Drivers of modern New Zealand glacier change

Lauren J Vargo

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ABSTRACT

Glaciers across the Southern Alps of New Zealand have been photographed annually since 1977, creating a rare record of Southern Hemisphere glacier change. Here, we revisit these historic photographs and use structure from motion photogrammetry to quantitatively measure glacier change from the images. To establish this new method, it is initially applied to Brewster Glacier (1670 – 2400 m a.s.l.), one of the 50 monitored glaciers. We derive annual equilibrium line altitude (ELA) and length records from 1981 – 2017, and quantify the uncertainties associated with the method. Our length reconstruction shows largely continuous terminus retreat of 365 ± 12 m for Brewster Glacier since 1981. The ELA record, which compares well with glaciological mass-balance data measured between 2005 and 2015, shows pronounced interannual variability. Mean ELAs range from 1707 ± 6 m a.s.l. to 2303 ± 5 m a.s.l. The newly developed ELA chronology from Brewster shows several years since 1981 with especially high mass loss, all of which occurred in the past decade. Investigation using reanalysis data shows that these extreme mass-loss years occur when surface air temperatures, sea surface temperatures, and mean sea level pressure are anomalously high. In particular, the three highest mass-loss years on record, 2011, 2016, and 2018, each had a 2-month mean surface air temperature anomaly of at least $+1.7^\circ\text{C}$ between November and March, which is exclusive to these three years over the time investigated (April 1980 – March 2018). Using event attribution — a methodology using climate model simulations with and without human-induced forcings to calculate the anthropogenic influence on extreme events — we calculate the anthropogenic influence on these surface air temperature anomalies. The positive temperature anomalies during extreme mass-loss years have probabilities of $0 - <1\%$ of occurring in a natural world, but probabilities of $1 - 10\%$ of occurring with anthropogenic forcing, showing a clear human influence on the drivers of extreme glacier mass loss. Finally, we use event attribution methods, with the added step of simulating glacier mass balance, to calculate the anthropogenic influence on the two highest glacier mass-loss years: 2011 and 2018. We show that mass loss in 2011 was at least 10 times ($>90\%$ confidence) more likely to occur with anthropogenic forcing, and in once case in 2018 could not have occurred ($>90\%$ confidence) without anthropogenic forcing. This increased likelihood is driven by present-day temperatures $\sim 1.0^\circ\text{C}$ above the pre-industrial average, confirming a connection between rising anthropogenic greenhouse gases, warming temperatures, and high annual ice loss.

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DEDICATION

To Trevor - this work was made possible through your love of the mountains,
your curiosity of glaciers, and your foresight to begin the snowline survey

Chapter 1

Introduction

Glaciers are iconic sentinels of climate change, and are often used as evidence of anthropogenic warming. Fluctuations in glacier mass balance (accumulation minus ablation) are largely driven by changes in temperature and precipitation. Glacier length is a result of mass balance integrated over years to decades for each glacier (Oerlemans, 2005). Therefore, glacier retreat reflects long-term climate trends (Oerlemans, 2010). Glaciers around the world have been retreating to historical minimum lengths (Zemp et al., 2015) and decadal mass-loss rates have been increasing since 1980 (Zemp et al., 2019), suggesting that increasing temperatures (Masson-Delmotte et al., 2018) are dominating modern glacier change.

While New Zealand glaciers contain less than 1 mm of sea level equivalent (Radić and Hock, 2010; Huss and Hock, 2015), they are important for water resources, tourism, and biodiversity (e.g. Fitzharris et al., 1999; Chinn, 2001; Purdie, 2013; Anderson et al., 2016). Studying how and why New Zealand glaciers are changing is important for having complete global inventories of glacier change (e.g. Hock et al., 2019; Zemp et al., 2019), and for understanding how other less accessible and less extensively studied glaciers may be changing (e.g. Horgan et al., 2015). The maritime climate that characterizes New Zealand glaciers makes them interesting to study (e.g. Anderson and Mackintosh, 2012), and to compare with more continental glaciers (e.g. Medwedeff and Roe, 2017). New Zealand glaciers also provide rare records of Southern Hemisphere glacier change. Past reconstructions of New Zealand glacier advances and retreats have been used to show paleoclimate similarities and differences between Northern and Southern Hemispheres (e.g. Denton and Hendy, 1994; Schaefer et al., 2009; Kaplan et al., 2010).

Finally, the glaciers of New Zealand were well known to Māori, the original inhabitants of Aotearoa New Zealand. Several glaciers have individual names, including Franz Josef/Kā Roimata o Hine Hukatere, translating roughly to ‘the tears of Hine Hukatere’. According to legend, the snow maiden Hine Hukatere once persuaded her lover Wawe to accompany her in the mountains, but Wawe

slipped and fell. After Wawe’s death, Hine Hukatere never left the mountains, but instead wanders the ice looking for Wawe and crying tears of ice that feed the glacier, pushing it slowly towards the sea (Grzelewski, 1993).

1.1 Global glacier change

The World Glacier Monitoring Service collates data on glacier fluctuations, including mass-balance, length, area, and volume measurements (WGMS, 2018). Included in this database are hundreds of years of observations and reconstructions of glacier length, and decades of glaciological and geodetic mass-balance measurements (Zemp et al., 2015). Glaciological mass-balance measurements are made by measuring mass balance at points on a glacier and then interpolating those points over the glacier surface. Geodetic mass-balance measurements are made by differencing elevation models and then using density to convert volume changes to mass changes. These records of glacier change show that glacier retreat over the past century is occurring globally, and that measured mass-loss rates are unprecedented within observations (Zemp et al., 2015; WGMS, 2018). Included in the inventory are ‘reference glaciers’, glaciers with over 30 years of ongoing glaciological mass-balance measurements (Zemp et al., 2009). There are presently 41 reference glaciers, 40 of which are in the Northern Hemisphere (Fig. 1.1). These reference glaciers show that extreme mass-loss years, defined as the 90th percentile of negative mass balances for each individual glacier, are becoming more common for most glaciers around the world (Fig. 1.1).

1.2 New Zealand glaciers in a global context

Many studies looking to understand how glaciers are changing and will change in the future use general circulation model (GCM) output for simulations of different Representative Concentration Pathway (RCP) scenarios as inputs into glacier models. RCP scenarios reflect different possible trajectories of greenhouse gas concentrations in the atmosphere from 2000 – 2100. There are four different RCP scenarios, 2.6, 4.5, 6.0, and 8.5. RCP8.5 includes the highest greenhouse gas emissions, is often referred to as the ‘worst case scenario’, and is the scenario that global emissions are closest to as of 2018 (Riahi et al., 2011; Meinshausen et al., 2011; Le Quéré et al., 2018).

Previous works have measured how New Zealand glaciers have changed and projected how they may change in the future as parts of global studies, largely to quantify the contribution of glaciers to sea level rise (e.g. Meier, 1984; Kaser et al., 2006; Radić and Hock, 2011; Huss and Hock, 2015; Bosson et al., 2019).

Figure 1.1: All global glaciers (RGI, 2017) (black), including all glaciers with >30 years of ongoing mass-balance measurements (WGMS, 2018) (open black circles). Pie charts show the timing, by decade, of extreme mass-loss years for each glacier, with the years of mass-balance measurements noted. Extreme mass-loss years are defined as the 90th percentile of negative mass balances for each individual glacier.

However, these measurements and projections are characterized by large uncertainties. From 2006 – 2016, New Zealand glaciers were losing mass at a rate of $\sim 1.1\%$ each year, with a specific mass-change rate of -0.68 ± 1.15 m w.e. per year, a higher uncertainty than any other region (Fig. 1.2) (Zemp et al., 2019). One global study calculated New Zealand glacier area and contribution to sea level rise from 2003 – 2009 using glaciological measurements (Gardner et al., 2013), despite direct mass-balance measurements from only one New Zealand glacier within that time (Cullen et al., 2017). In the future, New Zealand glaciers are projected to lose from $\sim 15 - 95\%$ of their volume by 2100 (Radić and Hock, 2011; Huss and Hock, 2015). The large uncertainty is due to different RCP scenarios (RCP2.6, RCP4.5, and RCP8.5) and differences between GCMs. A recent glacier model comparison study looking to reduce uncertainties in global glacier projections suggests that New Zealand glaciers will lose 44 – 89% of their volume by 2100, following RCP8.5 (Hock et al., 2019). These studies show that past and future New Zealand glacier change has higher uncertainties than most other regions globally (Fig. 1.2) (Hock et al., 2019; Zemp et al., 2019), with some global studies excluding New Zealand glaciers from parts of analysis due to a lack of data (Zemp et al., 2015). These large uncertainties, especially in the regional specific balance (Zemp et al., 2019), high-

lights the need for more regional measurements to better constrain New Zealand glacier changes.

Figure 1.2: Estimates for annual glacier mass-change rates in meters of water equivalent per year from 2006 – 2016. Error bars show 95% confidence intervals (figure modified from Zemp et al. (2019)).

1.3 Measuring New Zealand glacier change

Field-based observations and remote sensing measurements have been used to monitor the current state of New Zealand glaciers, and changes in the glaciers over time. Approximately 3150 glaciers existed in 1978, with a total area of 1158 km² and volume of 54.5 km³ (Chinn, 2001). As of 2016, New Zealand glaciers covered an area of about 858 km², a reduction of 29% since 1978 (Baumann et al., in review). Approximately 24% of the number of glaciers disappeared completely between 1978 and 2016 (Baumann et al., in review). The majority of New Zealand glaciers are in the South Island, with investigations of specific glaciers focused primarily on Haupapa/Tasman, Fox/Te Moeka o Tuawe, Franz Josef/Kā Roimata o Hine Hukatere, Ivory, Brewster, and Rolleston Glaciers (e.g. Anderton and Chinn, 1978; Anderson et al., 2008, 2010; Purdie et al., 2014, 2015; Cullen et al., 2017). Length records from Franz Josef/Kā Roimata o Hine Hukatere and Fox/Te Moeka o Tuawe Glaciers, which are among the longest records in the Southern Hemisphere, show major advances from ~1983 – 2008 (Purdie et al., 2014), a time when most glaciers around the world were retreating (Zemp et al., 2015; WGMS, 2018). Mass balance is currently only directly measured for Brewster (since 2005) and Rolleston (since 2010) Glaciers (Stumm, 2011; Purdie et al., 2015; Cullen et al., 2017).

Mass balance has been monitored indirectly from aerial photographs through

the end-of-summer-snowline survey since 1977 (Chinn, 1999; Chinn et al., 2012). At the end of the accumulation season, winter snowpack on a glacier is close to a maximum, with the greatest snow depths at the highest altitudes and decreasing snow depths with elevation. During the following ablation season, this snowpack melts and exposes bare glacier ice and firn. This boundary between fresh snow and exposed ice or firn is referred to as the snowline. Throughout the ablation season, as melt continues, this transient snowline becomes higher in elevation, until reaching a maximum elevation at the end of the ablation season. This maximum elevation snowline at the end of the ablation season is the end-of-summer-snowline. The end-of-summer-snowline is hereafter referred to as the snowline in this thesis, and discussion of snowlines measured at other times are referred to as transient snowlines. The snowline can be visually identified in photographs as the boundary between fresh snow from the previous winter in the accumulation area (above the snowline) and darker firn or glacier ice of the ablation area (below the snowline) (Fig. 1.3). The snowline elevation is an approximation for the annual equilibrium line altitude (ELA), and can therefore be used to infer changes in mass balance (LaChapelle, 1962; Oerlemans, 2010). Throughout this thesis, snowline elevation and ELA are used interchangeably.

Figure 1.3: Example end-of-summer-snowline (EoSS; black) digitized on Brewster Glacier, 2009.

Glaciers across the Southern Alps of New Zealand have been photographed since 1977 with the goal of capturing the snowline (Chinn, 1999; Chinn et al., 2012). At the end of the mass-balance year (March – April), 50 glaciers are photographed by hand from a light aircraft (Fig. 1.3) (Willsman et al., 2018). The original snowline chronology calculates mean annual ELA deviations from ELA_0 , which is considered to be an equilibrium state ELA (Fig. 1.4) (Willsman et al., 2018). Negative departures indicate low snowline elevations and positive mass-balance years, and positive departures indicate high snowline elevations and

negative mass-balance years (Fig. 1.4). The chronology shows high interannual variability, suggesting both positive and negative mass-balance years have occurred since 1977. However, the chronology also shows that since ~ 2006 there have been several years with especially high snowline elevations, and no years with the low snowline elevations that characterized previous years (1983 – 1985, 1991 – 1996, 2003 – 2005) (Fig. 1.4).

Figure 1.4: Original end-of-summer-snowline record (1977 – 2017) showing raw (black) and normalized (red) mean ELA departures (m) (figure modified from Willsman et al. (2018)).

In this original snowline record, ELAs were calculated by either: 1) manually transcribing the snowline from oblique photographs onto a base map, digitizing the maps, and using the total ablation area and the glacier’s area-altitude curve to calculate the mean ELA; 2) visually arranging images for all years by decreasing snow cover, allowing a visual comparison and ELA estimate to be made based on the entire historic sequence; or 3) when the snowline is not visible or clear in the image, following the same steps as in 2), but comparing the size of annual snow patches surrounding each glacier (Willsman et al., 2015). All of these approaches are qualitative, and therefore have a relatively low repeatability and provide little transparency about how past ELAs were initially determined. Additionally, these approaches do not contain clear estimates of error for how each photograph and snowline was evaluated. Finally, the sole output of the survey is a record of snowline elevations (Fig. 1.4), despite images also recording changes in glacier length and area.

Advances in the photogrammetric technique structure from motion photogrammetry (SfMP) have enabled quantitative measurement of glacier change from photographs. Previous works have successfully used SfMP with modern photographs in Earth Science research, including to quantify changes in snow depth, and glacier

volume and mass balance (Westoby et al., 2012; Nolan et al., 2015; Piermattei et al., 2015). SfMP uses multiple, overlapping images of an object to match features automatically identified in the images. The software can then be used to generate a 3D model of the object, and solve for interior and exterior camera parameters, including the location from which images were taken. These techniques therefore provide the means to 1) calculate the camera parameters for historic snowline images in order to quantitatively measure past glacier changes, and 2) generate 3D models using modern, georeferenced photographs, in order to measure modern glacier snowline elevations and lengths.

1.4 New Zealand glacier response to climate

New Zealand glaciers are characterized by a maritime climate and high precipitation, which increases from east to west, of $\sim 2 - 10$ m per year (Henderson and Thompson, 1999; Tait et al., 2006; Cullen and Conway, 2015). This maritime climate, as well as large-scale atmospheric circulation, have been shown to heavily influence New Zealand glacier mass balance (Chinn, 1995; Fitzharris et al., 1997; Clare et al., 2002). Enhanced southerly and westerly flow leads to more positive mass balance, and enhanced northerly and northeasterly flow leads to more negative mass balance (Fitzharris et al., 1997; Clare et al., 2002; Fitzharris et al., 2007; Mackintosh et al., 2017). Positive sea surface temperature anomalies and positive atmospheric pressure anomalies have been linked with glacier mass loss (Clare et al., 2002; Fitzharris et al., 2007; Mackintosh et al., 2017).

