algorithm developed for this thesis follows their approach with minor modifications.

![Figure 3.34: Simplified time series with only four periods $T_1$ to $T_4$. The average elevation difference between two periods can be calculated using two pairs of periods. An example is provided for $\Delta H_{1,3}$.](image)

Figure 3.34: Simplified time series with only four periods $T_1$ to $T_4$. The average elevation difference between two periods can be calculated using two pairs of periods. An example is provided for $\Delta H_{1,3}$. 
The observations are divided into N periods with time step $\Delta t$. The shortest possible $\Delta t$ is 30 days, CS-2’s orbit sub-cycle. However in this work 90 days or 120 days is used, given that the algorithm was applied to comparatively smaller areas such as the ablation/accumulation area of an ice cap (Chapter 4) or individual glaciers (Chapter 5).

In the simplest case, each time period $T_j$ (with $j > 1$) is compared to the first one. For each observation in period $T_j$, the closest data point in period $T_1$ is selected. If the distance between the two is within a prescribed threshold, the elevation difference is computed and corrected for the slope using a reference DEM. Typically, the maximum distance is 400 m (Gray et al., 2015), corresponding to CS-2 along-track sampling. Elevation differences whose absolute value is above three times the median absolute deviation are discarded before calculating the average elevation difference:

$$\Delta H_{1,j} = \text{avg}(h_j - h_1)$$  \hspace{1cm} (3.17)

where $h_j$ and $h_1$ represent all the matching elevations in period $T_j$ and $T_1$, respectively. The output is illustrated conceptually in the first row of Table 3.2 and shown in Figure 3.35 (black line). However, it is possible to improve on this approach by using a combination of average elevation differences between different periods Gray et al. (2015). Figure 3.34 provides an illustrative example where the data are divided into four periods. All the possible combinations $\Delta H_{p,q}$ (with $p \neq q$) are calculated beforehand and populate an upper diagonal matrix (Table 3.2). This is computationally efficient since each average value in Table 3.2 is used multiple times. Subsequently, the average elevation difference, e.g., between periods $T_1$ and $T_3$ can be calculated as the sum ($\Delta H_{1,2} + \Delta H_{2,3}$) or the difference ($\Delta H_{1,4} - \Delta H_{3,4}$) (Figure 3.34). The formula can be generalised to:

$$\Delta H_{1,j}^{(m)} = \begin{cases} 
\Delta H_{1,m} + \Delta H_{m,j} & m < j \\
\Delta H_{1,m} - \Delta H_{j,m} & j < m 
\end{cases}$$  \hspace{1cm} (3.18)

Including the initial difference $\Delta H_{1,3}$, this approach generates three estimates for the same quantity. These can be averaged (median) together to provide a more robust
Table 3.2: Upper diagonal matrix with all possible $\Delta H_{p,q}$ computations.

- $\Delta H_{1,2}$ $\Delta H_{1,3}$ $\Delta H_{1,4}$ $\Delta H_{1,5}$
- - $\Delta H_{2,3}$ $\Delta H_{2,4}$ $\Delta H_{2,5}$
- - - $\Delta H_{3,4}$ $\Delta H_{3,5}$
- - - - $\Delta H_{4,5}$

Table 3.3: All possible computations of $\Delta H_{p,q}^{(k)}$. The diagonal entries $\Delta H_{1,k}^{(k)}$ are always null.

- $\Delta H_{1,2}^{(1)}$ $\Delta H_{1,3}^{(1)}$ $\Delta H_{1,4}^{(1)}$
- - $\Delta H_{1,3}^{(2)}$ $\Delta H_{1,4}^{(2)}$
- $\Delta H_{1,2}^{(3)}$ - $\Delta H_{1,4}^{(3)}$
- $\Delta H_{1,2}^{(4)}$ $\Delta H_{1,3}^{(4)}$ -

estimate of average elevation difference between the two given periods. When applied to all period pairs, this procedure produces N-1 time series of elevation change if the data is divided into N periods. Each time series is one row of Table 3.3.

Differently from Gray et al. (2015), weights are applied when combining different averages together, according to the fraction of data used to calculate each value $\Delta H_{p,q}$. Thus Eq. 3.18 becomes:

$$\Delta H_{1,j}^{(m)} = \begin{cases} 
\frac{w_{1,m} \Delta H_{1,m} + w_{m,j} \Delta H_{m,j}}{w_{1,m} + w_{m,j}} & m < j \\
\frac{w_{1,m} \Delta H_{1,m} - w_{j,m} \Delta H_{j,m}}{w_{1,m} + w_{j,m}} & j < m 
\end{cases}$$ 

where each weight $w_{p,q}$ is equal to the number of common elevations between periods $T_q$ and $T_p$ normalized to the total amount of observations in the dataset.

The time series of elevation change for the ablation area of Vatnajökull (Iceland) is provided as a realistic example (Figure 3.35). The black line shows the time series
Figure 3.35: Time series of elevation change for Vatnajökull (Iceland) at elevation below 1200 m.

without using period pairs, the gray lines are all the other possibilities and the red line is the median-average.
Chapter 4

Surface elevation change and mass balance of Icelandic ice caps derived from swath mode CryoSat-2 altimetry

Exceptionally cloud free view of Iceland taken from ESA Envisat on 21, July 2010.
The processing chain described in Chapter 3 was first applied to ice caps in Iceland, which include the largest in Europe (by volume): Vatnajökull. Glaciers in Iceland cover some 11% of the land and the six largest ice caps analysed in this Chapter represent about 90% of it. Their complex spatial patterns of elevation change are investigated in detail and linked to a number of diverse causes from climate, ice dynamics and sub-glacial geothermal and magmatic processes.

Icelandic ice caps have been monitored for the last few decades, thus providing the opportunity to compare the output of the methodology in this thesis to results available in the literature as well as to data acquired in the same time period. Specifically, the geodetic estimate of mass change of the Langjökull ice cap and Brúarjökull basin (Vatnajökull) are compared to those based on *in situ* data.

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CHAPTER 4. Surface elevation change and mass balance of Icelandic ice caps derived from swath mode CryoSat-2 altimetry


**Author contributions:** L.F. and N.G. designed the research. L.F. processed the data. L.F. analysed the results, with input from N.G., P.N. and F.P. H.B. and F.P. provided additional data for comparison. L.F. wrote the paper, with input from all co-authors.

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4.1 Abstract

We apply swath processing to CryoSat-2 interferometric mode data acquired over the Icelandic ice caps to generate maps of rates of surface elevation change at 0.5 km postings. This high-resolution mapping reveals complex surface elevation changes in the region, related to climate, ice dynamics and sub-glacial geothermal and magmatic processes. We estimate rates of volume and mass change independently for the six major Icelandic ice caps, 90% of Iceland’s permanent ice cover, for five glaciological years between October 2010 and September 2015. Annual mass balance is highly variable; during the 2014/15 glaciological year, the Vatnajökull ice cap (∼70% of the glaciated area) experienced positive mass balance for the first time since 1992/93. Our results indicate that between glaciological years 2010/11 and 2014/15 Icelandic ice caps have lost $5.8 \pm 0.7$ Gt a$^{-1}$ on average, ∼40% less than the preceding 15 years, contributing $0.016 \pm 0.002$ mm a$^{-1}$ to sea level rise.

4.2 Introduction

It is estimated that glaciers and ice caps worldwide, including the periphery of the Greenland and Antarctic ice sheets, contribute about 47% of all land ice mass loss and 30% of current sea level rise (Vaughan et al., 2013; Gardner et al., 2013). Although satellite laser (LA) and radar (RA) altimetry observations have been crucial in estimating ice cap contributions to sea level change (Bolch et al., 2013; Moholdt et al., 2010a,b; Nuth et al., 2010; Rinne et al., 2011b,a; Gardner et al., 2011; Moholdt et al., 2012; Nilsson et al., 2015a; McMillan et al., 2014a), a comprehensive assessment is still lacking because of their complex topography, high slopes and small size with respect to satellite ground track spacing (7.5 km and 40 km at 60°N for Icesat and ENVISAT, respectively) and footprint (2-10 km in diameter for ENVISAT). The
European Space Agency (ESA) CryoSat-2 (CS-2) satellite (Wingham et al., 2006a) carries a state-of-the-art radar altimeter for land ice applications. CS-2 improves upon previous missions in three ways: (1) narrow inter-track spacing (4km at 60°N) provides higher observation density, (2) synthetic aperture radar (SAR) processing along-track reduces the footprint size from \(~1.65 \times 1.65\) km\(^2\) (pulse limited) to \(~1.65 \times 0.305\) km\(^2\) (pulse-Doppler limited) and (3) the interferometer on board CS-2, in the so-called SARIn mode, allows the position of the surface reflection to be accurately located (Wingham et al., 2006a). Although these characteristics make standard CS-2 SARIn elevations better suited to monitoring relatively small ice bodies characterized by complex and steep terrain (McMillan et al., 2014a; Gray et al., 2015), conventional Point-Of-Closest-Approach (POCA) altimetry tends to provide inhomogeneous spatial coverage due to the tendency of POCA towards sampling topographic highs (Figure 4.6 and 4.8) (Gray et al., 2015).

Iceland is located at the boundary between polar and mid-latitude atmospheric circulation cells and between the warm Irminger and cold East Greenland / East Iceland oceanic currents. As a consequence, Icelandic ice caps are very sensitive to climatic shifts (Björnsson et al., 1998, 2013; Adalgeirsdóttir et al., 2005; Flowers et al., 2005) and are estimated to have the highest static mass balance sensitivities among glaciers and ice caps north of 60° (De Woul and Hock, 2005). They also display highly complex and dynamic behaviour unique to Iceland; about 60% of the current glaciated area lies over active volcanoes (Björnsson and Pálsson, 2008) and subglacial eruptions episodically trigger rapid ice loss albeit on short time scales (<1 year, Björnsson et al. (2013)). Furthermore, surge-type outlet glaciers are present in all Icelandic ice caps, and cover 75% of Vatnajökull’s surface (Björnsson et al., 2003); surges in Iceland can cause significant mass transport to the ablation area and advance the terminus by up to 10 km during surge, with an opposite effect during multi-decadal post-surge periods (Björnsson et al., 2003; Björnsson and Pálsson, 2008; Gourmelen et al., 2011). Icelandic ice caps have been losing mass since the mid-1990s, in response to rising air temperatures
caused by changes in atmospheric and oceanic circulation around Iceland, possibly
induced by a global strengthening of the Atlantic meridional overturning circulation
(Björnsson et al., 2013, and references therein). Vatnajökull, with a loss of 6.58 Gt
a\(^{-1}\) between 1995 and 2010, is the main contributor to the overall regional mass loss,
followed by Langjökull (1.31 Gt a\(^{-1}\) between 1997 and 2010) and Hofsjökull (1.24
Gt a\(^{-1}\) between 1995 and 2010) in the central highlands (Table 4.1) (Björnsson et al.,
2013). Iceland as a whole has lost mass at a rate of \(~11.0 \pm 1.5\) Gt a\(^{-1}\) in the period
2003-2010 and contributed 0.03 \pm 0.004 mm a\(^{-1}\) to sea level rise (e.g. Björnsson et al.,
1998, 2002, 2013; Gudmundsson et al., 2011; Jacob et al., 2012; Gardner et al., 2013;
Pálsson et al., 2012; Jóhannesson et al., 2013; Hannesdóttir et al., 2015; Magnússon
et al., 2016; Pope et al., 2016). However, inter-annual variability is high, with rates
of mass loss varying from 2 to 25 Gt a\(^{-1}\) between 1995 and 2009 (Björnsson et al.,
2013). This reflects both variability in tephra deposition on the ice caps (e.g. Möller
et al., 2014) as well as their high sensitivity to temperature and precipitation (Björnsson
et al., 2013; Adalgeirsdóttir et al., 2006; De Woul and Hock, 2005).

Here, we extend mass balance estimates of the Icelandic ice caps from 2010 to 2015,
by exploiting CS-2 as a swath altimeter. We estimate the annual rate of mass change
of Iceland’s six largest ice caps, Vatnajökull, Langjökull, Hofsjökull, Mýrdalsjökull,
Drangajökull and Eyjafjallajökull, corresponding to 90\% of the island’s permanent ice
cover, and over 99\% of its volume (Björnsson and Pálsson, 2008).

4.3 Methods

We measure time dependent elevation over the ice caps using swath processing of CS-
2 level 1b SARIn data (SwSARIn). In contrast to the conventional POCA method,
SwSARIn exploits the full radar waveform to provide a dense swath of elevation
measurements across the satellite ground track (beyond POCA) when signal and
surface conditions are favourable (see section 4.7.1; Hawley et al., 2009; Gray et al., 2013; Christie et al., 2016; Ignéczí et al., 2016). As a reference, we also use elevations derived from the operational CS-2 level 2 POCA product to assess ice cap elevation changes (see section 4.7.1), where POCA refers to the CS-2 heights obtained via conventional retracking (Wingham et al., 2006a). For both datasets, we use CS-2 baseline C data which are available from July 2010 to present.

We compute rates of surface elevation change \( \dot{h} \) from SwSARIn data using a plane-fit algorithm (section 3.2.2; McMillan et al., 2014b) over five glaciological years: 2010/11 to 2014/15 (Figure 4.1). We define one glaciological year as the period between 1\(^{st}\), October in year n and 30\(^{th}\) September in year n+1. The dense elevation field provided by SwSARIn processing allows gridding at 0.5 km posting. In each pixel, the time dependent elevation is obtained by:

\[
z(x, y, t) = c_0 x + c_1 y + \dot{h} t + c_2
\]

(4.1)

where x, y, t are easting, northing and time respectively. The time dependent coefficient retrieved from the model fit is the linear rate of surface elevation change, \( \dot{h} \). The model is iteratively fitted to the data, excluding elevation differing from the model by more than 3 standard deviations, until no more outliers are detected. The pixel rate uncertainty \( \epsilon_{\dot{h}} \) is extracted from the covariance matrix of the model parameters (see section 4.7.2). Pixels are discarded whenever a set of quality thresholds are exceeded (see section 4.7.4) and final coverages of the rates of surface elevation change maps are 80\% (Vatnajökull), 75\% (Langjökull), 87\% (Hofsjökull), 69\% (Mýrdalsjökull), 65\% (Drangajökull) and 27\% (Eyjafjallajökull), respectively. No smoothing is applied, in order to minimize the correlation between adjacent measurements that would otherwise impact on the analysis of spatial variability in \( \dot{h} \), and is permitted by the high observation density provided by SwSARIn.

We interpolate gaps in the maps of surface elevation change rates (Figure 4.1) using
hypsometric averaging (e.g. Moholdt et al., 2010a; Nilsson et al., 2015a) as a form of regionalization method and calculate ice cap volume changes from the gap filled maps (we do not use the method to extrapolate beyond the locus of the SWSARIn measurements). We apply the regionalization independently for all of the ice caps except for Eyjafjallajökull which has relatively few measurements and is therefore processed together with the neighbouring Mýrdalsjökull. The resulting $h$ map is divided into 50 m elevation bands using an external DEM from the National Land Survey of Iceland (Landmælingar Íslands, www.lmi.is) and the volume change $V_k$ of each band $k$ is calculated as the product of the mean $h_k$ and the surface area $A_k$. The DEM spatial resolution is downscaled to the $h$ grid resolution so that pixels elevations and elevation bands areas are representative of the pixels size. Volume change estimates for all bands are added together and then converted to a mass balance rate $\dot{M}$ using the density of glacial ice. Although this simplification ignores potential variations in snow/firn density (e.g. with elevation and thus melt), it is commonly used when deriving mass change and sea level contribution from ice caps (e.g. Magnússon et al., 2016; Nilsson et al., 2015a; Nuth et al., 2010; Moholdt et al., 2010a; Björnsson et al., 2013). For comparison, we also provide a mass balance estimate assuming a dual density scenario (e.g. Gardner et al., 2011; Moholdt et al., 2010b) to account for density differences between the ablation and accumulation area. We propagate rate errors $\epsilon_{\dot{h}}$ of the individual pixels to estimate uncertainties for $\dot{V}$ and $\dot{M}$ (see section 4.7.2).
Table 4.1: Mass balance of Icelandic ice caps

Estimates from SwSARIn data for five glaciological years between October 2010 and September 2015, as well as from the current literature (w.r.t. the specified time period). Mass change $\dot{M}$ is given in Gt a$^{-1}$ as well as $m_{we}$ a$^{-1}$ (specific mass balance). Ice caps areas and volumes after Björnsson and Pálsson (2008). References in table: (1) Björnsson et al. (2013), (2) Jóhannesson et al. (2013), (3) Magnússon et al. (2016), (4) Gudmundsson et al. (2008), (5) Pálsson et al. (2012), (6) Gardner et al. (2013), (7) Jacob et al. (2012) and (8) Nilsson et al. (2015a). * Mass balance of Vatnajökull between October 2010 and September 2014 is $-4.93 \pm 0.80$ Gt a$^{-1}$ ($-0.69 \pm 0.11$ m$w$e a$^{-1}$).

<table>
<thead>
<tr>
<th>Ice Cap</th>
<th>A [km$^2$]</th>
<th>V [km$^3$]</th>
<th>$\dot{M}$ [Gt a$^{-1}$] (period)</th>
<th>$\dot{M}$ [Gt a$^{-1}$]</th>
<th>$\dot{M}$ [m$w$e a$^{-1}$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vatnajökull</td>
<td>8100</td>
<td>3100</td>
<td>-6.58 $^1$ (1995-2010)</td>
<td>-3.68* ± 0.61</td>
<td>-0.52* ± 0.09</td>
</tr>
<tr>
<td>Langjökull</td>
<td>900</td>
<td>190</td>
<td>-1.31 $^1$ (1997-2010)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.91 $^4$ (1999-2007)</td>
<td>-0.70 ± 0.20</td>
<td>-0.81 ± 0.23</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-1.20 $^5$ (1999-2007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hofsjökull</td>
<td>890</td>
<td>200</td>
<td>-1.24 $^1$ (1995-2010)</td>
<td>-0.45 ± 0.10</td>
<td>-0.66 ± 0.15</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.92 $^2$ (2004-2008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mýrdalsjökull + Eyjafjallajökull</td>
<td>590</td>
<td>+ 140</td>
<td>-0.78 $^4$ (1999-2007)</td>
<td>-0.21 ± 0.16</td>
<td>-0.39 ± 0.29</td>
</tr>
<tr>
<td></td>
<td>80</td>
<td></td>
<td>-0.06 $^2$ (2004-2010)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drangajökull</td>
<td>160</td>
<td>24</td>
<td>-0.07 $^3$ (2005-2011)</td>
<td>-0.05 ± 0.07</td>
<td>-0.28 ± 0.40</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.05 $^2$ (1990-2011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Iceland</td>
<td>∼11,000</td>
<td>∼3,600</td>
<td>{[9-11]} $^1$ ± [1-3]$^{1,6,7,8}$ ($\sim$1995-2010)</td>
<td>-5.83 ± 0.74</td>
<td>-0.59 ± 0.07</td>
</tr>
</tbody>
</table>
4.4 Results

SwSARIn provides a step-change in surface coverage (Figure 4.1), generating ~10 million elevation measurements over Vatnajökull between October 2010 and September 2015 and allowing the retrieval of rates of surface elevation change over 80% of the ice cap area (Figure 4.7). In comparison, ICESat acquired 851 elevation measurements over all Icelandic ice caps between 2003 and 2009 (Nilsson et al., 2015a). With the conventional POCA approach, CS-2 delivers ~60,000 observations over Vatnajökull (October 2010 to September 2015) and provides rates of surface elevation change over 40% of the ice cap area, preferentially along topographic highs (see section 4.7.3) and Figure 4.6). Over the Langjökull ice cap, the particular hypsometry accentuates the concentration of elevations over the ice divide (inset in Figure 4.1, Figure 4.8). There is almost no POCA observation close to the marginal areas of the northern dome (Figure 4.10, middle) and only ~10 observation per km² over the southern dome (Figure 4.10, right), which is insufficient to estimate robust rates of surface elevation change. In turn, limited sampling at the margins where most of the thinning is occurring impacts on the representativity of the POCA rates of volume and mass change (see section 4.7.3).

The time series of surface elevation change over the Vatnajökull ice cap (Figure 4.2) shows a clear seasonal pattern with an increase in surface elevation during the accumulation period followed by a rapid decrease during the melt season, with amplitudes of about 3 m similar to observations over other Arctic ice caps (Gray et al., 2015). Additionally, the elevation time series show an absence of sharp jumps in elevation that would otherwise be indicative of a sudden and unusual change in scattering horizon, and would introduce a bias in the estimated rates of surface elevation change (Nilsson et al., 2015b; McMillan et al., 2016).

The data reveal a clear pattern of thinning, with rates of up to 10 m a⁻¹ over
Figure 4.1: Rates of surface elevation change maps of Icelandic ice caps between 2010 and 2015 at 0.5 km posting based on SwSARIn heights as well as location of the ice caps in Iceland. V (Vatnajökull), L (Langjökull), H (Hofsjökull), M (Mýrdalsjökull), D (Drangajökull), E (Eyjafjallajökull). Basin outlines are shown in thin black lines. Selected basins over Vatnajökull and Langjökull are: Brúarjökull (Br), Síðujökull (Si), Dyngjujökull (Dy), Gjálp (Gj), Hagafellsjökull West (Hw) and Hagafellsjökull East (He) (thick black outlines). Ice caps areas after Björnsson and Páisson (2008). Contour elevations are shown in grey. The inset shows the location of individual elevation measurements using SwSARIn and POCA approaches over Langjökull.
most of the marginal areas of the ice caps, while change in the ice caps interior is more heterogeneous with both thinning and thickening observed (Figure 4.1). This variability in the interior is particularly apparent over Vatnajökull, where several basins - e.g. Brúarjökull (Br), Síðujökull (Si), Dyngjújökull (Dy) - are thickening at high elevation while Skeiðarárjökull (east of Si) is thinning over almost its entire area. Thinning of Langjökull in the central highlands is widespread on the ice cap’s surface up to, and including, the ice divide, while neighbouring Hofsjökull shows thickening over the centre and thinning over the margins. In the south of Iceland, relatively high rates of thickening (up to 3 m a\(^{-1}\)) are widespread over Mýrdalsjökull’s central plateau. Thinning is visible particularly on its northern slopes which lie at low elevations as well as on the steeper southern margins. In the same region and despite being exposed to a similar climate, Eyjafjallajökull shows signs of thinning at its summit; however coverage here is limited due to the small area (~80 km\(^2\)) and steep hypsometry.

Figure 4.2: Vatnajökull elevation time series (60 days step) produced from SwSARIn elevations above and below 1200 m, used as an approximate ice cap wide ELA. Dark grey bands highlight the accumulation period between October and May; the non-shaded area corresponds to the ablation period between June and September. The two trends show mean rates of elevation change between 2010-2014 and between 2014-2016.
(∼700-1560 m). Drangajökull (northwest) mostly displays a thickening pattern in the comparatively large accumulation area.

We use the CS-2 derived rates of surface elevation change to compute mean annual rates of ice cap volume and mass change over five glaciological years from October 2010 to September 2015 (Table 4.1). During this time, we estimate that the Vatnajökull ice cap (∼70% of Iceland’s glaciated area) is losing mass at a rate of 3.68 ± 0.61 Gt a⁻¹ (-0.52 ± 0.09 m_we a⁻¹) and is the main contributor (63%) to mass loss in Iceland, followed by Langjökull (12%) and Hofsjökull (8%) in central Iceland (Table 4.1). Langjökull is the fastest changing ice cap with -0.81 ± 0.23 m_we a⁻¹ specific mass balance, followed by Hofsjökull and Vatnajökull with -0.66 ± 0.15 m_we a⁻¹ and -0.52 ± 0.09 m_we a⁻¹, respectively (Table 4.1). A combined estimate is generated for Mýrdalsjökull and Eyjafjallajökull (3.6% of loss) since data coverage over the latter is limited and the two ice caps are exposed to similar climatic conditions. To the northwest, Drangajökull appears to be close to balance (-0.05 ± 0.07 Gt a⁻¹; -0.28 ± 0.40 m_we a⁻¹); the uncertainty is comparatively large due to the small aerial extent and steep hypsometry of the ice cap (Table 4.1). Summing contributions from the six ice caps analyzed in this study, and rescaling for the remaining 10% glacierized area not included in our survey, we estimate that Iceland lost ice at a rate of 5.83 ± 0.74 Gt a⁻¹ (-0.59 ± 0.07 m_we a⁻¹ ) between October 2010 and September 2015, corresponding to 0.016 ± 0.002 mm a⁻¹ eustatic sea level change. Assuming a dual density scenario in the ablation and accumulation areas with \( \rho_{abl}=900 \text{ kg m}^{-3} \) and \( \rho_{acc}=650 \text{ kg m}^{-3} \), the mass loss and contribution to sea level change estimates are higher by just 4%, within the uncertainty of the single density case. During the glaciological year 2014/15, the Vatnajökull ice cap had positive mass balance (Figure 4.2), an unprecedented observation in the last two decades (Björnsson et al., 2013) and due to anomalously high winter precipitation. This anomaly is reflected in the time series of surface elevation change where the trends in both the ablation and accumulation areas change after October 2014 (Figure 4.2). In the 4 glaciological years before 2014/15,
we find that Vatnajökull’s rate of mass loss was 4.93 ± 0.80 Gt a\(^{-1}\) (-0.69 ± 0.11 m\(\text{we}\) a\(^{-1}\)), or ∼34% larger than the period 2010/11 to 2014/15.

We compared our geodetic estimates for the Langjökull ice cap and the Brúarjökull basin of the Vatnajökull ice cap against *in-situ* field derived mass balance observations from ongoing surveys (e.g. Björnsson et al., 1998, 2002, 2013; Pálsson et al., 2012; Jóhannesson et al., 2013). We restricted the datasets to the same time period, four glaciological years from October 2010 to September 2014. The geodetic estimate for Langjökull, -0.76 ± 0.25 Gt a\(^{-1}\) (-0.92 ± 0.30 m\(\text{we}\) a\(^{-1}\)), is 38% less negative than that from the *in-situ* data, -1.05 ± 0.36 Gt a\(^{-1}\) (-1.28 ± 0.30 m\(\text{we}\) a\(^{-1}\)), but the two values agree within uncertainties. Over the Brúarjökull basin the agreement is good, -0.51 ± 0.09 Gt a\(^{-1}\) (-0.37 ± 0.07 m\(\text{we}\) a\(^{-1}\)) compared to -0.49 ± 0.22 Gt a\(^{-1}\) (-0.35 ± 0.30 m\(\text{we}\) a\(^{-1}\)) for the geodetic and *in-situ* values respectively. Using a dual density scenario, Langjökull’s and Brúarjökull’s geodetic mass balance estimates change by +17% and -18%, respectively.

### 4.5 Discussion

The heterogeneity of the rates of surface elevation change can be linked to the heterogeneity of ice caps hypsometry as well as their exposure to local climatic conditions, active volcanoes and glacier surge events. Individual basins of the Vatnajökull ice cap display distinct behaviours, either thinning across their entire length or experiencing thickening at high elevation. Three basins, namely Brúarjökull, Síðujökull and Dynjújökull (Figure 4.1), show large areas of thickening at higher elevation, as they are currently in a post-surge stage, responding to surges that occurred in 1963, 1995 and 1999, respectively (Björnsson et al., 2003; Fischer et al., 2003). Thickening in the Gjálp area (Figure 4.1), by an average of 0.7 m a\(^{-1}\), is related to a combination of snow drift and ice inflow into the depression created by the 1996 subglacial volcanic
eruption; these uplift rates are down from 40 m a\(^{-1}\) as measured in the year following the eruption (Gudmundsson et al., 2002). North of Gjálp, over the Bárðarbunga central volcano caldera ice surface, the strong subsidence pattern is the surface response to the Bárðarbunga eruption that occurred between August 2014 and March 2015 (Sigmundsson et al., 2014; Gudmundsson et al., 2016). This event deflated a magma chamber below the \(\sim 700\) m thick ice; little or no ice was melted, but the caldera bedrock floor lowered by tens of metres and the ice above lowered similarly forming a cauldron like surface subsidence with a volume of \(\sim 1.9\) km\(^3\) (Sigmundsson et al., 2014; Gudmundsson et al., 2016). The impact of this area on the ice cap wide rate of volume change is 0.05 km\(^3\) a\(^{-1}\) (\(\sim 1\%\) of Vatnajökull’s total volume change). In the central highlands, and despite their close proximity and similar climatic conditions, the pattern of rates of surface elevation change of the Langjökull and Hofsjökull ice caps differ considerably, most likely due to their differing hypsometry. Despite having similar area and volume (\(\sim 900\) km\(^2\) and \(\sim 200\) km\(^3\)), Langjökull has a lower elevation range (430-1440 m above sea level (asl)) than Hofsjökull (620-1790 m a.s.l) (Björnsson and Pálsson, 2008; Gudmundsson et al., 2009) and a large portion of the surface of Langjökull therefore lies close to the current equilibrium line altitude (ELA) (Pálsson et al., 2012). Thickening is visible in the accumulation area of the West and East Hagafellsjökull basins of the Langjökull ice cap (Figure 4.1) and is a dynamic response to the 1980 and 1999 surge events, respectively (Björnsson et al., 2003). The central part of the Mýrdalsjökull ice cap is thickening at rates of about 1-3 m a\(^{-1}\) although the surface elevation of the plateau has not changed compared to 1999. The thickening is most likely induced by the extreme precipitation in winter 2015, which deposited 10-15 m of snow on the ice cap. Over Eyjafjallajökull’s summit, the surface is thinning as ice flows into the crater created by the Eyjafjallajökull eruption in 2010 (Oddsson et al., 2016). Over Drangajökull (northwest), despite the relatively small size of the ice cap as well as the steep elevation range, SwSARIn data captures the thinning pattern across the ablation area. This allows us to generate a robust estimate of mass balance, a result that cannot
be achieved with conventional POCA processing (see section 4.7.3 and Table 4.2 and 4.3).

Geodetic mass balance derived from repeat altimetry is dependent on the regionalization method chosen to derive volume change from the rates of surface elevation change (e.g. Nilsson et al., 2015a). The high density of measurements provided by SwSARIn allows us to regionalize at the ice cap scale and in some cases at the basin scale (e.g. Brúarjökull), better accounting for local differences, in contrast to datasets with a lower density of observations which require mean hypsometric related rates of surface elevation change to be averaged at the scale of Iceland as a whole (Nilsson et al., 2015a). Thus, the hypsometric averaging method applied at the basin scale shows good agreement with the in-situ estimate for one of Vatnajökull’s largest basins: Brúarjökull. Comparing the SWSARIn and in-situ mass balance estimates over the Langjökull ice cap instead shows a difference between the two approaches. Current inter-drainage basin variability in rates of surface elevation change is relatively large in Iceland and is related to dynamic adjustment after glacier surges and sub-glacial eruptions as well as contrasting climatic conditions, e.g. due to inland precipitation shadow, hypsometry or distance from the south coast (the North-Atlantic low path). For example, the southeastern basins of Vatnajökull (e.g. as in Adalgeirsdóttir et al., 2006) reach low elevations at their termini, are exposed to high precipitation and have infrequent surges (Björnsson et al., 2003). In contrast, basins in the northwest are more affected by surges and their termini are above 700 m elevation. Applying a hypsometric model at the ice cap scale would clearly not capture this complexity. SwSARIn provides a step change from previous altimetry-based techniques in mapping the complexity of ice caps’ response to internal and external forcing as it enables the independent monitoring of individual ice caps. Additionally, the method can be used to derive mass balance estimates at the individual basin scale (e.g Brúarjökull).
4.6 Conclusions

CryoSat-2 swath radar interferometric altimetry (SwSARIn) increases the density of surface elevation measurements over Icelandic ice caps by 2 and 5 orders of magnitude with respect to the conventional point-of-closest-approach (POCA) method applied to the CryoSat-2 and ICESat missions, respectively. Compared to POCA measurements, which tend to concentrate on topographic highs, SwSARIn samples a wider range of elevations which helps generate more reliable estimates of mass balance, particularly for Icelandic ice caps with complex hypsometry. Swath altimetry allows high resolution mapping of surface elevation and its temporal change revealing complex spatio-temporal patterns of surface elevation change related to climatic, dynamic, and sub-glacial processes in Iceland. We estimate that Icelandic ice caps have lost a total of $5.8 \pm 0.7$ Gt a$^{-1}$ ($-0.6 \pm 0.1$ mwe a$^{-1}$) between October 2010 and September 2015, equivalent to $0.016 \pm 0.002$ mm a$^{-1}$ eustatic sea level change. This estimate suggests that over this 5 year period, the mass balance was 40% less negative than the preceding 15 years, a fact which partly reflects the anomalous positive balance year across Vatnajökull in 2014/15. Our observations also demonstrate the capability of SwSARIn elevations to image glaciological processes occurring at the subcatchment scale, and to infer global, time-dependent, mass balance over region of complex hypsometry such as ice caps and ice sheet margins.