Large-scale circulation patterns are connected with climate oscillations and have been shown to influence New Zealand climate. These oscillations include El Niño Southern Oscillation, the Southern Annular Mode (SAM), and the Interdecadal Pacific Oscillation (IPO) (Jiang et al., 2013). Specific connections have been made between El Niño events, SAM and the IPO, and glacier mass balance (Fitzharris et al., 1992, 1997, 2007; Purdie et al., 2011). Negative phases of SAM and the IPO and El Niño events are linked with enhanced westerly or southerly flow, lower temperatures in the Southern Alps, and lower sea surface temperatures around New Zealand, leading to glacier advance and positive mass-balance years (Fitzharris et al., 1992, 1997, 2007; Purdie et al., 2011). Positive phases of SAM and the IPO and La Niña events are linked with enhanced northerly or easterly flow, increased temperatures in the Southern Alps, and increased sea surface temperatures around New Zealand, leading to more negative mass-balance years (Fitzharris et al., 1992, 1997, 2007; Purdie et al., 2011). The large-scale atmospheric wave pattern, Zonal Wave 3, for which certain phases encourage southerly flow in the New Zealand region, has also been linked with periods of glacier ad-

vance and positive mass balance (Mackintosh et al., 2017).

1.5 New Zealand glacier modeling

Numerical models are often used to simulate glacier mass balance in order to understand the drivers of past or modern glacier change and to project how glaciers may change in the future. The degree-day, or temperature index, model is commonly used to simulate glacier surface mass balance as it is 1) computationally inexpensive, and 2) calculates melt using air temperature, which is more widely available than other measures of climate (e.g. Jóhannesson et al., 1995; Oerlemans et al., 1998; Hock, 2003). In the degree-day model, accumulation is calculated when mean daily temperature is less than a threshold, usually $0 - 1^{\circ}\text{C}$, and when daily precipitation is >0 . Melt (M) is calculated following:

$$M = M_T T \quad (1.1)$$

using daily positive temperature sums (T) and a temperature factor (M_T) that is commonly determined for individual glaciers or regions through model calibration (e.g. Hock, 2003). The degree-day model has been shown to accurately simulate glacier mass balance, especially on a catchment scale (Hock, 2005). However, the degree-day model assumes an empirical relationship between temperature and melt, compared with the physically-based approach of calculating the energy available for melt using an energy balance model (Hock, 2003).

To improve upon the degree-day model, an enhanced degree-day model that uses an added input of radiation has been established (Hock, 1999; Pellicciotti et al., 2005). In this enhanced degree-day model, melt (M) is calculated following:

$$M = M_T T + M_R(1 - a)Q \quad (1.2)$$

using a radiation factor (M_R), albedo (a), and incoming shortwave radiation (Q) added to the original melt calculation. This enhanced degree-day model, using temperature, precipitation, and incoming shortwave radiation as inputs, has been shown to simulate glacier mass balance almost as accurately as the physically-based energy balance model that includes all energy fluxes to and from the glacier surface, without requiring as many inputs as the energy balance model (Pellicciotti et al., 2005; Carenzo et al., 2009). This thesis therefore uses an enhanced degree day model, developed following Pellicciotti et al. (2005), to simulate glacier mass balance.

Glacier modeling has been used in regional studies to investigate the links between climate and New Zealand glacier mass balance. Previous analyses of modern

New Zealand glacier changes show high sensitivity to temperature and precipitation, (Oerlemans, 1997; Anderson and Mackintosh, 2006, 2012; Mackintosh et al., 2017), with turbulent heat fluxes playing a smaller but critical role in controlling mass balance (Cullen and Conway, 2015; Mackintosh et al., 2017). New Zealand glacier sensitivity to temperature change includes some of the highest globally reported values: $1.1 - 4.0 \text{ m w.e. yr}^{-1} \text{ }^{\circ}\text{C}^{-1}$ (Anderson et al., 2010; Anderson and Mackintosh, 2012). Model sensitivity has been used to show increases in precipitation from 30 – 82% would be required to offset 1°C of warming (Oerlemans, 1997; Anderson et al., 2010; Anderson and Mackintosh, 2012). Mass-balance modeling has also been used to investigate the role of seasonality on glacier mass balance, showing that summer temperatures are the most important driver of Franz Josef Glacier/Kā Roimata o Hine Hukatere, while temperatures throughout the year and winter precipitation also influence mass balance, more so than for glaciers in drier climates (Oerlemans and Reichert, 2000).

1.6 Attribution of glacier change

1.6.1 Previous attribution

Despite the evidence for glacier mass loss accelerating (e.g. Zemp et al., 2019) as greenhouse gas levels and temperatures rise (Masson-Delmotte et al., 2018), few works have directly linked glacier retreat and mass loss to anthropogenic forcing (Oerlemans, 2000; Marzeion et al., 2014; Roe et al., 2017). Glacier modeling and statistical assessment have suggested that centennial-scale retreat of glaciers around the world is driven by human influences (Oerlemans, 2000; Roe et al., 2017). However, glacier length is a result of mass balance integrated over different timescales, often over decades, for each glacier (Oerlemans, 2005). Therefore, glacier retreat reflects long-term climate trends, whereas mass balance is the most direct connection between glaciers and climate (Oerlemans, 2010). Attribution of global glacier mass loss to anthropogenic forcing has been carried out on decadal timescales, and provided categorical evidence of long-term climate change (Marzeion et al., 2014). However, this method does not accurately resolve the most negative mass-balance years for New Zealand (Fig. 1.5) (Marzeion et al., 2014). Figure 1.5 shows the most negative modeled mass-balance years (1990, 2000, and 2011; black line) are all more negative than simulated mass balance in the anthropogenic forcing scenarios (red shading) (Fig. 1.5) (Marzeion et al., 2014). This method also requires long-term records of mass-balance measurements, for which records >30 years are currently available for only 41 glaciers worldwide (WGMS, 2018). Furthermore, the required long-term mass balance-measurements reduce

the resolution of extreme mass-loss years that have become more prevalent in recent decades (Fig. 1.1) (WGMS, 2018).

Figure 1.5: Modeled New Zealand glacier mass balance (black), compared with New Zealand glacier mass balance simulated using output from 12 general circulation models for natural-only (natural; green) and natural and anthropogenic (full; red) forcings (figure from Mackintosh et al. (2017), natural and full forcings simulations from Marzeion et al. (2014)).

1.6.2 Extreme event attribution

As the climate system has warmed, changes in the intensity and frequency of weather and climate have been observed since 1950 (Masson-Delmotte et al., 2018). While warming temperatures can be confidently attributed to human activities, human influence on individual, extreme events is more difficult to determine (Masson-Delmotte et al., 2018). In order to calculate the anthropogenic influence on extreme climate events, a methodology referred to as extreme event attribution, referred to herein as event attribution, has been developed (Allen, 2003; Pall et al., 2011; King, 2017). Event attribution methods involve using ensembles of general circulation model (GCM) simulations with and without human-induced forcing, to show changes in climate means, variability, and symmetry with anthropogenic forcing (Fig. 1.6). Probabilities of measured extreme climate events occurring in natural forcing scenarios are then compared with probabilities of the same event occurring in scenarios including natural and anthropogenic forcing. Previous works have used event attribution to calculate the anthropogenic influence on extreme heat, drought, and rainfall events (Lewis and Karoly, 2013; King et al., 2017).

Figure 1.6: Example output of event attribution methods of temperature probability distribution for weather with and without climate change (figure modified from Field et al. (2012)).

By combining glacier mass balance modeling and snowline measurements with existing event attribution methods, we calculate the human-influence on extreme glacier mass-loss years. This method requires measured mass-balance and snowline elevations to compare with modeled output. Having this formal and specific link between anthropogenic warming and glacier mass loss will validate the public debate linking the reduction of glacier mass over short timescales with human activities.

1.7 Objectives

The overall goal of this thesis is to quantify how New Zealand glaciers have changed over the past decades, and to better understand the drivers of those changes. The specific objectives are:

1. Develop a method to quantitatively measure glacier changes from historic and modern images using photogrammetry techniques. Revisit the historic snowline images, and use the developed method to generate 1) chronologies of quantitatively measured snowline elevations and, 2) new chronologies of glacier length changes.
2. Use reanalysis data to identify the climatic drivers of extreme glacier mass-loss years identified in ELA chronologies, and use event attribution methods to calculate the anthropogenic signal on the identified drivers of extreme glacier mass loss.
3. Calculate the snowline elevations for extreme glacier mass-loss years and calculate the anthropogenic influence on these extreme glacier mass-loss years

using event attribution methods. This includes the added step of modeling glacier mass balance and snowlines using an enhanced degree-day model.

1.8 Thesis structure

This thesis is divided into five chapters. Chapter 2 details the development of the method that uses structure from motion photogrammetry to quantitatively measure glacier snowline elevations and lengths (1981 – 2017) from historic and modern images. The uncertainties associated with the method are also quantified. Initial application of the method is to Brewster Glacier.

Chapter 3 uses climate reanalysis data to identify the climate anomalies driving extreme glacier mass-loss years that are observed in the newly developed snowline chronology. Event attribution methods are then used to calculate the human influence on the identified climate anomalies.

Chapter 4 uses the newly developed method from Chapter 2 to measure snowline elevations of extreme mass-loss years for additional glaciers. Simulating glacier mass balance is then added to the event attribution methods used in Chapter 3. Snowline measurements and existing mass-balance measurements are then used to calculate the anthropogenic influence on extreme glacier mass-loss years.

The final chapter summarizes the key results, puts them into a wider context of the the interactions between humans, glaciers and climate change, and comments on future work and the future of New Zealand glacier monitoring.

1.9 Statement of authorship

Chapters 2 and 4 of this thesis are published and in review, respectively. While these chapters involve collaboration with coauthors, as noted below, the work presented in this thesis is my own. The word ‘we’ is used throughout this thesis to refer to this work.

Chapter 2 is published as:

Vargo LJ, Anderson BM, Horgan HJ, Mackintosh AN, Lorrey AM and Thornton M (2017) Using structure from motion photogrammetry to measure past glacier changes from historic aerial photographs. *Journal of Glaciology*, 63(242), 1105 – 1118.

I developed the SfMP workflow with input from BMA and HJH. I processed field data, applied the workflow to Brewster Glacier, and wrote the manuscript. MT provided assistance in the field and supplied the historical DEMs. All authors contributed editorial input. Appendix A transformations were developed by BMA.

An earlier version of Chapter 4 is in review as:

Vargo LJ, Anderson BM, Dadic R, Horgan HJ, Mackintosh AN, King AD, and Lorrey AM (in review, *Nature Climate Change*), Anthropogenic warming forces extreme annual glacier mass loss.

I developed the enhanced degree day model with input from BMA, HJH, and RD, using an original degree day model from BMA. I applied event attribution methods to glacier mass balance with help from ADK. I measured snowline elevations, performed modeling simulations, performed the analysis, and wrote the manuscript. All authors contributed to the design of the study, discussed the results, and contributed editorial input.

Chapter 2

Quantifying glacier change from historic photographs

Abstract

Quantifying historic changes in glacier size and mass balance is important for understanding how the cryosphere responds to climate variability and change. Airborne photogrammetry enables glacier extent and equilibrium line altitudes (ELAs) to be monitored for more glaciers at lower cost than traditional mass-balance programs and other remote sensing techniques. Since 1977, end-of-summer-snowlines, which are a proxy for annual ELAs, have been recorded for 50 glaciers in the Southern Alps of New Zealand using oblique aerial photographs. In this study, we use structure from motion photogrammetry to estimate the camera parameters, including position, for historic photographs, which we then use to measure glacier change. We apply this method to a small maritime New Zealand glacier (Brewster Glacier, 1670 – 2400 m a.s.l.) to derive annual ELA and length records between 1981 and 2017, and quantify the uncertainties associated with the method. Our length reconstruction shows largely continuous terminus retreat of 365 ± 12 m for Brewster Glacier since 1981. The ELA record, which compares well with glaciological mass-balance data measured between 2005 and 2015, shows pronounced interannual variability. Mean ELAs range from 1707 ± 6 m a.s.l. to 2303 ± 5 m a.s.l., with the highest ELAs occurring in the last decade.

2.1 Introduction

Establishing records of glacier change is important for understanding how the cryosphere responds to natural and anthropogenic climate change. Glaciers respond to multiple climatic conditions on intra-annual to decadal time scales. Therefore, chronologies of past glacier volume, length, equilibrium line altitude (ELA), and mass balance provide a valuable means for developing and testing predictive models, as well as environmental evidence that help us understand how past climate variability and change impacted glacial systems. From this understanding, we can better evaluate how glaciers will change in the future.

The Randolph Glacier Inventory (RGI, 2017) includes the location and elevation of most of the world's glaciers, as well as mass balance, ELA, and length changes for glaciers that have been more thoroughly studied. Included in that database are the >3100 glaciers in Southern Alps of New Zealand. These New Zealand glaciers were inventoried in 1978, at which time they had an area of approximately 1160 km² (Chinn, 2001; Radić and Hock, 2010). New Zealand glaciers are characterized by high precipitation, over 10 m water equivalent (w.e.) per year in some locations, due to prevailing westerly winds and orographically-enhanced precipitation (Henderson and Thompson, 1999). The high precipitation and low elevation of Southern Alps termini results in glaciers with a high mass turnover and a high sensitivity to climatic perturbations (Oerlemans and Fortuin, 1992; Anderson and Mackintosh, 2012). New Zealand glaciers make up only a small percentage of Earth's glaciers and contain only 0.21 mm of global sea level equivalent (Radić and Hock, 2010). However, their response to South Pacific climate variations is important for understanding the relationship between glaciers and regional climate variability (Mackintosh et al., 2017). Additionally, their high sensitivity to climate makes them excellent indicators of climatic changes (Oerlemans, 1994), and their location provides one of the few Southern Hemisphere records of maritime glacier variability (Oerlemans, 2005; Schaefer et al., 2009).

A subset of 50 New Zealand glaciers have been monitored since 1977 as a part of the end-of-summer-snowline, herein referred to as the snowline, survey (Fig. 2.1a). The snowline can be visually identified as the highest elevation of bare or exposed glacier ice or firn, and assuming that all melt water refrozen during the previous winter has melted during the ablation season, the snowline can be used as a proxy for the annual ELA (LaChapelle, 1962; Oerlemans, 2010; Chinn et al., 2012). This is an assumption that has been made for New Zealand glaciers before (Chinn et al., 2005, 2012), and is again made in this study. Snowline surveys involve taking hand-held oblique photographs of Southern Alps glaciers from a light aircraft to capture the snowline at the end of the glacier mass-balance

year (March – April). Until now, ELAs were calculated by either: 1) manually transcribing the snowline from oblique photographs onto a base map, digitizing the maps, and using the total ablation area and the glacier’s area-altitude curve to calculate the mean ELA; 2) visually arranging images for all years by decreasing snow cover, allowing a visual comparison and ELA estimate to be made based on the entire historic sequence; or 3) when the snowline is not visible or clear in the image, following the same steps as in 2), but comparing the size of annual snow patches surrounding each glacier (Willsman et al., 2015). All of these approaches are qualitative, and therefore have a relatively low repeatability and provide little transparency about how past ELAs were initially determined. Additionally, these approaches do not contain clear estimates of error for how each photograph and snowline was evaluated.

Figure 2.1: (a) Glaciers located on the South Island of New Zealand (blue) (WGMS, 2017), the 50 New Zealand index glaciers included in the end-of-summer-snowline survey (white), Brewster Glacier (red), Fox Glacier/Te Moeka o Tuawe (green) and Franz Josef Glacier/Kā Roimata o Hine Hukatere (orange). (b) Orthophoto with ground control points (yellow) and (c) digital elevation model (DEM) of Brewster Glacier from 11 March 2016 produced using structure from motion photogrammetry (SfMP). Both have a resolution of 0.26 m.

We have established a technique whereby we use structure from motion photogrammetry (SfMP) to revisit the historical snowline photographs and quantitatively measure past glacier fluctuations. Previous works have successfully used SfMP in Earth science research, including to quantify changes in snow depth, and glacier volume and mass balance (Westoby et al., 2012; Nolan et al., 2015; Piermattei et al., 2015). SfMP uses multiple overlapping images, georeferenced either with ground control points (GCPs) or camera coordinates for each image, and feature-matching algorithms to generate a 3-D point cloud of the glacier. The point cloud is a set of (X,Y,Z) points defining the glacier surface, which are then

interpolated to produce high-resolution digital elevation models (DEMs) and orthophoto mosaics of the glacier. In addition to the geometry of the glacier, SfMP solves for the interior (principal point and focal length) and exterior (position and orientation) camera parameters, making it possible to use a set of modern georeferenced images to determine the locations from which the historic snowline images were taken.

Here we use the SfMP method to quantitatively measure terminus positions and annual ELAs from historic images of one snowline glacier, Brewster Glacier (Fig. 2.1), for which a set of historic images have been captured. Application of this method will enable others to revisit historic photographs of glaciers and use the images to quantitatively measure glacier change. Our three main objectives are to: 1) investigate the accuracy of georeferencing image locations, using Global Navigation Satellite System (GNSS) and a precise timer, for SfMP models; 2) identify the ELA and terminus position in georeferenced historic images and assess the uncertainty of this methodology. These uncertainties are mainly due to i) the interior and exterior camera parameters of the historic images calculated using the SfMP algorithms, ii) the back-projection of the ELA image coordinates into real world coordinates using DEMs, and iii) the auto-identification of the terminus position in historic images; 3) compare the SfMP-derived ELA and length records for Brewster Glacier with previous measurements of mass balance and terminus positions.

2.2 Study site

Brewster Glacier is located to the west of the Southern Alps main drainage divide at 44.08°S, 169.43°E. The glacier has a surface area of approximately 2 km² and spans an elevation of 1670 – 2400 m a.s.l. An automatic weather station installed in front of the glacier at 1650 m a.s.l. from 2004 through 2008 measured mean annual near-surface air temperature of 2.5°C and annual precipitation of 5.3 m (Anderson et al., 2010). Brewster Glacier snowlines have been photographed during 36 of the past 40 years (1978 – 2017), and have been used as a mass-balance proxy. ELAs estimated from images of snowlines suggest that the glacier has been in a positive balance for 21 of the 38 years (1978 – 2015), but has been in mostly negative mass balance since 2008 (Willsman et al., 2015). Brewster Glacier ELAs are shown to have a correlation of 0.83 with mean ELAs for all 50 snowline glaciers, indicating that Brewster ELA fluctuations are representative of ELA fluctuations in the Southern Alps (Willsman et al., 2015).

Brewster Glacier has been extensively monitored and studied in addition to the snowline survey. Mass balance has been monitored since 2004, with measure-

ments showing years with high positive net balances and years with high negative net balances (Stumm, 2011; Cullen et al., 2017). Modeling results indicate that Brewster mass balance is extremely sensitive to changes in temperature and that even moderate temperature increases could lead to significant ice loss (Anderson et al., 2010). Additional unpublished data from Brewster includes terminus positions recorded by GNSS foot surveys between 12 March and 20 April every year since 2005, with an exception in 2006 when the survey was taken on 20 January. GNSS foot surveys of the glacier surface elevation have also been collected in 1997, 2005, and 2008 – 16.

2.3 Methodology

To develop Brewster length and ELA records, we use historic annual images, a large dataset of georeferenced images taken in 2017, and modern and historic DEMs of the glacier. Following data acquisition, the snow and ice in all images are masked out and, using the SfMP software AgiSoft PhotoScan, the images are oriented to generate a base map of the bedrock surrounding the glacier. Having the georeferenced 2017 images makes it possible to calculate interior and exterior parameters for the historic images, which are then used to calculate ELAs and terminus positions. Figure 2.2 shows an overview of the data acquisition and processing methodology, which is detailed below.

Figure 2.2: An overview of the workflow used to calculate glacier length and ELA from historic images, with the inputs for the transformations and back-projection shown in italics.

2.3.1 Data acquisition

2.3.1.1 Snowline images

While the first snowline images of Brewster Glacier were taken in 1978, we use images starting in 1981. This is because the images from 1978 were taken far from the glacier, resulting in high errors in the SfMP-calculated camera parameters, no images were taken in 1979, and clouds obscured the glacier in 1980. This results in 200 images of Brewster Glacier from 1981 – 2014 (Table 2.1), which we refer to as historic images. There is year-to-year variability in the types of cameras used to obtain historic glacier imagery. Single-lens reflex (SLR) film cameras were used prior to 2009, and digital SLR cameras (Sony DSC-W50, Pentax K100D, Nikon D200) were used from 2005 – 14 (Table 2.1). For historical imagery in analog format, all snowline slides and film strips were digitally scanned and archived in 2015 – 17 using a Hasselblad X5 high-resolution drum scanner. The only metadata available for these images is the date they were taken.

2.3.1.2 Modern georeferenced image acquisition

Starting with the 2015 snowline flight, a larger number of digital images (>60, referred to as modern images) were taken by hand and georeferenced (Table 2.1) specifically for 1) generating high-resolution modern DEMs and orthophotos, and 2) determining the interior and exterior camera parameters of historic images using SfMP. Oblique photographs were taken manually using a Nikon D800E camera while the aircraft circled the glacier. The camera is a 36.3 megapixel professional-grade full-frame digital SLR camera. A Nikon 50 mm lens was used in 2015, and a Nikon 85 mm lens in 2016 and 2017. This focal length, which may not be optimal for Brewster Glacier, was selected to best photograph all snowline glaciers, and is within the range suggested in Mosbrucker et al. (2017). The focus was fixed at infinity while taking photos.

To determine positions of images taken during the flights, a dual frequency GNSS receiver was mounted in the aircraft. On the 2015 and 2016 flights, we used a Trimble GeoXH GNSS receiver with positions logged at 1 s intervals. The data were post-processed using Trimble Pathfinder Office against a network of base stations located near the study site that also logged data at 1 s intervals, the closest sites being Makarora (24 km) and Haast (52 km). On 30 March 2016, we also used a Trimble R8 GNSS receiver with positions logged at 1 s intervals. The data were post-processed using Canadian Spatial Reference System Precise Point Positioning (NRCan, 2016). On the 2017 flight, we used a Septentrio PolaRx5, sampling at 1 s and 0.1 s intervals, and post-processed using Canadian Spatial Reference System Precise Point Positioning (NRCan, 2016).

Table 2.1: Details of historic (1981 – 2014) and modern (2015 – 17) images taken of Brewster Glacier annually, including the number of film images, number of digital images, and type of digital SLR used.

Year ^a	Number of film images	Number of digital images	Digital SLR used
1981	3	0	N/A
1982	1	0	N/A
1983	1	0	N/A
1984	2	0	N/A
1985	3	0	N/A
1986	3	0	N/A
1987	3	0	N/A
1988	2	0	N/A
1989	3	0	N/A
1992	1	0	N/A
1993	2	0	N/A
1994	2	0	N/A
1995	6	0	N/A
1996	6	0	N/A
1997	5	0	N/A
1998	4	0	N/A
1999	19	0	N/A
2000	11	0	N/A
2001	4	0	N/A
2002	6	0	N/A
2003	1	0	N/A
2004	2	0	N/A
2005	4	1	Sony DSC-W50
2006	3	1	Sony DSC-W50
2007	3	19	Sony DSC-W50
2008	1	5	Nikon D200
2009	0	7	Pentax K100D, Nikon D200
2010	0	3	Nikon D200
2011	0	17	Pentax K100D, Nikon D200
2012	0	13	Nikon D200
2013	0	10	Pentax K100D, Nikon D200
2014	0	24	Pentax K100D, Nikon D200
2015	0	66	Nikon D800E
2016 ^b	0	118	Nikon D800E
2016 ^b	0	195	Nikon D800E
2017	0	192	Nikon D800E

^a No images taken in 1990 or 1991

^b 118 images taken 11 March 2016 and 195 images taken 30 March 2016

One of the uncertainties in image positions is associated with timing. The Nikon D800E records the time of digitization at 0.1 s resolution, but as the aircraft’s average speed over Brewster Glacier is c. 70 m s⁻¹, we can only estimate image position within 7 m. Camera-GNSS synchronization was done in 2016 and 2017 using a precise timer to capture the image timing at the millisecond level. The precise timer is a GNSS-synchronized timer connected to the flash synchro-

nization connector on the camera that records the time of image acquisition at better than 1×10^{-3} s resolution. This enhanced temporal resolution makes it possible to reduce the timing component of the image position error to c. 0.07 m.

2.3.1.3 Field data

Field data were acquired in March 2016 in order to georeference and validate our SfMP models. We collected 10 ground control points (GCPs) from bedrock around Brewster Glacier. The GCPs, easily visible in the modern and historic aerial images, are used to georeference the models and are used as check points in order to assess the accuracy of the models. GCPs were collected using the Trimble R8 receiver, logging at 1 s intervals, and post-processed using Canadian Spatial Reference System Precise Point Positioning (NRCan, 2016). A surface elevation survey of the glacier was conducted on 25 – 27 March 2016 using the Trimble R8 receiver, and the data were also post-processed also using Canadian Spatial Reference System Precise Point Positioning (NRCan, 2016).

2.3.1.4 Historic DEMs

The calculation of ELAs from historic photographs uses the surface elevation of the glacier. As the glacier surface elevation is not constant over the 40-year period, we use DEMs spanning the period of the chronology (Table 2.2) that were developed by Thornton (2017), instead of exclusively using the 2017 DEM generated from SfMP. The 1967 and 1986 DEMs are derived from New Zealand topographic maps, the 2000 DEM is from the Satellite Radar Topography Mission (Reuter et al., 2007), and the other DEMs were generated from annual GNSS foot surveys of the glacier surface and then interpolated using the co-kriging approach (Goovaerts, 1998; Thornton, 2017). The vertical errors for the 1967, 1986, and 1997 DEMs are calculated as one standard deviation of the difference between the ice-free parts of each of these DEMs and the 2017 SfMP DEM, assumed to have a 0 m error. The vertical errors from the foot surveys are calculated as the mean standard error from the co-kriging approach. The error is inversely proportional to the number of GNSS points and the coverage of points, with the low error in 1997 due to almost full coverage of the glacier surface (Thornton, 2017).

2.3.2 SfMP processing

2.3.2.1 Modern DEMs and orthophotos

We use SfMP and the large dataset of georeferenced images taken between 2015 and 2017 to generate high-resolution DEMs and orthophotos for each of these

Table 2.2: Brewster Glacier DEMs used to calculate ELAs, including the vertical error and source for each.

Year (month)	Vertical error (m)	Source
1967	27.6	Topographic map (NZMS)
1986	9.16	Topographic map (NZDEM sos V1.0)
1997 (Jan)	0.68	Glacier surface GNSS survey
2000 (Feb)	7.59	SRTM
2005 (Feb)	1.23	Glacier surface GNSS survey
2008 (Apr)	2.62	Glacier surface GNSS survey
2009 (Mar)	6.19	Glacier surface GNSS survey
2010 (Mar)	5.18	Glacier surface GNSS survey
2011 (Mar)	1.24	Glacier surface GNSS survey
2012 (Mar)	1.25	Glacier surface GNSS survey
2013 (Mar)	3.35	Glacier surface GNSS survey
2014 (Apr)	2.14	Glacier surface GNSS survey

years. The SfMP models are georeferenced with camera locations and five of the GCPs, with the other five used as check points. Each of the GCPs are manually identified when visible in an image. The workflow that results in the lowest model root mean squared error (RMSE) when building the point cloud is: 1) set the camera location accuracy to 0.1 m, GCP accuracy to 0.005 m, and define the coordinate system; 2) match and align cameras; 3) import camera locations and GCPs; 4) repeat alignment. After building the point cloud, the workflow includes generating a dense cloud and model, all with the following settings. The point cloud alignment settings include ‘high’ accuracy, pair preselection disabled, key point limit of 100000 and tie point limit of 6000, and adaptive camera model fitting enabled. The dense cloud settings include ‘high’ accuracy and ‘moderate’ depth filtering. The model settings include height field surface type, dense cloud source data, interpolation disabled, ‘high’ face count, generic mapping mode, mosaic blending mode, texture size of 4096 x 4096, color correction disabled, and hole filling enabled. For each year, the same set of interior camera parameters, determined by the SfMP software, are used for all images.

2.3.2.2 Determining historic camera parameters

Interior and exterior camera parameters, including image position, are determined using AgiSoft PhotoScan software (now known as AgiSoft Metashape), which includes a SfMP algorithm (Koenderink and van Doorn, 1991; Westoby et al., 2012). We tested three different methods to identify the best for processing of the historic

images, with the following method resulting in the most historic images oriented with the point cloud, and the most accurate camera parameters (determined using GCPs). We generate one SfMP point cloud of only the bedrock surrounding Brewster Glacier. This is generated using the 192 images taken in March 2017 and all 200 historic Brewster snowline images. The model is georeferenced with the 2017 camera positions and five of the GCPs, with the other five used as check points. The same set of interior camera parameters, determined by the SfMP software, are used for all 2017 images. Snow and ice are masked out of all images, historic and modern, using a modified form of the Otsu (1975) thresholding method to distinguish snow and ice from the bedrock. This is done because snow and ice vary annually, while we assume that the bedrock is stable and can therefore be used to orient all images over the 40-year period. The SfMP algorithm matches points in the bedrock of the historic images with the 2017 images in order to orient the historic images and calculate the camera parameters, including the position from which the images were taken. The point cloud alignment settings include ‘high’ accuracy, pair preselection disabled, key point limit of 200000 and tie point limit of 15000, and adaptive camera model fitting enabled. Historic images without enough common features to be identified by the SfMP software, due to the presence of cloud cover or little bedrock in the images, do not orient in the model and therefore the camera parameters cannot be calculated.

We note that this workflow, of using SfMP to calculate camera parameters for historic images and then using that information in the transformations and back-projection, is necessary for working with these snowline image datasets. There are multiple years for which only one image of the terminus or ELA exists for Brewster Glacier (Table 2.1). However, for years with multiple images of each part of the glacier, the following SfMP workflow is also possible: 1) orient all masked images (historic and modern), 2) disable all photos except those from a single year, 3) build a dense cloud, DEM, and orthophoto for that year. Here, we exclusively use the back-projection method to keep the ELA and length calculations consistent.