4.7 Supporting Information

4.7.1 SwSARIn and POCA processing

CS-2 uses Ku-band radar frequency to image a region of about 15 km in width and record the returned echoes within that footprint. Commonly, the echo corresponding
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to the surface location closest to the satellite (i.e. the Point-Of-Closest-Approach, POCA) is identified via a ‘retracking’ procedure, while all others are discarded. Swath processing exploits high coherence (>0.8) returns to produce a ~5km wide swath of between 10-100 geocoded elevation measurements every ~400 m in the direction of the satellite flight, rather than a single elevation as with the standard POCA approach (Hawley et al., 2009; Gray et al., 2013; Christie et al., 2016; Ignéczi et al., 2016). Hawley et al. (2009) first tested the technique using airborne radar interferometry data, and achieved a 75 fold increase in observation density without significant quality deterioration compared to conventional POCA processing (1.67 m RMS difference w.r.t reference laser data as opposed to 1.33 m for conventional POCA). Similarly, Gray et al. (2013) demonstrated the method directly on CS2 SARIn L1b data by generating a Digital Elevation Model (DEM) of the Devon Ice Cap (Nanavut, Canada) where previous radar altimeters had provided only sparsely sampled data. The swath derived DEM had a mean elevation difference of 0.49 ± 0.75 m compared to reference airborne laser data. In application of the technique, Christie et al. (2016) used rates of surface elevation change from SwSARIn in order to derive thickness at grounding line along the Bellinghausen coastline in West Antarctica and Ignéczi et al. (2016) used a DEM derived from SwSARIn to map the location of supra-glacial lakes at the surface of the Greenland Ice Sheet.

To generate swath processed (SwSARIn) elevations, we download CryoSat-2 L1b baseline C SARIn data from the European Space Agency (ESA) database and generate elevation measurements similarly to Hawley et al. (2009), Gray et al. (2013), Christie et al. (2016) and Ignéczi et al. (2016). After filtering the waveform to reject samples with low coherence (<0.8) and unwrapping on a per-waveform basis (Gray et al., 2013), we convert the range, across-track look angle, platform attitude and orbit parameters of all echoes into a swath of elevations relative to a reference ellipsoid. The resulting elevation dataset can be affected by phase ambiguity errors in regions of high terrain slope (Gray et al., 2015); we solve for these by applying to each waveform the 2π multiple that minimizes elevation differences with respect to a reference DEM from
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Figure 4.3: Density map of SwSARIn elevations over Vatnajökull corrected for phase ambiguity. Areas with across track slope lower than 0.54 degrees, where phase ambiguity should not occur, are shown in cyan. The slope map is produced at 400 m spatial resolution, equivalent to the CS2 SARIn along track footprint size.

Areas with across track slope lower than 0.54 degrees, where phase ambiguity should not occur, are shown in cyan. The slope map is produced at 400 m spatial resolution, equivalent to the CS2 SARIn along track footprint size.

do not hallucinate.

the National Land Survey of Iceland (Landmælingar Íslands, www.lmi.is). Over the Vatnajökull ice cap, about 40% of SwSARIn elevations are corrected for this ambiguity and their location is shown in Figure 4.3 and 4.4. Areas with across track slope lower than 0.54 degrees, where phase ambiguity should not occur, are highlighted in cyan; the number of SwSARIn elevations corrected for phase ambiguity is shown as a density scatterplot at the same spatial resolution as the slope maps. The spatial resolution is representative of the CS-2 SARIn footprint size, i.e. 400 m along track (Figure 4.3) and 1600 m across track (Figure 4.4). We also discard elevations that differ more than 100 m w.r.t. the DEM. Such high discrepancies may not be attributed to real surface elevation change. Over Vatnajökull, they represent less than 1% of the total amount of observations between October 2010 and September 2015.

Point-Of-Closest-Approach (POCA) CS-2 data are as downloaded from the ESA archive (L2 baseline C product).
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Figure 4.4: As Figure 4.3 but the slope map is produced at 1600 m spatial resolution, equivalent to the CS2 SARIn across track footprint size.

4.7.2 Error budget

We assign an uncertainty to the rate of surface elevation change of each individual pixel. Consider the equation:

\[ z(x, y, t) = c_0 x + c_1 y + \dot{h} t + c_2 \]  \hspace{1cm} (4.2)

where \( x, y, t \) are easting, northing and time respectively. The error \( \epsilon_{\dot{h}} \) on the rate of surface elevation change \( \dot{h} \) is taken from the unit model covariance matrix \( \text{cov}_m \), calculated as:

\[ \text{cov}_m = G^{-1} \left[ G^{-1} \right]^T \]  \hspace{1cm} (4.3)

where the vector \( m = [c_0 \ c_1 \ \dot{h} \ c_2] \) represents the model parameters and \( G = [x \ y \ t \ 1] \) is the model matrix, \( G^{-1} \) is its inverse and \( [G^{-1}]^T \) is the transpose of the inverse. The diagonal of \( \text{cov}_m \) are the variances of the model parameters, therefore \( \epsilon_{\dot{h}} \) can be
Figure 4.5: Uncertainty map for SwSARIn rates of surface elevation change at 0.5 km posting calculated over the Vatnajökull ice cap in the period October 2010 to September 2015. Note the non-linear colormap. 94% (86%) of errors are below 1 m a\(^{-1}\) (0.5 m a\(^{-1}\)).

extracted as follows:

\[
\epsilon_h = \sqrt{\text{diag} \left( \text{cov}_u \mathbf{m} \right)}_3
\]  \hspace{1cm} (4.4)

where \(\text{diag}()_3\) is the third element on the diagonal.

Figure 4.5 shows Vatnajökull’s error map for SwSARIn data posted at 0.5 km resolution. We then propagate rate uncertainties when applying the hypsometric averaging method and calculating the mean elevation change rate in each 50 m elevation bin (hereafter bin):

\[
E_h(k) = \sqrt{\frac{\sum_{m=1}^{N(k)} \epsilon_h(m)^2}{N(k)}}
\]  \hspace{1cm} (4.5)

where \(\epsilon_h\) is the error on the rates of elevation change for the individual pixels, \(E_h(k)\) is the mean elevation change error in each bin k and \(N(k)\) is the number of valid observations in that bin. If a bin has no valid data (e.g. at low elevation for bins with small spatial extent), we use a two-term decreasing exponential fit to generate
an interpolated value. The choice of fit reflects the general $E_h$ decreasing trend with increasing elevation.

We multiply the bin area extent $A(k)$ to the related $E_h(k)$ and sum all contributions to estimate the total uncertainty on the rate of volume change:

$$E_V = \sum_k E_h(k) \times A(k).$$ \hspace{1cm} (4.6)

With this method, the volume change uncertainty is only related to that area of the ice cap where there are valid rates of surface elevation change, but does not account for incomplete data coverage. For this reason, $E_V$ is rescaled by the average data coverage in the ablation and accumulation areas. This procedure generates a rather conservative error estimate since it assumes that the lack in data coverage has a direct impact on the total error estimate, which does not hold if the sampling is sufficiently uniform.

Finally, when converting volume to mass change, we include an error on the density as in Nilsson et al. (2015a) and Moholdt et al. (2010b):

$$E_\rho = \frac{1}{2} \left( \rho_{\text{ice}} - \rho_{\text{firn}} \right).$$ \hspace{1cm} (4.7)

The final mass balance error is then calculated as follows:

$$E_M = |\dot{M}| \sqrt{\left( \frac{E_V}{V} \right)^2 + \left( \frac{E_\rho}{\rho_{\text{ice}}} \right)^2}.$$ \hspace{1cm} (4.8)

### 4.7.3 SwSARIn - POCA comparison

The conventional POCA processing of CS2 SARIIn data provides more than 60,000 observations over Vatnajökull between October 2010 and September 2015, a 70 fold increase w.r.t. the number of measurements ICESat acquired over all Icelandic ice
caps in a similar time span Nilsson et al. (2015a). In spite of the large number of observations, the spatial distribution of POCA is controlled by surface topography and tends to be preferentially clustered along topographic highs such as ice divides, while at lower elevations the density of measurements is limited, particularly over smaller ice caps (Figure 4.6 and 4.8). Swath processing provides 160 times more elevation measurements w.r.t. POCA over Vatnajökull (October 2010 to September 2015) and, importantly, delivers almost uniform spatial coverage (Figure 4.7 and 4.9). Over the Langjökull ice cap (Figure 4.8 and 4.9 for SwSARIn and POCA respectively), where the particular hypsometry accentuates the concentration of POCA elevations over the ice divide, we observe over one order of magnitude more measurements per km² from SwSARIn than POCA (Figure 4.10).

The increase in spatial density of observations provided by SwSARIn is not at the expense of precision; a direct comparison between co-located SwSARIn and POCA derived rates of surface elevation change (2 km posting) gives a mean difference of $-0.05 \pm 0.64$ m a$^{-1}$ (Figure 4.11-c) and no dependency on surface slopes (Figure 4.11a-b) (Gray et al., 2013). The density of SwSARIn observations allows to gridding data at sub-kilometer spatial resolution revealing a detailed pattern of surface elevation change (Figure 4.1). For example, the thickening pattern in the accumulation area of the East Hagafellsjökull basin (Langjökull) - gaining mass after a surge in 1998/99 - is not as clearly visible at lower resolution (Figure 4.1 versus Figure 4.12). For comparison, POCA rates of surface elevation change gridded at 0.5 and 2 km resolution are shown in Figure 4.13 and 4.14.

SwSARIn mass balance estimates from data posted at 0.5 and 2 km are generally comparable (Table 4.2), which indicate that such high resolution is adequate when quantifying mass change using SwSARIn elevations. POCA estimates of mass balance show higher variability and, with the exception of Vatnajökull (roughly ten times larger than the other ice caps), rates of mass change are less negative than SwSARIn’s. This may be due to POCA preferentially sampling topographic highs where less or no thinning is occurring. Drangajökull mass change is erroneously estimated as positive
Figure 4.6: Figure S4 - Location of POCA heights over Vatnajökull, Iceland. The solid black lines indicate the approximate Equilibrium Line Altitude (ELA) for the south-eastern basins (1000 m) and for the north-western ones (1200-1300 m) (Björnsson and Pálsson, 2008).

When gridding data at 2 km resolution (SwSARIn and POCA) as well as 0.5 km resolution (POCA), due to the relatively small surface area as well as steep hypsometry of the ice cap, the lower resolution is too coarse to capture the different signals in the accumulation and ablation areas. However, the density of POCA observations is insufficient to resolve the thinning in the ablation area also when gridding at 0.5 km resolution.

4.7.4 Filters on surface elevation change rates

In order to remove noise from the surface elevation change rates $\dot{h}$, we apply a set of parameter thresholds. We discard a pixel if i) the rate $\dot{h}$ is unrealistic, i.e. less than -20 m a$^{-1}$ or more than 5 m a$^{-1}$, ii) the time span is shorter than 2 years, iii) the standard
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Figure 4.7: Location of SwSARIn heights over Vatnajökull, Iceland (See Figure 4.6 caption).

Figure 4.8: Location of POCA heights over Langjökull, Iceland. The solid black lines indicate the approximate ELA for the southern and northern domes (1000 m and 1200 m, respectively) (Pálsson et al., 2012).
error is larger than 10 m a$^{-1}$. Additionally, we compute a median smoothed map of surface elevation change rates and discard pixels which differ from that more than three times the mean absolute deviation between the original rates and their smoothed values.
Figure 4.10: Number of SwSARIn (blue) and POCA (cyan) observations per km$^2$ per elevation band (50m intervals) on a logarithmic scale for the entire Langjökull ice cap (left panel) and its northern and southern domes separately (central and right panel, respectively).
Figure 4.11: Difference between SwSARIn and POCA surface elevation change rates \((\dot{h}_s - \dot{h}_p)\) over Vatnajökull at 2 km posting with respect to (a) along-track and (b) across-track surface slope. (c) Histogram of differences between SwSARIn and POCA rates of surface elevation change.

Table 4.2: Mass balance of Icelandic ice caps

<table>
<thead>
<tr>
<th></th>
<th>POCA 0.5 km</th>
<th>POCA 2 km</th>
<th>SwSARIn 0.5 km</th>
<th>SwSARIn 2 km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vatnajökull</td>
<td>-3.26 ± 0.66</td>
<td>-2.94 ± 0.55</td>
<td>-3.68 ± 0.61</td>
<td>-3.9 ± 0.55</td>
</tr>
<tr>
<td>Langjökull</td>
<td>-0.38 ± 0.25</td>
<td>-0.38 ± 0.16</td>
<td>-0.70 ± 0.20</td>
<td>-0.59 ± 0.09</td>
</tr>
<tr>
<td>Hofsjökull</td>
<td>-0.40 ± 0.18</td>
<td>-0.21 ± 0.10</td>
<td>-0.45 ± 0.10</td>
<td>-0.16 ± 0.03</td>
</tr>
<tr>
<td>Mýrdalsjökull</td>
<td>0.16 ± 0.18</td>
<td>-0.07 ± 0.11</td>
<td>-0.21 ± 0.16</td>
<td>-0.28 ± 0.05</td>
</tr>
<tr>
<td>Eyafjallajökull</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drangajökull</td>
<td>+0.12 ± 0.04*</td>
<td>+0.27 ± 0.04*</td>
<td>-0.05 ± 0.07</td>
<td>+0.13 ± 0.02*</td>
</tr>
<tr>
<td>Iceland</td>
<td>-4.49 ± 0.83</td>
<td>-3.66 ± 0.65</td>
<td>-5.83 ± 0.74</td>
<td>-5.28 ± 0.62</td>
</tr>
</tbody>
</table>
CHAPTER 4. Surface elevation change and mass balance of Icelandic ice caps derived from swath mode CryoSat-2 altimetry

Figure 4.12: Surface elevation change maps of Icelandic ice caps based on SwSARIn heights at 2 km posting as well as location of the ice caps in Iceland (inset). V (Vatnajökull), L (Langjökull), H (Hofsjökull), M (Mýrdalsjökull), D (Drangajökull), E (Eyjafjallajökull). Basin outlines are shown in thin black lines. Selected basins over Vatnajökull and Langjökull are: Brúarjökull (Br), Siðújökull (Si), Dyngiujökull (Dy), Gjálp (Gj), Hagafellsjökull West (Hw) and Hagafellsjökull East (He) (thick black outlines). Ice caps’ areas after Björnsson and Pálsson (2008). Contour elevations (gray) are 1000 m and 1400 m (700 m and 900 m for D).
Figure 4.13: Surface elevation change maps of Icelandic ice caps based on POCA heights at 0.5 km posting as well as location of the ice caps in Iceland (inset). V (Vatnajökull), L (Langjökull), H (Hofsjökull), M (Mýrdalsjökull), D (Drangajökull), E (Eyjafjallajökull). Basin outlines are shown in thin black lines. Selected basins over Vatnajökull and Langjökull are: Brúarájökull (Br), Síðujökull (Si), Dyngjujökull (Dy), Gjálp (Gj), Hagafellsjökull West (Hw) and Hagafellsjökull East (He) (thick black outlines). Ice caps’ areas after Björnsson and Pálsson (2008). Contour elevations (gray) are 1000 m and 1400 m (700 m and 900 m for D).
CHAPTER 4. Surface elevation change and mass balance of Icelandic ice caps derived from swath mode CryoSat-2 altimetry

Figure 4.14: Surface elevation change maps of Icelandic ice caps based on POCA heights at 2 km posting as well as location of the ice caps in Iceland (inset). V (Vatnajökull), L (Langjökull), H (Hofsjökull), M (Mýrdalsjökull), D (Drangajökull), E (Eyjafjallajökull). Basin outlines are shown in thin black lines. Selected basins over Vatnajökull and Langjökull are: Brúarjökull (Br), Síðujökull (Si), Dyngjufjöll (Dy), Gjálp (Gj), Hagafellsjökull West (Hw) and Hagafellsjökull East (He) (thick black outlines). Ice caps’ areas after Björnsson and Pállsson (2008). Contour elevations (gray) are 1000 m and 1400 m (700 m and 900 m for D).
Table 4.3: Specific mass balance of Icelandic ice caps
As in Table 4.2 with mass change $\dot{M}$ given in $m_{we} \text{ a}^{-1}$.

<table>
<thead>
<tr>
<th></th>
<th>POCA 0.5 km</th>
<th>POCA 2 km</th>
<th>SwSARIn 0.5 km</th>
<th>SwSARIn 2 km</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Vatnajökull</strong></td>
<td>-0.46 ± 0.09</td>
<td>-0.41 ± 0.08</td>
<td>-0.52 ± 0.09</td>
<td>-0.55 ± 0.08</td>
</tr>
<tr>
<td><strong>Langjökull</strong></td>
<td>-0.44 ± 0.29</td>
<td>-0.44 ± 0.18</td>
<td>-0.81 ± 0.23</td>
<td>-0.68 ± 0.10</td>
</tr>
<tr>
<td><strong>Hofsjökull</strong></td>
<td>-0.58 ± 0.26</td>
<td>-0.31 ± 0.15</td>
<td>-0.66 ± 0.15</td>
<td>-0.24 ± 0.04</td>
</tr>
<tr>
<td><strong>Mýrdalsjökull</strong></td>
<td>-0.29 ± 0.33</td>
<td>-0.13 ± 0.20</td>
<td>-0.39 ± 0.29</td>
<td>-0.51 ± 0.09</td>
</tr>
<tr>
<td>** + Eyjafjallajökull**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Drangajökull</strong></td>
<td>+0.68 ± 0.23*</td>
<td>+1.53 ± 0.23*</td>
<td>-0.28 ± 0.40</td>
<td>+0.74 ± 0.11*</td>
</tr>
</tbody>
</table>
Chapter 5

Heterogeneous and rapid ice loss over the Patagonian Ice Fields revealed by CryoSat-2 swath radar altimetry.
The previous Chapter showed the advantage of using CS-2 swath processed elevations, enabling the monitoring of ice caps in Iceland at high spatial and temporal resolution with satellite radar altimetry data and comparing well with results obtained from *in situ* data. The current Chapter turns to the Southern Patagonian ice fields. Technically, this region has historically been a challenge for satellite radar altimeters because of its rugged topography, similar to that of mountain glaciers, and represents a more complex test case for the technique used in this thesis. Scientifically, changes occurring over these ice fields are less well known compared to ice caps in Iceland since only sparse observations are available to the scientific community.

The same methodology used in Chapter 4, with the modified swath algorithm described in section 3.1.6, was applied to investigate elevation, volume and mass changes over the Patagonian ice fields. The technique allowed to quantify the mass balance of individual glaciers with surface area as small as ∼300 km$^2$ and revealed a heterogeneous picture of elevation and mass change, albeit with overall rapid mass loss caused by a combination of warming temperatures and dynamic changes.


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CHAPTER 5. Heterogeneous and rapid ice loss over the Patagonian Ice Fields revealed by CryoSat-2 swath radar altimetry

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Author contributions: L.F. and N.G. designed the research. F.W. improved the swath processing algorithm. L.F. processed the data and analysed the results, with input from N.G and P.N. L.F. wrote the paper, with input from all co-authors.

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5.1 Abstract

The Northern and Southern Patagonian Ice Fields (NPI and SPI) in South America are the largest bodies of ice in the Southern hemisphere outside of Antarctica and the largest contributors to eustatic sea level rise (SLR) in the world, per unit area. Here we exploit swath processed CryoSat-2 interferometric data to produce maps of surface elevation change at sub-kilometer spatial resolution over the Ice Fields for six glaciological years between April 2011 and March 2017. Mass balance is calculated independently for nine sub-regions, including six individual glaciers larger than 300 km$^2$. Overall, between 2011 and 2017 the Patagonian Ice Fields have lost mass at a combined rate of $21.29 \pm 1.98$ Gt a$^{-1}$, contributing $0.059 \pm 0.005$ mm a$^{-1}$ to SLR. We observe widespread thinning on the Ice Fields, particularly north of 49°S. However the pattern of surface elevation change is highly heterogeneous, partly reflecting the importance of dynamic processes on the Ice Fields. The Jorge Montt glacier (SPI), whose tidewater terminus is approaching flotation, retreated $\sim 2.5$ km during our study period and lost mass at the rate of $2.20 \pm 0.38$ Gt a$^{-1}$ ($4.64 \pm 0.80$ m wa a$^{-1}$). In contrast with the general pattern of retreat and mass loss, Pio XI, the largest glacier in South America, is advancing and gaining mass at $0.67 \pm 0.29$ Gt a$^{-1}$ rate.

5.2 Introduction

The Northern and Southern Patagonian Ice Fields are the two largest ice bodies in the Southern Hemisphere excluding Antarctica, with areas of about 4,200 and 13,000 km$^2$ and volumes of about 1,200 and 4,300 km$^3$ (Carrivick et al., 2016), respectively, and elevation ranging from sea level to about 3,900 m. They experience relatively warm and wet climatic conditions (Sagredo and Lowell, 2012) and lie on top of the narrow Andean mountain range, which forms an efficient barrier to the predominantly westerly
winds and moisture rich air transported inland from the Pacific Ocean (e.g. Garreaud et al., 2013). The mountain and associated ice divide separates areas with contrasting climatic conditions. On the western side, orographic uplift of moist air produces extreme annual precipitation of up to 10 m a$^{-1}$ (e.g. Lenaerts et al., 2014; Sakakibara and Sugiyama, 2014, and references within) as well as extensive and persistent cloud coverage with associated low shortwave and high longwave energy fluxes (Lenaerts et al., 2014). To the east of the divide, the Ice Fields are in the rain shadow and receive comparatively high amounts of shortwave energy (Lenaerts et al., 2014). Thus, the glaciers west and east of the ice divide are thought to be more sensitive to changes in precipitation and air temperature respectively (Rivera and Casassa, 1999; Warren and Sugden, 1993).

The two Ice Fields have been experiencing long-term thinning and retreat. Between the end of the Little Ice Age (LIA, $\sim$1870) and 2011, their area shrank by $\sim$12.5% on average (Davies and Glasser, 2012), associated with a combined mass loss of about 1.70±0.25 Gt a$^{-1}$ (Glasser et al., 2011). However, geodetic studies based on gravimetry (Chen et al., 2007; Ivins et al., 2011; Jacob et al., 2012; Gardner et al., 2013) and comparisons of Digital Elevation Models (DEM; Rignot et al., 2003; Willis et al., 2012a,b; Jaber, 2016) estimated that between 1975 and 2012 the rate of mass loss of the ice fields has been in the range of 15 to 35 Gt a$^{-1}$, one order of magnitude more compared to the long term trend.

During the last 50 years, the Patagonian Ice Fields contributed an estimated 10% to the total mass loss from glaciers and ice caps, excluding those at the periphery of the Greenland and Antarctic ice sheets (Glasser et al., 2011, and references within), increasing to 15.4% in the first decade of the 21st century (Jacob et al., 2012; Gardner et al., 2013), second only to glaciers in Alaska and the Canadian Arctic, and larger than high mountain Asia (Brun et al., 2017) which all extend over areas $\sim$5-8 times larger. Currently, the Patagonian Ice Fields are the largest contributor to sea level rise per unit area in the world (Gardner et al., 2013; Carrivick et al., 2016).

Velocities of glaciers draining the Ice Fields (up to 10 km a$^{-1}$) are amongst the
fastest in the world (Sakakibara and Sugiyama, 2014; Mouginot and Rignot, 2015) and substantial ice flow acceleration has been observed, coincident with rapid frontal retreat, for a number of tidewater and lacustrine glaciers (Sakakibara and Sugiyama, 2014). These observations implicate the importance of the role of dynamics and tidewater glacier calving in the rapid wastage of the Ice Fields. In fact, more than 80% of them terminate in proglacial lakes (mostly across the NPI and east of the SPI) or fjords (western side of the SPI) (Sugiyama et al., 2016, and references within).

Since 2010, the European Space Agency (ESA) radar altimetry mission CryoSat-2 (CS-2) (Drinkwater et al., 2005; Wingham et al., 2006a) has been acquiring topography data over land ice. Radar instruments are particularly suited to land ice applications since they can penetrate through clouds and do not depend on sunlight. Radar altimetry data have been previously exploited to map elevation change over ice caps (Rinne et al., 2011b,a), but the technique has not been applied widely due to the limitation caused by the large radar footprint. CS-2’s state-of-the-art radar altimeter uses Synthetic Aperture Radar (SAR) along-track to reduce the footprint size as well as interferometry across-track to accurately locate the position of the surface reflection (SARIn mode; Wingham et al., 2006a). Additionally, its orbit inclination of 92° and repeat cycle of 369 days provides an inter-track spacing of ~5 km on average over the Patagonian Ice Fields. Finally, CS-2’s relatively short wavelength (2.2 cm; Ku band) restricts the penetration of the radar pulse in the snowpack, compared to, e.g., sensors working in C or X bands. These characteristics make CS-2 better suited for monitoring changes in glacier areas with frequent cloud cover and considerable slopes. CS-2 SARIn data have successfully mapped topographic changes over Arctic ice caps (McMillan et al., 2014a; Gray et al., 2015). Additionally, swath processing (Hawley et al., 2009) of CS-2 SARIn data has been applied to generate high resolution DEMs of ice caps and selected areas of the Greenland and Antarctic ice sheets (Gray et al., 2013; Ignéczi et al., 2016; Gourmelen et al., 2017a) and to produce sub-kilometer maps of surface elevation change (Christie et al., 2016; Foresta et al., 2016; Gourmelen et al., 2017a,b), with a wide range of
applications such as the identification of supraglacial lakes in NE Greenland (Ignéctzi et al., 2016), subglacial lakes in West Antarctica and regions of subsidence in Iceland (Smith et al., 2017; Gourmelen et al., 2017a) as well as quantifying channelized basal melt under the Dotson ice shelf in West Antarctica (Gourmelen et al., 2017b) and volume and mass change of individual ice caps in Iceland (Forest et al., 2016).

Despite their important contribution to ice mass loss and global SLR, studies quantifying mass changes of the Patagonian Ice Fields are limited in number and do not cover the most recent period. This paper focuses on quantifying the mass balance of the NPI and SPI during six glaciological years between April 2011 and March 2017. To this aim, we exploit swath processed CS-2 SARIn data to generate maps of surface elevation change rates at sub-kilometer spatial resolution, and convert them into estimates of glacier volume and mass change. For a number of large catchments on the SPI, such estimates are derived at the basin scale. Additionally, the dense L2swath elevation field enables the production of time series of elevation change for different sub-regions of the Ice Fields exhibiting contrasting patterns of change.

5.3 Data and Methods

We exploit swath processed CS-2 SARIn baseline C data (L2swath) as this technique (Hawley et al., 2009; Gray et al., 2013; Foresta et al., 2016; Gourmelen et al., 2017a) can generate up to two orders of magnitude more data than conventional Point-Of-Closest-Approach (POCA) processing and, importantly, provides more homogeneous spatial coverage over relatively small glaciated regions with considerable topography (Foresta et al., 2016; Gourmelen et al., 2017a). The L2swath processing scheme is similar to Foresta et al. (2016) and Gourmelen et al. (2017a), but we use a different procedure to discard noisy waveform samples before performing the phase unwrapping. This procedure, first developed for InSAR images (Weissgerber, 2016)
and updated for CS-2 SARIn data (Weissgerber et al., 2017), was shown to further increase the density of the L2swath elevation field and to improve the spatial coverage of the Jakobshavn glacier, Greenland (Weissgerber and Gourmelen, 2017) (section 5.7). The L2swath algorithm makes use of an external DEM to improve the precision of elevation measurements in the presence of slopes larger than 0.54°, where an entire waveform may be affected by a phase shift. Without this correction, observations may be wrong by several tens of meters in elevation and a few kilometres in geo-location (Gourmelen et al., 2017a). It is not straightforward to predict the accuracy needed for the DEM (Gourmelen et al., 2017a). However given the magnitude of the geolocation and elevation shifts, the DEM need not be extremely accurate. We used the SRTM C band DEM (Farr et al., 2007) acquired in 2000 as a reference for elevation, after including a correction to account for the elevation change occurred between 2000 and 2011 (section 5.8). L2swath data are then used to compute rates of surface elevation change for six glaciological years between April 2011 and April 2017 using a plane-fit algorithm (e.g. McMillan et al., 2014b). One glaciological year is defined as the period between 1st April in year n and 31st March in year n+1. CS-2s acquisition dates vary spatially for different pixels due to the satellites orbital path as well as to the local topography, so that the temporal resolution at the pixel scale is non-uniform and longer than monthly. However, seasonality biases are avoided given the regular flight path followed by CS-2, which ensures that data within each pixel are acquired at the same epochs (within a few days) in each glaciological year. L2swath data are gridded at 500m x 500m spatial resolution and for each pixel, we model elevation $z(x,y,t)$ using a linear relationship in space and time:

$$
z(x,y,t) = c_0 x + c_1 y + \dot{h} t + c_2$$

(5.1)

where $x$, $y$ and $t$ are measured easting, northing, and acquisition time, respectively, and $c_0$, $c_1$, $\dot{h}$ and $c_2$ are the model coefficients. The time-dependent coefficient $\dot{h}$ retrieved from the model fit is the linear rate of surface elevation change for each given pixel.
Each observation is assigned a weight according to the sample power as in (Gourmelen et al., 2017a). We iteratively fit the model to the data using $3\sigma$ clipping until there are no more outliers. The formal uncertainty $\epsilon_{\dot{h}}$ on each pixel’s rate of elevation change $\dot{h}$ is extracted from the model covariance matrix $M$:

$$P = \text{cov}(p) = G^{-1} \text{cov}(z) \left[G^{-1}\right]^T \tag{5.2}$$

where $p$ is the vector of coefficients $[c_0 \ c_1 \ \dot{h} \ c_2]$ of the model parameters, $z$ are the input elevations and $G = [x \ y \ t \ 1]$ is the model matrix. We simplify the data covariance matrix $\text{cov}(z)$ to a variance matrix whose diagonal values are the squared elevation differences between the observed and modelled estimates $(z-z')^2$. The square root of the diagonal elements of $P$ represents the standard deviations of the model parameters $p$.