2.3.3 Snowline and terminus position selection

To identify snowlines and terminus positions in photographs, all images are enhanced using the contrast limited adaptive histogram equalization (Pizer et al., 1987). This increases the contrast within subregions of the images and enhances the difference between ice and snow on the glacier, especially helping with identification of the snowline (Fig. 2.3). The snowline is identified as the highest elevation of exposed glacier ice or firn (LaChapelle, 1962; Oerlemans, 2010), and is manually digitized for each image. Identification of terminus positions is automated by

thresholding pixel values. Grayscale pixel intensity values for each snowline image are used to identify minimum and maximum pixel value thresholds, resulting in discrimination of the glacier from bedrock (Fig. 2.3b).

Figure 2.3: Example scanned snowline image from 1995, (a) original and (b) enhanced by contrast limited adaptive histogram equalization, with the terminus position (gray) identified using pixel thresholding, and the snowline (blue) manually digitized.

2.3.4 Transformations

In order to determine the real world positions in the New Zealand Transverse Mercator (NZTM) projection from image (x, y) coordinates of snowlines and terminus positions, transformations of image geometry and conversions of (x, y) image coordinates to real-world (NZTM) coordinates are performed. These steps are fully described in Appendix A. Using a standard ideal camera model that considers interior camera parameters (Ma et al., 2012), we calculate the relationship between glacier features in the real world and pixels in an image. Lens distortion is corrected for, with total distortion calculated as the combination of radial distortion and tangential (decentering) distortion. We then complete a back-projection,

calculating the position of snowline and terminus (x, y) image coordinates in real-world (NZTM) coordinates. The back-projection uses the interior and exterior camera parameters, a DEM of the glacier surface, and (x, y) image coordinates of snowlines and termini. The real-world (NZTM) coordinates of an image pixel are calculated by intersecting a ray from the camera location with a DEM, and using a stepping scheme to calculate the intersection point.

2.3.5 Calculating uncertainties and compiling chronologies

2.3.5.1 ELA uncertainties

Uncertainty in the ELA comes from 1) errors in the DEMs used in the back-projection and 2) errors in the SfMP-calculated camera interior and exterior parameters. We use DEMs spanning the period of the chronology (Table 2.2) to calculate ELAs. For years with no DEM, we use the closest previous year and later year with DEMs to interpolate annual glacier surfaces. This method of using distinct DEMs in the snowline back-projection for each year (1981 – 2014) accounts for changes in the glacier surface over time.

We calculate the uncertainties in ELAs due to the DEMs used in the back-projection (E_D). For each DEM in Table 2.2, we add the vertical error to the glacier surface to represent the maximum possible surface elevation. Again, for years with no DEMs, we interpolate the glacier surface for each year. We repeat the back-projection and calculate ELAs using these maximum surface elevations (S_{Dh}). These steps are then repeated for the minimum surface elevations by subtracting the vertical error from each DEM surface and calculating ELAs using these minimum surface elevations (S_{Dl}). We calculate the differences between the ELAs calculated using the non-adjusted surface elevations (S_D) and ELAs calculated using the minimum and maximum surface elevations, and use the largest absolute difference to represent the uncertainties in each ELA from DEMs, so that E_D is equal to RMS error of either S_D and S_{Dh} , or S_D and S_{Dl} , whichever is larger. For each image, the calculated E_D is between 0 and 30 m, with a mean value of 5 m. E_D is larger for images towards the beginning of the chronology, when the vertical DEM errors are largest. ELAs with E_D over 10 m correspond to ELAs higher than 2150 m a.s.l. This is due to the slope of the glacier being steepest above 2100 m a.s.l., leading to larger differences in ELAs back-projected onto the non-adjusted, minimum, and maximum surface elevations.

In order to assess the accuracy of the camera positions, we use the previously described GCPs. Two GCPs, selected as the easiest to accurately identify in images, were located in each historic image in which they were present. The GCP (x, y) points selected in each image were back-projected following the same steps as

the snowlines and terminus positions. For each image with a GCP, the horizontal distance between the back-projected point and the coordinates of the GCP was calculated and considered to be representative of the back-projection and camera parameter uncertainty for that image. The distances are averaged for images with the two GCPs, and considered to be the horizontal error for each image (E_{hG}). Images with no visible GCP (36 of the 200 historic images), due to image coverage, cloud cover, or image resolution, were not used in the chronologies.

As the DEM uncertainty is represented by vertical error, we use this horizontal GCP error and the glacier slope to calculate the associated vertical GCP error. Using the 2017 SfMP DEM, we calculate the mean slope of the entire glacier (21.2°) and the mean slope of the accumulation area (34.6°), where the glacier is the steepest. We use the slope of the accumulation area to provide an upper estimate, and calculate the vertical GCP error (E_{vG}) following $E_{vG} = E_{hG} \cdot \tan(34.6^\circ)$. The total uncertainty of each ELA (E_S) includes errors from the DEM used (E_D) and the vertical error from the camera parameters, calculated using GCPs (E_{vG}), and is calculated following $E_S = \sqrt{(E_D)^2 + (E_{vG})^2}$. To compile the chronology, we calculate each ELA as the mean elevation of the digitized points. For years with only one image of the snowline, the calculated ELA and corresponding error (E_S) are used in the chronology. For a year with multiple images, we first select all individual ELAs with a vertical GCP error (E_{vG}) under 24 m. If the year had no ELA with E_{vG} under 24 m, the threshold is increased to 69 m and all ELAs with E_{vG} below that value were selected. The thresholds are determined by visually analyzing the data to exclude images with high errors while still including most images. We set thresholds using E_{vG} instead of E_D or E_S because E_D are relatively consistent for all ELAs, while E_{vG} can vary between 0 and 100 m depending on the accuracy of the calculated camera parameters. We use this thresholding step to eliminate ELAs calculated from images with high errors in the calculated camera parameters. When this thresholding of uncertainties results in years with multiple ELAs (due to multiple images), we calculate the weighted mean and resulting uncertainties to determine the mean annual ELA.

2.3.5.2 Length record

We calculate glacier length, following Purdie et al. (2014), as the furthest connected ice at the terminus perpendicular to the centerline, defined by the mass-balance program (Cullen et al., 2017). We use the 2017 SfMP DEM for all terminus back-projections and do not consider E_D , as the RMSE of the DEM is ~ 0.5 m. We can use the 2017 DEM instead of annual DEMs for the terminus back-projection because the terminus is always being identified as the furthest point on the glacier,

and as 2017 is the shortest glacier extent in the chronology, the terminus position is always being projected onto bedrock. We calculate E_{hG} for each terminus position in the same way it was calculated for ELAs.

We also estimate the error associated with the automated terminus identification (E_a). This was done by selecting a subset of images and determining the variation in the identified terminus position. All variation fell between ± 15 m, so for each terminus position E_a is 15 m. The total uncertainties in each terminus position (E_T) are calculated following $E_T = \sqrt{(E_{hG})^2 + (E_a)^2}$. For years with only one image of the terminus position, the calculated length and corresponding error (E_T) are used in the chronology. For a year with multiple images of the glacier terminus, we select all terminus positions with E_{hG} below 35 m, and if the year has no terminus positions below that error, the threshold is increased to 90 m. Again, thresholds are determined by visually analyzing the data to exclude images with high errors while still including most images. We then further filter the terminus positions by calculating the mean length ($\bar{L}_i$) and standard deviation (σ_i) for a year. For each year (i), each calculated length for that year that falls outside of $\bar{L}_i \pm \sigma_i$ is not considered. This is done to discard lengths calculated from images for which the automated terminus identification may have incorrectly selected a feature, including shadows on ice, clouds, or water. We then calculate the weighted mean of the positions for each year to determine annual length and resulting uncertainties.

2.4 Results and Discussion

2.4.1 Modern SfMP models

We first show that it is possible to produce a high-accuracy SfMP modern model of Brewster Glacier with georeferenced images, with and without GCPs (Table 2.3). We generate SfMP models of Brewster Glacier from images taken between 2015 and 2017, and test the accuracy of georeferencing the models with camera locations only (acquired with and without the precise timer), GCPs only, and both camera locations and GCPs. When using only camera locations for georeferencing, we use all 10 GCPs as check points, and when georeferencing with GCPs (with and without camera locations), we use five of the GCPs as check points and the other five for georeferencing. Check points are not used to georeference the model, and instead give an idea of the true model error as the mean distance between GNSS-measured GCPs and the position of the GCPs in the SfMP model.

The camera location RMSE is the mean distance between sampled GNSS (X, Y, Z) image locations (acquired with and without the precise timer) and the

Table 2.3: Details and accuracy of the 2015 – 17 SfMP models, including whether precise timing (P.T.) was used or not. Model RMSE is reported for georeferencing using 1) GCPs and camera locations, 2) GCPs only, and 3) camera locations only. For 1 and 2, we report the GCP check error, determined using five of the 10 GCPs not used to georeference the model but only used to estimate the true model error. For 3, we report the camera location error and the GCP check error, determined from all 10 GCPs.

Date	Number images	P.T.	GCP camera RMSE (m)	GCP-only RMSE (m)	Camera-only RMSE (m)	
					Camera loc.	GCP check
17 Mar '15	66	No	1.44	1.46	2.59	1.80
11 Mar '16	118	No	0.97	0.97	2.46	1.40
11 Mar '16	118	Yes	0.82	0.97	0.73	1.53
30 Mar '16	195	No	1.82	1.82	2.29	2.39
9 Mar '17	192	No	0.53	0.53	3.11	1.25
9 Mar '17	192	Yes	0.51	0.53	0.61	0.85

(X, Y, Z) image locations calculated by the SfMP software. We show that using the precise timer, on 11 March 2016 and 9 March 2017, the camera location RMSE is reduced to 0.73 m and 0.61 m, respectively (Table 2.3). For the 2017 model, the GCP check point RMSE is 0.85 m, showing that we can georeference SfMP models exclusively with camera locations with accuracies under 1 m. However, the GCP check point RMSE for the 2016 model is about double the camera location error, suggesting that the larger dataset of images acquired in 2017 (192 images) compared with 2016 (118 images) may help to improve model accuracy when using the precise timer and camera positions.

For all models, using only GCPs for georeferencing improves model error compared with using only camera locations (Table 2.3). However, future work includes applying this method to the additional 49 snowline glaciers. Therefore, accurate georeferencing of the SfMP models exclusively using camera positions makes the development of additional glacier chronologies possible without having to collect GCPs in the field at all glaciers. Two limitations of the acquisition of modern images that we do not account for include the offset between the GNSS receiver and the position of the camera, and the distortions caused by taking images through the aircraft windows, which vary with each image. Accounting for this offset and distortion in the future would likely further decrease the model RMSE when georeferenced only with camera positions.

Comparison of the surface elevation survey, conducted 25 – 27 March 2016, with the SfMP DEM from 30 March 2016 shows that the two datasets are largely in agreement with each other and further validates the SfMP workflow for generating modern DEMs (Fig. 2.4). The mean difference between the two datasets is -

0.0088 m, and the standard deviation is 0.500 m. Some of the largest elevations differences, including the positive differences up to 2 m to the NE section of the survey, occur due to a step change in GNSS elevation of -1.8 m, possibly due to the loss of satellite coverage below Mt. Brewster to the NE. In addition, negative differences between the DEM and GNSS elevation are likely in part due to crevasses that are captured in the DEM, but stepped over during the foot survey. These results support our conclusion that it is possible to accurately map glaciers from an aircraft using SfMP without the need for GCPs.

Figure 2.4: Comparison of 30 March 2016 SfMP Brewster Glacier DEM with the 25 – 27 March 2016 GNSS foot survey, with the frequency distribution of the elevation differences shown in the insert.

2.4.2 ELA record

We present ELAs from 1981 through 2017 calculated from historic oblique aerial images and SfMP orthophotos (Fig. 2.5, Table 2.4). Missing data include 1982, 1984, and 1988 when snowlines were obscured by clouds, and 1990 and 1991 when no images were taken. Each annual ELA between 1981 and 2014 is calculated from between one and six historic images. The associated error includes the uncertainty in calculated camera parameters and back-projection, and the uncertainty in the DEMs used to represent the glacier surface. The 2015 – 17 ELAs are calculated from SfMP orthophotos and DEMs, with the errors from the SfMP models.

The chronology shows the interannual variability in mean ELAs, with elevations ranging between 1707 ± 6 m a.s.l. and 2303 ± 5 m a.s.l. Lower elevations occur in 1981 – 1997 and in the early to mid 2000s, at the same time that many New Zealand glaciers were advancing (Purdie et al., 2014; WGMS, 2017). Higher ELAs occur in 1998 – 2000, and the highest occur more recently in 2008, 2011, 2012, and 2016.

Figure 2.5: Brewster Glacier mean ELAs 1981 – 2017 (cloudy or no images in 1982, 1984, 1988, 1990, and 1991). Each annual ELA (1981 – 2014) is calculated as the weighted mean of up to 6 historic images (shown with blue). The 2015 – 17 ELAs (red) were calculated from SfMP orthophotos and DEMs.

Projection of equilibrium lines onto the March 2017 SfMP orthophoto of Brewster Glacier shows a trimodal distribution (Fig. 2.6). The majority of equilibrium lines are either close to the terminus (a, 1700 – 1800 m a.s.l.), just below the steep accumulation area (b, 1900 – 1950 m a.s.l.), or at the top of the accumulation area (c, 2100 – 2300 m a.s.l.). No mean ELAs occur between ~ 1950 and 2100 m a.s.l. (Fig. 2.5 and 2.6). This distribution is a result of the glacier geometry. Because of the low glacier gradient between areas (a) and (b), only a small difference in annual climate (temperature or snow cover) would drive the equilibrium line between the two areas of the glacier. This finding agrees with previous theoretical and observational work showing that glacier slope influences the sensitivity of glaciers to changes in climate, with gently sloping glaciers being more sensitive than steep glaciers (Oerlemans, 2001; Leclercq et al., 2014).

Figure 2.6: Brewster Glacier annual equilibrium lines (1981 – 2017) shown on the March 2017 SfMP orthophoto. The equilibrium line with the lowest error was chosen for each year, with the earliest years shown in white, and the most recent years shown in dark blue. There are no equilibrium lines for 1982, 1984, 1988, 1990, and 1991. The grey lines are 50 m contours.

2.4.3 Comparison of SfMP-ELAs with original ELAs and mass-balance data

The extensive monitoring of Brewster Glacier makes it possible to compare our results with other work. Figure 2.7 shows the SfMP-calculated ELAs, the original ELA data, and the annual mass-balance measurements over the entire time series. ELAs are shown as the departure from the mean SfMP ELA (1919 m a.s.l.). Comparison of the SfMP-calculated ELA record and the original ELA data (Willsman et al., 2015) shows that ELAs are within ± 100 m most years (Fig. 2.7), and the two datasets have an r^2 value of 90%. Differences between the ELA datasets are due to differences between the methods, or a human introduced bias in the selection of snowlines in images, not captured by our formal treatment of uncertainty. SfMP ELAs are calculated exclusively from digitizing snowlines on historic images, while the original ELA data were calculated by either 1) digitizing the accumulation or ablation area to identify the ELA, or by visually arranging images for all years by 2) decreasing snow cover or 3) snow patch size. We refer to ELAs calculated by step 1 as digitized ELAs, and ELAs calculated by steps 2 and 3 (these types are not differentiated by Willsman et al. (2015)) as inferred ELAs. In addition to these differences in the method of calculating ELAs, the

actual identification of the snowline from images contributes to the difference in the two chronologies. We identified snowlines as the highest visible ice or firn on the glacier, and all were identified by the same person to keep the data consistent.

Figure 2.7: Comparison of Brewster Glacier SfMP-calculated ELAs (blue) with associated errors, ELAs calculated using the original method, distinguished between digitized (black) and inferred ELAs (gray) (Willsman et al., 2015), and annual mass balance (green) (Cullen et al., 2017). ELAs are shown as the departure from the mean SfMP ELA (1919 m a.s.l.). Note that an original ELA of 1918 m a.s.l. does exist for 1989.

Comparing ELAs with measured mass-balance data is important for understanding whether mass balance can be reconstructed from remote sensing methods. Figure 2.8a shows the relationship between Brewster Glacier ELAs calculated using SfMP and the mass-balance record (Cullen et al., 2017). The curve fit to the data, following the standard form of the quadratic equation, has a gradual slope until the ELA reaches approximately 2000 m a.s.l. Above this elevation, the slope of the curve becomes steeper. This relationship suggests that due to the considerable increase in glacier slope at 2000 m a.s.l., the ELA becomes more sensitive, and a large change in ELA within this part of the glacier may correspond with a small change in mass balance. This finding is consistent with results from Cullen et al. (2017), which compared the same mass-balance data with the original ELA data. While the majority of years fall on or close to the curve fitting the data, 2009 and 2012 do not. In 2009, the ELA is within 10 m of the 2015 ELA, but 2009 was quite a negative mass-balance year (-702 mm w.e.) while 2015 was slightly positive (215 mm w.e.) (Cullen et al., 2017). The snowline survey in 2009 occurred 2 weeks before the mass-balance survey. There was no snowfall between the two surveys (Willsman et al., 2009), suggesting that additional ablation occurred after the snowline was photographed and before the mass-balance survey, and highlighting the importance of the timing of the snowline and mass-balance surveys.

Figure 2.8b shows the comparison of SfMP ELAs and ELAs calculated from mass balance. ELAs from mass balance were calculated by applying a geostatistical co-kriging approach to spatially adjust mass balance, and each annual ELA was interpolated between sampling elevations (Cullen et al., 2017). Within the errors of both datasets, the majority of years fall on the 1:1 ratio line, while 2006 and 2007 fall slightly below the line, and 2008 and 2012 are further above it. Comparison of ELAs calculated from mass balance and original ELA data (Willsman et al., 2015) in Cullen et al. (2017) show a similar bias of 2007 falling below the 1:1 ratio line and 2008 and 2012 falling above it. These differences may be due to differences in the methods, with both methods having associated uncertainties. For example, the annual mass balance is almost identical for 2008 and 2011 (Fig. 2.8a), however, the ELAs calculated from mass balance for those years are over 200 m apart (Fig. 2.8b). Additional differences are likely due to differences in sampling time. For example, in 2008 the ELA calculated from mass balance, surveyed on 20 April, is almost 200 m lower than the SfMP ELA, photographed on 14 March. As the first winter snowfall usually occurs by early April (Willsman et al., 2015), snowfall may have occurred following the snowline survey but before the mass-balance survey, with new snow cover obscuring measurements made for the mass-balance survey.

Figure 2.8: Comparison of Brewster Glacier SfMP-calculated ELAs (2005 – 15) with (a) mass balance and (b) annual ELAs calculated from mass balance (Cullen et al., 2017).

One source of differences between SfMP ELAs and mass-balance measurements arise from the timing of each monitoring program. The goal of the end-of-summer-snowline monitoring is to take images of the glaciers at the end of the melt season, and before any new snow has fallen. All flights for 2005 – 15 occurred between

3 and 15 March, with a supplemental flight in 2011 on 30 March after little to no snowfall following the first flight. However, ablation measurements for mass balance occurred over a longer window of time, between 13 February and 20 April. This means that in some years the two surveys are conducted within days of each other, while in other years the two surveys are over a month apart. In years when the two surveys are conducted at different times, there is the potential for additional melt between the two surveys, biasing the first survey towards lower ELAs or higher mass balance. There is also potential for new accumulation following the first survey, biasing the second survey towards lower ELAs or higher mass balance.

2.4.4 ELA uncertainties

The ELA record includes errors from the DEMs used to represent the glacier surface, and errors in the calculated camera parameters and back-projection. An additional source of unquantified uncertainty comes from the manual digitization of the snowlines from images. While the terminus selection is automated, we have not successfully automated the selection of the snowline. This is due to the small differences between snow and ice in some images, as well as some years when the previous year's firn is visible. To minimize this uncertainty, digitization was completed by one person to keep the selection consistent, and then reviewed and agreed upon amongst the authors. However, as some years do not have one clear snowline, there is uncertainty associated with this step. The uncertainty is greater when ELAs are above ~ 2100 m a.s.l., as this is the steepest part of the glacier and small differences in the selection of the snowline can lead to large differences in the resulting mean ELA.

Even when the snowline is perfectly identified in an image, for the end-of-summer-snowline to represent the ELA, images need to be captured at the end of the melt season but before any new snowfall. The timing of the flight is therefore chosen carefully each year, and there have been several years with multiple flights in order to capture the end-of-summer-snowline as accurately as possible. However, as there are years with snowfall before the flight and years with melt after the flight, the end-of-summer-snowline remains an imperfect proxy for the ELA.

We also investigate the influence of using historic DEMs in the ELA back-projection. ELAs calculated with DEMs for each year vary only slightly from ELAs calculated with the high-resolution and high-accuracy 2017 SfMP DEM. For each year in the chronology (1981 – 2014), we calculate S_i , the difference between the ELAs calculated using the two different methods. We find that for all except four years, ELAs calculated with annual DEMs are higher in elevation

than ELAs calculated with the 2017 DEM alone. For each year in the chronology, S_i is between -31 m and +5 m, with a mean value of -11 m. S_i correlates with the ELA, with more negative values for years with lower equilibrium lines, due to faster surface elevation lowering down-glacier compared with slower surface elevation loss of the accumulation area. S_i is also more negative for years earlier in the chronology, when the difference between the year-of-interest DEM and the 2017 DEM is the greatest, and S_i becomes less negative and slightly positive in the last decade of the chronology. These relatively small values of S_i suggests that even when historical DEMs are not available for the back-projection, this method can be applied to calculate glacier fluctuations using a modern DEM and including this uncertainty.

2.4.5 Length record

Here we present the first annual Brewster Glacier length record extending through 1981 (Fig. 2.9, Table 2.4). Glacier lengths from 1981 through 2014 are calculated from historic images, and associated error includes the uncertainty in calculated camera parameters and back-projection, and in the automated terminus selection. Glacier lengths from 2015 – 17 are calculated from SfMP orthophotos, with errors from the respective SfMP models. The record shows 365 ± 12 m of terminus retreat since 1981, with significant retreat occurring 1981 through 1989, a period of slower retreat and slight advances between 1991 – 2008, and continuous retreat 2006 – 17.

Figure 2.9: Brewster Glacier lengths from 1981 through 2017 (no image match in 1982, and no images in 1990 and 1991). Each calculated length (1981 – 2014) is the weighted mean of up to seven images (shown with blues). The 2015 – 17 lengths (red) were calculated from SfMP orthophotos.

Table 2.4: Annual mean ELA, ELA range, and glacier length, 1981 – 2017.

Year	Mean ELA (m a.s.l.)	ELA range (m a.s.l.)	Length (m)
1981	1918 ± 7	1894 – 1950	2339 ± 11
1982	no match	no match	no match
1983	1780 ± 11	1739 – 1789	2301 ± 17
1984	clouds	clouds	2294 ± 16
1985	1795 ± 6	1756 – 1808	2293 ± 19
1986	1834 ± 7	1786 – 1866	2270 ± 16
1987	1817 ± 5	1779 – 1840	2253 ± 12
1988	clouds	clouds	2228 ± 15
1989	1928 ± 5	1868 – 1990	2203 ± 11
1990	no image	no image	no image
1991	no image	no image	no image
1992	1707 ± 6	1686 – 1730	2148 ± 12
1993	1767 ± 4	1755 – 1780	2171 ± 13
1994	1834 ± 3	1789 – 1853	2155 ± 11
1995	1776 ± 3	1725 – 1797	2153 ± 16
1996	1910 ± 2	1878 – 1951	2163 ± 11
1997	1792 ± 2	1752 – 1813	2156 ± 11
1998	2108 ± 3	2082 – 2117	2125 ± 11
1999	2189 ± 14	2067 – 2297	2130 ± 8
2000	2159 ± 9	2075 – 2306	2106 ± 10
2001	1789 ± 5	1750 – 1810	2125 ± 19
2002	1956 ± 4	1933 – 1967	2101 ± 10
2003	1749 ± 6	1709 – 1762	2117 ± 17
2004	1793 ± 6	1761 – 1809	2085 ± 14
2005	1762 ± 2	1725 – 1857	2092 ± 16
2006	1791 ± 3	1755 – 1833	2101 ± 13
2007	1815 ± 3	1773 – 1843	2077 ± 7
2008	2297 ± 4	2290 – 2346	2080 ± 16
2009	1944 ± 26	1894 – 2066	2074 ± 15
2010	1899 ± 24	1864 – 1928	2067 ± 15
2011	2303 ± 5	2297 – 2348	2048 ± 10
2012	2201 ± 4	2068 – 2354	2048 ± 10
2013	1861 ± 18	1771 – 1930	2033 ± 16
2014	1912 ± 6	1894 – 1931	2015 ± 12
2015 ^a	1943 ± 3	1903 – 1974	2008 ± 3
2016 ^a	2246 ± 1	2200 – 2295	2000 ± 1
2017 ^a	1833 ± 1	1800 – 1885	1974 ± 1

^a 2015 – 17 ELAs and lengths calculated from SfMP orthophotos for each year

2.4.6 SfMP length record comparison with field data

We compare field measurements of terminus positions with our length measurements (2005 – 14) in Figure 2.10. All lengths match with the field measurements within uncertainties, except for 2005 and 2007. The 2005 and 2007 SfMP-calculated lengths underestimate the true glacier length because some historic images for those years were taken from angles that miss the furthest extent of the glacier, and were not recognized by the automated terminus identification.

The match between the two length records shows that we can accurately calculate changes in glacier length from historic images. The difference in lengths in 2005 and 2007 demonstrates the need for more, higher quality images, and highlights the areas for improvement in the automated terminus identification.

Figure 2.10: Brewster Glacier length time series (2005 – 14) compared with field measurements of the terminus position.

2.4.7 New Zealand glacier fluctuations

Comparison of Brewster Glacier length changes with fluctuations of New Zealand glaciers that have been more extensively studied help us to better understand Brewster Glacier dynamics. While most glaciers around the world have been retreating and losing mass since ~1950 (Zemp et al., 2015), a subset of New Zealand glaciers advanced between 1983 and 2008 (Purdie et al., 2014; WGMS, 2017). Of the New Zealand glaciers that advanced within that time, Fox Glacier/Te Moeka o Tuawe and Franz Josef Glacier/Kā Roimata o Hine Hukatere have been especially well-monitored (Purdie et al., 2014). Both glaciers are longer than Brewster, at 12.4 and 9.9 km long, respectively, and are located 80 – 90 km northeast of Brewster. Fox Glacier/Te Moeka o Tuawe and Franz Josef Glacier/Kā Roimata o Hine Hukatere both react to climate variability within three to four years (Purdie et al., 2014), much faster than most valley glaciers, which react to climate variations in 10 – 50 years (Oerlemans, 1994). Both glaciers advanced from 1983 – 1999 and 2003 – 07 in response to lower air temperatures (Mackintosh et al., 2017), but have been retreating quickly since 2011 (Fig. 2.11). In contrast, Brew-

ster Glacier does not show the same length fluctuations, and instead experienced largely continuous retreat over the past 37 years (Fig. 2.11). This difference is due to Brewster Glacier responding more slowly to climate variability compared with Fox Glacier/Te Moeka o Tuawe and Franz Josef Glacier/Kā Roimata o Hine Hukatere. The slower response of Brewster Glacier is influenced by Brewster being a smaller glacier with a more gradual slope (Bahr et al., 1998), and because Brewster has no steep, narrow glacier tongue, and therefore has a more even hypsometry compared with Fox Glacier/Te Moeka o Tuawe and Franz Josef Glacier/Kā Roimata o Hine Hukatere (McGrath et al., 2017). Brewster Glacier response time, defined as the time to complete $\sim 63\%$ of its adjustment to a change in mass balance (Cuffey and Paterson, 2010), is calculated following Jóhannesson et al. (1989) as 33 years (based on the 2017 thickness) to 43 years (based on the 1967 thickness) (Thornton, 2017). Because Brewster Glacier responds more slowly to climate variations, it is also likely that Brewster Glacier's retreat has been largely driven by 20th century warming and less by decadal climate variations that influence Fox Glacier/Te Moeka o Tuawe and Franz Josef Glacier/Kā Roimata o Hine Hukatere.

Figure 2.11: Brewster Glacier length record (blue) compared with length records of Fox Glacier/Te Moeka o Tuawe (green) and Franz Josef Glacier/Kā Roimata o Hine Hukatere (orange) (Purdie et al., 2014).

2.5 Conclusions

We present a new method for quantitatively measuring glacier fluctuations from historic images, and detail the associated uncertainties. The method includes using modern georeferenced images and structure from motion photogrammetry to determine the interior and exterior parameters of the historic images, including the location from which they were taken. We apply this method to Brewster Glacier, resulting in annual ELA and length records (1981 – 2017). Mean uncertainties associated with the method, quantified using ground control points, are 7 and 12 m for the ELA and length records, respectively. This method can be further applied to any glacier with historic images, and can be used to measure past changes in glacier width, area, and surface elevation in addition to ELA and length.

The Brewster Glacier ELA record shows pronounced interannual variability, with elevations between 1707 ± 6 m a.s.l. and 2303 ± 5 m a.s.l. Lower ELAs occur in 1981 – 1997 and in the early to mid 2000s, while the highest elevations occur more recently, in 1998 – 2000 and in 2008, 2011, 2012, and 2016. Our ELA record compares well with the original snowline elevation data for Brewster Glacier, and with measured mass-balance data (2005 – 15). Brewster Glacier’s terminus retreated, largely continuously, 365 ± 12 m since 1981, with the most retreat occurring 1981 – 1989, and more recently in 2008 – 17. Comparison with length variations of Fox Glacier/Te Moeka o Tuawe and Franz Josef Glacier/Kā Roimata o Hine Hukatere, shows that Brewster Glacier responds more slowly to climate variations, suggesting that Brewster retreat has been dominantly forced by 20th century warming.