Due to the complex topography (see section 5.5), the $\dot{h}$ maps do not have complete coverage. We use the relation between elevation and elevation change to model estimates for the gaps in the maps of surface elevation change rates (i.e. hypsometric averaging, see e.g. Moholdt et al., 2010b; Nilsson et al., 2015a; Foresta et al., 2016), using the SRTM DEM for the elevation field. Polynomial models of order 1 to 3 are fitted to the data and used to generate elevation change rates for the individual pixels without an estimate. In order to avoid over-fitting the data, the F-test is used to evaluate if the improvement of the additional model parameters on the fit is statistically significant at the 99% confidence level. The median rate of elevation change is then computed in each 50 m elevation band $k$ and multiplied to the area $A_k$, extracted from the DEM, to produce elevation dependent volume change $\dot{V}_k$. The sum of these contributions represents the total rate of volume change. Uncertainties are calculated by error propagation using the same method as in Foresta et al. (2016), summarised in section 5.9.

This interpolation scheme is applied independently for the NPI and for different sub-regions of the SPI displaying highly contrasting patterns of change at similar elevations (Fig. 5.2). Finally, we assume that all changes relate to the gain or loss of ice of density
5.3 Data and Methods

\[ \rho_{ic} = 900 \text{ kg m}^{-3} \] when converting the rate of volume change to mass balance. This simplification is based on the assumption that at least part of the observed changes are due to dynamics (see section 5.5) and ignores possible differences in snow pack density below and above the firn line. To explore mass loss related to material with lower density, we calculate mass balance estimates using a dual density scenario. In this case the densities of glacial ice and firn are used when converting volumetric changes occurring, respectively, in the ablation and accumulation areas. We assign \( f_{irn} = 600 \) kg m\(^{-3}\) (Malz et al., 2018, and references within). We used Equilibrium Line Altitude (ELA) values as reported in De Angelis (2014) and Barcaza et al. (2009), respectively, for the glaciers on the SPI and NPI. For each group of glaciers (SPI-G\(_1\), SPI-G\(_2\), NPI), we computed an average ELA from all glaciers with surface area larger than 100 km\(^2\) in the given catchment.

Glacier outlines over the Ice Fields record their extent in 2000-2001 (RGI Consortium, 2017) and the Upsala and Jorge Montt glaciers (SPI) have retreated considerably since then and, for the latter, even during our study period. Their front positions in 2017 were manually digitized using Landsat8 scenes (section 5.10, Table 5.3) and their mass loss between 2011 and 2017 is calculated against their updated fronts. Area changes between 2011 and 2017 are not included in our estimates of mass loss. The only exception is Jorge Montt (SPI), which retreated considerably in this time period and for which we provide an additional estimate of mass loss due to area change. The front outline of the Jorge Montt and Upsala, as well as of Pio XI (SPI), was additionally digitized for a number of years between 2005 and 2017 (section 5.10, Table 5.3). This data is used for context in the Discussion (subsections Jorge Montt, Upsala and Pio XI) and is not employed for calculating mass balance.

Finally, we produce time series of mean observed glacier elevation change with the same methodology as Gray et al. (2015) and Foresta et al. (2016). The time series are generated at the catchment scale for each of the nine sub-regions with 90 (Pio XI, SPI-G\(_2\), SPI) or 120 days time step (Fig. 5.3).
5.4 Results

Swath processing of CryoSat-2 SARIn data provides 6.7 and 26.6 million valid observations of ice topography over the NPI and SPI, respectively, with the rate of elevation change for a single pixel being constrained by \( \sim 1,700 \) elevations (median) over a period of 5.6 years (median) between April 2011 and March 2017. For comparison conventional CS-2 POCA delivers about 17,000 and 55,000 observations over the NPI and SPI respectively. Fig. 5.1 displays the maps of observed rates of elevation change over the Ice Fields. On the SPI, different catchments show distinct patterns of change over the study period (Fig. 5.1). Given such heterogeneity, we apply the hypsometric averaging model independently for six large glaciers on the SPI, namely Jorge Montt, Viedma, Upsala, Pio XI, Grey and Tyndall. The spatial coverage of \( h \) estimates, at 500 m posting, ranges between 61-73\% of total catchment areas (Table 5.1), with the exception of Grey and Tyndall (\( \sim 52\% \)). We combine data from the rest of the SPI in two groups of neighbouring glaciers, labelled SPI-G\(_1\) and SPI-G\(_2\). The former includes all glaciers north of Pio XI and Viedma excluding Jorge Montt, while the latter is composed of all the glaciers west and south of Upsala excluding Grey and Tyndall (Fig. 5.1). Over the NPI, all glaciers are analysed together. Combining data from different glaciers is needed if coverage is insufficient to provide a representative figure of elevation change in each and is justified providing that they show a similar pattern of change.

The observed median rates of elevation change for these nine sub-regions are shown as a function of cumulative surface aerial extent (10\% steps; Fig. 5.1, side panels) and as a function of elevation (50 m steps; Fig. 5.2, side panels). Widespread thinning is occurring in the northern part of the SPI across all elevations, with average rates of 2 m a\(^{-1}\) on the plateau up to and above 1,400 m elevation (SPI-G\(_1\)) and in excess of 10 m a\(^{-1}\) at the terminus margins of Jorge Montt (tidewater), Viedma and Upsala (both lacustrine) glaciers. Most glaciers in the south/southwest are close to balance (SPI-G\(_2\)).
5.4 Results

Figure 5.1: Maps of observed rates of surface elevation change of the Northern and Southern Patagonian Ice Fields between April 2011 and March 2017 based on CS-2 L2swath elevations. The insets show observed median rates of elevation change (black lines with dots) against cumulative glacier surface area (10% steps), together with the uncertainty envelope (grey shade). Elevation (non-linear) is also shown for clarity.
CHAPTER 5. Heterogeneous and rapid ice loss over the Patagonian Ice Fields revealed by CryoSat-2 swath radar altimetry

Figure 5.2: Maps of modelled rates of surface elevation change of the Northern and Southern Patagonian Ice Fields between April 2011 and March 2017 based on CS-2 L2swath elevations. The insets show observed median rates of elevation change (black lines with dots) against elevation (50 m bands), together with the polynomial model (red line) fitted to the original rates of elevation change (not shown for clarity). The normalised histograms of the distribution of glacier area and data coverage versus elevation are shown in grey (continuous line and shaded patch, respectively).
with the exception of Grey and Tyndall on the eastern side. Pio XI glacier is thickening at rates of \( \sim \) 2 and 1 m a\(^{-1}\) below 1,000 m and between 1,000 and 1,500 m elevation, respectively, and thinning by about 1 m a\(^{-1}\) above 1,500 m altitude. Similar to the northern part of the SPI, the NPI is experiencing widespread thinning of up to 8 m a\(^{-1}\) with the exception of the ice divide close to the eastern margin of the ice field (Fig. 5.1 and 5.2). Hypsometric averaging is applied in each sub-region (Fig. 5.2, red lines) to generate maps of modelled elevation change rates for the Ice Fields (Fig. 5.2), from which mass change is computed (Table 5.1). The polynomial models (Fig. 5.2, red lines) compare well with the observed median rates of elevation change (Fig. 5.2, black lines with dots). A few exceptions are visible over the Tyndall and Upsala glaciers (at low and high elevation respectively) as well as over the Pio XI glacier below 1,000 m and above 2,500 m elevation. Model misfits have marginal impact on the glacier mass change when glacier area is negligible or data coverage is high (Fig. 5.2). For example the rate of mass loss of glacier Tyndall, assuming no elevation change below 350 m elevation, is reduced by about 9% (or 0.054 Gt a\(^{-1}\)), which is well within its associated uncertainty (Table 5.1). Similarly for Pio XI glacier, the thinning predicted by the model above 2,500 m elevation reduces the glacier net mass gain by only 6% (or 0.04 Gt a\(^{-1}\)). However, at low elevation where the area of Pio XI glacier is not negligible and where there are no observations to constrain the elevation change (Fig. 5.1 and 5.2), the impact of the misfit on the glacier mass balance may be significant (see section 5.5).

Between April 2011 and April 2017, the NPI and SPI have been losing mass at rates of \(-6.79 \pm 1.16\) and \(-14.50 \pm 1.60\) Gt a\(^{-1}\), respectively, contributing \(0.059 \pm 0.005\) mm a\(^{-1}\) to eustatic SLR. About 35% of the SPI mass loss is concentrated on glaciers in the SPI-G\(_1\) group \((-5.07 \pm 0.79\) Gt a\(^{-1}\)), which represent 28% of the SPI surface. The Upsala glacier is the single largest contributor to the mass loss \((-2.68 \pm 0.40\) Gt a\(^{-1}\)) and is also the glacier with the second highest rate of loss per unit area (Table 5.1) after Jorge Montt. Both glaciers have retreated between 2011 and 2017, by about 0.5 and 2.5 km, respectively. Pio XI is the only glacier in the Patagonian Ice Fields with positive mass balance \(0.67 \pm 0.29\) Gt a\(^{-1}\). Its southern tidewater and northern lacustrine termini have
CHAPTER 5. Heterogeneous and rapid ice loss over the Patagonian Ice Fields revealed by CryoSat-2 swath radar altimetry

Table 5.1: Estimates of mass balance $\dot{M} \ [\text{Gt} \ \text{a}^{-1}]$ and specific mass balance $\dot{mb} \ [\text{mwe} \ \text{a}^{-1}]$ as well as area A [km$^2$] and spatial coverage [%] of the maps of surface elevation change rates $\dot{h}$ for the NPI and individual sub-regions of the SPI based on CS-2 L2swath data at 500 m spatial resolution. *Frontal retreat of Jorge Montt (SPI) amounts to an additional $\sim 0.07 \ \text{Gt} \ \text{a}^{-1}$ (see section 5.5).

<table>
<thead>
<tr>
<th></th>
<th>A [km$^2$]</th>
<th>$\dot{h}$ coverage</th>
<th>$\dot{M}$ [Gt a$^{-1}$]</th>
<th>$\dot{mb}$ [mwe a$^{-1}$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPI</td>
<td>4,046.4</td>
<td>45.7</td>
<td>-6.79±1.16</td>
<td>-1.68±0.29</td>
</tr>
<tr>
<td>Jorge Montt*</td>
<td>474.4</td>
<td>68.0</td>
<td>-2.20±0.38</td>
<td>-4.64±0.80</td>
</tr>
<tr>
<td>Upsala</td>
<td>863.1</td>
<td>61.3</td>
<td>-2.68±0.40</td>
<td>-3.11±0.46</td>
</tr>
<tr>
<td>Viedma</td>
<td>992.3</td>
<td>72.7</td>
<td>-2.27±0.36</td>
<td>-2.29±0.36</td>
</tr>
<tr>
<td>SPI G$_1$</td>
<td>3,570.1</td>
<td>47.4</td>
<td>-5.07±0.79</td>
<td>-1.42±0.22</td>
</tr>
<tr>
<td>SPI G$_2$</td>
<td>4,829.5</td>
<td>39.1</td>
<td>-1.66±1.16</td>
<td>-0.34±0.24</td>
</tr>
<tr>
<td>Tyndall</td>
<td>332</td>
<td>49.9</td>
<td>-0.60±0.14</td>
<td>-1.81±0.42</td>
</tr>
<tr>
<td>Grey</td>
<td>333.3</td>
<td>54.0</td>
<td>-0.69±0.23</td>
<td>-2.07±0.69</td>
</tr>
<tr>
<td>Pio XI</td>
<td>1,242.6</td>
<td>65.0</td>
<td>0.67±0.29</td>
<td>0.54±0.23</td>
</tr>
<tr>
<td>SPI total</td>
<td>12,637.2</td>
<td>49.9</td>
<td>-14.50±1.60</td>
<td>-1.15±0.13</td>
</tr>
<tr>
<td>NPI+SPI</td>
<td>16,683.6</td>
<td>-21.29±1.98</td>
<td>1.28±0.12</td>
<td></td>
</tr>
</tbody>
</table>

both advanced, respectively by about 500 m and 800 m during our study period. Using a dual density scenario, the rates of mass change in the nine sub-regions are lower by 11-19% compared to using the density of glacial ice at all elevations and the total rate of mass loss of the Ice Fields is 17.89±2.03 Gt a$^{-1}$ (Table 5.2). For most basins, dynamic processes are dominating the mass loss and hence the ice density scenario is the preferred option. However, in a few sectors the dual density scenario may be more accurate. For example, over the Pio XI glacier (SPI), where surface thickening is suspected (Malz et al., 2018), the mass change is 0.67±0.29 Gt a$^{-1}$ and 0.57±0.25 Gt a$^{-1}$ for the single and dual density scenarios, respectively.
### 5.4 Results

**Table 5.2:** Estimates of mass balance $\dot{M}$ [Gt a$^{-1}$] for the NPI and individual sub-regions of the SPI based on CS-2 L2swath data at 500 m spatial resolution using two different density scenarios (see text).

<table>
<thead>
<tr>
<th></th>
<th>ELA [m]</th>
<th>Single density $\dot{M}$ [Gt a$^{-1}$]</th>
<th>Dual density $\dot{M}$ [Gt a$^{-1}$]</th>
<th>Abs Diff $\dot{M}$ [Gt a$^{-1}$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPI</td>
<td>1005</td>
<td>-6.79±1.16</td>
<td>-5.67±1.26</td>
<td>1.13</td>
</tr>
<tr>
<td>Jorge Montt</td>
<td>930</td>
<td>-2.20±0.38</td>
<td>-1.96±0.41</td>
<td>0.25</td>
</tr>
<tr>
<td>Upsala</td>
<td>1170</td>
<td>-2.68±0.40</td>
<td>-2.29±0.46</td>
<td>0.39</td>
</tr>
<tr>
<td>Viedma</td>
<td>1260</td>
<td>-2.27±0.36</td>
<td>-1.90±0.40</td>
<td>0.38</td>
</tr>
<tr>
<td>SPI G$_1$</td>
<td>1077</td>
<td>-5.07±0.79</td>
<td>-4.17±0.90</td>
<td>0.90</td>
</tr>
<tr>
<td>SPI G$_2$</td>
<td>1096</td>
<td>-1.66±1.16</td>
<td>-1.35±1.03</td>
<td>0.31</td>
</tr>
<tr>
<td>Tyndall</td>
<td>940</td>
<td>-0.60±0.14</td>
<td>-0.53±0.14</td>
<td>0.07</td>
</tr>
<tr>
<td>Grey</td>
<td>980</td>
<td>-0.69±0.23</td>
<td>-0.59±0.20</td>
<td>0.09</td>
</tr>
<tr>
<td>Pio XI</td>
<td>930</td>
<td>0.67±0.29</td>
<td>0.57±0.25</td>
<td>0.10</td>
</tr>
<tr>
<td>NPI + SPI</td>
<td></td>
<td>-21.29±1.98</td>
<td>-17.89±2.03</td>
<td>3.40</td>
</tr>
</tbody>
</table>
Time series of mean observed glacier elevation change (Fig. 5.3) show negative trends for all sub-regions with the exception of Pio XI, which shows increasing elevation. Most sub-regions display a seasonal oscillation on the order of 1-3 m. The amplitude is highest (4 m) for the Grey Glacier, while it is less discernible for glaciers with the strongest mass losses per unit area (Jorge Montt and Upsala), possibly reflecting the importance of dynamic thinning also during the accumulation period.
Figure 5.3: Time series of cumulative mean observed elevation change for the nine sub-regions (Table 5.1), including the SPI as a whole (grey), in order of increasingly negative specific mass balance (top to bottom).
5.5 Discussion

Spatial Coverage

The Patagonian Ice Fields are a challenging region for radar altimetry. The topography is similar to mountain glaciers, with elevation ranging from sea level to above 2,000 m over distances of less than 30 km. Furthermore, the flow of most glaciers on the Ice Fields is almost perpendicular to CS-2’s approximately north-south flight direction so that elevations change abruptly (>1,000 m) over short distances (400 m) along the flight track (Fig. 5.4), increasing the occurrence of loss-of-lock in the altimetric record and leading to gaps in the collected data (Dehecq et al., 2013). Over the Southern Patagonian ice field, conventional CS-2 POCA altimetry provides about 30% spatial coverage at 500 m posting. Although swath altimetry is affected by loss-of-lock as much as POCA, enhanced spatial coverage is achieved because a swath of heights, rather than one single elevation, is acquired when the on board tracker correctly sets the range window. Swath altimetry thereby provides 61-73% surface coverage over the large (A>400 km$^2$) glaciers in the northern part of the SPI and between 47% and 54% in other areas (Table 5.1). The only exception is SPI-G$_2$ (39%), where the ice field is narrower and where there are no observations over a number of glaciers with relatively small surface area (Fig. 5.1 and Fig. 5.2, inset). Despite the limited extent, their mass loss may be non-negligible. For example HPS12 (south of Pio XI) has an area of 165 km$^2$ and lost 0.63 Gt a$^{-1}$ between 2000 and 2011/12 (Willis et al., 2012b).

In comparison, work based on high resolution radar TanDEM-X DEMs have almost complete coverage at higher spatial resolution (Jaber et al., 2013; Jaber, 2016; Malz et al., 2018), although this data does not allow yet to generating time series of elevation change. Compared to TanDEM-X DEMs, optical ASTER DEMs achieve similarly high spatial coverage for decadal periods, decreasing to 57-73% for the entirety of the Ice Fields over shorter time periods comparable to that in this paper (Willis et al., 2012b). Despite CS-2 L2swaths lower spatial coverage, we still capture in detail the
Figure 5.4: (left panel) Example ascending and descending CS-2 sub-satellite tracks (red) displayed over the SRTM topography for the SPI. Glacier outlines from RGI v6 are plotted in black. (right panel) Along-track topography (black) for the same sub-satellite tracks (red). For reference, the SPI (light blue) is shown in the background.
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Figure 5.5: Estimates of mass balance $\dot{M}$ [Gt a$^{-1}$] for the Patagonian Ice Fields combined (a) and separate (b) as published in the literature as well as calculated in this study. Note that the time line is not linear. The estimate from Gardner et al. (2013) is for the whole of the Southern Andes.

various patterns of change. Furthermore, using a single sensor and frequent repeat measurements is advantageous as it limits penetration biases associated both with using multiple sensor types (e.g. optical vs radar or radar with varying wavelengths) and seasonal variations in surface mass density, thereby limiting the impact on surface elevation change estimates (Jaber et al., 2013; Jaber, 2016; Willis et al., 2012b; Malz et al., 2018). Given the similarity of the Patagonian Ice Fields to mountain glaciers, swath altimetry may also provide one additional tool for monitoring elevation change over these complex areas (Paul et al., 2015).

Rates of mass change

Spatial patterns in the rates of surface elevation change (Fig. 5.1 and 5.1) are comparable with those observed over the period 2000-2011/16 (Willis et al., 2012b,a; Jaber et al., 2013; Jaber, 2016; Malz et al., 2018). The NPI and the northern part of the SPI (SPI-G, Jorge Montt, Viedma and Upsala) are thinning very rapidly and account for 89% of the mass loss of the Patagonian Ice Fields between 2011 and 2017 (Table 5.1). The rate of mass loss of the Patagonian Ice Fields has increased in recent decades (Fig. 5.5-a), with our estimated mass loss rate (21.29±1.98 Gt a$^{-1}$), being 46% higher than between 1944 and 1996 (Aniya, 1999), 42% higher than between 1975-2000 (Rignot et al., 2003) and 24% higher than between 2000-2012/14 (Jaber,
However, for the period 2000-2011/12 Willis et al. (2012b) estimate a total rate loss of 24.39±1.20 Gt a⁻¹, comparable to those based on gravimetry data (Chen et al., 2007; Ivins et al., 2011; Jacob et al., 2012; Gardner et al., 2013) but 30% more negative than that of Jaber (2016) (Fig. 5.5-a). GRACE-based estimates rely on model predicted corrections for postglacial rebound and land water storage, which are a large source of uncertainty to the estimated rates of mass loss in Patagonia (e.g. Chen et al., 2007; Jacob et al., 2012). Additionally, mass loss from glaciers and ice fields in the vicinity (Möller and Schneider, 2008; Melkonian et al., 2013; Falaschi et al., 2017) may impact on the estimate since gravimetry methods are always sensitive to mass leakage effects from neighbouring areas (e.g. Sørensen et al., 2017). The disagreement between Willis et al. (2012b) and Jaber (2016) may be related to the 2 m elevation correction applied to the SRTM data by Willis et al. (2012b) in order to account for potential radar penetration through the glacier surface. However, analysis of the SRTM mean backscattering coefficient suggests wet surface conditions on the Ice Fields at the time of the SRTM acquisition (Jaber, 2016), which would be expected to prevent the radar signal from penetrating through the surface (Nilsson et al., 2015b). Additionally, Dussaillant et al. (2018) find that radar penetration over the NPI occurs only above 2,900 m elevation, i.e. less than 0.75% of the ice field’s area. In absolute value, this correction has a larger impact on the SPI than on the NPI (Willis et al., 2012b), where the estimates from Willis et al. (2012b) and Jaber (2016) differ by only 10%.

Separating the contributions of the Ice Fields (Fig. 5.5-b) shows the difference in the progressive increase in mass loss between the NPI and SPI. Between 2011 and 2017 the NPIs rate of loss (6.79±1.16 Gt a⁻¹) is ~70% more negative compared to the previous decade (about 4 Gt a⁻¹, Willis et al., 2012a,b; Jaber, 2016; Dussaillant et al., 2018), which in turn was ~37% higher than between 1975-2000 (Rignot et al., 2003) (Fig. 5.5-b). Compared to the latter, Rivera et al. (2007) record higher rates of mass loss in a similar time period (1979-2001) (Fig. 5.5-b), but their estimate is based on data mostly lying in the ablation zone of the NPI. In contrast, the mass loss over the SPI varies by just 8-10% between these three periods (Rignot et al., 2003;
Jaber, 2016; Malz et al., 2018) (Fig. 5.5-b) although its rate of loss is still more than twice that of the NPI. Estimates from Jaber (2016) and Malz et al. (2018), both based on comparing TanDEM-X data to the SRTM DEM, differ by 1.29 Gt a$^{-1}$ although they agree within their uncertainties. The difference may be due to the 4 years longer time period analysed by Malz et al. (2018), who report positive elevation changes in the southernmost part of the SPI between 2011/12 and 2015/16. We observe only a slightly positive trend in elevation change in this time period, followed by a marked drop after 2015/16 (Fig. 5.3, SPI-G$_2$). However, our time series for SPI-G$_2$ is representative of an area roughly twice as large than that analysed by Malz et al. (2018) over multiple time periods. Finally, the estimated SPIs rate loss of 34.83±3.96 Gt a$^{-1}$ between 1995 and 2000 (Rignot et al., 2003), which is even more negative than any estimate for both Ice Fields combined (Fig. 5.5-a), appears out of line with other values.

**Glacier Dynamics**

We observe a sharp transition around 49°S (Fig. 5.1-5.2, dashed green line) from intense thinning in the north to a large area facing limited mass loss (SPI-G$_2$), which spans about 4,800 km$^2$ or about 40% of the total surface of the SPI (Table 5.1). This pattern is in agreement with earlier observations between 2000 and 2012/16 (Willis et al., 2012b; Jaber et al., 2013; Jaber, 2016; Malz et al., 2018), therefore suggesting constant behaviour over decadal time scales. The topography of the northern and southern parts of the SPI has different characteristics, with a greater proportion of the northerly ice field lying at lower altitudes. In fact, about 72% of SPI-G$_1$’s surface lies below 1,500 m elevation, 12% more than SPI-G$_2$’s at the same altitude (Fig. 5.1, insets SPI-G$_1$ and SPI-G$_2$). The Ice Field also narrows and steepens south of 49° S and even at low elevations the southern SPI shows only moderate thinning. Glaciers Grey and Tyndall, at the south-eastern tip, are the exception to this pattern. However the latter lies almost entirely below 1,500 m altitude (Fig. 5.1, inset Tyndall) and both glaciers receive scarce precipitation due to their location east of the ice divide. The NPI has similar area-altitude distribution as SPI-G$_1$ (Fig. 5.1, inset SPI-G$_1$ and NPI)
Figure 5.6: Median observed rates of surface elevation change for the two Ice Fields every tenth of a degree of latitude and for different elevation bands at [0-800m], [800-1000m], [1000-1200m], [1200-1500m], [1500-1800m] and [1800-2200m]. The Pio XI glacier is not included in this analysis due to its anomalous and unique behaviour (see section 5.5). Note that the scale on the x-axis varies to display the strong thinning at lower elevations.
Figure 5.7: Frontal retreat of Jorge Montt Glacier (SPI). The glacier retreated almost 2 km between 2000 and 2011 and receded a further ~2.5 km in our study period. Water depth at the glacier front was 400 m in 2013. Bathymetry data after Piret et al. (2017).

and the two areas show comparable mass losses per unit area (Table 5.1). However, the northern part of the SPI contains some of the fastest flowing glaciers on the Ice Fields, including Jorge Montt and Upsala (Sakakibara and Sugiyama, 2014; Mouginot and Rignot, 2015) which accelerated significantly (>500 m a-1) in the period 1984-2000 (Jorge Montt) and 2000-2010 (Upsala), coincident with rapid frontal retreat (Sakakibara and Sugiyama, 2014). These observations confirm the importance of dynamics in impacting the overall mass balance of the northern part of the SPI (e.g. Sakakibara and Sugiyama, 2014; Mouginot and Rignot, 2015), where three of the largest glaciers (Jorge Montt, Upsala and Viedma) are thinning very rapidly (Table 5.1 and Fig 5.1-5.3).

**Jorge Montt glacier**

Jorge Montt, a tidewater glacier at the northernmost tip of the SPI, has been retreating since 1898 when it reached its LIA maximum extent (Rivera et al., 2012b). Its recession has been linked to fjord water depth, with periods of stable front positions corresponding to shallow depths and underwater pinning points (Rivera et al., 2012b).
Additionally, water temperatures at depth (>100 m) have been shown to be as high as 8°C in summer 2012 only 1 km from the glacier front (Moffat, 2014), which may further destabilise the glacier through submarine melting (Straneo and Heimbach, 2013). By 2011 Jorge Montt had retreated almost 20 km w.r.t 1898, with the highest rates of recession between 1990 and 1997 (993 m a\(^{-1}\)) occurring when water depths beneath the glacier increased sharply to ∼300m (Rivera et al., 2012b). The recent retreat history of Jorge Montts reveals a slowdown to about 100-300 m a\(^{-1}\) in the early 2000s, followed by increased retreat after 2009 initiated at a location where bathymetry data reveals the deepest trough in the fjord (Rivera et al., 2012b; Moffat, 2014, Fig. 5.7).

Between 2010 and 2011, Jorge Montt retreated almost 1 km (Rivera et al., 2012a,b) and calved at a rate of 2.4 km\(^3\) a\(^{-1}\), when the terminus was floating (Rivera et al., 2012a). Manual delineation of the glacier front between 2011 and 2017 using Landsat optical data (Fig. 5.7) indicates that Jorge Montt retreated by an additional ∼2.5 km, likely through enhanced calving following retreat into deeper water (Rivera et al., 2012b). Given an average glacier freeboard height of 22 m above sea level at the terminus (Rivera et al., 2012a) and width of 1.15 km, the glacier frontal retreat amounts to a mass loss rate of 0.07 Gt a\(^{-1}\) (∼3% of the catchments loss due to thinning, Table 5.1) between 2011 and 2017. This value is however likely underestimated since the slope of the glacier surface, and thus upglacier thickening, has not been considered.

Due to the uncertainty associated with this calculation, and that at least part of the glacier terminus was floating in 2010/11 (Rivera et al., 2012a) and likely during our observational period, we report this loss separately in Table 5.1 and do not include it in our total estimate of glacier contribution to sea level rise. Between 2011 and 2017, Jorge Montt shows the highest mass loss per unit area, 4 times above the average for the SPI as a whole (Table 5.1). Its absolute rate of mass loss (2.20±0.38 Gt a\(^{-1}\)) is comparable to what reported by Jaber (2016) for the period 2011-2014 (2.59 Gt a\(^{-1}\), uncertainty not reported), which increased by 50% compared to the 1.72 Gt a\(^{-1}\) (uncertainty not reported) rate of mass loss between 2000 and 2011 (Jaber, 2016).
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Figure 5.8: Front location of Upsala glacier (SPI). The glacier receded about 500 m between 2011 and 2017. Thinning rates from this study are also shown in the range -12 to 0 m a\(^{-1}\).

**Upsala glacier**

Upsala, a freshwater calving glacier located on the north-eastern side of the SPI and draining into Argentino Lake, has also been retreating since the late 1970s (Naruse et al., 1997). Between 2008 and 2011, retreat rates quadrupled w.r.t the previous 8 years and the glacier retreated by almost 3 km (Sakakibara et al., 2013), while simultaneously speeding up by 20-50% (Sakakibara et al., 2013; Mouginot and Rignot, 2015) and thinning at a maximum rate of \(\sim 40\) m a\(^{-1}\) near the terminus (Sakakibara et al., 2013).

The rapid retreat may have been caused by the glacier front reaching an area where the lake depth exceeds 560 m (Sugiyama et al., 2016). In early 2013 the glacier's velocity at the front was 2.9 m d\(^{-1}\) (Moragues et al., 2018), 33% lower compared to 2008 and more similar to values recorded in the early 2000s (Sakakibara et al., 2013). Moragues et al. (2018) report a doubling in maximum velocity between 2013 and 2014. However this increase is unlikely to have been sustained in time. In fact, between 2011 and 2017, the glacier front has been comparatively stable (Fig. 5.8), with a retreat rate of \(\sim 85\) m a\(^{-1}\) similar to the period 2000-2008 (Sakakibara et al., 2013). Coincident with a more stable position, the average thinning rate within 16 km of the terminus decreased by a factor two from 13.4 m a\(^{-1}\) between 2006-2010 (Sakakibara et al., 2013).
5.5 Discussion

Figure 5.9: Front location of Pio XI glacier (SPI). The tidewater (south) and lacustrine (north) termini advanced about 500 m and 800 m, respectively, between 2011 and 2017.

2013) to 6.2 m a\(^{-1}\) between 2011-2017 (Fig. 5.8). Bertacchi Glacier, a tributary of Upsala, shows a similar pattern with current rates of elevation change decreasing to 8.5 m a\(^{-1}\) (Fig. 5.8) from \(~15\) m a\(^{-1}\) between 2008-2011 (Sakakibara et al., 2013). We observe maximum thinning rates of \(~12\) m a\(^{-1}\) 5 km from the terminus of Upsala glacier, comparable to estimates at the front in the early 1990s (Naruse et al., 1997). Despite these reduced thinning rates, Upsala remains the glacier with the second most negative specific mass balance in the Patagonian Ice Fields after Jorge Montt, and is the largest single contributor to net mass loss amongst individual glaciers (Table 5.1 and Fig. 5.1-5.3).