Chapter 3

Climate drivers of extreme glacier mass loss

Abstract

Original and newly developed records of New Zealand glacier change show that many of the highest mass-loss years have occurred in the past decade (2010 – 2019). Here, we look to better understand the climate drivers of extreme glacier mass loss, and to quantify the anthropogenic influence on those drivers. We use the end-of-summer-snowline record (1977 – 2018) to identify extreme glacier mass-loss years: 1990, 2011, 2016, and 2018. Using monthly ERA-Interim reanalysis data, we show that highest glacier mass-loss years are characterized by positive surface air temperature anomalies over New Zealand for at least two months during the ablation season (October – March), positive sea level pressure anomalies over the Tasman Sea at the start of the ablation season (October – December), and positive sea surface temperature anomalies in the Tasman Sea towards the end of the ablation season (February – March). Surface air temperatures in 2011, 2016, and 2018 each had a 2-month mean anomaly within the ablation season of at least $+1.7^{\circ}\text{C}$, which is exclusive to these three years over the time investigated (1980 – 2018). Using event attribution, we show that positive surface air temperature anomalies calculated from ERA-Interim for extreme mass-loss years were all more likely to have occurred with anthropogenic forcing. All positive monthly and multi-month surface air temperature anomalies investigated have probabilities of $0 - < 1\%$ of occurring in a natural world, but probabilities of $1 - 10\%$ of occurring in the present world with anthropogenic forcing.

3.1 Introduction

The newly developed Brewster Glacier (New Zealand) equilibrium line altitude (ELA) record (Fig. 2.5), as well as the original snowline record (Fig. 1.4), both show several years with especially high ELAs occurring in the past decade (Willsman et al., 2018). Years with high ELAs correspond to high glacier mass-loss years. Modern New Zealand glacier fluctuations are most sensitive to temperature and precipitation (Anderson and Mackintosh, 2006, 2012; Mackintosh et al., 2017), suggesting that increases in mean and extreme global temperatures (Stocker et al., 2013; Masson-Delmotte et al., 2018) are driving the increase in frequency and intensity of high glacier mass-loss years.

Glaciers in the Southern Alps of New Zealand are characterized by a maritime climate and high precipitation, which increases from east to west, of $\sim 2 - 10$ m per year (Henderson and Thompson, 1999; Tait et al., 2006; Cullen and Conway, 2015). The high precipitation and low elevation of glacier extents results in glaciers with a high mass turnover and a high sensitivity to changes in climate (Oerlemans and Fortuin, 1992; Anderson and Mackintosh, 2012). New Zealand glacier sensitivity to temperature change includes some of the highest globally reported values: $1.1 - 4.0$ m w.e. $\text{yr}^{-1} \text{ } ^\circ\text{C}^{-1}$ (Anderson et al., 2010; Anderson and Mackintosh, 2012). Model sensitivity also shows increases in precipitation from 30 – 82% would be required to offset 1°C of warming (Oerlemans, 1997; Anderson et al., 2010; Anderson and Mackintosh, 2012).

Previous works have investigated the links between climate anomalies and changes in New Zealand glaciers. Atmospheric circulation has been shown to heavily influence New Zealand glacier mass balance, with enhanced southerly and westerly flow leading to more positive mass balance, and anomalous northerly and northeasterly flow leading to more negative mass balance (Fitzharris et al., 1997; Clare et al., 2002; Fitzharris et al., 2007; Mackintosh et al., 2017). Positive sea surface temperature anomalies and positive atmospheric pressure anomalies have been linked with glacier mass loss (Clare et al., 2002; Fitzharris et al., 2007; Mackintosh et al., 2017). These climate anomalies have been connected with climate oscillations, including El Niño Southern Oscillation and the Southern Annular Mode (SAM). Glacier advance and positive mass-balance years are linked with negative phases of SAM and El Niño events, while high glacier mass loss is linked with positive phases of SAM and La Niña events (Fitzharris et al., 1992, 1997, 2007; Purdie et al., 2011).

Marine heatwaves, resulting from high sea surface temperatures, may also be influencing glacier mass loss. Marine heatwaves have been shown to be increasing globally in both frequency and duration (Oliver et al., 2018). The Tasman Sea

2017/18 marine heatwave, occurring December 2017 – February 2018, was the most intense on record (Perkins-Kirkpatrick et al., 2019). Event attribution methods — using model simulations with and without human-induced forcings to calculate the anthropogenic influences on extreme climate events (King, 2017) — showed that high sea surface temperatures measured during the Tasman Sea 2017/18 marine heatwave would not have occurred without anthropogenic forcing (Perkins-Kirkpatrick et al., 2019). This marine heatwave also corresponds to one of the highest glacier mass-loss year on record.

Glacier mass loss has been linked with northerly flow anomalies, high pressure, and high sea surface temperatures (Fitzharris et al., 1997; Clare et al., 2002; Fitzharris et al., 2007; Mackintosh et al., 2017). However, more precisely identifying the climate drivers of extreme glacier mass-loss is important for 1) projecting how glaciers will change in the future, and 2) understanding the influence of natural versus anthropogenic forcing on the cryosphere. Here, we aim to better understand the climatic drivers behind the largest New Zealand glacier mass-loss years. We first use reanalysis data to analyze the climate anomalies that occurred during the years of extreme mass loss. Next, we use event attribution methods to calculate the anthropogenic influence on the identified climate anomalies driving high glacier mass loss.

3.2 Methods

3.2.1 Extreme mass-change years

We identify the extreme mass-loss years using the snowline record extending 1977 – 2017 (Willsman et al., 2018), with 2018 data from a subset of glaciers (Fig. 4.1). Extreme mass-loss years are defined as the 90th percentile of high snowline elevations, which are assumed to correspond to the 90th percentile of negative mass balances. Extreme mass-gain years, investigated for comparison with mass-loss years, are defined as the 90th percentile of low snowline elevations, corresponding to positive mass balances. Extreme mass-loss years are identified as 1990, 2011, 2016, and 2018, and extreme mass-gain years are identified as 1983, 1993, 1995, and 1997 (Willsman et al., 2018). While the EoSS record shows 1990 as an extreme mass-loss year (Willsman et al., 2018), there was no snowline flight that year. Mass-balance modeling, following the methods and for the glaciers described in Chapter 4, does show 1990 as an extreme mass-loss year. For each year discussed, we are describing the glacier mass-balance year, running from April of the previous year through March of the noted year.

3.2.2 Climate anomalies

We use ERA-Interim reanalysis at 0.25° spatial resolution (Dee et al., 2011), which covers 1979 – present, to identify monthly climate anomalies occurring in extreme mass-loss and mass-gain years. We calculate monthly anomalies relative to mean climate April 1979 – March 2009. To calculate mean climate anomalies, we define a region encompassing the Tasman Sea for sea surface temperature and mean sea level pressures, and a region encompassing the glaciers on the South Island of New Zealand for surface air temperatures and precipitation. Surface air temperature refers to near-surface (2 m) air temperature. The Tasman Sea region is defined as 26° – 46° S, 135° – 174° E, and the glaciated region on the South Island of New Zealand is defined as 42° – 46° S, 167° – 173° E (Fig. 3.1). We consider anomalies during the accumulation season (April – September) and ablation season (October – March).

Figure 3.1: Domain over which climate anomalies are analyzed (full map). Sea surface temperature and mean sea level pressure anomalies are calculated over the Tasman Sea region (dashed red box), and surface air temperature and precipitation anomalies are calculated over the glaciated regions of the New Zealand South Island (solid red box).

3.2.3 Event attribution

For attribution calculations, we use two different ensembles of general circulation model (GCM) output. First, we use a multi-model ensemble: one ensemble member (rli1p1) for 16 different GCMs that are all part of Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012). Natural climate is defined as HistoricalNat simulations 1901 – 2005. Present climate is defined as Representative Concentration Pathway (RCP) 8.5 2006 – 2026 (King et al., 2017). Second, we use a single-model ensemble: 34 ensemble members from the Community Earth System Model Large Ensemble (CESM) (Kay et al., 2015). For CESM,

natural climate is defined as the full 1800-year control run, and present climate is defined as 2006 – 2026 from each RCP8.5 ensemble member. Using the two model ensembles provides a more robust calculation of attribution, as CMIP5 accounts for variations across models, and CESM accounts for model internal variability and initial conditions.

Climate influenced only by natural forcings, referred to herein as the natural world, is represented by simulations that include greenhouse gas concentrations at pre-industrial levels and natural forcing (Taylor et al., 2012; Kay et al., 2015). RCP8.5 simulations, which include natural variability and anthropogenic forcings, represent the anthropogenically-modified climate, referred to herein as the present world. To quantify the role of anthropogenic forcings we compare the probability of climate anomalies of extreme mass-loss years occurring in the natural world, with the probability of occurrence in the present world.

We calculate mean surface air temperatures over GCM grid cells containing glaciated regions in the South Island of New Zealand, defined as 42° – 46° S, 167° – 173° E. Monthly anomalies are calculated relative to mean monthly climatology in Historical simulations from each GCM from 1975 – 2004. This time period was selected as the Historical simulations end in 2004, but as to still overlap as much as possible with the climatology calculated from ERA-Interim data, which starts in 1979.

To calculate attribution uncertainties, we estimate the 5th – 95th percent confidence interval of GCM ensembles from 10,000 bootstrapped subsamples from half of natural and present simulations (King et al., 2017). For CMIP5 simulations there are 1,680 years (16 models, 105-year scenarios) of natural world climate and 336 years (16 models, 21-year scenarios) of present world climate, and for CESM simulations there are 1,800 years (1 control run, 1,800-year scenario) of natural world climate and 714 years (34 ensemble members, 21-year scenarios) of present world climate. For each ensemble and climate scenario, half of all years were randomly sampled with replacement, and this was done 10,000 times.

3.3 Results

3.3.1 Climate anomalies of extreme mass-loss years

First we show accumulation and ablation seasonal and annual climate anomalies that occur during extreme mass-loss and mass-gain years, averaged for the four extreme years (Fig. 3.2). For both surface air and sea surface temperatures, warmer temperatures occur over New Zealand and the Tasman Sea during mass-loss years, with more positive anomalies during the ablation season than in the

Figure 3.2: Climate anomalies during extreme glacier mass-loss and mass-gain years. Mean a) sea surface temperature (SST; $^{\circ}\text{C}$) and mean sea level pressure (MSLP; Pa), b) surface air temperature ($^{\circ}\text{C}$), and c) precipitation (%) anomalies calculated for extreme glacier mass-loss and mass-gain years using ERA-Interim data. Anomalies are relative to April 1979 – March 2009 mean climate. MSLP contours are 50 Pa, 0 is bold, negative anomalies are dashed, and positive anomalies are solid lines. See digital version for clearest MSLP contours.

accumulation season (Fig. 3.2a,b). Conversely, cold surface air and sea surface temperature anomalies occur during mass-gain years, again with more negative anomalies in the ablation season than in the accumulation season (Fig. 3.2a,b). Mean sea level pressure anomalies around New Zealand and the Tasman Sea are positive during both the accumulation and ablation seasons of mass-loss years, and negative during the accumulation season for mass-gain years (Fig. 3.2a). Precipitation over New Zealand is higher in the ablation season of mass-loss years, and conversely lower in the ablation season of mass-gain years (Fig. 3.2c). These results are largely consistent, but show more spatial detail, with a similar analysis of climate anomalies in the coarser resolution NCEP/NCAR reanalysis for mass-loss and mass-gain years defined using different methods (Mackintosh et al., 2017).

Next we investigate the significance of the climate anomalies of extreme mass-loss years shown in Figure 3.2. To do this, we use the bootstrapping method of randomly selecting with replacement four years from April 1979 – March 2018, with one year being a glaciological mass-balance year from April of the previous year through March of the year noted. The mean climate anomalies of those four years were calculated for the accumulation season (April – September), ablation season (October – March), and annually (April – March). Anomalies are calculated from ERA-Interim data, relative to April 1979 – March 2009 mean climate, over New Zealand for surface temperature, and over the Tasman Sea region for SSTs and MSLP. This was then repeated 100 times. Figure 3.3 shows the resulting distributions of climate anomalies for randomly selected years, compared with the anomalies calculated for the extreme glacier mass-loss years. We find that the high surface temperature anomalies occurring during the ablation season of extreme mass-loss years do not occur in any of the randomly selected years (Fig. 3.3b), indicating that the anomalies are unique to extreme mass-loss years. All of the other climate anomalies calculated for extreme mass-loss years do occur in at least one of the randomly selected samples. However, for both annual surface temperatures and ablation season sea surface temperatures, only 1% of randomly selected samples have anomalies higher than the extreme mass-loss years (Fig. 3.3c,e).

Next we analyze the climate anomalies during each of the extreme mass-loss years. We look at surface air and sea surface temperature December – February, the peak of the ablation season, and mean sea level pressure anomalies in November, leading into the ablation season (Perkins-Kirkpatrick et al., 2019). Mean sea level pressure anomalies are positive all four years, with the highest positive anomalies in 2011 and 2018, which are the two most extreme mass-loss years. Tasman sea surface temperature anomalies are positive all years, again with the highest positive anomalies in 2011 and 2018. Surface air temperature anomalies

Figure 3.3: Distributions of climate anomalies for 100 samples (each sample is the mean of four years randomly selected with replacement) for surface air temperature ($^{\circ}\text{C}$; a – c), sea surface temperatures ($^{\circ}\text{C}$; d – f) and mean sea level pressure (Pa; g – i) for the accumulation season (April – September), ablation season (October – March), and annually (April – March). Mean climate anomalies of the 4 identified extreme mass-loss years (1990, 2011, 2016, and 2018) are shown by red lines. Anomalies are calculated from ERA-Interim data, relative to April 1979 – March 2009 mean climate.

are positive across the South Island in all years except 1990, with the highest positive anomalies in 2016 (Fig. 3.4).

We analyze monthly climate anomalies averaged over the South Island of New Zealand for surface air temperature and precipitation, and averaged over the Tasman Sea for sea surface temperatures and mean sea level pressure (Fig. 3.5). During 2011, 2016, and 2018 there are at least 2 months when surface air temperature anomalies are over 1.7°C , but the timing of these high temperatures can occur throughout the ablation season and are not the same across all mass-loss years. Surface air temperature anomalies in 1990 were not as extreme, ranging $0.8 - 1.1^{\circ}\text{C}$, and occurring August – November, from the end of the accumulation

Figure 3.4: Sea surface temperature (SST; °C), mean sea level pressure (MSLP; Pa), and surface air temperature (°C) anomalies during individual years of extreme glacier mass-loss. Sea surface temperature and surface air temperature anomalies are shown for December – February means, MSLP anomalies are shown for November means. MSLP contours are 200 Pa, 0 is bold, negative anomalies are dashed, and positive anomalies are solid lines.

season through early in the ablation season. Precipitation anomalies generally vary, with the most notable anomaly being 132% of normal precipitation in January 2018. Positive sea surface temperature anomalies in 1990 and 2016 occur in February and March, while positive anomalies in 2011 occur December – March. In 2018, positive sea surface temperature anomalies occur in all but one month of year, and are over 1°C December – March, highlighting the 2017/2018 marine

Figure 3.5: Surface air temperature (TS; °C), precipitation (%), sea surface temperature (SST; °C), and mean sea level pressure (MSLP; Pa) monthly anomalies for years of extreme glacier mass-loss.

heatwave. Positive mean sea level pressure anomalies occur during all four years in November and December, but all years except 1990 are followed by negative pressure anomalies January – March. These results suggest that the primary driver of extreme glacier mass-loss is high surface air temperatures occurring for at least two months some time during the ablation season, likely influenced by high pressure occurring in November and December of the high mass-loss years (Fig. 3.5).