Pio XI glacier

Pio XI, the largest glacier on the SPI and in South America, is the only glacier of the Patagonian Ice Fields to have experienced a net large advance since 1926 and the only known surge-type glacier on the SPI (Rivera et al., 1997a; Wilson et al.,
CHAPTER 5. Heterogeneous and rapid ice loss over the Patagonian Ice Fields revealed by CryoSat-2 swath radar altimetry

2016). Published data of frontal changes, ice flow velocity at the termini, elevation change and mass balance, summarized in Fig. 5.10, reveal a complex history (section 5.11). Between 1951-1963, the glaciers westward and southward advance dammed a proglacial river originating from Greve glacier to the north, forming the current Lake Greve for at least the second time since 1926 (Rivera et al., 1997a). Since then, the glacier has been terminating in Ejre Fjord to the south and Lake Greve to the north. From 1945 to present, the tidewater terminus advanced \(~13\) km and is currently at its Neoglacial maximum (Wilson et al., 2016, Fig. 5.9 and 5.10). Looped supraglacial moraines were used to identify up to six surge events since 1926 (Rivera et al., 1997b; Wilson et al., 2016), two of which were concurrent with front retreat, possibly due to enhanced calving at the tidewater terminus (Wilson et al., 2016, Fig. 5.10). The glacier has been thickening in the ablation area since the late 1970s, with the highest rates recorded at the termini, while the picture is more complicated in the accumulation area where data is sparse (Fig. 5.10). Between 2011 and 2017, we observe thickening at almost all elevations, by about 2.33 m a\(^{-1}\) and 0.57 m a\(^{-1}\) (median value) in the ablation and accumulation areas respectively (Fig. 5.1; Pio XI inset) with thinning at the highest elevations above 1,500 m altitude; findings which match those described in Jaber (2016). There is however no coverage in our data close to the two termini. Assuming a thickening trend at the two fronts, which was sustained for the last four decades (Rignot et al., 2003; Willis et al., 2012b; Jaber et al., 2013; Jaber, 2016; Wilson et al., 2016), we estimate that the Pio XI glacier is gaining mass at a rate of 0.67\(\pm\)0.29 Gt a\(^{-1}\) between 2011 and 2017 (Table 5.1 and Fig. 5.10). However the rate is likely underestimated since the hypsometric averaging model for Pio XI glacier predicts less thickening compared to the observations below 1,000 m elevation (Fig. 5.2, inset). The mass gain is likely a result of complex dynamics associated with both surge mechanisms and terminus calving processes, since Pio XI is the only advancing glacier within the Patagonian Ice Fields and air temperature has increased over the last 50 years (Rasmussen et al., 2007).
5.6 Conclusions

CryoSat-2 swath radar altimetry is employed successfully to map elevation change over the Patagonian Ice Fields at sub-kilometer spatial resolution. Despite the challenging topography, similar to that of mountain glaciers, the technique can be used to observe changes over individual glaciers or catchments with an area as small as 300 km$^2$. The northern part of the SPI displays a high degree of complexity, although most of the area is thinning at all elevations, with Jorge Montt, Viedma and Upsala glaciers losing mass at rates higher than 2 Gt a$^{-1}$. Jorge Montt additionally retreated $\sim$2.5 km between 2011 and 2017, likely by enhanced calving in deeper fjord waters. The only exception to the overall pattern of thinning and retreat is the Pio XI glacier, which continues to advance at both its tidewater and lacustrine termini. The glacier, which is currently at its Neoglacial maximum, is estimated to have gained mass at a rate of 0.67$\pm$0.29 Gt a$^{-1}$ during our study period. Between April 2011 and March 2017, the Ice Fields lost mass at a combined rate of 21.29$\pm$1.98 Gt a$^{-1}$ (equivalent to 0.059$\pm$0.005 mm a$^{-1}$ eustatic sea level rise), an increase of 24% and 42% when compared to the periods 2000-2012/14 and 1975-2000, respectively. We find that the NPI (-6.79$\pm$1.16 Gt a$^{-1}$), which is responsible for a third of the total loss, is losing mass 70% faster compared to the first decade of the 21$^{st}$ century. Given the ongoing and rapid wastage of the Patagonian Ice Fields, and their important contribution to the global budget of mass loss from glaciers and ice caps, continuous observations with excellent spatial and temporal resolution are essential. CryoSat-2 swath altimetry provides an important tool for monitoring these rapidly changing areas and quantifying their ongoing mass loss.
5.7 Appendix A  Filtering CS2 SARIn waveform samples

Selecting waveform samples based on fixed thresholds on coherence and power is an empirical approach which has been applied successfully to infer glacial topography and higher products based on it such as topography changes (Gray et al., 2013; Christie et al., 2016; Ignéczí et al., 2016; Foresta et al., 2016; Gourmelen et al., 2017a). However, in this paper we use a different procedure to discard noisy waveform samples before performing the phase unwrapping. This method relies entirely on the phase difference field and consists in identifying, within each waveform, groups of consecutive samples which can be modelled by a straight line. The original phase difference is divided into overlapping segments, their length being set to 64 samples and the overlap half of the length. The slope of the phase difference is then calculated independently in each segment. Instead of applying a linear regression, the algorithm applies a Fourier transform on the normalized complex coherence \( e^{i\delta \phi} \), where \( \delta \phi \) is the phase difference field. Compared to linear regression, this approach is both more efficient computationally as well as independent on phase wrapping. The Fourier transform enables to testing a large number of possible slopes and the one with the highest correlation with the input data is selected. The signal is oversampled to take into account that the slope of CS-2’s phase difference can represent non-integer frequencies. Thus, each overlapping section has two possible slopes. A correlation is applied again to the data in each overlapping section, this time using only its two estimated slope values. Sections whose correlation is below a set threshold (for this work, 0.95) are considered noisy and discarded. Finally, the remaining segments are used to unwrap the phase difference. With this procedure, no smoothing is applied to the phase difference and no threshold is set on the power or coherence.
A number of freely available DEMs covering Southern Patagonia exist, namely: the SRTM (i) C and (ii) X band DEMs (Farr et al., 2007), the (iii) ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) GDEM2 (Tachikawa et al., 2011) and (iv) the ALOS (Advanced Land Observing Satellite) AW3D30 v1.1 (Tadono et al., 2014; Takaku et al., 2014; Tadono et al., 2016; Takaku et al., 2016). The latter is the most recent, but has large gaps over the SPI, which are filled using the SRTM C band DEM. Version 1 of the ASTER GDEM was known to be affected by large artefacts (Arefi and Reinartz, 2011) and, despite large overall improvements, version 2 still has high frequency noise, particularly over glacial terrain (Meyer et al., 2011). Visual comparison between the SRTM C band and ASTER GDEM2 DEMs shows evident noise in the latter, with differences at times on the order of tens of meters between neighbouring pixels. Finally, the SRTM X band DEM does not have complete coverage and gaps over the Ice Fields are significant. Therefore, we used the SRTM C band DEM as a reference for elevation, which fully covers the Patagonian Ice Fields, resampled at 300 m posting and referenced to the WGS84 vertical datum. The down-sampling of the DEM is mostly dictated by achieving a satisfactory performance in computing time whilst keeping the spatial resolution somewhat comparable to that of an individual elevation based on CryoSat-2 interferometric data (300 m in the along-track direction). We use linear interpolation when querying the DEM.

The SRTM DEM is based on data acquired in February 2000, and a few areas at the margins of the SPI have thinned by at least 80 m since then (Willis et al., 2012b; Jaber et al., 2013; Jaber, 2016). This magnitude is comparable to the elevation offset caused by a $2\pi$ shift on CS-2s phase (section 5.3; Fig. 3 in Gourmelen et al. (2017a)). Thus, over areas which experienced intense thinning rates, the swath algorithm may select an incorrect $2\pi$ multiple which best matches current observations to the glacier topography from 2000. In order to avoid that, the SRTM DEM needs to be registered to
the beginning of our study period. To this purpose, we applied a first order correction of the SRTM DEM based on a visual inspection of results in Willis et al. (2012b) and assuming constant rates of elevation change between the SRTM and CS-2 periods. This approach was sufficient to improve the phase unwrapping, leading to further pixels meeting the quality criteria for robust rates of surface elevation change. We refer to this corrected DEM simply as the SRTM DEM in this study. The correction of the SRTM DEM only affects the terminus areas of Jorge Montt and Upsala glaciers (SPI) since there are no CS-2 swath altimetry observations over smaller glaciers on the Ice Fields which experienced similar thinning rates in the period 2000-2011/12 (e.g. HPS12, SPI; Willis et al., 2012b; Jaber et al., 2013; Jaber, 2016).
5.9 Appendix C - Error budget

The errors on the mass balance estimates are calculated as in (Foresta et al., 2016). The uncertainties $\epsilon_h$ on the observed rates of elevation change for the individual pixels, extracted from the model covariance matrix (see section 5.3), are propagated when applying the hypsometric averaging method:

$$E_{h}(k) = \frac{\sqrt{\sum_{m=1}^{N(k)} \epsilon_{h}(m)^2}}{N(k)}$$

(5.3)

where $E_{h}(k)$ is the elevation change error in elevation band $k$ and $N(k)$ is the number of valid observations in the elevation band. A two-term decreasing exponential is used to interpolate values for elevation bands with no observations (e.g. at low elevation for bands with limited spatial extent). We multiply the area extent $A(k)$ of the elevation band to the related $E_{h(k)}$ and sum all contributions to estimate the total uncertainty on the rate of volume change:

$$E_V = \sum_k E_{h(k)} A(k) .$$

(5.4)

With this method, the volume change uncertainty is only related to that area of the ice cap where there are valid rates of surface elevation change, but does not account for incomplete data coverage. The volume change uncertainty is therefore rescaled according to the data coverage (Table 5.1). This procedure generates a rather conservative (i.e. larger) error estimate since it assumes that the lack in data coverage has a direct impact on the total error estimate, which does not hold if the sampling is sufficiently uniform. Finally, we include an error on the density:

$$E_{\rho} = \frac{1}{2} \left( \rho_{\text{ice}} - \rho_{\text{firm}} \right)$$

(5.5)

when converting volume to mass change (e.g. Nilsson et al., 2015a).
### 5.10 Appendix D - Landsat scenes

Table 5.3: List of Landsat scenes used to manually delineate the front positions of glaciers Jorge Montt, Upsala and Pio XI (SPI).

<table>
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<th>Year</th>
<th>Scene ID</th>
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<tbody>
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<tr>
<td></td>
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<td>LE72320942009156EDC00</td>
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<tr>
<td></td>
<td>2010</td>
<td>LE72310942010088COA00</td>
</tr>
<tr>
<td></td>
<td>2011</td>
<td>LE72320942011050EDC00</td>
</tr>
<tr>
<td></td>
<td>2013</td>
<td>LE72320942013087ASN00</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>LC82310942014075LGN00</td>
</tr>
<tr>
<td></td>
<td>2015</td>
<td>LC82320942015021LGN00</td>
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<td></td>
<td>2016</td>
<td>LC82320942016072LGN00</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>LC82320942017106LGN00</td>
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<tr>
<td>Upsala</td>
<td>2011</td>
<td>LE72310952011123EDC00</td>
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<tr>
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<td>2017</td>
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<tr>
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<td>2011</td>
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<td></td>
<td>2017</td>
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</table>
5.11 Appendix E - Pio XI glacier (SPI): summary of published data

Fig. 5.10 summarises published data of frontal changes, ice flow velocity at the fronts, elevation change and mass balance (Rivera et al., 1997b,a; Rivera and Casassa, 1999; Rignot et al., 2003; Lopez et al., 2010; Willis et al., 2012b; Jaber et al., 2013; Sakakibara and Sugiyama, 2014; Wilson et al., 2016).
CHAPTER 5. Heterogeneous and rapid ice loss over the Patagonian Ice Fields revealed by CryoSat-2 swath radar altimetry

Figure 5.10: Chart summarizing published data for the Pio XI glacier (SPI). (a) Cumulative front advance of the tidewater and lacustrine termini; (b) ice flow velocity; (c) mass change. Elevation change in the (d) ablation and (e) accumulation area. Potential surges concurrent with advance (Rivera et al., 1997a) or retreat (Wilson et al., 2016) of the tidewater front are highlighted in light and dark grey, respectively. All relevant references are listed in the inset.
5.11 Appendix E - Pio XI glacier (SPI): summary of published data
Chapter 6

Synthesis and conclusions

The aim of this thesis was to exploit swath processed interferometric data from the ESA CryoSat-2 radar altimetry mission for observing spatial and temporal changes in surface elevation. This information was then converted into estimates of volume and mass change over ice fields and ice caps, with the ultimate aim of quantifying their contribution to global sea level rise. The motivation for this work was two-fold. On the technical side, it showed that swath altimetry is able to deliver additional insight in the spatial patterns of elevation change, compared to the conventional approach, by providing a higher density of observations. Such increase in topographic data allowed to investigate glacier elevation change at sub-kilometer spatial resolution over areas which have proved challenging to monitor with satellite altimeters. Glaciologically, this work was motivated by the significant contribution (∼30%) of glaciers, ice caps and ice fields to global sea level rise between 2003 and 2009, comparable to that of the two ice sheets combined (Gardner et al., 2013), as well as by the need to provide observations with improved spatial and temporal resolution during the most recent period. In fact, glacier extents are out of balance with current climatic conditions, an indication that they will continue to shrink in the future (Vaughan et al., 2013), so that continuous and improved monitoring is needed in order to further improve our understanding of glaciological processes and to more accurately quantify the mass changes of these regions.

The complete processing chain described in Chapter 3, from generating swath processed elevations to computing rates of surface elevation, volume and mass change,
was applied first to Icelandic ice caps (Chapter 4) and later to the Patagonian ice fields (Chapter 5). In Iceland, the six largest ice caps span a wide range of sizes and hypsometries; in this case, maps of surface elevation change rates were derived at multiple spatial resolutions with both the POCA and swath approaches. One of study aims was to compare results of the two techniques for the different topographic conditions of these ice caps. These results are summarised in section 6.1. Additionally, Icelandic ice caps have been monitored for decades so that their recent mass loss is known and hence data is available for comparison within the same time frame analysed in this thesis. Results on the patterns of surface elevation change as well as on the mass balance of Icelandic ice caps are presented in section 6.2. The Patagonian ice fields, on the other hand, are comparatively less well studied. Mass changes over these areas, at least in part linked to glacier dynamics, are less well understood and their complex topography represents a challenge for radar altimeters. Nevertheless, the high density of observations provided by CS-2 swath altimetry is particularly valuable in this region, where mass balance was quantified over individual catchments with an area as small as 300 km$^2$. Results over the Patagonian ice fields are presented in section 6.3, before discussing the limitations of this research (section 6.4) and summarising the research undertaken within this project in the concluding remarks (section 6.5).

6.1 CryoSat-2 swath vs POCA altimetry over ice caps and ice fields

The six largest ice caps in Iceland (about 90% of the glaciated terrain) range in size from $\sim$80 km$^2$ (Eyjafjallajökull) to $\sim$8,100 km$^2$ (Vatnajökull, the largest in Europe by volume), and have different hypsometry as well as topography. For example, Langjökull ($\sim$900 km$^2$) is quite narrow, about 15 km across in the northern part, while most other ice caps are dome shaped. This provides a range of conditions over
which CryoSat-2 swath and POCA altimetry could be tested and compared (section 4.7.3). This research shows how swath processing improves upon the shortcoming of conventional radar altimetry in regions with considerable slope. In such areas, the spatial distribution of POCA elevations is controlled by surface topography and most of the observations are located on topographic highs such as ice divides. This result is particularly evident over the long and narrow Langjökull ice cap (Fig. 4.8), where there are less than 10 POCA elevations per km$^2$ close to the margins (Fig. 4.10), insufficient to derive robust estimates of rates of surface elevation change. Swath processing generates 2 and 5 orders of magnitude more data than conventional POCA altimetry based on CryoSat-2 SARIn and ICESat laser data, respectively, and provides almost uniform sampling (Fig. 4.7 and 4.9). This results in high spatial coverage (65% to 80% when gridding data at 500 m resolution) for all of the ice caps, with the exception of Eyjafjallajökull (27%) whose surface area is smaller than 100 km$^2$.

The work additionally shows that the increase in spatial density of observations does not negatively affect the measurements’ accuracy. Directly comparing co-located swath and POCA derived rates of surface elevation change at 2 km posting results in a mean difference of $-0.05 \pm 0.64$ m a$^{-1}$ (Figure 4.11-c). Furthermore, the rate difference does not show any dependence on surface slope either along or across track (Figure 4.11a-b) (Gray et al., 2013).

The density of swath observations allows for the gridding of data at sub-kilometer spatial resolution while maintaining the high spatial coverage mentioned above. This revealed a detailed pattern of surface elevation change (Figure 4.1) which was linked to geophysical processes (section 6.2). The additional insight, compared to maps of surface elevation change based on POCA data, is particularly evident over ice caps smaller than Vatnajökull (Fig. 4.1, 4.13 and 4.14).

Finally, Table 4.2 shows that swath-based estimates of mass change of Icelandic ice caps are generally comparable when varying the grid resolution, an indication that
6.2 Icelandic ice caps

High resolution (sub-kilometer) is adequate when quantifying mass change using swath processed elevations. Excluding Vatnajökull, there is a larger variability in the mass balance estimates based on CS-2 POCA altimetry, possibly caused by the preferential sampling of POCA (see above).

Over the Southern Patagonian ice field, conventional CS-2 POCA altimetry provides about 30% spatial coverage at 500 m posting. The topography in this area is similar to mountain glaciers, where elevation under the satellite track may vary by thousands of meters over short (<400 m) distances. In this case, the chance of loss-of-lock (section 2.1) is more likely. When this happens, both POCA and swath altimetry are affected as the entire waveform has to be discarded. However, in an indirect way swath altimetry helps maximising the spatial coverage since a swath of heights, instead of one single elevation, is acquired when the on board tracker correctly sets the range window. Despite larger gaps than over Icelandic ice caps, swath processed elevations at 500 m posting provided spatial coverage between 60-71% for four individual large glaciers (>400 km²) on the SPI and between 39-53% for other areas.

6.2 Icelandic ice caps

The dense elevation field provided by swath processing (~10 million observations) allowed for the generation of maps of surface elevation change rates at 500 m spatial resolution over the six largest ice caps in Iceland for 5 glaciological years between October 2010 and September 2015, from which mass balance was computed. Overall, mass loss in the region averaged 5.8 ± 0.7 Gt a⁻¹, contributing 0.016 ± 0.002 mm a⁻¹ to sea level rise. The high resolution mapping is a key improvement, as it revealed complex spatiotemporal patterns of surface elevation change related to climate, ice dynamics, and subglacial geothermal and magmatic processes in Iceland. Results show widespread thinning, with rates of up to 10 m a⁻¹ over the marginal areas of
the ice caps, while in the interior the picture is more complex, with different basins displaying either thinning or thickening at higher elevations. Dynamic thickening in the accumulation area of a number of catchments of the Vatnajökull and Langjökull ice caps is clearly visible and linked to surge events which occurred between 1963 and 1999. Thickening in the Gjálp basin (Vatnajökull) is instead related to the 1996 subglacial volcanic eruption which created a surface depression into which ice is now flowing. More recently, in 2014/15, the Bárðarbunga subglacial eruption (Vatnajökull) caused the surface to lower by about 40 m due to the deflation of a subglacial magma chamber. The subsidence pattern is clearly detected by the technique used in this thesis.

The high spatial resolution and coverage achievable with swath processed data provides the opportunity to measure mass balance of individual catchments, which was tested over the Brúarjökull basin (Vatnajökull). The geodetic estimate (-0.51 ± 0.09 Gt a⁻¹) compared well with the estimate of mass balance produced from in situ data (-0.49 ± 0.22 Gt a⁻¹). The ability to estimate mass balance at the catchment scale is an important step forward compared to previous methods using satellite altimetry and is especially important in areas where neighbouring basins display contrasting patterns of surface elevation change (e.g. Vatnajökull and section 6.3).

Finally, this work showed that swath elevations can be exploited to produce time series of elevation change. This investigation produced two important results. First, it highlighted the clear seasonal cycle in both the ablation and accumulation area of the Vatnajökull ice cap, with an increase in elevation in the accumulation period followed by rapid decrease during the melt season. Additionally, it revealed the positive trend in the accumulation area after October 2014, concurrent with a less negative trend in the ablation area. This shift reflects the fact that during the glaciological year 2014/15, Vatnajökull experienced positive mass balance for the first time since the mid-1990s.
6.3 Patagonian ice fields

In contrast to Iceland, the Patagonian ice fields are comparatively understudied. The methods discussed above were applied to this area in order to quantify their mass change in the most recent period, namely six glaciological years between April 2011 and March 2017. Combined together, the two ice fields lost mass at an average rate of $20.66 \pm 1.98 \text{ Gt a}^{-1}$, contributing $0.057 \pm 0.005 \text{ mm a}^{-1}$ to SLR. However, the Patagonian ice fields display a larger degree of spatial variability compared to ice caps in Iceland, not only in the patterns of surface elevation change, but also in the sign and magnitude of mass change. Analysis of the sub-kilometer maps of surface elevation change rates highlighted three broad areas which display contrasting patterns of change. Widespread thinning occurs at almost every elevation on the NPI and in the northern part of the SPI, which contrasts with the thickening visible over the Pio XI glacier (SPI). No change is detected over the southern part of the SPI, with the exception of the two southernmost glaciers Grey and Tyndall which are losing substantial mass.

Swath processed elevations provide enough coverage of six large glaciers (with area larger than 300 km$^2$) to allow their mass balance to be computed independently. This is important since some of them are dynamically thinning at rates far higher than the rest and thus combining them together would smooth these differences and lose valuable information as shown in section 3.3.3 for the Vatnajökull ice cap. Four of these glaciers lie in the northern part of the SPI, which shows the highest degree of complexity. In this area, three glaciers (Upsala, Jorge Montt and Viedma) are losing mass at rates higher than 2 Gt a$^{-1}$. The Upsala glacier is the single largest contributor to the mass loss on the Patagonian ice fields ($-2.68 \pm 0.40 \text{ Gt a}^{-1}$) and the glacier with the second highest loss per unit area. Jorge Montt (tidewater), whose specific mass balance is up to $\sim$3 times more negative than other glaciers on the ice fields, is the fastest changing glacier. Jorge Montt additionally retreated $\sim$2.5 km between 2011 and 2017, likely
driven by enhanced calving in deep water. In the same geographical area, Pio XI is the only glacier in the Patagonian ice fields exhibiting positive mass balance (0.67 ± 0.29 Gt a\(^{-1}\)) and its lacustrine and tidewater termini advanced by ∼500 and 800 m between 2011 and 2017. The glacier is currently at its Neoglacial maximum. Given the overall thinning and retreat of neighbouring glaciers, as well as the increase in air temperatures over the last 50 years (Rasmussen et al., 2007), its localized mass gain is likely the result of complex terminus dynamics combined with surge mechanisms.

The Patagonian ice fields lost mass at rates 20% and 37% higher than between 2000-2012/14 and 1975-2000 respectively. The increase in mass loss is particularly pronounced on the NPI, whose mass loss rate is 70% higher compared to the first decade of the 21\(^{st}\) century.

### 6.4 Limitations and future directions

The CS-2 radar signal penetrates through the glacier surface, potentially up to several metres for cold dry snow and firn conditions with little or no liquid water content at the surface. A change in surface conditions, and therefore in the penetration depth of the signal, may generate artifacts in elevation trends. This effect was shown in Greenland, where the exceptional melt in summer 2012 shifted the radar horizon from within the snow pack to the ice-sheet surface (Nilsson et al., 2015b). Within this thesis, it has been assumed that the radar penetration in the ice does not change in time, so that the penetration bias cancels out when calculating rates of surface elevation change. This assumption is justified by the fact that Iceland and southern Patagonia receive abundant precipitation and experience a relatively moist climate. Therefore, surface conditions in both regions are typically relatively wet, which should limit the variability in radar wave penetration. Furthermore, time series of elevation change in Iceland showed a clear seasonal pattern with no indication of artifacts (Chapter 4). However,
by analysing CS-2 based time series of elevation change, Gray et al. (2015) found a bias between the mean CS-2 elevation and the glacier surface. This pattern, at a minimum in summer and increasing with winter accumulation, was consistently observed over four ice caps in the Canadian Arctic (Penny, 67° N; Barnes, 70° N; Devon, 75° N; Agassiz, 80° N), and the Austfonna ice cap (Svalbard, 79° N) (Gray et al., 2015). Therefore, further work on CS-2 waveforms, possibly identifying geographical areas or time periods where volume scattering prevails on surface scattering or the balance between the two has changed, may help refine the estimates of volume and mass change.

The estimated rate of elevation change may be additionally affected by non-uniform temporal coverage within a cell. As mentioned in Chapter 5, cells on the Patagonian ice fields span a median time period of 5.6 years within the six glaciological years considered. The time span is long enough to generate an average rate of surface elevation change in the cell which is representative of the total period. However, a small bias may be introduced if only part of a glaciological year is included at the beginning or end of the period considered. Future work may ensure that rates of change are normalized to exactly the same time span in all individual cells. Additionally, the weights applied to the observations also influence the outcome of the inversion used to calculate rates of elevation change (section 3.2.4). Weights based on the power measured by the satellite do improve considerably the smoothness of the resulting surface elevation change map compared to, for example, those based on the signal coherence (section 3.2.4) or to the solution with no weighting. However, further work in this direction may help determine quantitatively which method, or combination of methods, provides the most precise results.

The findings in this thesis pave the way for a wider application of swath radar altimetry based on CryoSat-2 SARIn data (section 2.2). Amongst all land ice regions covered by CS-2 interferometric data, ice caps and ice fields in the Arctic are particularly interesting targets because of their pronounced rates of mass loss (Gardner et al.,
and because of the recent publication of the Arctic DEM (pgc.umn.edu/data/arcticdem). The method discussed in this work benefits from the use of a up-to-date DEM when inferring glacier height (section 3.1.5). The Arctic DEM, spanning all land ice areas north of 60° N at 5 m spatial resolution, is beneficial since it covers regions where previous DEMs were outdated or not publicly available. An example is the Russian Arctic, which is comparatively understudied respect to other ice caps, e.g. in Canada and Svalbard (Moholdt et al., 2012). Repeat CS-2 swath altimetry may help quantifying the most recent mass budget of the Russian ice caps, which are spread over a large and remote region where only limited observations are currently available. In general, the technique may be employed over all Arctic ice caps to provide an estimate of the most recent (2010 - onwards) mass budget in the entire region, possibly leaving Alaskan glaciers as last due to their complex topography which may result in data gaps induced by loss-of-lock (section 2.1).

6.5 Concluding remarks

CryoSat-2 was launched in 2010 with the aim of accurately determining trends in land and marine ice fields on Earth (Wingham et al., 2006a). Amongst many improvements, its novel design includes a second antenna in the receiving channel (section 2.2). This configuration enables the use of interferometry to measure the across-track angle of arrival of the surface reflection, a key information which was missing with previous radar altimeters. This technical advancement opened the way to further exploitation of the radar echoes beyond the first return from the surface. Early work from Hawley et al. (2009) and Gray et al. (2013) demonstrated the potential of generating a swath of heights, rather than a single elevation, from an individual radar waveform, delivering up to two orders of magnitude more observations of the glacier surface compared to conventional radar altimetry. This technique, labelled swath radar altimetry, was further developed and validated by the ESA funded STSE CryoTop Consortium over
a number of test sites at the periphery of the Greenland and Antarctic ice sheets (Gourmelen et al., 2017a).

The work undertaken in this thesis has contributed to this emerging monitoring technique by providing technical support in the development, validation and large scale deployment of the algorithm (Chapter 3). This thesis then focused on the application of swath altimetry for monitoring surface elevation change of ice caps (Chapter 4) and ice fields (Chapter 5) and in quantifying their mass balance and contribution to sea level rise. Beyond providing knowledge on their overall mass budget, it demonstrated that the dense elevation field generated by the technique allows for the mapping of changes at the surface at sub-kilometer spatial resolution. In Iceland, this high resolution allowed for complex surface elevation changes to be linked to climate, ice dynamics and subglacial, geothermal and magmatic processes (Chapter 4). Furthermore, this thesis successfully tested the potential of using satellite swath altimetry data to quantifying mass changes at the catchment scale (Chapter 4 and 5), validated by comparison with estimates based on in situ data (Chapter 4).

The ability to monitor land ice at high spatial and temporal resolution is key to improving our understanding of glacial processes and to understand how the earth’s ice masses are responding to our changing climate. CryoSat-2 and swath radar altimetry are an important step forward in this direction, providing considerable potential for continuous monitoring of ice mass change at high temporal and spatial resolution.
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Appendix A

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Surface elevation change and mass balance of Icelandic ice caps derived from swath mode CryoSat-2 altimetry

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Abstract

We apply swath processing to CryoSat-2 interferometric mode data acquired over the Icelandic ice caps to generate maps of rates of surface elevation change at 0.5 km postings. This high-resolution mapping reveals complex surface elevation changes in the region, related to climate, ice dynamics, and subglacial geothermal and magmatic processes. We estimate rates of volume and mass change independently for the six major Icelandic ice caps, 90% of Iceland’s permanent ice cover, for five glaciological years between October 2010 and September 2015. Annual mass balance is highly variable; during the 2014/2015 glaciological year, the Vatnajökull ice cap (~70% of the glaciated area) experienced positive mass balance for the first time since 1992/1993. Our results indicate that between glaciological years 2010/2011 and 2014/2015 Icelandic ice caps have lost 5.8 ± 0.7 Gt a\(^{-1}\) on average, ~40% less than the preceding 15 years, contributing 0.016 ± 0.002 mm a\(^{-1}\) to sea level rise.

1. Introduction

It is estimated that glaciers and ice caps worldwide, including the periphery of the Greenland and Antarctic ice sheets, contribute about 47% of all land ice mass loss and 30% of current sea level rise [Intergovernmental Panel on Climate Change, 2013; Gardner et al., 2013]. Although satellite laser and radar altimetry observations have been crucial in estimating ice cap contributions to sea level change [Bolch et al., 2013; Moholdt et al., 2010a, 2010b; Nuth et al., 2010; Rinne et al., 2011a, 2011b; Gardner et al., 2011; Moholdt et al., 2012; Nilsson et al., 2015a; McMillan et al., 2014a], a comprehensive assessment is still lacking because of their complex topography, high slopes, and small size with respect to satellite ground track spacing (7.5 km and 40 km at 60° N for Icesat and Envisat, respectively) and footprint (2–10 km in diameter for Envisat). The European Space Agency CryoSat-2 (CS2) satellite [Wingham et al., 2006] carries a state-of-the-art radar altimeter for land ice applications. CS2 improves upon previous missions in three ways: (1) narrow intertrack spacing (4 km at 1.65 × 1.65 km\(^2\) (pulse limited) to ~1.65 × 0.305 km\(^2\) (pulse-Doppler limited), and (3) the interferometer onboard CS2, in the so-called SARIn mode, allows the position of the surface reflection to be accurately located [Wingham et al., 2006]. Although these characteristics make standard CS2 SARIn elevations better suited to monitoring relatively small ice bodies characterized by complex and steep terrain [McMillan et al., 2014a; Gray et al., 2015], conventional point-of-closest-approach (POCA) altimetry tends to provide inhomogeneous spatial coverage due to the tendency of POCA toward sampling topographic highs (Figures 54 and 56 in the supporting information) [Gray et al., 2015].