We look at time series of surface air temperature and sea surface temperature anomalies to investigate whether there is a temperature threshold above which leads to extreme mass-loss years. Three of the four extreme mass-loss years (2011, 2016, 2018) have mean monthly surface air temperature anomalies above 1.8°C (Fig. 3.6a). There are several other months with anomalies as high, but none that occur during the ablation season. Next we calculate monthly surface air temperature anomalies with a 2-month running mean to investigate whether there is a similar threshold but one that requires at least two months of sustained high temperature anomalies. Again, 2011, 2016, and 2018 all have two-month mean temperature anomalies during the ablation season of 1.7°C or greater (Fig. 3.6b). There are other times in the record that temperatures exceed this threshold, in

Figure 3.6: a) Surface air temperature ($^{\circ}\text{C}$), b) 2-month surface air temperature running mean ($^{\circ}\text{C}$), and c) sea surface temperature ($^{\circ}\text{C}$) anomalies (April 1980 – March 2018). Red shading indicates extreme mass-loss years, and blue shading indicates extreme mass-gain years. Red lines provide references for extreme mass-loss years.

1981 and 2001, but in those years the positive temperature anomalies occur during the accumulation season. While this analysis of monthly and 2-month mean surface air temperature anomalies shows high positive anomalies in 2011, 2016, and 2018, the positive anomalies in 1990 do not stand out in the record (Fig. 3.6a,b). Sea surface temperature anomalies show less of a relationship between high mass-loss years and high anomalies (Fig. 3.6c). While the highest sea surface temperature anomalies in the record occur during 2018, the other high mass-loss years do not have especially high sea surface temperature-anomalies relative to other years.

3.3.2 Anthropogenic influence

As the analysis of climate anomalies shows surface air temperature as the common driver of each of the extreme mass-loss years, we focus on investigating the anthropogenic influence on high surface air temperatures in extreme mass-loss years. First we calculate the anthropogenic influence on mean austral summer (December – February) temperatures (Fig. 3.7). Figure 3.7 shows the probability of a specific summer temperature anomaly occurring in a year. For 2011, 2016, and 2018,

these anomalously high summer temperatures have much higher probabilities of occurring with anthropogenic forcing than in a natural world. The 1990 summer temperature anomaly has a closer probability of occurring in the natural world as in the present world. However, as we’ve shown that extreme mass-loss years are driven by high temperatures occurring at some time during the ablation season (October – March), not necessarily during summer months, we also calculate the anthropogenic influence on identified monthly and multi-month anomalies for each extreme mass-loss year.

Figure 3.7: Probability distributions for mean austral summer (December – February) surface air temperature anomalies over the South Island of New Zealand for natural (nat.; black) and present world (pres.; red) ensembles for CMIP5 (solid) and CESM (dashed). Temperature anomalies calculated from ERA-Interim data are marked with dashed lines.

Here we use calculated monthly surface air temperature anomalies for each of the extreme mass-loss years (Fig. 3.5), in order to identify months or multiple months with the highest positive anomalies for each year. Annual probability distributions (Fig. 3.8) and calculated probabilities (Fig. 3.9) show that for each event, the probability of occurring in the natural world in a given year is $0 - <1\%$, while the probability of occurring in the present world is $1 - 10\%$. There are two climate anomaly events, mean August – November temperatures in 1990, and mean November – January temperatures in 2018, for which ERA-Interim temperature anomalies do not occur in any simulations in our natural world ensembles, leading to a 0% probability of occurring without anthropogenic forcing. The 90% confidence level is shown as the 5th – 95th percentile confidence intervals (Fig. 3.9). Within the 90% confidence level there are four scenarios

for which the minimum probability of the temperature anomaly occurring in the present world is greater than the maximum probability of occurring in the natural world: August – September 1990, August – November 1990, October – March 2016, and November – January 2018. Interestingly, while calculated surface air temperature anomalies in 1990 are not as strong and occur earlier in the ablation season than the other extreme mass-loss years (Fig. 3.5), the anthropogenic signal in 1990 temperature anomalies is not distinct from the other years (Figs. 3.8 & 3.9).

Figure 3.8: Annual probability distributions for mean monthly or seasonal surface air temperature anomalies over the South Island of New Zealand for natural (nat.; black) and present world (pres.; red) ensembles for CMIP5 (solid) and CESM (dashed). Temperature anomalies calculated from ERA-Interim data are marked with dashed lines. Note that axes are not the same for each panel.

Event & Temperature anomaly (°C)	1990 Aug - Sept (1.03 °C)	1990 Aug - Nov (0.94 °C)	2016 Oct - Mar (1.16 °C)	2011 Nov - Dec (1.78 °C)	2018 Nov - Jan (1.51 °C)	2018 Dec (2.22 °C)	2016 Feb (2.68 °C)	2016 Feb - Mar (2.34 °C)
Natural	<1% (0-<1%)	0% (0%)	<1% (0-<1%)	<1% (0-<1%)	0% (0%)	<1% (0-<1%)	<1% (0-<1%)	<1% (0-<1%)
Present	7% (4-11%)	9% (6-13%)	10% (6-14%)	2% (<1-3%)	3% (1-5%)	2% (<1-3%)	1% (0-2%)	1% (0-2%)

Figure 3.9: Probabilities of extreme mass-loss year temperature anomalies occurring in natural and present worlds. Mean values are presented, with the 90% confidence level (5th – 95th percentile confidence intervals) shown in parentheses.

3.4 Discussion

3.4.1 Seasonal climate anomalies

Our results suggest that high positive temperature anomalies during the ablation season are a driver of extreme glacier mass loss. This result indicates that temperature and resulting ablation are more important in driving variability of glacier annual mass balance than precipitation and accumulation. This finding is consistent with previous work showing that summer temperatures and summer balance are the main driver of annual glacier mass balance. Summer temperatures are the most significant driver of Franz Josef Glacier (New Zealand) mass balance (Oerlemans and Reichert, 2000). Modeled Brewster Glacier mass balance (2004 – 2008) shows much larger variation in summer balances than winter balances, suggesting that summer balance is the primary driver of interannual mass-balance variability (Anderson et al., 2010). This modeling result is consistent with mass-balance measurements from Brewster Glacier (2005 – 2018), where variation in summer balances is greater than winter balances (Cullen et al., 2017). Years with the most negative annual mass balances (2008, 2011, 2016, 2018) are not the lowest in the record, but it is the summer balance for each of the years that is especially negative. Conversely, the most positive mass-balance year (2005) winter balance was not the highest on record, but the summer balance is the least negative in the entire record. This importance of seasonality is highlighted by the finding that the same weather anomalies, enhanced northeasterly flow anomalies, around Brewster Glacier lead to both high ablation and large snowfalls, depending on the season of the circulation anomaly (Cullen et al., 2019).

3.4.2 Event attribution

Upon finding that extreme glacier mass-loss years each have positive surface air temperature anomalies during the ablation season (Fig. 3.5), we calculate the anthropogenic influence on these high positive temperature anomalies. Further analysis could include attribution of the high mean sea level pressures that occur during the extreme mass-loss years between October – December (Fig. 3.5). However, previous work has calculated the anthropogenic influence on positive mean sea level pressure anomalies in November 2017, in relation to the 2017/18 Tasman Sea marine heatwave (Perkins-Kirkpatrick et al., 2019). Results showed that while high temperatures associated with the marine heatwave can be attributed to anthropogenic forcing, the probability of high mean sea level pressure occurring is the same for natural and present world scenarios (Perkins-Kirkpatrick et al., 2019). This suggests that the positive mean sea level pressure anomalies occurring

in other high mass-loss years would not have a distinct anthropogenic influence, and could occur in a natural climate. Finally, attribution could be carried out for the high sea surface temperatures that occur during extreme mass-loss years (Fig. 3.5). In Perkins-Kirkpatrick et al. (2019), surface air temperature is used as a proxy for sea surface temperatures, as the CESM LE control run is not a fully coupled model, and only includes atmosphere and land components (Kay et al., 2015). However, analysis of each of the extreme mass-loss years shows that surface air temperature is not a perfect proxy for sea surface temperatures. For example, 2011, 2016, and 2018 each have at least 2 months of surface air temperature anomalies over $+1.7^{\circ}\text{C}$, but 2018 is the only year with sea surface temperature anomalies over $+0.75^{\circ}\text{C}$ (Fig. 3.5). Further attribution of sea surface temperature anomalies using only fully-coupled CMIP5 GCMs (Taylor et al., 2012) may be useful in understanding the anthropogenic influence on marine heatwaves, and their influence on glacier mass loss.

3.4.3 Extreme mass-loss years

In the previous analysis we found that surface air and sea surface temperatures in 1990 were not as extreme as the other three high mass-loss years. In particular, we found that 2011, 2016, and 2018 each had monthly surface air temperature anomalies of $\geq +1.8^{\circ}\text{C}$ occurring for at least one month in the ablation season (October – March). However, the most positive monthly temperature anomaly in 1990 during the ablation season was $+0.9^{\circ}\text{C}$ (Fig. 3.5), and monthly surface air temperature anomalies in 1990 were not distinct from other years on record that did not have high mass loss (Fig. 3.6). Further investigation of how the 1990 snowline was calculated, as there was no snowline flight that year, brings question to the accuracy of the 1990 snowline (personal com. A. Willsman). Initial analysis of data from the 2019 snowline survey, through the number of glaciers completely snow-free and the 2019 Brewster Glacier snowline elevation, suggests that 2019 is in the 90th percentile of extreme mass-loss years.

3.5 Conclusions

Using ERA-Interim reanalysis, we show that extreme New Zealand glacier mass-loss years (1990, 2011, 2016, and 2018) are all characterized by positive surface air temperature over New Zealand, and positive sea surface temperature and sea level pressure anomalies over the Tasman Sea. These positive anomalies are generally more pronounced in the ablation season (October – March) than in the accumulation season (April – September). In 2011, 2016, and 2018 surface air temperature

anomalies of at least $+1.8^{\circ}\text{C}$ occurred for at least one month during the ablation season (October – March). Furthermore, 2011, 2016, and 2018 each had a 2-month mean surface air temperature anomaly within the ablation season of at least $+1.7^{\circ}\text{C}$, which is exclusive to these three years over the time investigated (1980 – 2018). Monthly temperature anomalies in 1990 were less extreme ($+0.8 - 1.1^{\circ}\text{C}$), but occurred for four months from the end of the accumulation season through early in the ablation season (August – November). The differences in temperature anomalies between 1990 and the other extreme mass-loss years, and further investigation into the method used to calculate the 1990 snowline, suggest that 1990 is not in the 90th percentile of negative mass-balance years (Willsman et al., 2018).

Using event attribution methods (King, 2017) and two GCM ensembles, we show that positive surface air temperature anomalies that occurred during extreme mass-loss years were all more likely to have occurred with anthropogenic forcing. Each of the positive monthly and seasonal surface air temperature anomalies identified have probabilities of $0 - <1\%$ of occurring in a natural world, but probabilities of $1 - 10\%$ of occurring in the present world with anthropogenic forcing. This result suggests that as temperatures continue to rise (Stocker et al., 2013; Masson-Delmotte et al., 2018) and extreme heat events become more common (King et al., 2017; Perkins-Kirkpatrick et al., 2019), the anthropogenic influence on warming will continue to increase. Years of extreme glacier mass loss will likely become more common, which is already seen with the three most negative mass-balance years on record (2011, 2016, 2018) occurring in the past decade.

Chapter 4

Anthropogenic influences on extreme annual glacier mass loss

Abstract

Glaciers are unique indicators of climate change. While global-scale glacier decline in recent decades has been attributed to anthropogenic forcing, direct links between climate forcing and years of extreme glacier mass loss have not been documented. Here we address this gap by applying event attribution methods to calculate the anthropogenic influence on extreme glacier mass-loss years at a regional scale, targeting the two years of highest observed mass-loss (2011 and 2018) across New Zealand's Southern Alps. We simulate glacier mass balance using temperature and precipitation from multi-model and single-model ensembles of climate model output. We show that mass loss in 2011 was at least 10 times ($>90\%$ confidence) more likely to occur with anthropogenic forcing, and in once case in 2018 could not have occurred ($>90\%$ confidence) without anthropogenic forcing. This increased likelihood is driven by present-day temperatures $\sim 1.0^{\circ}\text{C}$ above the pre-industrial average, confirming a connection between rising greenhouse gas concentrations from anthropogenic forcing, warming temperatures, and high annual ice loss. Glaciers will likely continue to melt and retreat under present and future climate conditions. As warming and extreme heat events continue and intensify, we expect more glacier mass loss attributable to human influence in the coming decades.

4.1 Introduction

Glaciers worldwide are exhibiting historically-unprecedented retreat and mass loss (WGMS, 2018). Global glacier retreat, based on length records spanning decades to centuries (WGMS, 2018), is often presented as evidence of anthropogenic climate change. Formal statistical assessment has shown that centennial-scale retreat of glaciers around the world is driven by human influences (Roe et al., 2017). However, glacier length is a result of mass balance integrated over different timescales, which can range from 3 – 100 years for glaciers with varying response times (Oerlemans, 2005). Therefore, glacier retreat reflects climate trends occurring on different timescales, determined by the glacier response time, whereas mass balance is the most direct connection between glaciers and climate (Oerlemans, 2010). Attribution of global glacier mass loss to anthropogenic forcing has been carried out on decadal timescales, and provided categorical evidence of long-term climate change (Marzeion et al., 2014). However, the previously employed attribution methods do not accurately resolve each region, and require long-term records of mass-balance measurements (Marzeion et al., 2014). These long-term records dampen extreme mass-loss years that have become more prevalent in recent decades (WGMS, 2018), and records >30 years are currently available for fewer than 50 glaciers worldwide (WGMS, 2018) (Fig. 4.1).

Event attribution (King, 2017) — using model simulations with and without human-induced forcings to calculate the anthropogenic influences on extreme climate events — has previously been applied to extreme heat, drought, and rainfall events (Lewis and Karoly, 2013; King et al., 2017). Application of event attribution methods to annual glacier mass change will enable the ongoing assessment of human impacts on global glacier change. This is especially important as glacier retreat will likely accelerate in the future (Radić and Hock, 2011; Marzeion et al., 2012; Huss and Hock, 2015; Zemp et al., 2019), contributing to sea level rise (Radić and Hock, 2011; Marzeion et al., 2012; Huss and Hock, 2015; Zemp et al., 2019) and impacting biodiversity, ecosystems, and human societies (Xu et al., 2009; Huss and Hock, 2018). Here, we establish a method for attribution of annual changes in glacier mass to natural or anthropogenic forcings using direct or proxy mass-balance measurements.