Iceland is located at the boundary between polar and midlatitude atmospheric circulation cells and between the warm Irmingen and cold East Greenland/East Iceland oceanic currents. As a consequence, Icelandic ice caps are very sensitive to climatic shifts [e.g., Björnsson et al., 1998, 2013; Aðalgeirsdóttir et al., 2005; Flowers et al., 2005] and are estimated to have the highest static mass balance sensitivities among glaciers and ice caps north of 60° [de Woul and Hock, 2005]. They also display highly complex and dynamic behavior unique to Iceland; about 60% of the current glaciated area lies over active volcanoes [Björnsson and Pálsson, 2008] and subglacial eruptions episodically trigger rapid ice loss albeit on short time scales (<1 year [Björnsson et al., 2013]). Furthermore, surge-type outlet glaciers are present in all Icelandic ice caps and cover 75% of Vatnajökull’s surface [Björnsson et al., 2003]; surges in Iceland can cause significant mass transport to the ablation area and advance the terminus by up to 10 km during surge, with an opposite effect during multidecadal postsurge periods [Björnsson et al., 2003; Björnsson and Pálsson, 2008; Gourmelen et al., 2011]. Icelandic ice caps have been losing mass since the mid-1990s, in response to rising air temperatures caused by changes...
in atmospheric and oceanic circulation around Iceland, possibly induced by a weakening of the North Atlantic subpolar gyre [Björnsson et al., 2013 and references therein]. Vatnajökull, with a loss of 6.58 Gt a\(^{-1}\) between 1995 and 2010, is the main contributor to the overall regional mass loss, followed by Langjökull (1.31 Gt a\(^{-1}\) between 1997 and 2010) and Hofsjökull (1.24 Gt a\(^{-1}\) between 1995 and 2010) in the central highlands (Table 1) [Björnsson et al., 2013]. Iceland as a whole has lost mass at a rate of ~11.0 \pm 1.5 Gt a\(^{-1}\) in the period of 2003–2010 and contributed 0.03 \pm 0.004 mm a\(^{-1}\) to sea level rise [e.g., Björnsson et al., 1998, 2002, 2013; Guldmundsson et al., 2011; Jacob et al., 2012; Gardner et al., 2013; Pålsson et al., 2012; Jóhannesson et al., 2013; Hannesdóttir et al., 2015; Magnússon et al., 2016; Pope et al., 2016]. However, interannual variability is high, with rates of mass loss varying from 2 to 25 Gt a\(^{-1}\) between 1995 and 2009 [Björnsson et al., 2013]. This reflects both variability in tephra deposition on the ice caps [e.g., Möller et al., 2014] as well as their high sensitivity to temperature and precipitation [Björnsson et al., 2013; Aðalgeirsdóttir et al., 2006; de Woul and Hock, 2005].

Here we extend mass balance estimates of the Icelandic ice caps from 2010 to 2015, by exploiting CS2 as a swath altimeter. We estimate the annual rate of mass change of Iceland’s six largest ice caps, Vatnajökull, Langjökull, Hofsjökull, Mýrdalsjökull, Drangajökull, and Eyjafjallajökull, corresponding to 90% of the island’s permanent ice cover, and over 99% of its volume [Björnsson and Pálsson, 2008].

2. Methods

We measure time-dependent elevation over the ice caps by using swath processing of CS2 level 1b SARIn data (SwSARln). In contrast to the conventional POCA method, SwSARln exploits the full radar waveform to provide a dense swath of elevation measurements across the satellite ground track (beyond POCA) when signal and surface conditions are favorable (see the supporting information) [Hawley et al., 2009; Gray et al., 2013; Christie et al., 2016; Ignéczi et al., 2016]. As a reference, we also use elevations derived from the operational CS2 level 2 POCA product to assess ice cap elevation changes (see the supporting information), where POCA refers to the CS2 heights obtained via conventional retracking [Wingham et al., 2006]. For both data sets, we use CS2 baseline C data which are available from July 2010 to present.

We compute rates of surface elevation change \( \dot{h} \) from SwSARIn data by using a plane-fit algorithm [McMillan et al., 2014b] over five glaciological years: 2010/2011 to 2014/2015 (Figure 1). We define one glaciological year as the period between 1 October in year \( n \) and 30 September in year \( n + 1 \). The dense elevation field provided by SwSARln processing allows gridding at 0.5 km posting. In each pixel, the time-dependent elevation is obtained by

\[
z(x, y, t) = c_0x + c_1y + \dot{h}t + c_2
\]

(1)

where \( x, y, t \) are easting, northing, and time, respectively. The time-dependent coefficient retrieved from the model fit is the linear rate of surface elevation change, \( \dot{h} \). The model is iteratively fitted to the data, excluding elevation differing from the model by more than 3 standard deviations, until no more outliers are detected. The pixel rate uncertainty \( \sigma_i \) is extracted from the covariance matrix of the model parameters (see Text S2 in the supporting information). Pixels are discarded whenever a set of quality thresholds are exceeded (see Text S4), and final coverages of the rates of surface elevation change maps are 80% (Vatnajökull), 75% (Langjökull), 87% (Hofsjökull), 69% (Mýrdalsjökull), 65% (Drangajökull), and 27% (Eyjafjallajökull), respectively. No smoothing is applied, in order to minimize the correlation between adjacent measurements that would otherwise impact on the analysis of spatial variability in \( \dot{h} \), and is permitted by the high observation density provided by SwSARln.

We interpolate gaps in the maps of surface elevation change rates (Figure 1) by using hypsometric averaging [e.g., Moholdt et al., 2010a; Nilsson et al., 2015a] as a form of regionalization method and calculate ice cap volume changes from the gap filled maps (we do not use the method to extrapolate beyond the locus of the SWSARln measurements). We apply the regionalization independently for all of the ice caps except for Eyjafjallajökull which has relatively few measurements and is therefore processed together with the neighboring Mýrdalsjökull. The resulting \( \dot{h} \) map is divided into 50 m elevation bands by using an external digital elevation model (DEM) from the National Land Survey of Iceland (Landmælingar Íslands, www.lmi.is), and the volume change \( V_k \) of each band \( k \) is calculated as the product of the mean \( \bar{h}_k \) and the surface area \( A_k \).
The DEM spatial resolution is downscaled to the grid resolution so that pixel elevations and elevation bands areas are representative of the pixel size. Volume change estimates for all bands are added together and then converted to a mass balance rate $M$ by using the density of glacial ice. Although this simplification ignores potential variations in snow/ firn density (e.g., with elevation and thus melt), it is commonly used when deriving mass change and sea level contribution from ice caps [e.g., Magnússon et al., 2016; Nilsson et al., 2015a; Nuth et al., 2010; Moholdt et al., 2010b; Björnsson and Pálsson, 2011]. For comparison, we also provide a mass balance estimate assuming a dual density scenario [e.g., Gardner et al., 2011; Moholdt et al., 2010] to account for density differences between the ablation and accumulation area. We propagate rate errors $\sigma_M$ of the individual pixels to estimate uncertainties for $V$ and $M$ (see the supporting information).

### 3. Results

SwSARIn provides a step-change in surface coverage (Figure 1), generating ~10 million elevation measurements over Vatnajökull between October 2010 and September 2015 and allowing the retrieval of rates of surface elevation change over 80% of the ice cap area (Figure S5). In comparison, ICESat acquired 851 elevation measurements over all Icelandic ice caps between 2003 and 2007 [Nilsson et al., 2015a]. With the conventional POCA approach, CS2 delivers ~60,000 observations over Vatnajökull (October 2010 to September 2015) and provides rates of surface elevation change over 40% of the ice cap area, preferentially along topographic highs (see Text S3 and Figure S4). Over the Langjökull ice cap, the particular hypsometry accentuates the concentration of elevations over the ice divide (inset in Figures 1; Figure S6). There is almost no POCA observation close to the marginal areas of the northern dome (Figure S8, middle) and only ~10 observation per km$^2$ over the southern dome (Figure S8, right), which is insufficient to estimate robust rates of surface elevation change. In turn, limited sampling at the margins where most of the thinning is occurring impacts on the representativeness of the POCA rates of volume and mass change (see Text S3).

The time series of surface elevation change over the Vatnajökull ice cap (Figure 2) shows a clear seasonal pattern with an increase in surface elevation during the accumulation period followed by a rapid decrease during the melt season, with amplitudes of about 3 m similar to observations over other Arctic ice caps [Gray et al., 2015]. Additionally, the elevation time series show an absence of sharp jumps in elevation that would otherwise be indicative of a sudden and unusual change in scattering horizon and would introduce a bias in the estimated rates of surface elevation change [Nilsson et al., 2015b; McMillan et al., 2016].

The data reveal a clear pattern of thinning, with rates of up to 10 m a$^{-1}$ over most of the marginal areas of the ice caps, while change in the ice cap interior is more heterogeneous with both thinning and thickening.

---

**Table 1.** Mass Balance of Icelandic Ice Caps

<table>
<thead>
<tr>
<th>Ice Cap</th>
<th>$A$ (km$^2$)</th>
<th>$V$ (km$^3$)</th>
<th>$M$ (Gt a$^{-1}$) (period)</th>
<th>$M$ (Gt a$^{-1}$)</th>
<th>$M$ (m$_{wae}$ a$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vatnajökull</td>
<td>8,100</td>
<td>3,100</td>
<td>$-6.58^a$ (1995–2010)</td>
<td>$-3.68^a \pm 0.61$</td>
<td>$-0.52^a \pm 0.09$</td>
</tr>
<tr>
<td></td>
<td>900</td>
<td>190</td>
<td>$-1.31^a$ (1997–2010)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Langjökull</td>
<td>890</td>
<td>200</td>
<td>$-1.20^a$ (1999–2007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>590 + 80</td>
<td>140</td>
<td>$-0.92^b$ (2004–2008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hofsjökull</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>160</td>
<td>24</td>
<td>$-0.07^c$ (2005–2011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$-0.05^d$ (1990–2011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mýrdalsjökull + Eyjafjallajökull</td>
<td>900</td>
<td>190</td>
<td>$-0.21 \pm 0.16$</td>
<td>$-0.39 \pm 0.29$</td>
<td></td>
</tr>
<tr>
<td>Drangajökull</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>~11,000</td>
<td>~3,600</td>
<td>$-9.11 \pm 1.31^{a,b,d,g}$</td>
<td></td>
<td>$-0.59 \pm 0.07$</td>
</tr>
</tbody>
</table>

Estimates from SwSARIn data for five glaciological years between October 2010 and September 2015, as well as from the current literature (with respect to the specified time period). Mass change $M$ is given in Gt a$^{-1}$ as well as m$_{wae}$ a$^{-1}$ (specific mass balance). Ice cap areas and volumes after Björnsson and Pálsson (2008). *Björnsson et al. (2013).*

$^a$Johannesson et al. (2013).

$^b$Magnússon et al. (2016).

$^c$Pálsson et al. (2012).

$^d$Gardner et al. (2013).

$^e$Jacob et al. (2012).

$^f$Nilsson et al. (2015a).

$^g$Mass balance of Vatnajökull between October 2010 and September 2014 is $-4.93 \pm 0.80$ Gt a$^{-1}$ ($-0.69 \pm 0.11$ m$_{wae}$ a$^{-1}$).
observed (Figure 1). This variability in the interior is particularly apparent over Vatnajökull, where several basins—e.g., Brúarjökull (Br), Síðujökull (Si), and Dyngjujökull (Dy)—are thickening at high elevation, while Skeiðarárjökull (east of Si) is thinning over almost its entire area. Thinning of Langjökull in the central highlands is widespread on the ice cap’s surface up to, and including, the ice divide, while neighboring Hofsjökull shows thickening over the center and thinning over the margins. In the south of Iceland, relatively high rates of thickening (up to 3 m a⁻¹) are widespread over Mýrdalsjökull’s central plateau. Thinning is visible particularly on its northern slopes which lie at low elevations as well as on the steeper southern margins.
In the same region and despite being exposed to a similar climate, Eyjafjallajökull shows signs of thinning at its summit; however, coverage here is limited due to the small area (~80 km²) and steep hypsometry (~700–1560 m). Drangajökull (northwest) mostly displays a thickening pattern in the comparatively large accumulation area.

We use the CS2-derived rates of surface elevation change to compute mean annual rates of ice cap volume and mass change over five glaciological years from October 2010 to September 2015 (Table 1). During this time, we estimate that the Vatnajökull ice cap (~70% of Iceland’s glaciated area) is losing mass at a rate of 3.68 ± 0.61 Gt a⁻¹ (−0.52 ± 0.09 mwe a⁻¹) and is the main contributor (63%) to mass loss in Iceland, followed by Langjökull (12%) and Hofsjökull (8%) in central Iceland (Table 1). Langjökull is the fastest changing ice cap with −0.81 ± 0.23 mwe a⁻¹ specific mass balance, followed by Hofsjökull and Vatnajökull with −0.66 ± 0.15 mwe a⁻¹ and −0.52 ± 0.09 mwe a⁻¹, respectively (Table 1). A combined estimate is generated for Myrdalsjökull and Eyjafjallajökull (3.6% of loss) since data coverage over the latter is limited and the two ice caps are exposed to similar climatic conditions. To the northwest, Drangajökull appears to be close to balance (−0.05 ± 0.07 Gt a⁻¹; −0.28 ± 0.40 mwe a⁻¹); the uncertainty is comparatively large due to the small aerial extent and steep hypsometry of the ice cap (Table 1). Summing contributions from the six ice caps analyzed in this study, and rescaling for the remaining 10% glacierized area not included in our survey, we estimate Iceland lost ice at a rate of 5.83 ± 0.74 Gt a⁻¹ (−0.59 ± 0.07 mwe a⁻¹) between October 2010 and September 2015, corresponding to 0.016 ± 0.002 mm a⁻¹ eustatic sea level change.

Assuming a dual-density scenario in the ablation and accumulation areas with ρ = 900 kg m⁻³ and ρ = 650 kg m⁻³, the mass loss and contribution to sea level change estimates are higher by just 4%, within the uncertainty of the single-density case. During the glaciological year 2014/2015, the Vatnajökull ice cap had positive mass balance (Figure 2), an unprecedented observation in the last two decades [Björnsson et al., 2013] and due to anomalously high winter precipitation. This anomaly is reflected in the time series of surface elevation change where the trends in both the ablation and accumulation areas change after October 2014 (Figure 2). In the four glaciological years before 2014/2015, we find that Vatnajökull’s rate of mass loss was 4.93 ± 0.80 Gt a⁻¹ (−0.69 ± 0.11 mwe a⁻¹) or ~34% larger than the period of 2010/2011 to 2014/2015.

We compared our geodetic estimates for the Langjökull ice cap and the Brúarjökull basin of the Vatnajökull ice cap against in situ field-derived mass balance observations from ongoing surveys [e.g., Björnsson et al., 1998, 2002, 2013; Pálsson et al., 2012; Jóhannesson et al., 2013]. We restricted the data sets to the same time period, four glaciological years from October 2010 to September 2014. The geodetic estimate for Langjökull, −0.76 ± 0.25 Gt a⁻¹ (−0.92 ± 0.30 mwe a⁻¹), is 38% less negative than that from the in situ data, −1.05 ± 0.36 Gt a⁻¹ (−1.28 ± 0.30 mwe a⁻¹), but the two values agree within uncertainties. Over the Brúarjökull basin the agreement is good, −0.51 ± 0.09 Gt a⁻¹ (−0.37 ± 0.07 mwe a⁻¹) compared to −0.49 ± 0.22 Gt a⁻¹ (−0.35 ± 0.30 mwe a⁻¹) for the geodetic and in situ values, respectively. Using a dual-density scenario, Langjökull’s and Brúarjökull’s geodetic mass balance estimates change by +17% and −18%, respectively.

4. Discussion

The heterogeneity of the rates of surface elevation change can be linked to the heterogeneity of ice cap hypsometry as well as their exposure to local climatic conditions, active volcanoes, and glacier surge events.
Individual basins of the Vatnajökull ice cap display distinct behaviors, either thinning across their entire length or experiencing thickening at high elevation. Three basins, namely, Brúarjökull, Síðujökull, and Dynjújökull (Figure 1), show large areas of thickening at higher elevation, as they are currently in a post-surge stage, responding to surges that occurred in 1963, 1995, and 1999, respectively (Björnsson et al., 2003; Fischer et al., 2003). Thickening in the Gjálp area (Figure 1), by an average of 0.7 m a⁻¹, is related to a combination of snow drift and ice inflow into the depression created by the 1996 subglacial volcanic eruption; these uplift rates are down from 40 m a⁻¹ as measured in the year following the eruption (Guðmundsson et al., 2002). North of Gjálp, over the Bárðarbunga central volcano caldera ice surface, the strong subsidence pattern is the surface response to the Bárðarbunga eruption that occurred between August 2014 and March 2015 (Sigurðsson et al., 2014; Guðmundsson et al., 2016). This event deflated a magma chamber below the ~700 m thick ice; little or no ice was melted, but the caldera bedrock floor lowered by tens of meters and the ice above lowered similarly forming a caldron like surface subsidence with a volume of ~1.9 km³ (Sigurðsson et al., 2014; Guðmundsson et al., 2016). The impact of this area on the ice cap wide rate of volume change is 0.05 km³ a⁻¹ (~1% of Vatnajökull’s total volume change). In the central highlands, and despite their close proximity and similar climatic conditions, the pattern of rates of surface elevation change of the Langjökull and Hofsjökull ice caps differs considerably, most likely due to their differing hypsometry. Having similar area and volume (~900 km² and ~200 km³), Langjökull has a lower elevation range (430–1440 m above sea level (asl)) than Hofsjökull (620–1790 m asl) (Björnsson and Pálsson, 2008; Guðmundsson et al., 2009), and a large portion of the surface of Langjökull therefore lies close to the current equilibrium line altitude (ELA) (Pálsson et al., 2012). Thickening is visible in the accumulation area of the West and East Hagafellsjökull basins of the Langjökull ice cap (Figure 1) and is a dynamic response to the 1980 and 1999 surge events, respectively (Björnsson et al., 2003). The central part of the Mýrdalsjökull ice cap is thickening at rates of about 1–3 m a⁻¹, although the surface elevation of the plateau has not changed compared to 1999. The thickening is most likely induced by the extreme precipitation in winter 2015, which deposited 10-15 m of snow on the ice cap. Over Eyjafjallajökull’s summit, the surface is thinning as ice flows into the crater created by the Eyjafjallajökull eruption in 2010 (Oddsson et al., 2016). Over Drangajökull (northwest), despite the relatively small size of the ice cap as well as the steep elevation range, SwSARIn data capture the thinning pattern across the ablation area. This allows us to generate a robust estimate of mass balance, a result that cannot be achieved with conventional POCA processing (see Text S3 and Tables S1 and S2).

Geodetic mass balance derived from repeat altimetry is dependent on the regionalization method chosen to derive volume change from the rates of surface elevation change (e.g., Nilsson et al., 2015a). The high density of measurements provided by SwSARIn allows us to regionalize at the ice cap scale and in some cases at the basin scale (e.g., Brúarjökull), better accounting for local differences, in contrast to data sets with a lower density of observations which require mean hypsometric related rates of surface elevation change to be averaged at the scale of Iceland as a whole (Nilsson et al., 2015a). Thus, the hypsometric averaging method applied at the basin scale shows good agreement with the in situ estimate for one of Vatnajökull’s largest basins: Brúarjökull. Comparing the SWSARIn and in situ mass balance estimates over the Langjökull ice cap instead shows a difference between the two approaches. Current interdrainage basin variability in rates of surface elevation change is relatively large in Iceland and is related to dynamic adjustment after glacier surges and subglacial eruptions as well as contrasting climatic conditions, e.g., due to inland precipitation shadow, hypsometry, or distance from the south coast (the North-Atlantic low path). For example, the southeastern basins of Vatnajökull (e.g., as in Aðalgeirsdóttir et al. [2006]) reach low elevations at their termini, are exposed to high precipitation, and have infrequent surges (Björnsson et al., 2003). In contrast, basins in the northwest are more affected by surges and their termini are above 700 m elevation. Applying a hypsometric model at the ice cap scale would clearly not capture this complexity. SwSARIn provides a step change from previous altimetry-based techniques in mapping the complexity of ice caps’ response to internal and external forcing as it enables the independent monitoring of individual ice caps. Additionally, the method can be used to derive mass balance estimates at the individual basin scale (e.g Brúarjökull).

5. Conclusions

CryoSat-2 swath radar interferometric altimetry (SwSARIn) increases the density of surface elevation measurements over Icelandic ice caps by 2 and 5 orders of magnitude with respect to the conventional
point-of-closest-approach (POCA) method applied to the CryoSat-2 and ICESat missions, respectively. Compared to POCA measurements, which tend to concentrate on topographic highs, SwSARIn samples a wider range of elevations which helps generate more reliable estimates of mass balance, particularly for Icelandic ice caps with complex hypsometry. Swath altimetry allows high-resolution mapping of surface elevation and its temporal change revealing complex spatiotemporal patterns of surface elevation change related to climatic, dynamic, and subglacial processes in Iceland. We estimate that Icelandic ice caps have lost a total of 5.8 ± 0.7 Gt a⁻¹ (−0.6 ± 0.1 mm we a⁻¹) between October 2010 and September 2015, equivalent to 0.016 ± 0.002 mm a⁻¹ eustatic sea level change. This estimate suggests that over this 5 year period, the mass balance was 40% less negative than the preceding 15 years, a fact which partly reflects the anomalous positive balance year across Vatnajökull in 2014/2015. Our observations also demonstrate the capability of SwSARIn elevations to image glaciological processes occurring at the subcatchment scale, and to infer global, time-dependent, mass balance over region of complex hypsometry such as ice caps and ice sheet margins.

References


Geophysical Research Letters

Supporting Information for

Surface Elevation Change And Mass Balance Of Icelandic Ice Caps

Derived From Swath Mode Cryosat-2 Altimetry

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Introduction

This document includes information on SwSARIn and POCA data processing (Text S1 and Fig. S1-S2), how surface elevation, volume and mass change uncertainties are calculated (Text S2 and Fig. S3), a comparison between the SwSARIn and POCA datasets (Text S3) in terms of their spatial coverage (Fig. S4 to S9), rates of surface elevation change at different spatial resolution (Fig.1 and Fig S10 toS12) and mass balance estimates (Tables S1-S2) as well as details on filters used to remove noise from the surface elevation change rates (Text S4).
CryoSat-2 (CS2) uses Ku-band radar frequency to image a region of about 15 km in width and record the returned echoes within that footprint. Commonly, the echo corresponding to the surface location closest to the satellite (i.e. the Point-Of-Closest-Approach, POCA) is identified via a ‘retracking’ procedure, while all others are discarded. Swath processing exploits high coherence (>0.8) returns to produce a ~5km wide swath of between 10-100 geocoded elevation measurements every ~400 m in the direction of the satellite flight, rather than a single elevation as with the standard POCA approach. [Hawley et al., 2009; Gray et al., 2013; Christie et al., 2016; Ignéczi et al., 2016]. Hawley et al. [2009] first tested the technique using airborne radar interferometry data, and achieved a 75 fold increase in observation density without significant quality deterioration compared to conventional POCA processing (1.67 m RMS difference w.r.t reference laser data as opposed to 1.33 m for conventional POCA). Similarly, Gray et al. [2013] demonstrated the method directly on CS2 SARIn L1b data by generating a Digital Elevation Model (DEM) of the Devon Ice Cap (Nanavut, Canada) where previous radar altimeters had provided only sparsely sampled data. The swath derived DEM had a mean elevation difference of 0.49±0.75 m compared to reference airborne laser data. In application of the technique, Christie et al. [2015] used rates of surface elevation change from SwSARIn in order to derive thickness at grounding line along the Bellinghausen coastline in West Antarctica and Ignéczi et al. [2015] used a DEM derived from SwSARIn to map the location of supra-glacial lakes at the surface of the Greenland Ice Sheet. To generate swath processed (SwSARIn) elevations, we download CryoSat-2 (CS2) L1b baseline C SARIn data from the European Space Agency (ESA) database and generate elevation measurements similarly to Hawley et al. [2009], Gray et al. [2013], Christie et al. [2016] and Ignéczi et al. [2016]. After filtering the waveform to reject samples with low
coherence (<0.8) and unwrapping on a per-waveform basis [Gray et al., 2013], we convert the range, across-track look angle, platform attitude and orbit parameters of all echoes into a swath of elevations relative to a reference ellipsoid. The resulting elevation dataset can be affected by phase ambiguity errors in regions of high terrain slope [Gray et al., 2015]; we solve for these by applying to each waveform the $2\pi$ multiple that minimizes elevation differences with respect to a reference Digital Elevation Model (DEM) from the National Land Survey of Iceland (Landmælingar Íslands, www.lmi.is). Over the Vatnajökull ice cap, about 40% of SwSARIn elevations are corrected for this ambiguity and their location is shown in Fig S1 and S2. Areas with across track slope lower than 0.54 degrees, where phase ambiguity should not occur, are highlighted in cyan; the number of SwSARIn elevations corrected for phase ambiguity is shown as a density scatterplot at the same spatial resolution as the slope maps. The spatial resolution is representative of the CS2 SARIn footprint size, i.e. 400 m along track (Fig. S1) and 1600 m across track (Fig. S2). We also discard elevations that differ more than 100 m w.r.t. the DEM. Such high discrepancies may not be attributed to real surface elevation change. Over Vatnajökull, they represent less than 1% of the total amount of observations between October 2010 and September 2015.

Point-Of-Closest-Approach (POCA) CS2 data are as downloaded from the ESA archive (L2 baseline C product).

**Text S2. Error budget**

We assign an uncertainty to the rate of surface elevation change of each individual pixel. Consider the equation:

$$z(x, y, t) = c_0 x + c_1 y + \dot{h} t + c_2$$

where $x$, $y$, $t$ are easting, northing and time respectively. The error $\varepsilon_{\dot{h}}$ on the rate of surface elevation change $\dot{h}$ is taken from the unit model covariance matrix $\text{cov}_u \mathbf{m}$, calculated as:
where the vector \( \mathbf{m} = [c_0 \ c_1 \ \dot{h} \ c_2] \) represents the model parameters and \( \mathbf{G} = [x \ y \ t \ 1] \) is the model matrix, \( \mathbf{G}^{-1} \) is its inverse and \( \mathbf{G}^{-1}\mathbf{T} \) is the transpose of the inverse. The diagonal of \( \text{cov}_{u\mathbf{m}} \) are the variances of the model parameters, therefore \( \varepsilon_{\dot{h}} \) can be extracted as follows:

\[
\varepsilon_{\dot{h}} = \sqrt{\text{diag}(\text{cov}_{u\mathbf{m}})_{3}}
\]

where \( \text{diag}(\cdot) \) is the third element on the diagonal.

Fig. S3 shows Vatnajökull’s error map for SwSARIn data posted at 0.5 km resolution. We then propagate rate uncertainties when applying the hypsometric averaging method and calculating the mean elevation change rate in each 50 m elevation bin (hereafter bin):

\[
E_{\dot{h}}(k) = \sqrt{\frac{\sum_{m=1}^{N(k)} \varepsilon_{\dot{h}}(m)^2}{N(k)}},
\]

where \( \varepsilon_{\dot{h}} \) is the error on the rates of elevation change for the individual pixels, \( E_{\dot{h}}(k) \) is the mean elevation change error in each bin \( k \) and \( N(k) \) is the number of valid observations in that bin. If a bin has no valid data (e.g. at low elevation for bins with small spatial extent), we use a two-term decreasing exponential fit to generate an interpolated value. The choice of fit reflects the general \( E_{\dot{h}} \) decreasing trend with increasing elevation.

We multiply the bin area extent \( A(k) \) to the related \( E_{\dot{h}}(k) \) and sum all contributions to estimate the total uncertainty on the rate of volume change:

\[
E_{\dot{V}} = \sum_k E_{\dot{h}}(k) \ast A(k)
\]

With this method, the volume change uncertainty is only related to that area of the ice cap where there are valid rates of surface elevation change, but does not account for incomplete
data coverage. For this reason, $E_\psi$ is rescaled by the average data coverage in the ablation and accumulation areas. This procedure generates a rather conservative error estimate since it assumes that the lack in data coverage has a direct impact on the total error estimate, which does not hold if the sampling is sufficiently uniform.

Finally, when converting volume to mass change, we include an error on the density as in Nilsson et al. [2015] and Moholdt et al. [2010]:

$$E_\rho = \frac{1}{2} (\rho_{ice} - \rho_{furn}) .$$

The final mass balance error is then calculated as follows:

$$E_M = |\dot{M}| \sqrt{\left(\frac{E_\psi}{V}\right)^2 + \left(\frac{E_\rho}{\rho_{ice}}\right)^2} .$$

Text S3. SwSARIn - POCA comparison

The conventional POCA processing of CS2 SARIn data provides more than 60,000 observations over Vatnajökull between October 2010 and September 2015, a 70 fold increase w.r.t. the number of measurements ICESat acquired over all Icelandic ice caps in a similar time span [Nilsson et al., 2015]. In spite of the large number of observations, the spatial distribution of POCA is controlled by surface topography and tends to be preferentially clustered along topographic highs such as ice divides, while at lower elevations the density of measurements is limited, particularly over smaller ice caps (Fig. S4 and S6). Swath processing provides 160 times more elevation measurements w.r.t. POCA over Vatnajökull.
(October 2010 to September 2015) and, importantly, delivers almost uniform spatial coverage
(Fig. S5 and S7). Over the Langjökull ice cap (Fig. S6 and S7 for SwSARIn and POCA
respectively), where the particular hypsometry accentuates the concentration of POCA
elevations over the ice divide, we observe over one order of magnitude more measurements
per km² from SwSARIn than POCA (Fig. S8).
The increase in spatial density of observations provided by SwSARIn is not at the expense of
precision; a direct comparison between co-located SwSARIn and POCA derived rates of
surface elevation change (2 km posting) gives a mean difference of -0.05±0.64 m a⁻¹ (Fig.
S9c) and no dependency on surface slopes (Fig. S9a-b) [Gray et al. 2013]. The density of
SwSARIn observations allows to gridding data at sub-kilometer spatial resolution revealing a
detailed pattern of surface elevation change (Fig. 1). For example, the thickening pattern in
the accumulation area of the East Hagafellsjökull basin (Langjökull) - gaining mass after a
surge in 1998/99 - is not as clearly visible at lower resolution (Fig. 1 versus Fig. S10). For
comparison, POCA rates of surface elevation change gridded at 0.5 and 2 km resolution are
shown in Fig. S11 and S12.
SwSARIn mass balance estimates from data posted at 0.5 and 2 km are generally comparable
(Table S1), which indicate that such high resolution is adequate when quantifying mass
change using SwSARIn elevations. POCA estimates of mass balance show higher variability
and, with the exception of Vatnajökull (roughly ten times larger than the other ice caps), rates
of mass change are less negative than SwSARIn’s. This may be due to POCA preferentially
sampling topographic highs where less or no thinning is occurring. Drangajökull mass change
is erroneously estimated as positive when gridding data at 2 km resolution (SwSARIn and
POCA) as well as 0.5 km resolution (POCA). Due to the relatively small surface area as well
as steep hypsometry of the ice cap, the lower resolution is too coarse to capture the different
signals in the accumulation and ablation areas. However, the density of POCA observations
is insufficient to resolve the thinning in the ablation area also when gridding at 0.5 km resolution.

Text S4 – Filters on surface elevation change rates

In order to remove noise from the surface elevation change rates \( \dot{h} \), we apply a set of parameter thresholds. We discard a pixel if i) the rate \( \dot{h} \) is unrealistic, i.e. less than \(-20 \text{ m a}^{-1}\) or more than \(5 \text{ m a}^{-1}\), ii) the time span is shorter than 2 years, iii) the standard error is larger than \(10 \text{ m a}^{-1}\). Additionally, we compute a median smoothed map of surface elevation change rates and discard pixels which differ from that more than three times the mean absolute deviation between the original rates and their smoothed values.
**Figure S1** - Density map of SwSARIn elevations over Vatnajökull corrected for phase ambiguity. Areas with across track slope lower than 0.54 degrees, where phase ambiguity should not occur, are shown in cyan. The slope map is produced at 400 m spatial resolution, equivalent to the CS2 SARIn along track footprint size.

**Figure S2** - As Fig. S1 but the slope map is produced at 1600 m spatial resolution, equivalent to the CS2 SARIn across track footprint size.
Figure S3 - Uncertainty map for SwSARIn rates of surface elevation change at 0.5 km posting calculated over the Vatnajökull ice cap in the period October 2010 to September 2015. Note the non-linear colormap. 94% (86%) of errors are below 1 m a\(^{-1}\) (0.5 m a\(^{-1}\)).
Figure S4 - Location of POCA heights over Vatnajökull, Iceland. The solid black lines indicate the approximate Equilibrium Line Altitude (ELA) for the south-eastern basins (1000 m) and for the north-western ones (1200-1300 m) [Björnsson and Pálsson, 2008].

Figure S5 - Location of SwSARIn heights over Vatnajökull, Iceland (See Fig. S4 caption).
Figure S6 - Location of POCA heights over Langjökull, Iceland. The solid black lines indicate the approximate ELA for the southern and northern domes (1000 m and 1200 m, respectively) [Pálsson et al., 2012].

Figure S7 - Location of SwSARIn heights over Langjökull, Iceland. (See Fig. S6 caption).
Figure S8 – Number of SwSARIn (blue) and POCA (cyan) observations per km² per elevation band (50m intervals) on a logarithmic scale for the entire Langjökull ice cap (left panel) and its northern and southern domes separately (central and right panel, respectively).

Figure S9 – Difference between SwSARIn and POCA surface elevation change rates ($h_s - h_p$) over Vatnajökull at 2 km posting with respect to (a) along-track and (b) across-track surface slope. (c) Histogram of differences between SwSARIn and POCA rates of surface elevation change.
Figure S10 - Surface elevation change maps of Icelandic ice caps based on SwSARIn heights at 2 km posting as well as location of the ice caps in Iceland (inset). V (Vatnajökull), L (Langjökull), H (Hofsjökull), M (Myrdalsjökull), D (Drangajökull), E (Eyjafjallajökull). Basin outlines are shown in thin black lines. Selected basins over Vatnajökull and Langjökull are: Brúarjökull (Br), Siðujökull (Si), Dyngjujökull (Dy), Gjálp (Gj), Hagafellsjökull West (Hw) and Hagafellsjökull East (He) (thick black outlines). Ice caps’ areas after Björnsson and Pálsson [2008]. Contour elevations (gray) are 1000 m and 1400 m (700 m and 900 m for D).
Figure S11 - Surface elevation change maps of Icelandic ice caps based on POCA heights at 0.5 km posting as well as location of the ice caps in Iceland (inset). V (Vatnajökull), L (Langjökull), H (Hofsjökull), M (Mýrdalsjökull), D (Drangajökull), E (Eyjafjallajökull). Basin outlines are shown in thin black lines. Selected basins over Vatnajökull and Langjökull are: Brúarjökull (Br), Síðujökull (Si), Dyngjujökull (Dy), Gjálp (Gj), Hagafellsjökull West (Hw) and Hagafellsjökull East (He) (thick black outlines). Ice caps’ areas after Björnsson and Pálsson [2008]. Contour elevations (gray) are 1000 m and 1400 m (700 m and 900 m for D).
Figure S12 - Surface elevation change maps of Icelandic ice caps based on POCA heights at 2 km posting as well as location of the ice caps in Iceland (inset). V (Vatnajökull), L (Langjökull), H (Hofsjökull), M (Mýrdalsjökull), D (Drangajökull), E (Eyjafjallajökull). Basin outlines are shown in thin black lines. Selected basins over Vatnajökull and Langjökull are: Brúarjökull (Br), Síðujökull (Si), Dyngjujökull (Dy), Gjálp (Gj), Hagafellsjökull West (Hw) and Hagafellsjökull East (He) (thick black outlines). Ice caps’ areas after Björnsson and Pálsson [2008]. Contour elevations (gray) are 1000 m and 1400 m (700 m and 900 m for D).
Table S1 - Mass balance of Icelandic ice caps

Estimates from SwSARIn and POCA data at 0.5 km and 2 km posting for five glaciological years between October 2010 and September 2015. Mass change $\dot{M}$ is given in Gt a$^{-1}$. *These estimates are included for completeness but are not reliable (see Text S3).

<table>
<thead>
<tr>
<th></th>
<th>POCA 0.5 km</th>
<th>POCA 2 km</th>
<th>SwSARIn 0.5 km</th>
<th>SwSARIn 2 km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vatnajökull</td>
<td>-3.26 ± 0.66</td>
<td>-2.94 ± 0.55</td>
<td>-3.68 ± 0.61</td>
<td>-3.9 ± 0.55</td>
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<tr>
<td>Langjökull</td>
<td>-0.38 ± 0.25</td>
<td>-0.38 ± 0.16</td>
<td>-0.70 ± 0.20</td>
<td>-0.59 ± 0.09</td>
</tr>
<tr>
<td>Hofsjökull</td>
<td>-0.40 ± 0.18</td>
<td>-0.21 ± 0.10</td>
<td>-0.45 ± 0.10</td>
<td>-0.16 ± 0.03</td>
</tr>
<tr>
<td>Mýrdalsjökull</td>
<td>-0.16 ± 0.18</td>
<td>-0.07 ± 0.11</td>
<td>-0.21 ± 0.16</td>
<td>-0.28 ± 0.05</td>
</tr>
<tr>
<td>+ Eyafjallajökull</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drangajökull</td>
<td>+0.12 ± 0.04*</td>
<td>+0.27 ± 0.04*</td>
<td>-0.05 ± 0.07</td>
<td>+0.13 ± 0.02*</td>
</tr>
<tr>
<td>Iceland</td>
<td>-4.49 ± 0.83</td>
<td>-3.66 ± 0.65</td>
<td>-5.83 ± 0.74</td>
<td>-5.28 ± 0.62</td>
</tr>
</tbody>
</table>

Table S2 - Specific mass balance of Icelandic ice caps

As in Table S1 with mass change $\dot{M}$ given in m$w$e a$^{-1}$.

<table>
<thead>
<tr>
<th></th>
<th>POCA 0.5 km</th>
<th>POCA 2 km</th>
<th>SwSARIn 0.5 km</th>
<th>SwSARIn 2 km</th>
</tr>
</thead>
<tbody>
<tr>
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<td>-0.41 ± 0.08</td>
<td>-0.52 ± 0.09</td>
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<td>Langjökull</td>
<td>-0.44 ± 0.29</td>
<td>-0.44 ± 0.18</td>
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<td>-0.68 ± 0.10</td>
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<tr>
<td>Hofsjökull</td>
<td>-0.58 ± 0.26</td>
<td>-0.31 ± 0.15</td>
<td>-0.66 ± 0.15</td>
<td>-0.24 ± 0.04</td>
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<tr>
<td>Mýrdalsjökull</td>
<td>-0.29 ± 0.33</td>
<td>-0.13 ± 0.20</td>
<td>-0.39 ± 0.29</td>
<td>-0.51 ± 0.09</td>
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<tr>
<td>+ Eyafjallajökull</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Drangajökull</td>
<td>+0.68 ± 0.23*</td>
<td>+1.53 ± 0.23*</td>
<td>-0.28 ± 0.40</td>
<td>+0.74 ± 0.11*</td>
</tr>
</tbody>
</table>
References

Björnsson, H., and F. Pálsson (2008), Icelandic glaciers, Jökull, 58, 365-386.


Pálsson, F., S. Guðmundsson, H. Björnsson, E. Berthier, E. Magnússon and H. H. Haraldsson (2012), Mass and volume changes of Langjökull ice cap, Iceland, similar to 1890 to 2009, deduced from old maps, satellite images and in situ mass balance measurements, Jökull, 62, 81-96.
Appendix B

Gourmelen et al., 2017, Advances in Space Research
CryoSat-2 swath interferometric altimetry for mapping ice elevation and elevation change

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Abstract

For more than 25 years, satellite radar altimetry has provided continuous information on the state of the cryosphere and on its contribution to global sea-level rise. The technique typically delivers maps of ice-sheet elevation and elevation change with 3–10 km spatial resolution and seasonal to monthly temporal resolution. Here we show how the interferometric mode of CryoSat-2 can be used to map broad (5 km-wide) swaths of surface elevation with fine (500 m) spatial resolution from each satellite pass, providing a step-change in the capability of satellite altimetry for glaciology. These swaths of elevation data contain up to two orders of magnitude more surface elevation measurements than standard altimeter products, which provide single elevation measurements based on the range to the Point-Of-Closest-Approach (POCA) in the vicinity of the sub-satellite ground track. The swath elevations allow a more dense, statistically robust time series of elevation change to be formed with temporal resolution of a factor 5 higher than for POCA. The mean differences between airborne altimeter and CryoSat-2 derived ice sheet elevations and elevation rates range from $-0.93 \pm 1.17 \text{ m and } 0.29 \pm 1.25 \text{ m a}^{-1}$, respectively, at the POCA, to $-1.30 \pm 1.73 \text{ m and } 0.04 \pm 1.04 \text{ m a}^{-1}$, respectively, across the entire swath. We demonstrate the potential of these data by creating and evaluating elevation models of: (i) the Austfonna Ice Cap (Svalbard), (ii) western Greenland, and (iii) Law Dome (East Antarctica); and maps of ice elevation change of: (iv) the Amundsen Sea sector (West Antarctica), (v) Icelandic ice caps, and (vi) above an active subglacial lake system at Thwaites Glacier (Antarctica), each at 500 m spatial posting – around 10 times finer than possible using traditional approaches based on standard altimetry products.

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Keywords: Radar altimetry; CryoSat-2; Antarctica; Greenland; Iceland; Svalbard; Sub-glacial lakes; Swath processing; Interferometry; Cryosphere; Ice sheet; Ice shelves; Ice caps; Glaciers; DEM; Surface elevation change; Climate change; Sea level change; Surface mass balance

1. Introduction

Earth’s land ice, including the Greenland and Antarctic Ice Sheets (GIS and AIS respectively), ice caps and mountain glaciers, is losing mass, and is estimated to have contributed 31 mm towards global sea-level rise since 1992 (Shepherd et al., 2012; Gardner et al., 2013; IPCC, 2013).
During this period, satellite altimetry has revolutionised our ability to continuously monitor changes affecting the cryosphere, providing novel and critical observations to detect, monitor, quantify and understand land ice mass balance, sub-glacial water routing, ice-ocean interactions, and current and potential sea-level contribution (e.g. Zwally et al., 1989; Wingham et al., 1998; Shepherd et al., 2001; Shepherd et al., 2003; Zwally et al., 2005; Wingham et al., 2006a; Fricker et al., 2007; Pritchard et al., 2009; Wilson et al., 2010; Kaab et al., 2012; Bamber et al., 2013; McMillan et al., 2014b; Gourmelen et al., 2017). Nevertheless, pulse-limited altimetry was designed for ocean applications, and the relatively coarse ground resolution that can be achieved with the technique has been a limiting factor for glaciology – in particular when assessing changes in coastal sectors of the ice sheets and in mountain glaciers and ice caps (Dehecq et al., 2013). The ground resolution of early altimeter missions was limited by several factors, including the pulse-(1.6 km) and beam-(10–20 km) limited footprint size of radar altimeters, the relatively large separation of ground tracks (e.g. 20 km across track separation for IceSat at 70° of latitude) (Gourmelen et al., 2017), and the inability to pinpoint the location of echoes on sloping terrain (see Fig. 1).

The CryoSat-2 mission, launched by ESA in 2010, achieves improved ground resolution in three ways: the satellite benefits from a tight ground track network (7.5 km at the equator, 1.6 km at 70° of latitude), the radar employs Synthetic Aperture Radar (SAR) processing in the along-track direction to achieve a much reduced pulse-Doppler-limited along-track footprint and resolution of 305 m and 400 m, respectively (over a flat surface); and a second receiver antenna allows the across-track location of the ground echo to be precisely determined via radar interferometry (Drinkwater et al., 2005; Wingham et al., 2006). The so-called SAR Interferometry (SARIn) mode is activated above all land ice with a significant surface slope (e.g. ice sheet margins, ice caps, mountain glaciers) and provides an exact solution to the echo location uncertainty over sloping terrains (Brenner et al., 1983). Together, these advances allow CryoSat-2 to survey small and rugged areas of ice covered terrain, providing 5 and 6 times more data than ICESat and Envisat, respectively (McMillan et al., 2014b). A shared characteristic of standard radar altimetry methods is, however, that they all rely on the determination of the Point-Of-Closest-Approach (POCA), sampling a single elevation beneath the satellite. Here, we present a method for determining ice elevation across extended swaths of terrain utilising the information contained within CryoSat-2 altimeter SARIn echoes.

The Interferometric mode of CryoSat-2 provides the ability to resolve substantially more than just the elevation at the POCA. If the ground terrain slope is only a few degrees, the CryoSat-2 altimeter operates in a manner such that the interferometric phase of the altimeter echoes may be unwrapped to produce a wide swath of elevation measurements across the satellite ground track beyond the POCA (Wingham et al., 2006; Hawley et al., 2009), referred to in the remainder of this manuscript as L2swath or simply swath (Fig. 2).

An early proof of concept was performed on data acquired by the ASIRAS airborne prototype of the CryoSat-2 instrument over the Austfonna ice cap, Svalbard, in the spring of 2004 (Hawley et al., 2009). When...
evaluated against Airborne Laser Scanner (ALS) data, swath elevations show a root mean square (RMS) departure of 1.67 m in contrast to 1.33 m when only extracting the POCA. However, swath processing provided up to 2 orders of magnitude more elevation measurements than at the POCA alone. A study performed using CryoSat-2 data over a western section of the Devon Ice Cap identified similar relative accuracy between swath and POCA (Gray et al., 2013). Recent applications have shown the potential of the technique to image thinning rates at ice sheet margin (Christie et al., 2016), surface depression related to supraglacial lakes (Ignézi et al., 2016; Gray et al., 2017), surface elevation change related to sub-glacial lakes drainage (Smith et al., 2017), ice caps mass balance (Foresta et al., 2016), and basal melting under ice-shelf (Gourmelen et al., 2017) with much greater surface details.

Here, we describe a method to derive swath elevation from the SARIn mode of CryoSat-2, and illustrate the benefit of the approach to derive surface elevation and time-dependent surface elevation change. We present experimental elevation and elevation change products derived from swath processing over several sites in the GrIS, AIS and over ice caps in Iceland and Svalbard. We present validation results and compare the swath measurements and derived products with existing datasets generated from conventional CryoSat-2 POCA technique, as well as datasets generated from past and present optical and radar airborne and spaceborne missions.

2. Data and methods

2.1. Swath interferometric altimetry

The swath algorithm consists of (i) identifying suitable waveform echoes within the L1b SARIn mode product based on high phase coherence, amplitude and surface slopes, the threshold to use will depend on the local conditions (Gray et al., 2013; Foresta et al., 2016; Gray et al., 2017); (ii) determining the correct phase ambiguity (unwrapping) (as wrapping of the phase occurs for an arrival angle greater than \(\pi/2\)) by a combination of spatial unwrapping and quality control using a reference digital elevation model (Gray et al., 2015; Foresta et al., 2016) and (iii) mapping the range, across-track look angle, platform attitude and orbit parameters of each echo into a swath comprised of multiple elevation points above a reference ellipsoid (Fig. 3) (Wingham et al., 2006; Hawley et al., 2009; Gray et al., 2013; Foresta et al., 2016).

2.1.1. Input data

Swath processing takes as input multi-looked echo (L1b product, baseline C) from the Synthetic Aperture Radar Interferometric (SARIn) mode of CryoSat-2, containing the power, interferometer phase and coherence waveforms. All necessary input data are contained in the L1b product delivered by ESA (ftp://science-pds.cryosat.esa.int) with the exception of an external reference digital elevation model (DEM_{ref}).

Fig. 3. Swath processing workflow.
2.1.2. Smoothing
To reduce instrument noise, the phase and amplitude are filtered by recreating the interferogram, filtering its real and imaginary components with a low pass filter and retrieving the phase from the smoothed interferogram (Gray et al., 2013). We filter each waveform independently with a filter size equal to 3 bins to limit the loss of spatial resolution.

2.1.3. Local phase unwrapping
Phase difference can only be known within a $[-\pi, \pi]$ interval and so a phase ambiguity will be present when the angle of arrival exceeds about half a degree, a situation that can occur when e.g. the ground-surface slope exceeds about half a degree. Correction of phase ambiguities requires a phase unwrapping procedure which is applied to each waveform separately by adding or subtracting $2\pi$ when the absolute phase change between 2 consecutive bins exceeds $\pi$. In order to minimize phase unwrapping errors, phase values for which the coherence is below a threshold of 0.8 is masked.

2.1.4. Generation of latitude, longitude and elevation
The look angle $\theta$ is such that

$$\theta = \arcsin\left(\frac{\lambda \, \delta \phi}{2\pi \, B} \right) - \beta$$

with $\lambda$ the wavelength, $\delta \phi$ the phase difference, $B$ the interferometer baseline and $\beta$ the roll angle. The range $R$ at each waveform sample $n$ as:

$$R(n) = \frac{c}{2} \left( T + \frac{1}{2 \cdot F_s} \left( n - \frac{N}{2} \right) \right)$$

where $N$ is the total number of waveform samples, $n$ is the sample number in the $[0, N - 1]$ interval, $T$ is the window delay, in seconds, at bin $\frac{N}{2}$, $F_s$ is the instrument sampling frequency, and $c$ is the speed of light.

2.1.5. Global phase unwrapping
We introduce an additional step to account for phase ambiguities; the independent $\text{DEM}_\text{ref}$ is used to guide the phase unwrapping steps where phase ambiguity cannot be resolved from simple unwrapping (e.g. when the entire waveform is affected by a phase ambiguity). This approach potentially improves the measure of elevation for echoes whose across-track angle is above $\sim 0.54^\circ$ for all or part of the beam limited footprint, a condition found frequently for ice caps and locally along ice sheet margins.

In the presence of slopes exceeding $\sim 0.54^\circ$, the conventional unwrapping procedure described above will not be able to resolve the phase ambiguity as the first arrival measurement will be affected by a phase shift; in this situation we will need to apply a ‘global’ phase correction, i.e. adding or subtracting a suitable multiple of $2\pi$ to the phase values of a waveform. Without accounting for this correction, elevation estimates can be off by tens of meters and their location off by a few kilometers.

We implemented a procedure involving a reference DEM. For each waveform, latitude, longitude and elevation are computed for a number of $2\pi$ multiples (positive and negative). The correct $2\pi$ ambiguity is then chosen using two metrics. Firstly, we find the phase ambiguity that minimises the elevation difference between CryoSat-2 swath and the $\text{DEM}_\text{ref}$:

$$\sum_{i=1}^{N} |h_i - \text{DEM}_\text{refi}|$$

with $h_i$ and $\text{DEM}_\text{refi}$ respectively the swath elevation and $\text{DEM}_\text{ref}$ at the waveform sample number $i$. The second metric is the dispersion of the elevation difference defined as the Median Absolute Deviation:

$$\text{MAD}_\text{hd} = \text{median}[hd - \text{median}(hd)]$$

where $hd$ is a vector of the difference between the swath elevations at each waveform samples and the corresponding reference elevation. This second metric stems from the fact that an erroneous phase ambiguity will impact on the slope of the surface topography, hence leading to a large value of $\text{MAD}_\text{hd}$ (Fig. 4). This second metric adds robustness to the determination of the phase ambiguity.

Given the magnitude of the impact of a phase ambiguity on the planimetric positioning, elevation and surface slope of the swath measurement (Fig. 4), and although the reference DEM need to be relatively accurate or recent, a certain level of difference is acceptable. However, due to the complexity of surface terrain it is difficult to predict the level of accuracy needed. Distinct reference DEMs are used in this study for GrlS (Howat et al., 2014), AIS (Fretwell et al., 2013), Iceland (Landmælingar Íslands, www.lmi.is), and Svalbard (McMillan et al., 2014a).

We note that phase ambiguity is not only affecting swath but also POCA processing were a reference DEM is also needed to resolve phase ambiguity (Gray et al., 2015).

2.2. Digital elevation model and rates of surface elevation change
Because of the increased data density, L2swath altimetry provides a capability to determine changes in ice elevation at the maximum spatial resolution of the CryoSat-2 instrument, up to 0.4 km in the platform’s along-track direction. To assess this capability, we computed ice sheet surface elevation changes within 500 m grid cells by fitting a plane to the raw L2swath elevation measurements within a grid cell using a model function of spatial and temporal elevation change of the form:

$$Z(x, y, t) = ax + by + c + dt$$

where $Z$ is the swath elevation, $x$ and $y$ are the easting and northing coordinates of each swath data point, respectively, and $t$ is the time of data acquisition (Foresta et al.,...
Surface elevation and elevation change are then determined from the model parameters $a$, $b$, $c$ and $d$; $a$ corresponding to the eastward linear elevation trend, $b$ to the northward linear elevation trend, $c$ a constant, and $d$ the linear rate of temporal elevation change. In this model the spatial variation in elevation is determined as a bilinear function and the temporal variation of elevation as a linear term. The power field, $P$, is used to weight the individual elevation measurements during the inversion process; for each grid cell, the weight, $w$, is defined as:

$$w = \frac{P^2}{\max(P)^2}$$

This weighting strongly penalises measurement with low power. This inversion approach is similar to solutions applied to CryoSat-2 POCA data (McMillan et al., 2014b), only with a simplification of the terrain slope terms made possible by the finer spatial distribution of the input data. The use of either linear or quadratic polynomial to model the terrain slope within a grid cell does not affect markedly the values of elevation change compared to airborne data, with less than 1% difference under each scenario.

The advantage of this approach to determine a gridded CryoSat-2 swath digital elevation model (CSDEM), with respect to other approaches that average measurements acquired over a long time-period, is the ability of our model to account for the time-dependant aspect of the topography in regions of rapid and complex changes, and therefore to generate a DEM of high-temporal fidelity.

2.3. Validation

Swath elevation and derived gridded products are validated using surface elevation and elevation change from the NASA Operation IceBridge (OIB) Airborne Topographic Mapper (ATM) campaigns (Krabill 2016; Krabill 2015). OIB campaigns are a series of airborne missions to map Arctic and Antarctic ice sheets with laser altimetry between 2009 and 2016 (filling the gap between ICESat and ICESat-2). We have used the OIB ATM L2 Icessn Elevation, Slope, and Roughness product, Version 1. The ATM data are referenced to the ITRF-2005 reference frame and projected onto the WGS-84 ellipsoid. The footprint size of each individual elevation measurement is 1 m, which is set by the laser beam divergence (Krabill, 2016). Absolute elevation accuracy from the ATM is usually about 10 cm or better (Krabill, 2016) with geolocation accuracies of better than 1 m (Schenk et al., 1999).
ically for the OIB campaigns, the parameters of the ATM system are estimated to be (i) 74 cm horizontal accuracy, (ii) 6.6 cm vertical accuracy, and (iii) 3 cm vertical precision (Martin et al., 2012).

Due to the rapid changes at the margins of the ice sheets, only elevation data acquired as close in time as possible has been considered for validation purposes. The validation activities have also avoided rapid melting and precipitation periods and have been therefore concentrated for the northern hemisphere in the months of March, April and May and for the Southern Hemisphere in the months of October and November covered by OIB ATM acquisitions.

For each CryoSat-2 measurement we select the nearest validation measurement that satisfies the spatial and temporal baseline thresholds of 50 m and 10 days respectively. For the gridded CSDEM and rates of elevation change products, the spatial criterion is that the validation measurement is within half the grid spacing, or 250 m, and the temporal criterion is 1 repeat cycle (369 days) from the time stamps of the CSDEM which are usually set at the first CryoSat-2 record, i.e. 07/2010. We then define a measurement bias as the median value of the difference between the L2swath and the validation elevation, and a measurement dispersion as the Median Absolute Deviation defined as:

\[ \text{MAD} = \text{median}(\{ |(Z_n - Z^\text{val}_n) - \text{median}(Z_n - Z^\text{val}_n)| \}) \]  

where \( Z_n \) are the swath elevations and \( Z^\text{val}_n \) are the corresponding validation records.

Our validation test sites are located at the margins of the two ice sheets and include the glaciers of Petermann and Jakobshavn glaciers (GrIS), and the Pine Island and Thwaites glaciers in the Amundsen Sea sector of AIS.

3. Results

3.1. Swath elevation

3.1.1. Data coverage and volume

A capacity to sample elevation at locations beyond the POCA means that L2swath provides a snapshot of terrain in both along-track and across-track directions, turning CryoSat-2 into an instantaneous two-dimensional mapping sensor. The across-track width of swaths can reach several kilometres, the exact extent depending on surface slope (Fig. 5). Considering a range of glaciological targets, L2swath processing typically retrieves between 10 and 100 distinct elevation measurements from a single altimeter echo, by contrast to a single elevation measurement in the standard L2 product. The improvement in data quantity for each of the validation sites is provided in Table 1.

3.1.2. Validation

We evaluated the accuracy of L2swath data over GrIS and AIS marginal regions with respect to 344 \times 10^5 independent airborne altimeter elevation measurements acquired between 2011 and 2014 (Fig. 8 & Table 1). The differences between the airborne and CryoSat-2 swath elevations is \(-1.50 \pm 1.73\) m; the \(-1.5\) m bias reflects the greater penetration of Ku-band radar into the snow and firn compared to the ATM. For comparison, the differences between the airborne and POCA observations is \(-0.93 \pm 1.17\) m.

3.1.3. Baseline C versus baseline B

In 2015, CryoSat-2’s Instrument Processing Facilities was updated to Baseline C, improving the product’s quality and correcting several biases (Scagliola and Fornari, 2015). One improvement included in Baseline C is the removal of the waveform cut initially introduced in Baseline B during the oversampling of the 20 Hz waveform, that led to a loss of information. Baseline C now provides a range window of 240 m, double in length to that of baseline B. This leads to an increase in the number of elevations that L2swath is able to deliver (Fig. 6).

3.1.4. Roll bias

An inaccurate value of satellite’s roll angle will impact on the positioning of the elevation measurements, with a greater impact with large off-nadir angle. A roll bias of 0.1062° was identified in CryoSat’s baselineB dataset and corrected in CryoSat new latest release, baseline C (Scagliola and Fornari, 2015). It has been suggested that a residual roll bias is present in CryoSat’s baseline C (Gray et al., 2017). To explore this possibility, we calculate swath elevations using look angles calculated by introducing arbitrary roll angle biases \( \beta_h \) as follows:

\[ \theta = \arcsin \left( \frac{\lambda \ \delta \phi}{2\pi \ B} \right) - (\beta + \beta_h) \]  

We then use OIB elevation to explore the roll angle bias impact on the L2swath-OIB elevation differences (Fig. 7). When a roll angle bias is present, ascending and descending orbit will be affected in opposite direction leading to a double-peak histogram of the L2swath-OIB elevation differences (Fig. 7, lower-left). For a correct value of roll angle, the histogram will have the expected single peak (Fig. 7, lower-left). We then solve for the roll bias that minimises the histogram dispersion and found a value of 0.007°. If uncorrected, this directly translates in an offset of 87 m in geolocation in the across track direction, and in a vertical offset of 0.01 m at nadir and of 1.60 m at the edge of the footprint, of the elevation retrieval.

This value is likely to vary however as the roll bias depends on the temperature of the platform. There are two causes of temperature changes: short term variations (the platform is facing the sun with different incidents angles within an orbit) and long term variation (the orbit plane of the platform has different incidents angles within the 369 day cycle).

The noise of the roll is higher when the measurements are given by the Star Tracker that is not the coldest, but also there is a long-term variation due to the bending of the bench where the Star Tracker are placed.
The new CryoSat-2 baseline-C incorporates a Star Tracker processor in charge of computing the attitude measurements provided on the products with the stated roll bias and some smoothing algorithms. With that smoothing the noise of the roll measurement is compensated but the long-term variation cannot be addressed as it would require a long-term analysis. The external calibration analysis using data over a Transponder indicates that the roll bias in Baseline C is 0.0069 ± 0.003°C176 (Garcia-Mondejar et al., 2017).

A dataset of re-calibrated attitude information recently released by ESA (https://earth.esa.int/web/guest/missions/esa-eo-missions/cryosat/str-attref) is also tested (Fig. 7) and show that it largely corrects for the roll angle bias observed in the current baseline C dataset. The updated attitude will be incorporated in an upcoming baseline D release by ESA.

Table 1
Bias and dispersion of swath mode elevation and derived gridded products, POCA, with respect to Operation IceBridge Airborne Laser Scanner and comparative measurements density between POCA and swath mode.

<table>
<thead>
<tr>
<th>Region</th>
<th>Swath elevation (m)</th>
<th>POCA elevation (m)</th>
<th>Swath/POCA number of measures (10⁶)</th>
<th>Gain in spatial resolution</th>
<th>Swath DEM (m)</th>
<th>Swath dh/dt (m a⁻¹)</th>
<th>POCA dh/dt (m a⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Petermann</td>
<td>−1.3 ± 1.2</td>
<td>−1.1 ± 0.8</td>
<td>44.9/1.4</td>
<td>5 folds</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Jakobshavn</td>
<td>−1.2 ± 2.0</td>
<td>−0.6 ± 1.4</td>
<td>99.9/1.0</td>
<td>10 folds</td>
<td>−1.4 ± 1.8</td>
<td>0.04 ± 1.15</td>
<td>0.17 ± 1.54</td>
</tr>
<tr>
<td>Amundsen Sea Sector</td>
<td>−2.0 ± 2.0</td>
<td>−1.1 ± 1.3</td>
<td>199.3/3.3</td>
<td>8 folds</td>
<td>−1.7 ± 2.0</td>
<td>0.04 ± 0.92</td>
<td>0.40 ± 0.95</td>
</tr>
</tbody>
</table>

This exercise also demonstrates that swath processing could be a complementary approach to transponders for calibrating the attitude of interferometric radar altimeters with vastly improved spatial and temporal coverage.

3.2. Gridded digital elevation model and rates of surface elevation change

We generated and validated gridded DEMs and rates of surface elevation change at 500 m grid spacing for the Jakobshavn area (west GrIS) and for the Amundsen Sea sector of West Antarctica. In total we retrieve an elevation for 98.8% (Jakobshavn area) and 98.2% (Amundsen Sea sector) of the area over the grounded ice sheets. For comparison, studies at the scale of the entire AIS using CryoSat-2 POCA data found 96% coverage at 5 km by 5 km, and from Envisat cross-over POCA found 32% cover-age.
We also show case examples over the Law Dome (East Antarctica) as well as over ice caps in Iceland.

### 3.2.1. Digital elevation model

Validation of the L2swath DEM at 500 m grid spacing indicates a bias of $1.4$ m and a dispersion of $1.8$ m when swath elevation are compared to 39,139 collocated airborne measurements from OIB over the Jakobshavn area (Fig. 8). A similar intercomparison over the Amundsen Sea sector indicates bias of $1.7$ m and a dispersion of $2.0$ m when compared to 29,362 airborne measurements over grounded ice (Table 1) and $1.5$ m and a dispersion of $1.2$ m over floating ice (Gourmelen et al., 2017).

![Fig. 6. CryoSat swath elevation from baseline B (top left), baseline C (top right) and overlay (bottom left) showing the increase in elevation measurements provided by the new baseline C. We can also observe lower noise level in the baseline C product near the waveform’s leading edge (top) as described by (Scagliola and Fornari, 2015).](image)

![Fig. 7. Distribution of 39139 L2swath elevation minus OIB elevation over the Jakobshavn area (Fig. 8) with respect to experimental roll angle bias $b = 0.007^\circ$ and $-0.04^\circ$ (left). The roll bias that minimises the dispersion of the elevation difference is found at $b = 0.007^\circ$ (right). The same exercise using recently released corrected attitude information (Proto-baseline D data) shows that the roll angle is significantly improved (right).](image)
Improved spatial resolution offered by the greater density of swath measurements allows far greater definition of glacial terrain than has been possible to date. For example, at Law Dome in East Antarctica, a CSDEM produced at 500 m grid spacing (Fig. 9) clearly identifies surface features on length scales of 500–4000 m which are common in airborne data sets, but are not resolved in continental-scale products (Fretwell et al., 2013). Over the east flank of Law Dome, a system of surface gashes is well defined at 500 m resolution; the gashes’ system is the surface expression of a large canyon system in the underlying bedrock (Fig. 9).

3.2.2. Surface elevation change

3.2.2.1. Multi-annual change. In the Amundsen Sea Sector of West Antarctica, rates of elevation change determined from L2swath show a remarkable level of detail when compared to results that can be achieved using POCA elevation data alone (Figs. 10 & 11). Although CryoSat-2 POCA data are recorded within a much smaller ground footprint than conventional pulse-limited altimetry, they lead to only a modest (factor 2) improvement in spatial resolution of elevation changes due to the relatively long orbit repeat cycle which requires measurements to be
collated in space. In contrast, L2swath data allow for a 10-fold improvement in spatial resolution of elevation changes (Table 1). Measurements with such fine sampling allow the detailed pattern of thinning along tributaries of the Pine Island, Thwaites, Smith, Kohler and Pope Glaciers to be clearly identified, and ensure that signals of elevation change can be retrieved up to the ice sheet margin even over the floating ice shelves (Gourmelen et al., 2017). Over smaller features such as ice caps the benefit of L2swath is also apparent with a dramatic increase in surface coverage (Fig. 11). When comparing L2swath-derived rates of elevation change with POCA-derived estimates and with estimates of elevation change determined from repeat airborne surveys over the same period (Krabill, 2015), the L2swath data are in excellent agreement. For the Amundsen Sea Sector (Fig. 10), we observe a mean difference between swath and OIB of 0.04 ± 0.92 m a⁻¹, this value is comparable to the estimated certainty (0.40 ± 0.95 m a⁻¹) of POCA-derived elevation changes in the same region (McMillan et al., 2014b). Over ice caps we also observe a very good agreement and no noticeable impact of surface slopes (Fig. 12) (Foresta et al., 2016).

3.2.2.2. Seasonal or transient change. CryoSat’s repeat cycle of 369 days limits the temporal resolution at which localised changes can be mapped. Generating swath of elevation instead of POCA leads to overlap between adjacent tracks, leading to an increase in the temporal resolution at which elevation change can be determined. The improvement in spatial resolution is greater for deformation that are spatially and temporally localised. With L2swath data, we observe a 35-fold increase in the probability of sampling an area of 500 m² in size at 1–90 day time step (length of CryoSat-2’s orbital sub-cycle) (Fig. 13).

For example, the L2swath observations clearly identify a cluster of dislocated sites in the interior of the Thwaites Glacier drainage basin (Fig. 14) (Smith et al., 2017). In this 860 km² region, four sites of between 100 and 360 km² have lowered by 6–13 m over a 1 year period, similar to patterns of surface lowering above subglacial lakes that have drained in other sectors of Antarctica (Fricker et al., 2007; Wingham et al., 2006b). Observations using POCA data only partially cover the area (Fig. 14) leading to an incomplete mapping of the subsidence features and a 30% error in the total subsidence volume.
A second example of highly-localised and rapid changes in ice elevation mapped by forming and differencing sequential CryoSat-2 L2swath measurements is shown in Fig. 15. In the summer of 2014, the north-west sector of the Vatnajökull ice cap in the region of the Bárdarbunga caldera, Iceland, experienced high seismic activity followed by a volcanic eruption off-ice north of the seismic swarm (Sigmundsson et al., 2015; Gudmundsson et al., 2016). In this example, the entire caldera deformation was imaged by 6 swaths of CryoSat-2 data acquired just before the
onset of the event and up to the beginning of November 2014, revealing the extent of the subsidence that affected the region of the ice cap (Fig. 15). The L2swath data reveal that during the 4 month-period that followed the onset of seismic activity, a 25 km² region subsided by over 40 m, amounting to a 0.75 km³ deflation in agreement with airborne and GPS surveys - while the entire subsidence event lasted until February 2015 and amounted to 1.6 km³ of deflation with a maximum subsidence of 65 m (Gudmundsson et al., 2016). The width of the swath was sufficient to map the entire subsidence event, when POCA elevation data would only have provided a coarse picture.

Seasonal patterns of elevation change, e.g. related to the seasonal cycle of accumulation and ablation, have been retrieved from altimetry over large region, at the scale of an entire ice sheet (McMillan et al., 2016) or ice cap (Gray et al., 2015). Increase spatial resolution means that we can start focussing seasonal analysis from radar altimetry over smaller targets. An example over the Vatnajökull ice cap (Iceland) shows the seasonal pattern in elevation related to accumulation and ablation partitioned between the accumulation (above 1200 m) and ablation area (below 1200 m) (Fig. 16) (Forestà et al., 2016).

4. Discussion

The separation of CryoSat-2’s ground track ranges from 7.5 km at the equator to less than 1.6 km at latitudes higher

Fig. 12. Difference between L2swath and POCA surface elevation change rates \( \bar{h}_s - \bar{h}_p \) over Vatnajökull with respect to (a) along-track and (b) across-track surface slope. (c) Histogram of differences between L2swath and POCA rates of surface elevation change (Forestà et al., 2016).

Fig. 13. Increase in temporal resolution from conventional POCA to L2swath as a function of time interval and spatial posting. This has been calculated from real data over the Jakobshavn and Amundsen Sea sector areas.
Fig. 14. Surface elevation change between pre and post summer 2013 inland of the Thwaites glacier (location in Fig. 10) from L2swath, showing areas of surface lowering related to the drainage of 4 subglacial lakes in mid 2013 (Smith et al., 2017). Zoom on lake Thw142 showing the location of all measurements (white dots) acquired over a CryoSat-2 repeat cycle from POCA (top right) and from L2swath (bottom right); background image is L2swath derived surface elevation change in both cases.

Fig. 15. Rapid subsidence of the 4 km wide Bárðarbunga caldera, Vatnajökull ice cap, Iceland, after deflation of the magma chamber. Landsat-8 background image (September 6, 2014) shows contemporary Holuhraun lava flow. Elevation shown as 100 m equidistant contour lines.
than 70 °C. However, the actual separation of elevation measurements recorded by the altimeter can be significantly larger than this, because the POCA is dependent upon the surface slope and tends to follow topographic ridges. This effect occurs in marginal sectors of the polar ice sheets and ice caps and across mountain glaciers, where the terrain is typically steep. In such instances, features that are kilometre-scale or smaller may be under-sampled or missed altogether by standard altimeter measurements recorded at the POCA alone. L2swath data, however, overcome this problem because they map broad and continuous swaths of ice covered terrain, allowing surface elevation and surface elevation changes to be determined with 10 times finer spatial resolution than conventional altimetry (Fig. 9).

In addition to providing a denser network of elevation measurements around the POCA, swath interferometry allows for the retrieval of elevation data where the conventional POCA altimetry approach fails. This situation occurs where the POCA falls on incoherent surfaces, leading to retracker failure, or in regions of complex ice topography where the POCA tends to concentrate along topographic highs leaving topographic lows uncharted (McMillan et al., 2013). In contrast, L2swath is able to image the ice terrain beyond the POCA and to measure elevation in surface depressions providing they are within the limits of the altimeter’s sampling window (corresponding to 240 m elevation range for CryoSat-2 baseline C).

The step-change in the yield of valid elevation measurements means that L2swath provides an opportunity to extract continuous surface elevation at enhanced spatial resolution in comparison to previous altimetry-based products (Fretwell et al., 2013; DiMarzio et al., 2007a; Bamber et al., 2009). Although digital elevation models (DEMs) are often distributed on fine (500–1000 m) spatial grids, actual observations are generally oversampled. The effective resolution of existing products is typically an order of magnitude lower (DiMarzio et al., 2007a, 2007b, Griggs and Bamber, 2009), and many grid points are not constrained by measurements at all due to the paucity of primary observations. In addition to improved coverage, the accuracy of DEM’s derived from swath altimetry is also well within that of existing products. The example elevation models we have produced demonstrate that continuous DEM’s exhibiting true sub-kilometre spatial resolution are feasible with swath interferometric altimetry. The technique is now approaching the capabilities of airborne surveys (Howat et al., 2014; Krabill, 2016), and while the spatial resolution of the gridded products obtained here is not commensurate with that achieved by high-resolution sensors (Berthier et al., 2014; Howat et al., 2015; Dehecq et al., 2016), the technique benefits from frequent and regular, day-night, all-weather and global coverage as well as seamless aggregation. We also note that the non-gridded swath product can resolve elevation at metrical spatial resolution (Gray et al., 2017) in par with high-resolution imaging sensors. As a consequence of the increased spatial sampling, L2swath data allow ice elevations to be mapped with higher temporal frequency. Although the CryoSat-2 orbit repeat cycle is 369 days, which limits the observation of rapidly changing processes, the width of L2swath swaths provides greater overlap between adjacent ground tracks. At 70° latitude this translates into a three, five, ten and 35-fold increase in temporal sampling respectively at 5, 3, 1 and 0.5 km posting when compared to POCA measurements alone (Fig. 13). Improved sampling of ice elevation changes will improve our understanding of key glaciological processes. Although half of today’s sea level change is due to ice mass losses (IPCC, 2013), these losses are predominantly occurring in mountainous and coastal regions which present a challenge to conventional altimetry. However, because L2swath performs well over rugged ice covered terrain, more accurate estimates of glacier and ice sheet mass balance will become possible. The movement of water between lakes at the base of the Antarctic (Fricker et al., 2007; Wingham et al., 2006b) and Greenland (Joughin et al., 1996) ice sheets, has the capacity to affect ice flow (Smith et al., 2017; Stearns et al., 2008), release freshwater into the ocean (Fricker et al., 2007), deform glacial landforms (Lewis et al., 2006), and disturb subglacial habitats (Siegert et al., 2005). Although the surface expression of subglacial lake drainage has been recorded in pulse-limited (Wingham et al., 2006b) and laser (Fricker et al., 2007) altimetry, conventional measurements acquired at the POCA have been shown to preferentially sample the highest sections of surface depressions (McMillan et al., 2013). A consequence is that POCA tends to underestimate the deflation. For example, estimates of the volume change within depressions above presumed sub-glacial lake sites in the Thwaites Glacier catchment (Fig. 14) based on POCA L2swath elevation data differ by more than 40%. L2swath resolves this problem, and will lead to an improved inventory of active sub-glacial lakes (Smith et al., 2015).
et al., 2009; Wright and Siegert, 2012) and their water mass budgets. In Greenland and on the Antarctic Peninsula, supra-glacial lakes similarly create and occupy depressions on the ice sheet surface (Liestl et al., 1980; Scambos et al., 2000; McMillan et al., 2007), and the ability to map their shape in full (Ignáczi et al., 2016) will lead to an improved characterisation of their seasonal hydrology which is believed to influence rates of ice flow (Das et al., 2008) and ice shelf stability (Phillips et al., 2010).

5. Conclusions

Trends in the elevation of ice sheets, ice caps, and mountain glaciers derived from satellite altimetry are a key observation for quantifying and understanding the impacts of environmental change. We have described how swath interferometric processing of CryoSat-2 data provides a step change in the quantity of valid elevation data that can be derived from satellite radar altimetry. By applying the technique to CryoSat-2 measurements acquired over a range of geophysical targets, we demonstrate that a ten-fold gain in the density of data can be achieved in comparison to conventional satellite altimetry performed only at the POCA. Furthermore, we show that the increase in data density is not detrimental to data quality, with only a modest (up to 50% and surface dependent) degradation in the bias and variability of elevation measurements relative to standard POCA approaches. L2swath also provide a near continuous elevation field, making it possible to form digital elevation models and to map rates of surface elevation change at a true resolution of 500 m – an order of magnitude finer than is the current state of the art for the continental ice sheets. This leads to a more accurate picture of the complexity of surface topography and patterns of surface elevation change within ice stream tributaries, along the ice sheet margins, ice shelves, and in surface depressions linked with ice sheet hydrology. Applied extensively, these new observations will transform our understanding of cryospheric change.

Acknowledgments

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Hindmarsh, R.M.C., Bolch, T., Sharp, M.J., Hagen, J.O., van den Broeke, M.R.,


Appendix C

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Heterogeneous and rapid ice loss over the Patagonian Ice Fields revealed by CryoSat-2 swath radar altimetry

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ABSTRACT

The Northern and Southern Patagonian Ice Fields (NPI and SPI) in South America are the largest bodies of ice in the Southern Hemisphere outside of Antarctica and the largest contributors to eustatic sea level rise (SLR) in the world, per unit area. Here we exploit swath processed CryoSat-2 interferometric data to produce maps of surface elevation change at sub-kilometer spatial resolution over the Ice Fields for six glaciological years between April 2011 and March 2017. Mass balance is calculated independently for nine sub-regions, including six individual glaciers larger than 300 km\textsuperscript{2}. Overall, between 2011 and 2017 the Patagonian Ice Fields have lost mass at a combined rate of 21.29 ± 0.38 Gt a\textsuperscript{−1}, contributing 0.059 ± 0.005 mm a\textsuperscript{−1} to SLR. We observe widespread thinning on the Ice Fields, particularly north of 49° S. However the pattern of surface elevation change is highly heterogeneous, partly reflecting the importance of dynamic processes on the Ice Fields. The Jorge Montt glacier (SPI), whose tidewater terminus is approaching floatation, retreated ~2.5 km during our study period and lost mass at the rate of 2.20 ± 0.38 Gt a\textsuperscript{−1} (4.64 ± 0.80 m\textsubscript{wa} a\textsuperscript{−1}). In contrast with the general pattern of retreat and mass loss, Pio XI, the largest glacier in South America, is advancing and gaining mass at 0.67 ± 0.29 Gt a\textsuperscript{−1}.

1. Introduction

The Northern and Southern Patagonian Ice Fields are the two largest ice bodies in the Southern Hemisphere excluding Antarctica, with areas of about 4200 and 13,000 km\textsuperscript{2} and volumes of about 1200 and 4300 km\textsuperscript{3} (Carrivick et al., 2016), respectively, and elevation ranging from sea level to about 3900 m. They experience relatively warm and wet climatic conditions (Garreaud et al., 2013). The mountain and associated ice divide separates areas with contrasting climatic conditions. On the western side, orographic uplift of moist air produces extreme annual precipitation of up to 10 m a\textsuperscript{−1} (e.g. Chaix et al., 2007; Ivins et al., 2011; Jacob et al., 2012; Gardner et al., 2013) and comparisons of Digital Elevation Models (DEM; Rignot et al., 2003; Willis et al., 2012a, 2012b; Jaber, 2016) estimated that between 1975 and 2012 the rate of mass loss of the Ice Fields has been in the range of 15 to 35 Gt a\textsuperscript{−1}, one order of magnitude more compared to the long term trend.

During the last 50 years, the Patagonian Ice Fields contributed an estimated 10% to the total melt contribution from glaciers and ice caps, excluding those at the periphery of the Greenland and Antarctic ice sheets.
(Glasser et al., 2011 and references within), increasing to 15.4% in the first decade of the 21st century (Jacob et al., 2012; Gardner et al., 2013), second only to glaciers in Alaska and the Canadian Arctic, and larger than high mountain Asia (Brun et al., 2017) which all extend over areas ~5–8 times larger. Currently, the Patagonian Ice Fields are the largest contributor to sea level rise per unit area in the world (Gardner et al., 2013; Carrivick et al., 2016).

Velocities of glaciers draining the Ice Fields (up to 10 km a⁻¹) are amongst the fastest in the world (Sakakibara and Sugiyama, 2014; Mouginot and Rignot, 2015) and substantial ice flow acceleration has been observed, coincident with rapid frontal retreat, for a number of tidewater and lacustrine glaciers (Sakakibara and Sugiyama, 2014). These observations implicate the importance of the role of dynamics and tidewater glacier calving in the rapid wastage of the Ice Fields. In fact, >80% of them terminate in proglacial lakes (mostly across the NPI and east of the SPI) or fjords (western side of the SPI) (Sugiyama et al., 2016 and references within).

Since 2010, the European Space Agency (ESA) radar altimetry mission CryoSat-2 (CS2) (Drinkwater et al., 2005; Wingham et al., 2006) has been acquiring topography data over land ice. Radar instruments are particularly suited to land ice applications since they can penetrate through clouds and do not depend on sunlight. Radar altimetry data have been previously exploited to map elevation change over ice caps (Rinne et al., 2011a, 2011b), but the technique has not been applied widely due to the limitation caused by the large radar footprint. CS2’s state-of-the-art radar altimeter uses Synthetic Aperture Radar (SAR) along-track to reduce the footprint size as well as interferometry across-track to accurately locate the position of the surface reflection (SARIn mode; Wingham et al., 2006). Additionally, its orbit inclination of 92° and repeat cycle of 369 days provides an inter-track spacing of ~5 km on average over the Patagonian Ice Fields. Finally, CS2’s relatively short wavelength (2.2 cm; Ku band) restricts the penetration of the radar pulse in the snowpack, compared to, e.g., sensors working in C or X bands. These characteristics make CS2 better suited for monitoring changes in glacier areas with frequent cloud cover and considerable slopes. CS2 SARIn data have successfully mapped topographic changes over Arctic ice caps (McMillan et al., 2014a; Gray et al., 2015). Additionally, swath processing (Hawley et al., 2009) of CS2 SARIn data has been applied to generate high resolution DEMs of ice caps and selected areas of the Greenland and Antarctic ice sheets (Gray et al., 2013; Ignéczi et al., 2017a; Gourmelen et al., 2017a) and to produce sub-kilometer maps of surface elevation change (Christie et al., 2016; Foresta et al., 2016; Gourmelen et al., 2017a; Gourmelen et al., 2017b), with a wide range of applications such as the identification of supraglacial lakes in NE Greenland (Ignéczi et al., 2016), subglacial lakes in West Antarctica and regions of subsidence in Iceland (Smith et al., 2017; Gourmelen et al., 2017a) as well as quantifying channeled basal melt under the Dotson ice shelf in West Antarctica (Gourmelen et al., 2017b) and volume and mass change of individual ice caps in Iceland (Foresta et al., 2016).

Despite their important contribution to ice mass loss and global SLR, studies quantifying mass changes of the Patagonian Ice Fields are limited in number and do not cover the most recent period. This paper focuses on quantifying the mass balance of the NPI and SPI during six glaciological years between April 2011 and March 2017. To this aim, we exploit swath processed CS2 SARIn data to generate maps of surface elevation change rates at sub-kilometer spatial resolution, and convert them into estimates of glacier volume and mass change. For a number of large catchments on the SPI, such estimates are derived at the basin scale. Additionally, the dense L2swath elevation field enables the production of time series of elevation change for different sub-regions of the Ice Fields exhibiting contrasting patterns of change.

2. Data and methods

We exploit swath processed CS2 SARIn baseline C data (L2swath) as this technique (Hawley et al., 2009; Gray et al., 2013; Foresta et al., 2016; Gourmelen et al., 2017a) can generate up to two orders of magnitude more data than conventional Point-Of-Closest-Approach (POCA) processing and, importantly, provides more homogeneous spatial coverage over relatively small glaciated regions with consider- able topography (Foresta et al., 2016; Gourmelen et al., 2017a). The L2swath processing scheme is similar to Foresta et al. (2016) and Gourmelen et al. (2017a), but we use a different procedure to discard noisy waveform samples before performing the phase unwrapping. This procedure, first developed for InSAR images (Weissgerber, 2016) and updated for CS2 SARIn data (Weissgerber et al., 2018), was shown to further increase the density of the L2swath elevation field and to improve the spatial coverage of the Jakobshavn glacier, Greenland (Weissgerber and Gourmelen, 2017) (Appendix A). The L2swath algo- rithm makes use of an external DEM to improve the precision of ele- vation measurements in the presence of slopes larger than 0.54°, where an entire waveform may be affected by a phase shift. Without this correction, observations may be wrong by several tens of meters in elevation and a few kilometres in geo-localization (Gourmelen et al., 2017a). It is not straightforward to predict the accuracy needed for the DEM (Gourmelen et al., 2017a). However given the magnitude of the geolocation and elevation shifts, the DEM need not be extremely ac- curate. We used the SRTM C band DEM (Farr et al., 2007) acquired in 2000 as a reference for elevation, after including a correction to ac- count for the elevation change occurred between 2000 and 2011 (Appendix B). L2swath data are then used to compute rates of surface elevation change for six glaciological years between April 2011 and April 2017 using a plane-fit algorithm (e.g. McMillan et al., 2014b). One glaciological year is defined as the period between 1st April in year n and 31st March in year n + 1. CS2’s acquisition dates vary spatially for different pixels due to the satellite’s orbital path as well as to the local topography, so that the temporal resolution at the pixel scale is non-uniform and longer than monthly. However, seasonality biases are avoided given the regular flight path followed by CS2, which ensures that data within each pixel are acquired at the same epochs (within a few days) in each glaciological year. L2swath data are gridded at 500 m × 500 m spatial resolution and for each pixel, we model eleva- tion z(x,y,t) using a linear relationship in space and time:

\[
z(x,y,t) = c_0x + c_1y + c_2t + c_3
\]

where \(x\) and \(y\) are measured easting, northing, and acquisition time, respectively, and \(c_0, c_1, c_2, c_3\) are the model coefficients. The time-de- pendent coefficient \(c_3\) reflects the model fit is the linear rate of surface elevation change for each given pixel. Each observation is as- signed a weight according to the sample power as in Gourmelen et al. (2017a). We iteratively fit the model to the data using 3o clipping until there are no more outliers. The formal uncertainty \(c_3\) on each pixel's rate of elevation change \(\dot{h}\) is extracted from the model covariance matrix \(\mathbf{M}\):

\[
P = \text{cov}(p) = G^{-1} \text{cov}(z)(G^{-1})^T
\]

where \(p\) is the vector of coefficients \([c_0 c_1 h c_3]\) of the model parameters, \(z\) are the input elevations and \(G = [x \ y \ t \ 1]\) is the model matrix. We simplify the data covariance matrix \(\text{cov}(z)\) to a variance matrix whose diagonal values are the squared elevation differences between the observed and modelled estimates \(\{z-z^*\}^2\). The square root of the diagonal elements of \(P\) represents the standard deviations of the model parameters \(p\).

Due to the complex topography (see Discussion), the \(h\) maps do not have complete coverage. We use the relation between elevation and elevation change to model estimates for the gaps in the maps of surface elevation change rates (i.e. hypsometric averaging, see e.g. Moholdt et al., 2010; Nilsson et al., 2015a; Foresta et al., 2016), using the SRTM DEM for the elevation field. Polynomial models of order 1 to 3 are fitted to the data and used to generate elevation change rates for the in- dividual pixels without an estimate. In order to avoid over-fitting the

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data, the F-test is used to evaluate if the improvement of the additional model parameters on the fit is statistically significant at the 99% confidence level. The median rate of elevation change is then computed in each 50 m elevation band \( k \) and multiplied to the area \( A_c \), extracted from the DEM, to produce elevation dependent volume change \( V_c \). The sum of these contributions represents the total rate of volume change. Uncertainties are calculated by error propagation using the same method as in Foresta et al. (2016), summarized in Appendix C.

This interpolation scheme is applied independently for the NPI and for different sub-regions of the SPI displaying highly contrasting patterns of change at similar elevations (Fig. 2). Finally, we assume that all changes relate to the gain or loss of ice of density \( \rho_{ice} = 900 \text{ kg m}^{-3} \) when converting the rate of volume change to mass balance. This simplification is based on the assumption that at least part of the observed changes are due to dynamics (see Discussion) and ignores possible differences in snow pack density below and above the firn line. To explore mass loss related to material with lower density, we calculate mass balance estimates using a dual density scenario. In this case the densities of glacial ice and firn are used when converting volumetric changes occurring, respectively, in the ablation and accumulation areas. We assign \( \rho_{firn} = 600 \text{ kg m}^{-3} \) (Malz et al., 2018 and references within). We used Equilibrium Line Altitude (ELA) values as reported in De Angelis (2014) and Barcaza et al. (2009), respectively, for the glaciers on the SPI and NPI. For each group of glaciers (SPI-G1, SPI-G2, NPI), we computed an average ELA from all glaciers with surface area larger than 100 km\(^2\) in the given catchment.

Glacier outlines over the Ice Fields record their extent in 2000–2001 (RGI Consortium, 2017) and the Upsala and Jorge Montt glaciers (SPI) have retreated considerably since then and, for the latter, even during our study period. Their front positions in 2017 were manually digitized using Landsat8 scenes (Appendix D, Table D1) and their mass loss between 2011 and 2017 is calculated against their updated fronts. Area changes between 2011 and 2017 are not included in our estimates of mass loss. The only exception is Jorge Montt (SPI), which retreated considerably in this time period and for which we provide an additional estimate of mass loss due to area change. The front outline of the Jorge Montt and Upsala, as well as of Pio XI (SPI), was additionally digitized for a number of years between 2005 and 2017 (Appendix D, Table D1). This data is used for context in the Discussion (subsections Jorge Montt, Upsala and Pio XI) and is not employed for calculating mass balance.

Finally, we produce time series of mean observed glacier elevation change with the same methodology as Gray et al. (2015) and Foresta et al. (2016). The time series are generated at the catchment scale for each of the nine sub-regions with 90 (Pio XI, SPI-G2, SPI) or 120 days time step (Fig. 3).

3. Results

Swath processing of CryoSat-2 SARIn data provides 6.7 and 26.6 million valid observations of ice topography over the NPI and SPI, respectively, with the rate of elevation change for a single pixel being constrained by ~1700 elevations (median) over a period of 5.6 years (median) between April 2011 and March 2017. For comparison conventional CS2 POCA delivers about 17,000 and 55,000 observations over the NPI and SPI, respectively. Fig. 1 displays the maps of observed rates of elevation change over the Ice Fields. On the SPI, different catchments show distinct patterns of change over the study period (Fig. 1). Given such heterogeneity, we apply the hypsometric averaging model independently for six large glaciers on the SPI, namely Jorge Montt, Viedma, Upsala, Pio XI, Grey and Tyndall. The spatial coverage of \( k \) estimates, at 500 m posting, ranges between 61% and 73% of total catchment areas (Table 1), with the exception of Grey and Tyndall (~52%). We combine data from the rest of the SPI in two groups of neighbouring glaciers, labelled SPI-G1 and SPI-G2. The former includes all glaciers north of Pio XI and Viedma excluding Jorge Montt, while the latter is composed of all the glaciers west and south of Upsala excluding Grey and Tyndall (Fig. 1). Over the NPI, all glaciers are analysed together.

Combining data from different glaciers is needed if coverage is insufficient to provide a representative figure of elevation change in each and is justified providing that they show a similar pattern of change.

The observed median rates of elevation change for these nine sub-regions are shown as a function of cumulative surface aerial extent (10% steps; Fig. 1, side panels) and as a function of elevation (50 m steps; Fig. 2, side panels). Widespread thinning is occurring in the northern part of the SPI across all elevations, with average rates of \( 2 \text{ m a}^{-1} \) on the plateau up to and above 1400 m elevation (SPI-G1) and in excess of \( 10 \text{ m a}^{-1} \) at the terminus margins of Jorge Montt (tidewater), Viedma and Upsala (both lacustrine) glaciers. Most glaciers in the south/southwest are close to balance (SPI-G2), with the exception of Grey and Tyndall on the eastern side. Pio XI glacier is thickening at rates of ~2 and 1 m a\(^{-1}\) below 1000 m and between 1000 and 1500 m elevation, respectively, and thinning by about 1 m a\(^{-1}\) above 1500 m altitude. Similar to the northern part of the SPI, the NPI is experiencing widespread thinning of up to 8 m a\(^{-1}\) with the exception of the ice divide close to the eastern margin of the ice field (Figs. 1 and 2).

Hypsometric averaging is applied in each sub-region (Fig. 2, red lines) to generate maps of modelled elevation change rates for the Ice Fields (Fig. 2), from which mass change is computed (Table 1). The polynomial models (Fig. 2, red lines) compare well with the observed median rates of elevation change (Fig. 2, black lines with dots). A few exceptions are visible over the Tyndall and Upsala glaciers (at low and high elevation respectively) as well as over the Pio XI glacier below 1000 m and above 2500 m elevation. Model misfits have marginal impact on the glacier mass change when glacier area is negligible or data coverage is high (Fig. 2). For example the rate of mass loss of glacier Tyndall, assuming no elevation change below 350 m elevation, is reduced by about 9% (or 0.054 Gt a\(^{-1}\)), which is well within its associated uncertainty (Table 1). Similarly for Pio XI glacier, the thinning predicted by the model above 2500 m elevation reduces the glacier net mass gain by only 6% (or 0.04 Gt a\(^{-1}\)). However, at low elevation where the area of Pio XI glacier changes is negligible and where there are no observations to constrain the elevation change (Figs. 1 and 2), the impact of the misfit on the glacier mass balance may be significant (see Discussion). Between April 2011 and April 2017, the NPI and SPI have been losing mass at rates of \( -6.79 \pm 1.16 \text{ and } -14.50 \pm 1.60 \text{ Gt a}^{-1} \), respectively, contributing 0.059 ± 0.005 mm a\(^{-1}\) to eustatic SLR. About 35% of the SPI mass loss is concentrated on glaciers in the SPI-G1 group (~5.07 ± 0.79 Gt a\(^{-1}\)), which represent ~28% of the SPI surface. The Upsala glacier is the single largest contributor to the mass loss (~2.68 ± 0.40 Gt a\(^{-1}\)) and is also the glacier with the second highest rate of loss per unit area (Table 1) after Jorge Montt. Both glaciers have retreated between 2011 and 2017, by about 0.5 and 2.5 km, respectively. Pio XI is the only glacier in the Patagonian Ice Fields with positive mass balance (0.67 ± 0.29 Gt a\(^{-1}\)). Its southern tidewater and northern lacustrine termini have both advanced, respectively by about 500 m and 800 m during our study period. Using a dual density scenario, the rates of mass change in the nine sub-regions are lower by 11–19% compared to using the density of glacial ice at all elevations and the total rate of mass loss of the Ice Fields is 17.89 ± 2.03 Gt a\(^{-1}\) (Table 2). For most basins, dynamic processes are dominating the mass loss and hence the ice density scenario is the preferred option. However, in a few sectors the dual density scenario may be more accurate. For example, over the Pio XI glacier (SPI), where surface thickening is suspected (Malz et al., 2018), the mass change is 0.67 ± 0.29 Gt a\(^{-1}\) and 0.57 ± 0.25 Gt a\(^{-1}\) for the single and dual density scenarios, respectively.

Time series of mean observed glacier elevation change (Fig. 3) show negative trends for all sub-regions with the exception of Pio XI, which shows increasing elevation. Most sub-regions display a seasonal oscillation on the order of 1–3 m. The amplitude is highest (4 m) for the Grey Glacier, while it is less discernible for glaciers with the strongest mass losses per unit area (Jorge Montt and Upsala), possibly reflecting the importance of dynamic thinning also during the accumulation period.
Fig. 1. Maps of observed rates of surface elevation change of the Northern and Southern Patagonian Ice Fields between April 2011 and March 2017 based on CS2 L2swath elevations. The insets show observed median rates of elevation change (black lines with dots) against cumulative glacier surface area (10% steps), together with the uncertainty envelope (grey shade). Elevation (non-linear) is also shown for clarity.
Fig. 2. Maps of modelled rates of surface elevation change of the Northern and Southern Patagonian Ice Fields between April 2011 and March 2017 based on CS2 L2swath elevations. The insets show observed median rates of elevation change (black lines with dots) against elevation (50 m bands), together with the polynomial model (red line) fitted to the original rates of elevation change (not shown for clarity). The normalized histograms of the distribution of glacier area and data coverage versus elevation are shown in grey (continuous line and shaded patch, respectively).
4. Discussion

4.1. Spatial coverage

The Patagonian Ice Fields are a challenging region for radar altimetry. The topography is similar to mountain glaciers, with elevation ranging from sea level to above 2000 m over distances of < 30 km. Furthermore, the flow of most glaciers on the Ice Fields is almost perpendicular to CS2’s approximately north-south flight direction so that elevations change abruptly (> 1000 m) over short distances (400 m) along the flight track (Fig. 4), increasing the occurrence of loss-of-lock in the altimetric record and leading to gaps in the collected data (Dehecq et al., 2013). Over the Southern Patagonian ice field, conventional CS2 POCA altimetry provides about 30% spatial coverage at 500 m posting. Although swath altimetry is affected by loss-of-lock as much as POCA, enhanced spatial coverage is achieved because a swath of heights, rather than one single elevation, is acquired when the on-board tracker correctly sets the range window. Swath altimetry thereby provides 61–73% surface coverage over the large (A > 400 km²) glaciers in the northern part of the SPI and between 47% and 54% in other areas (Table 1). The only exception is SPI-G3 (39%), where the ice field is narrower and where there are no observations over a number of glaciers with relatively small surface area (Fig. 1 and Fig. 2, inset). Despite the limited extent, their mass loss may be non-negligible. For example HPS12 (south of Pio XI) has an area of 165 km² and lost 0.63 Gt a⁻¹ between 2000 and 2011/12 (Willis et al., 2012a, 2012b; Jaber et al., 2013; Jaber, 2016; Malz et al., 2018). In comparison, work based on high resolution radar TanDEM-X DEMs, optical ASTER DEMs achieve similarly high spatial coverage for decadal periods, decreasing to 57–73% for the entirety of the Ice Fields over shorter time periods comparable to that in this paper (Willis et al., 2012b). Despite CS2 L2swath’s lower spatial coverage, we still capture in detail the various patterns of change. Furthermore, using a single sensor and frequent repeat measurements is advantageous as it limits penetration biases associated both with using multiple sensor types (e.g. optical vs radar or radar with varying wavelengths) and seasonal variations in surface mass density, thereby limiting the impact on surface elevation change estimates (Jaber et al., 2013; Jaber, 2016; Willis et al., 2012b; Malz et al., 2018). Given the similarity of the Patagonian Ice Fields to mountain glaciers, swath altimetry may also provide one additional tool for monitoring elevation change over these complex areas (Paul et al., 2015).

4.2. Rates of mass change

Spatial patterns in the rates of surface elevation change (Figs. 1 and 2) are comparable with those observed over the period 2000–2011/16 (Willis et al., 2012a, 2012b; Jaber et al., 2013; Jaber, 2016; Malz et al., 2018). The

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### Table 1

Estimates of mass balance $M$ [Gt a⁻¹] and specific mass balance $m_b$ [m w.e. a⁻¹] as well as area $A$ [km²] and spatial coverage (%) of the maps of surface elevation change rates for the NPI and individual sub-regions of the SPI based on CS2 L2swath data at 500 m spatial resolution. Frontal retreat of Jorge Montt (SPI) amounts to an additional ~0.07 Gt a⁻¹ (see Discussion).

<table>
<thead>
<tr>
<th>Area [km²]</th>
<th>Coverage (%)</th>
<th>$M$ [Gt a⁻¹]</th>
<th>$m_b$ [m w.e. a⁻¹]</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPI</td>
<td>4046.4</td>
<td>45.7</td>
<td>6.79 ± 1.16</td>
</tr>
<tr>
<td>Jorge Montt</td>
<td>474.4</td>
<td>68.0</td>
<td>2.20 ± 0.38</td>
</tr>
<tr>
<td>Upsala</td>
<td>863.1</td>
<td>61.3</td>
<td>2.68 ± 0.40</td>
</tr>
<tr>
<td>Viedma</td>
<td>992.3</td>
<td>72.7</td>
<td>2.27 ± 0.36</td>
</tr>
<tr>
<td>SPI G1</td>
<td>3570.1</td>
<td>47.4</td>
<td>5.07 ± 0.79</td>
</tr>
<tr>
<td>SPI G2</td>
<td>4829.5</td>
<td>39.1</td>
<td>1.66 ± 1.16</td>
</tr>
<tr>
<td>Tyndall</td>
<td>332</td>
<td>49.9</td>
<td>0.60 ± 0.14</td>
</tr>
<tr>
<td>Grey</td>
<td>333.3</td>
<td>54.0</td>
<td>0.69 ± 0.23</td>
</tr>
<tr>
<td>Pio XI</td>
<td>1242.6</td>
<td>65.0</td>
<td>0.67 ± 0.29</td>
</tr>
<tr>
<td>SPI total</td>
<td>12,637.2</td>
<td>49.9</td>
<td>14.50 ± 1.60</td>
</tr>
<tr>
<td>NPI + SPI</td>
<td>16,683.6</td>
<td>21.9 ± 1.98</td>
<td>1.28 ± 0.12</td>
</tr>
</tbody>
</table>

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### Table 2

Estimates of mass balance $M$ [Gt a⁻¹] for the NPI and individual sub-regions of the SPI based on CS2 L2swath data at 500 m spatial resolution using two different density scenarios (see text).

<table>
<thead>
<tr>
<th>ELA [m]</th>
<th>Single density</th>
<th>Dual density</th>
<th>Abs Diff</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$M$ [Gt a⁻¹]</td>
<td>$M$ [Gt a⁻¹]</td>
<td>$M$ [Gt a⁻¹]</td>
</tr>
<tr>
<td>NPI</td>
<td>1005</td>
<td>-6.79 ± 1.16</td>
<td>-5.67 ± 1.26</td>
</tr>
<tr>
<td>Jorge Montt</td>
<td>930</td>
<td>-2.20 ± 0.38</td>
<td>-1.96 ± 0.41</td>
</tr>
<tr>
<td>Upsala</td>
<td>1170</td>
<td>-2.68 ± 0.40</td>
<td>-2.29 ± 0.46</td>
</tr>
<tr>
<td>Viedma</td>
<td>1260</td>
<td>-2.27 ± 0.36</td>
<td>-1.90 ± 0.40</td>
</tr>
<tr>
<td>SPI G1</td>
<td>1077</td>
<td>-5.07 ± 0.79</td>
<td>-4.17 ± 0.90</td>
</tr>
<tr>
<td>SPI G2</td>
<td>1096</td>
<td>-1.66 ± 1.16</td>
<td>-1.35 ± 1.03</td>
</tr>
<tr>
<td>Tyndall</td>
<td>940</td>
<td>-0.60 ± 0.14</td>
<td>-0.53 ± 0.14</td>
</tr>
<tr>
<td>Grey</td>
<td>980</td>
<td>-0.69 ± 0.23</td>
<td>-0.59 ± 0.20</td>
</tr>
<tr>
<td>Pio XI</td>
<td>930</td>
<td>+0.67 ± 0.29</td>
<td>+0.57 ± 0.25</td>
</tr>
<tr>
<td>NPI + SPI</td>
<td>-21.29 ± 1.98</td>
<td>-17.89 ± 2.03</td>
<td>3.40</td>
</tr>
</tbody>
</table>

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Fig. 3. Time series of cumulative mean observed elevation change for the nine sub-regions (Table 1), including the SPI as a whole (grey), in order of increasingly negative specific mass balance (top to bottom).
NPI and the northern part of the SPI (SPI-G1, Jorge Montt, Viedma and Upsala) are thinning very rapidly and account for 89% of the mass loss of the Patagonian Ice Fields between 2011 and 2017 (Table 1). The rate of mass loss of the Patagonian Ice Fields has increased in recent decades (Fig. 5a), with our estimated mass loss rate (21.29 ± 1.98 Gt a\(^{-1}\)) being 46% higher than between 1944 and 1996 (Aniya, 1999), 42% higher than between 1975 and 2000 (Rignot et al., 2003) and 24% higher than between 2000 and 2012/14 (Jaber, 2016). However, for the period 2000–2011/12 Willis et al. (2012b) estimate a total rate loss of 24.39 ± 1.20 Gt a\(^{-1}\), comparable to those based on gravimetry data (Chen et al., 2007; Ivins et al., 2011; Jacob et al., 2012; Gardner et al., 2013) but 30% more negative than that of Jaber (2016) (Fig. 5a). GRACE-based estimates rely on model predicted corrections for postglacial rebound and land water storage, which are a large source of uncertainty to the estimated rates of mass loss in Patagonia (e.g. Chen et al., 2007; Jacob et al., 2012). Additionally, mass loss from glaciers and ice fields in the vicinity (Möller and Schneider, 2008; Melkonian et al., 2013; Falaschi et al., 2017) may impact on the estimate since gravimetry methods are always sensitive to mass leakage effects from neighbouring areas (e.g. Sørensen et al., 2017). The disagreement between Willis et al. (2012b) and Jaber (2016) may be related to the 2 m elevation correction applied to the SRTM data by Willis et al. (2012b) in order to account for potential radar penetration through the glacier surface. However, analysis of the SRTM mean backscattering coefficient suggests wet surface conditions on the Ice Fields at the time of the SRTM acquisition (Jaber, 2016), which would be expected to prevent the radar signal from penetrating through the surface (Nilsson et al., 2015b). Additionally, Dussaillant et al. (2018) find that radar penetration over the NPI occurs only above 2900 m elevation, i.e. < 0.75% of the ice fields' area. In absolute value, this correction has a larger impact on the SPI than on the NPI (Willis et al., 2012b), where the estimates from Willis et al. (2012b) and Jaber (2016) differ by only ~10%.

Separating the contributions of the Ice Fields (Fig. 5b) shows the difference in the progressive increase in mass loss between the NPI and SPI. Between 2011 and 2017 the NPI's rate of loss (6.79 ± 1.16 Gt a\(^{-1}\)) is ~70% more negative compared to the previous decade (about 4 Gt a\(^{-1}\), Willis et al., 2012a, 2012b; Jaber, 2016; Dussaillant et al., 2018), which in turn was ~37% higher than between 1975 and 2000 (Rignot et al., 2003) (Fig. 5b). Compared to the latter, Rivera et al. (2007) record higher rates of mass loss in a similar time period (1979–2001) (Fig. 5b), but their estimate is based on data mostly lying in the ablation zone of the NPI. In contrast, the
mass loss over the SPI varies by just 8–10% between these three periods (Rignot et al., 2003; Jaber, 2016; Malz et al., 2018) (Fig. 5b) although its rate of loss is still more than twice that of the NPI. Estimates from Jaber (2016) and Malz et al. (2018), both based on comparing TanDEM-X data to the SRTM DEM, differ by 1.29 Gt a−1 although they agree within their uncertainties. The difference may be due to the 4 years longer time period analysed by Malz et al. (2018), who reported positive elevation changes in the southernmost part of the SPI between 2011/12 and 2015/16. We observe only a slightly positive trend in elevation change in this time period, followed by a marked drop after 2015/16 (Fig. 3, SPI-G2). However, our time series for SPI-G2 is representative of an area roughly twice as large than that analysed by Malz et al. (2018) over multiple time periods. Finally, the estimated SPI’s rate loss of 34.83 ± 3.96 Gt a−1 between 1995 and 2000 (Rignot et al., 2003), which is even more negative than any estimate for both Ice Fields combined (Fig. 5a), appears out of line with other values.

4.3. Glacier dynamics

We observe a sharp transition around 49° S (Figs. 1–2, dashed green line) from intense thinning in the north to a large area facing limited mass loss (SPI-G1), which spans about 4800 km² or about 40% of the total surface of the SPI (Table 2). This pattern is in agreement with earlier observations between 2000 and 2012/16 (Willis et al., 2012b; Jaber et al., 2013; Jaber, 2016; Malz et al., 2018), therefore suggesting constant behaviour over decadal time scales. The topography of the northern and southern parts of the SPI has different characteristics, with a greater proportion of the northernly ice field lying at lower altitudes. In fact, about 72% of SPI-G1’s surface lies below 1500 m elevation, about 12% more than SPI-G2’s at the same altitude (Fig. 1, insets SPI-G1 and SPI-G2). The Ice Field also narrows and steepens south of 49° S and even at low elevations the southern SPI shows only moderate thinning (Fig. 6). Glaciers Grey and Tydall, at the southeastern tip, are the exception to this pattern. However the latter lies almost entirely below 1500 m altitude (Fig. 1, inset Tydall) and both glaciers receive scarce precipitation due to their location east of the ice divide. The NPI has similar area-altitude distribution as SPI-G1 (Fig. 1, inset SPI-G1 and NPI) and the two areas show comparable mass losses per unit area (Table 1). However, the northern part of the SPI contains some of the fastest flowing glaciers on the Ice Fields, including Jorge Montt and Upsala (Sakakibara and Sugiyama, 2014; Mouginot and Rignot, 2015) which accelerated significantly (> 500 m a−1) in the period 1984–2000 (Jorge Montt) and 2000–2010 (Upsala), coincident with rapid frontal retreat (Sakakibara and Sugiyama, 2014). These observations confirm the importance of dynamics in impacting the overall mass balance of the northern part of the SPI (e.g. Sakakibara and Sugiyama, 2014; Mouginot and Rignot, 2015), where three of the largest glaciers (Jorge Montt, Upsala and Viedma) are thinning very rapidly (Table 1 and Fig. 1–3).

4.4. Jorge Montt glacier

Jorge Montt, a tidewater glacier at the northeastermost tip of the SPI, has been retreating since 1898 when it reached its LIA maximum extent (Rivera et al., 2012b). Its recession has been linked to fjord water depth, with periods of stable front positions corresponding to shallow depths and underwater pinning points (Rivera et al., 2012b). Additionally, water temperatures at depth (> 100 m) have been shown to be as high as 8 °C in summer 2012 only 1 km from the glacier front (Moffat, 2014), which may further destabilise the glacier through submarine melting (Straneo and Heimbach, 2013). By 2011 Jorge Montt had retreated almost 20 km w.r.t 1898, with the highest rates of recession between 1990 and 1997 (993 m a−1) occurring when water depths beneath the glacier increased sharply to ~300 m (Rivera et al., 2012b). The recent retreat history of Jorge Montt’s reveals a slowdown to about 100–300 m a−1 in the early 2000s, followed by increased retreat after 2009 initiated at a location where bathymetry data reveals the deepest trough in the fjord (Rivera et al., 2012b; Moffat, 2014; Fig. 7).

Between 2010 and 2011, Jorge Montt retreated almost 1 km (Rivera et al., 2012b; Rivera et al., 2012a) and calved at a rate of 2.4 km a−1, when the terminus was floating (Rivera et al., 2012a). Manual delineation of the glacier front between 2011 and 2017 using Landsat optical data (Fig. 7) indicates that Jorge Montt retreated by an additional ~2.5 km, likely through enhanced calving following retreat into deeper water (Rivera et al., 2012a). Given an average glacier freeboard height of 22 m above sea level at the terminus (Rivera et al., 2012a, 2012b) and width of 1.15 km, the glacier frontal retreat amounts to a mass loss rate of 0.07 Gt a−1 (~3% of the catchment’s loss due to thinning) between 2011 and 2017. This value is however likely underestimated since the slope of the glacier surface, and thus upglacier thickening, has not been considered. Due to the uncertainty associated with this calculation, and that at least part of the glacier terminus was floating in 2010/11 (Rivera et al., 2012a) and likely during our observational period, we report this loss separately in Table 1 and do not include it in our total estimate of glacier contribution to sea level rise. Between 2011 and 2017, Jorge Montt shows the highest mass loss per unit area, 4 times above the average for the SPI as a whole (Table 1). Its absolute rate of mass loss (2.20 ± 0.38 Gt a−1) is comparable to what reported by Jaber (2016) for the period 2011–2014 (2.59 Gt a−1, uncertainty not reported), which increased by 50% compared to the 1.72 Gt a−1 (uncertainty not reported) rate of mass loss between 2000 and 2011 (Jaber, 2016).

4.5. Upsala glacier

Upsala, a freshwater calving glacier located on the north-eastermost side of the SPI and draining into Argentine Lake, has also been retreating since the late 1970s (Naruse et al., 1997). Between 2008 and 2011, retreat rates quadrupled w.r.t the previous 8 years and the glacier retreated by almost 3 km (Sakakibara et al., 2013), while simultaneously speeding up by
Fig. 6. Median observed rates of surface elevation change for the two Ice Fields every tenth of a degree of latitude and for different elevation bands at [0-800 m], [800-1000 m], [1000–1200 m], [1200–1500 m], [1500–1800 m] and [1800–2200 m]. The Pio XI glacier is not included in this analysis due to its anomalous and unique behaviour (see Discussion). Note that the scale on the x-axis varies to display the strong thinning at lower elevations.

Fig. 7. Frontal retreat of Jorge Montt Glacier (SPI). The glacier retreated almost 2 km between 2000 and 2011 and receded a further ~2.5 km in our study period. Water depth at the glacier front was 400 m in 2013. Bathymetry data after Piret et al. (2017).
20–50% (Sakakibara et al., 2013; Mouginot and Rignot, 2015) and thinning at a maximum rate of ~40 m a\(^{-1}\) near the terminus (Sakakibara et al., 2013). The rapid retreat may have been caused by the glacier front reaching an area where the lake depth exceeds 560 m (Sugiyama et al., 2016). In early 2013 the glacier's velocity at the front was 2.9 m d\(^{-1}\) (Moragues et al., 2018), ~33% lower compared to 2008 and more similar to values recorded in the early 2000s (Sakakibara et al., 2013). Moragues et al. (2018) report a doubling in maximum velocity between 2013 and 2014. However this increase is unlikely to have been sustained in time. In fact, between 2011 and 2017, the glacier front has been comparatively stable (Fig. 8), with a retreat rate of ~85 m a\(^{-1}\) similar to the period 2000–2008 (Sakakibara et al., 2013). Coincident with a more stable front position, the average thinning rate within 16 km of the terminus decreased by a factor two from 13.4 m a\(^{-1}\) between 2006 and 2010 (Sakakibara et al., 2013) to 6.2 m a\(^{-1}\) between 2011 and 2017 (Fig. 8). Bertacchi Glacier, a tributary of Upsala, shows a similar pattern with current rates of elevation change decreasing to 8.5 m a\(^{-1}\) (Fig. 8) from ~15 m a\(^{-1}\) between 2008 and 2011 (Sakakibara et al., 2013). We observe maximum thinning rates of ~12 m a\(^{-1}\) 5 km from the terminus of Upsala glacier, comparable to estimates at the front in the early 1990s (Naruse et al., 1997). Despite these reduced thinning rates, Upsala remains the glacier with the second most negative specific mass balance in the Patagonian Ice Fields after Jorge Montt, and is the largest single contributor to net mass loss amongst individual glaciers (Table 1 and Figs. 1–3).

4.6. Pio XI glacier

Pio XI, the largest glacier on the SPI and in South America, is the only glacier of the Patagonian Ice Fields to have experienced a net large advance since 1926 and the only known surge-type glacier on the SPI (Rivera et al., 1997a; Wilson et al., 2016). Published data of frontal changes, ice flow velocity at the termini, elevation change and mass balance, summarized in Fig. E1, reveal a complex history (Appendix E). Between 1951 and 1963, the glacier's westward and southward advance dammed a proglacial river originating from Greve glacier to the north, forming the current Lake Greve for at least the second time since 1926 (Rivera et al., 1997a). Since then, the glacier has been terminating in Ejre Fjord to the south and Lake Greve to the north. From 1945 to present, the tidewater terminus advanced ~13 km and is currently at its Neoglacial maximum (Wilson et al., 2016; Fig. 9 and Fig. E1). Looped supraglacial moraines were used to identify up to six surge events since 1926 (Rivera et al., 1997a; Wilson et al., 2016), two of which were concurrent with front retreat, possibly due to enhanced calving at the tidewater terminus (Wilson et al., 2016; Fig. E1). The glacier has been thickening in the ablation area since the late 1970s, with the highest rates recorded at the termini, while the picture is more complicated in the accumulation area where data is sparse (Fig. E1). Between 2011 and 2017, we observe thickening at almost all elevations, by about 2.33 m a\(^{-1}\) and 0.57 m a\(^{-1}\) (median value) in the ablation and accumulation areas respectively (Fig. 1; Pio XI inset) with thinning at the highest elevations above 1500 m altitude; findings which match those described in Jaber (2016). There is however no coverage in our data close to the two termini. Assuming a thickening trend at the two fronts, which was sustained for the last four decades (Rignot et al., 2003; Willis et al., 2012b; Jaber et al., 2013; Jaber, 2016; Wilson et al., 2016), we estimate that the Pio XI glacier is gaining mass at a rate of 0.67 ± 0.29 Gt a\(^{-1}\) between 2011 and 2017 (Table 1 and Fig. E1). However the rate is likely underestimated since the hypsometric averaging model for Pio XI glacier predicts less thickening compared to the observations below 1000 m elevation (Fig. 2, inset). The mass gain is likely a result of complex dynamics associated with both surge mechanisms and terminus calving processes, since Pio XI is the only advancing glacier within the Patagonian Ice Fields and air temperature has increased over the last 50 years (Rasmussen et al., 2007).

5. Conclusions

CryoSat-2 swath radar altimetry is employed successfully to map elevation change over the Patagonian Ice Fields at sub-kilometer spatial resolution. Despite the challenging topography, similar to that of mountain glaciers, the technique can be used to observe changes over individual glaciers or catchments with an area as small as 300 km\(^2\). The northern part of the SPI displays a high degree of complexity, although most of the area is thinning at all elevations, with Jorge Montt, Viedma and Upsala glaciers losing mass at rates higher than 2 Gt a\(^{-1}\). Jorge Montt additionally

Fig. 8. Front location of Upsala glacier (SPI). The glacier receded about 500 m between 2011 and 2017. Thinning rates from this study are also shown in the range ~10 to 0 m a\(^{-1}\).
The Pio XI glacier, which is currently at its Neoglacial maximum, is estimated to have gained mass at a rate of $0.67 \pm 0.29 \text{ Gt a}^{-1}$ during our study period. Between April 2011 and March 2017, the Ice Fields lost mass at a combined rate of $21.29 \pm 1.98 \text{ Gt a}^{-1}$ (equivalent to $0.059 \pm 0.005 \text{ mm a}^{-1}$ eustatic sea level rise), an increase of 24% and 42% when compared to the periods 2000–2012/14 and 1975–2000, respectively. We find that the NPI ($-6.79 \pm 1.16 \text{ Gt a}^{-1}$), which is responsible for a third of the total loss, is losing mass 70% faster compared to the first decade of the 21st century. Given the ongoing and rapid wastage of the Patagonian Ice Fields, and their important contribution to the global budget of mass loss from glaciers and ice caps, continuous observations with excellent spatial and temporal resolution are essential. CS2 swath altimetry provides an important tool for monitoring these rapidly changing areas and quantifying their ongoing mass loss.

Acknowledgments

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Appendix A. Filtering CS2 SARIn waveform samples

Selecting waveform samples based on fixed thresholds on coherence and power is an empirical approach which has been applied successfully to infer glacial topography and higher products based on it such as topography changes (Gray et al., 2013; Christie et al., 2016; Ignéczi et al., 2016; Foresta et al., 2016; Gourmelen et al., 2017a). However, in this paper we use a different procedure to discard noisy waveform samples before performing the phase unwrapping. This method relies entirely on the phase difference field and consists in identifying, within each waveform, groups of consecutive samples which can be modelled by a straight line. The original phase difference is divided into overlapping segments, their length being set to 64 samples and the overlap half of the length. The slope of the phase difference is then calculated independently in each segment. Instead of applying a linear regression, the algorithm applies a Fourier transform on the normalized complex coherence $\hat{\phi}$, where $\phi$ is the phase difference field. Compared to linear regression, this approach is both more efficient computationally as well as independent on phase wrapping. The Fourier transform enables to testing a large number of possible slopes and the one with the highest correlation with the input data is selected. The signal is oversampled to take into account that the slope of CS2’s phase difference can represent non-integer frequencies. Thus, each overlapping section has two possible slopes. A correlation is applied again to the data in each overlapping section, this time using only its two estimated slope values. Sections whose correlation is below a set threshold (for this work, 0.95) are considered noisy and discarded. Finally, the remaining segments are used to unwrap the phase difference. With this procedure, no smoothing is applied to the phase difference and no threshold is set on the power or coherence.

Appendix B. SRTM DEM correction

A number of freely available DEMs covering Southern Patagonia exist, namely: the SRTM (i) C and (ii) X band DEMs (Farr et al., 2007), the (iii) ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) GDEM2 (Tachikawa et al., 2011) and (iv) the ALOS (Advanced Land
Observing Satellite) AW3D30 v1.1 (Tadono et al., 2014; Takaku et al., 2014; Tadono et al., 2016; Takaku et al., 2016). The latter is the most recent, but has large gaps over the SPI, which are filled using the SRTM C band DEM. Version 1 of the ASTER GDEM was known to be affected by large artefacts (Arefi and Reinartz, 2011) and, despite large overall improvements, version 2 still has high frequency noise, particularly over glacial terrain (Meyer et al., 2011). Visual comparison between the SRTM C band and ASTER GDEM2 DEMs shows evident noise in the latter, with differences at times on the order of tens of meters between neighbouring pixels. Finally, the SRTM X band DEM does not have complete coverage and gaps over the Ice Fields are significant. Therefore, we used the SRTM C band DEM as a reference for elevation, which fully covers the Patagonian Ice Fields, resampled at 300 m posting and referenced to the WGS84 vertical datum. The down-sampling of the DEM is mostly dictated by achieving a satisfactory performance in computing time while keeping the spatial resolution somewhat comparable to that of an individual elevation based on CryoSat-2 interferometric data (300 m in the along-track direction). We use linear interpolation when querying the DEM.

The SRTM DEM is based on data acquired in February 2000, and a few areas at the margins of the SPI have thinned by at least 80 m since then (Willis et al., 2012b; Jaber et al., 2013; Jaber, 2016). This magnitude is comparable to the elevation offset caused by a 2π shift on CS2’s phase (Data and methods, this paper; Fig. 3 in Gourmelen et al., 2017a, 2017b). Thus, over areas which experienced intense thinning rates, the swath algorithm may select an incorrect 2π multiple which best matches current observations to the glacier topography from 2000. In order to avoid that, the SRTM DEM needs to be registered to the beginning of our study period. To this purpose, we applied a first order correction of the SRTM DEM based on a visual inspection of results in Willis et al. (2012b) and assuming constant rates of elevation change between the SRTM and CS2 periods. This approach was sufficient to improve the phase unwrapping, leading to further pixels meeting the quality criteria for robust rates of surface elevation change. We refer to this corrected DEM simply as the SRTM DEM in this study. The correction of the SRTM DEM only affects the terminus areas of Jorge Montt and Upsala glaciers (SPI) since there are no CS2 swath altimetry observations over smaller glaciers on the Ice Fields which experienced similar thinning rates in the period 2000–2011/12 (e.g. HPS12, SPI; Willis et al., 2012b; Jaber et al., 2013; Jaber, 2016).

Appendix C. Error budget

The errors on the mass balance estimates are calculated as in Foresta et al. (2016). The uncertainties \( \epsilon_h \) on the observed rates of elevation change for the individual pixels, extracted from the model covariance matrix (see Data and methods), are propagated when applying the hypsometric averaging method:

\[
E_h(k) = \sqrt{\sum_{m=1}^{N(k)} \epsilon_h(m)^2} \frac{N(k)}{A(k)}
\]

where \( E_h(k) \) is the elevation change error in elevation band \( k \) and \( N(k) \) is the number of valid observations in the elevation band. A two-term decreasing exponential is used to interpolate values for elevation bands with no observations (e.g. at low elevation for bands with limited spatial extent). We multiply the area extent \( A(k) \) of the elevation band to the related \( E_h(k) \) and sum all contributions to estimate the total uncertainty on the rate of volume change:

\[
E_V = \sum_k E_h(k) A(k).
\]

With this method, the volume change uncertainty is only related to that area of the ice cap where there are valid rates of surface elevation change, but does not account for incomplete data coverage. The volume change uncertainty is therefore rescaled according to the data coverage (Table 1). This procedure generates a rather conservative (i.e. larger) error estimate since it assumes that the lack in data coverage has a direct impact on the total error estimate, which does not hold if the sampling is sufficiently uniform. Finally, we include an error on the density:

\[
E_p = \frac{1}{2} (\rho_{ref} - \rho_{obs})
\]

when converting volume to mass change (e.g. Nilsson et al., 2015a).

Appendix D. Landsat scenes

Table D1
List of Landsat scenes used to manually delineate the front positions of glaciers Jorge Montt, Upsala and Pio XI (SPI).

<table>
<thead>
<tr>
<th>Glacier</th>
<th>Year</th>
<th>Scene ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jorge Montt</td>
<td>2005</td>
<td>LT52310942005050COA00</td>
</tr>
<tr>
<td></td>
<td>2009</td>
<td>LE723209420916EDC00</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>LE7231094201088COA00</td>
</tr>
<tr>
<td></td>
<td>2011</td>
<td>LE72320942011050EDC00</td>
</tr>
<tr>
<td></td>
<td>2013</td>
<td>LE72320942013087ASN00</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>LCS2310942014075LGNN00</td>
</tr>
<tr>
<td></td>
<td>2015</td>
<td>LCS2310942015021LGNN00</td>
</tr>
<tr>
<td></td>
<td>2016</td>
<td>LCS2310942016072LGNN00</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>LCS2310942017106LGNN00</td>
</tr>
<tr>
<td>Upsala</td>
<td>2011</td>
<td>LE72310952011123EDC00</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>LCS2310952017035LGNN00</td>
</tr>
<tr>
<td>Pio XI</td>
<td>2011</td>
<td>LE07_L1TP_232094_20110219_20161210_01_T1</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>LCO8_L1TP_231094_20140401_20170424_01_T1</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>LCO8_L1TP_231094_20170204_20170216_01_T1</td>
</tr>
</tbody>
</table>
Appendix E. Pio XI glacier (SPI): summary of published data

Fig. E1 summarises published data of frontal changes, ice flow velocity at the fronts, elevation change and mass balance (Rivera et al., 1997a; Rivera et al., 1997b; Rivera and Casassa, 1999; Rignot et al., 2000; Lopez et al., 2010; Willis et al., 2012b; Jaber et al., 2013; Sakakibara and Sugiyama, 2014; Wilson et al., 2016).

Fig. E1. Chart summarizing published data for the Pio XI glacier (SPI). (a) Cumulative front advance of the tidewater and lacustrine termini; (b) ice flow velocity; (c) mass change. Elevation change in the (d) ablation and (e) accumulation area. Potential surges concurrent with advance (Rivera et al., 1997a) or retreat (Wilson et al., 2016) of the tidewater front are highlighted in light and dark grey, respectively. All relevant references are listed in the inset.