4.2 Methods

To assess the anthropogenic influence on glacier mass loss, we simulate mass balance using data from a multi-model ensemble of 16 Coupled Model Intercomparison Project Phase 5 (CMIP5) models (Taylor et al., 2012) (Fig. 4.6), and

Figure 4.1: Full map: All global glaciers (RGI, 2017) (black), including all glaciers with >30 years of ongoing mass-balance measurements (WGMS, 2018) (open black circles). Pie charts show the timing, by decade, of extreme mass-loss years for each glacier, with the years of mass-balance measurements noted. Extreme mass-loss years are defined as 90th percentile of negative mass balances for each individual glacier. Inset: Glaciers in the Southern Alps of New Zealand (RGI, 2017) (black), including the subset of glaciers used in this study (green).

a single-model ensemble with 34 members from the Community Earth System Model Large Ensemble (CESM) (Kay et al., 2015). Using the two model ensembles provides a more robust calculation of attribution (Perkins-Kirkpatrick et al., 2019), as CMIP5 accounts for variations across models, and CESM accounts for model internal variability and initial conditions. Climate influenced only by natural forcings, referred to herein as the natural world, is represented by simulations that include radiative forcing at pre-industrial levels and natural variability (Taylor et al., 2012; Kay et al., 2015). Representative concentration pathway (RCP) 8.5 simulations, which include natural variability and anthropogenic forcings, represent the present, anthropogenically-modified climate, referred to herein as the present world. To quantify the role of anthropogenic forcings we compare the probability of extreme measured glacier mass loss occurring in the natural world, with the probability of occurrence in the present world.

We apply this method to New Zealand glaciers (Fig. 4.1), which provide a rare record of glacier change in the Southern Hemisphere (Willsman et al., 2018), and have had several years in the past decade with especially high mass loss (Willsman et al., 2018; Cullen et al., 2017; Purdie et al., 2015). Indirect mass-

balance measurements from 11 glaciers (beginning 1977 – 1980) show that 2011 and 2018 were the two highest mass-loss years on record (Willsman et al., 2018). These measurements were obtained through oblique aerial photos that are taken at the end of each summer to record the end-of-summer-snowline elevation (Chinn et al., 2012), referred to herein as the snowline. We use the snowline as a proxy for the equilibrium line altitude and therefore mass balance (Oerlemans, 2010). Direct mass-balance measurements from two of those 11 glaciers, Brewster Glacier (since 2005) (Cullen et al., 2017), and Rolleston Glacier (since 2011) (Purdie et al., 2015) (Fig. 4.1), also show that 2011 and 2018 were extreme mass-loss years (WGMS, 2018).

4.2.1 Glaciological input data

We use digital elevation models (DEMs) to define the glacier surface elevation, and orthophoto mosaics to manually identify glacier perimeters, both generated with structure from motion photogrammetry (Vargo et al., 2017). The images used for structure from motion photogrammetry were collected in March 2018. Orthophoto mosaics are 0.1 – 0.5 m resolution, and DEMs were interpolated to 10 m resolution. DEM vertical errors are 0.3 – 1.7 m, largely depending on the image coverage of each glacier (Vargo et al., 2017).

Snowline elevations have been photographed annually at the end of summer (March – April) (Oerlemans, 2010) for 50 glaciers in the Southern Alps since 1977 – 1980 using oblique aerial photography (Chinn et al., 2012). From those 50 glaciers, we analyze the two glaciers with measured mass-balance data, as well as nine others, selected as those that provided a) the best spatial coverage, b) the most continuous records, and c) the largest glaciers, as some of the 50 glaciers are now almost nonexistent (Willsman et al., 2018). Using orthophoto mosaics and DEMs generated using structure from motion photogrammetry, we measure 2011 and 2018 mean snowlines (Vargo et al., 2017) (Fig. 4.2). To calculate shading for radiative forcing over each glacier domain, which requires spatial coverage beyond structure from motion photogrammetry DEMs, we use the Landcare Research 25 m DEM, interpolated to 10 m after calculating the shade grid.

4.2.2 Positive degree day model

Glacier mass balance is simulated using a positive degree-day model, with an additive radiation term in the calculation for total melt (Pellicciotti et al., 2005). Melt (M) is calculated following Equation 1.2:

$$M = M_T T + M_R(1 - a)Q \quad (4.1)$$

Figure 4.2: Example Brewster Glacier structure from motion photogrammetry orthophotos used to measure snowlines, with digitized snowlines shown in red. (a) 2011 orthophoto mosaic generated using four images taken in March 2011 and georeferenced with 2018 images, and (b) 2018 orthophoto mosaic generated and georeferenced using 192 geotagged images taken in March 2018.

using daily positive temperature sums (T), a temperature factor (M_T ; $\text{mm d}^{-1} \text{ } ^\circ\text{C}^{-1}$), radiation factor (M_R ; $\text{m}^2 \text{ mm W}^{-1} \text{ d}^{-1}$), albedo (a), and incoming shortwave radiation (Q). The model is run on a daily time step. Accumulation is calculated when mean daily temperature is less than 1°C , and when daily precipitation is >0 .

Shortwave radiation (Q) is calculated on an hourly timestep, which is then averaged for each day. Q and its two components, direct radiation and diffuse radiation, are calculated (Oerlemans, 1992). Q is a function of top-of-the-atmosphere insolation (Berger, 1978), zenith and azimuth angles of the sun, surrounding topography (Corripio, 2003), and cloudiness. Cloudiness is parameterized (Pellicciotti et al., 2011) by calculating a daily cloud factor as the ratio of measured incoming radiation (Tait and Liley, 2009) to clear-sky potential incoming radiation. We use a fresh snow albedo of 0.85 and ice albedo of 0.35 (Cuffey and Paterson, 2010), and parameterize changes in albedo following:

$$as = p_1 - p_2 \log_{10} Ta \quad (4.2)$$

where as is the changing albedo of snow, p_1 is the albedo of fresh snow, p_2 is the parameter 0.112 used in Brock et al. (2000), and Ta is accumulated daily maximum temperatures $>0^\circ\text{C}$ since snowfall (Brock et al., 2000).

Because only two glaciers have measured mass balance data, we calculated the snowline for a) model calibration and b) to calculate anthropogenic influence on mass loss for glaciers without measured mass-balance data. Snow thickness is calculated daily using the previous day snow depth, and any daily accumulation and melt. The snowline is then calculated at the end of the mass-balance year as the mean elevation of all grid cells with snow thickness between 15 and 150 mm. This range is defined for simulated snowlines to be comparable with measured snowlines. Differences in glacier size and elevation range influence the snowline probability distributions (Figs. 4.3c,d & 4.5). Because measured snowlines cannot be quantified when they are above or below the glacier, we imposed a similar restriction on simulated snowlines — those that fell below the minimum glacier elevation were set to the minimum glacier elevation, and those that fell above the maximum glacier elevation were set to the maximum glacier elevation. As a result, glaciers with small elevation ranges have higher probabilities that their simulated snowlines will be above or below the glacier. This distribution is especially prominent for Rolleston Glacier (Fig. 4.3d), where there is >50% likelihood that the snowline in the natural simulations will be at or below the lowest glacier elevation, and >50% likelihood that the snowline in the present simulations will be at or above the highest glacier elevation.

4.2.3 Climate data

We used daily temperature, precipitation, and shortwave radiation from the New Zealand Virtual Climate Station Network (VCSN) data (Tait et al., 2006; Tait and Liley, 2009; Tait and Macara, 2014) with a spatial resolution of 0.05° . For each glacier, we used climate from the VCSN grid box that includes the center of the glacier. Temperature is scaled with elevation to the structure from motion photogrammetry 10 m DEM with seasonal lapse rates for maximum and minimum daily temperatures (Tait and Macara, 2014), which we then used to calculate mean daily temperature.

For attribution calculations, we used monthly precipitation and 2 m surface air temperature from two different ensembles of general circulation model (GCM) output. First, we used a multi-model ensemble: one ensemble member (r1i1p1) for 16 different GCMs (listed in Fig 4.6) that are all part of CMIP5 (Taylor et al., 2012). Natural climate is defined as HistoricalNat simulations April 1901 – March 2005. Present climate with natural and anthropogenic forcing is defined as RCP8.5 April 2006 – March 2026 (King et al., 2017). RCP8.5 is selected because it is the RCP scenario that global emissions are closest to as of 2018 (Meinshausen et al., 2011; Le Quéré et al., 2018). Second, we used a single-model ensemble:

34 ensemble members from the CESM Large Ensemble (Kay et al., 2015). For CESM, natural climate is defined as the fully-coupled 1,800 year-long control run, using March of the first year through April of the last year to simulate 1,799 mass-balance years. Present climate is defined as April 2006 – March 2026 from each RCP8.5 ensemble member. For both the HistoricalNat simulations and the CESM control run, these natural climates are defined by greenhouse gas concentrations at pre-industrial levels (Kay et al., 2015; Taylor et al., 2012). While shortwave radiation is also an input in the degree-day model, we assumed that variations in shortwave radiation between the natural and present climates are minor, and did not use radiation from the GCMs.

The low spatial resolution of GCM simulations (ranging from $0.90^\circ \times 1.25^\circ$ to $2.81^\circ \times 2.81^\circ$) leads to systematic biases between GCM output and VCSN data. Because of these biases, instead of driving the glacier model directly with GCM output, we used the higher-resolution VCSN climate and the 'delta change method' to remove GCM biases while keeping GCM variability (Hay et al., 2000; Clarke et al., 2015). We calculated monthly GCM-adjusted temperature (T_{mon}) and precipitation (P_{mon}) following:

$$\begin{aligned} T_{mon}(x, y, t) &= T_{VCSN}(x, y, \bar{t}_m) + (T_{GCM}(x, y, t) - T_{GCMbase}(x, y, \bar{t}_m)) \\ P_{mon}(x, y, t) &= P_{VCSN}(x, y, \bar{t}_m) \cdot (P_{GCM}(x, y, t) / P_{GCMbase}(x, y, \bar{t}_m)) \end{aligned} \quad (4.3)$$

where $T_{VCSN}(x, y, \bar{t}_m)$ is monthly mean VCSN temperature at (x, y) for the 36-year period 1980 – 2015, $T_{GCM}(x, y, t)$ is monthly GCM temperature at (x, y) for each month t (past or present scenarios), and $T_{GCMbase}(x, y, \bar{t}_m)$ is monthly mean GCM base temperature at (x, y) , calculated from natural climate simulations 1961 – 1990.

The delta change method gives monthly adjusted temperature and precipitation, however, calculated glacier mass balance can be significantly influenced by the temporal resolution (Hock, 2003; Farinotti, 2013). We therefore used VCSN data and GCM-adjusted climate to calculate daily variability for temperature (T_{day}) and precipitation (P_{day}) adjusted from Naughten et al. (2018), following:

$$\begin{aligned} T_{day}(x, y, t) &= (T_{mon}(x, y, t_m) - T_{VCSN}(x, y, t_m)) + T_{VCSN}(x, y, t_d) \\ P_{day}(x, y, t) &= (P_{mon}(x, y, t_m) / P_{VCSN}(x, y, t_m)) \cdot P_{VCSN}(x, y, t_d) \end{aligned} \quad (4.4)$$

where $T_{VCSN}(x, y, t_d)$ is daily VCSN temperature, being added to the difference between the monthly mean GCM-adjusted temperature (T_{mon}) and monthly mean VCSN temperature ($P_{VCSN}(x, y, t_m)$). For VCSN climate, both daily and monthly,

we used the 36-year period 1980 – 2015. For GCM past climate scenarios that are longer than 36 years, the VCSN period is added to the GCM-adjusted climate in a repeating cycle. Daily adjusted precipitation is calculated in the same way as temperature, except for the precipitation adjustment being multiplicative, where temperature is additive.

4.2.4 Model calibration and validation

Model calibration is required because the gridded meteorological data is not accurate enough on the high-resolution glacier domains (Tait and Macara, 2014), and because the degree-day model does not capture all of the small scale mass-balance processes. We calibrated parameters using Brewster Glacier. Comparison of weather station data collected from below Brewster Glacier (2004 – 2008) (Anderson et al., 2010; Tait and Macara, 2014) with VCSN climate for the same period showed VCSN temperature should be reduced by 1.25°C , and precipitation should be increased by a factor of 1.3 to match the weather station data. We then used measured mass-balance data from Brewster Glacier (2005 – 2017) (Cullen et al., 2017) to calculate temperature and radiation factors. Comparison of the modeled and measured data (2005 – 2017) showed a root mean squared error (RMSE) of 560 mm w.e. for optimum temperature (M_T) and radiation (M_R) factors of 0.75 $\text{mm d}^{-1} \text{ }^{\circ}\text{C}^{-1}$ and $0.22 \text{ m}^2 \text{ mm W}^{-1} \text{ d}^{-1}$, respectively.

Because climate adjustments and model parameters at Brewster Glacier are not consistent for all New Zealand glaciers, we followed a three-step model calibration (Huss and Hock, 2015). We modified the original calibration method (Huss and Hock, 2015) by finding the minimum RMSE between modeled and measured snowlines (Willsman et al., 2018) for each glacier instead of matching mass balance to an average regional specific balance. This modification is done because the average regional specific balance calculated for New Zealand glaciers has high uncertainties (Fig. 1.2).

We modelled each glacier over the period 2005 – 2017 with initial parameters the same as those calculated for Brewster Glacier. We then adjusted precipitation within reason (by a factor of 0.8 – 2.0) until a minimum RMSE between modeled and measured snowlines is reached (step 1). We varied precipitation first as it has a higher spatial variation than temperature, which is adjusted from gridded climate data using lapse rates. If a minimum RMSE is not reached, we then adjusted M_T from 0.65 – 0.85 $\text{mm d}^{-1} \text{ }^{\circ}\text{C}^{-1}$, and adjusted M_R to keep the ratio of $M_T : M_R$ optimized values constant (step 2). If we had still not arrived at a minimum RMSE, we finally adjusted temperature (step 3). With the three-step calibration method, minimum RMSEs were found with measured snowlines for six

glaciers following step 1, two glaciers following step 2, and two following step 3.

4.2.5 Uncertainties

We estimated the 5th – 95th percent confidence interval of GCM ensembles from 10,000 bootstrapped subsamples from half of natural and present simulations (King et al., 2017). For CMIP5 simulations there are 1,664 years (16 models, 104-year scenarios) of natural world climate and 320 years (16 models, 20-year scenarios) of present world climate, and for CESM simulations there are 1,799 years (1 control run, 1,799-year scenario) of natural world climate and 680 years (34 ensemble members, 20-year scenarios) of present world climate. For each ensemble and climate scenario, half of all years were randomly sampled with replacement, and this is done 10,000 times.

4.3 Results

We find that for the two glaciers with direct mass-balance measurements, the probability of extreme mass loss occurring increases with anthropogenic influences (Figs. 4.3a,b & 4.4). Mass loss measured at Brewster Glacier in 2011 has a 0 – 0.2% chance of occurring in any given year in a climate influenced only by natural forcings, but 0.8 – 4.6% chance of occurring in the present, anthropogenically-modified climate (Figs. 4.3a & 4.4). Mass loss of Brewster Glacier is even greater in 2018 than in 2011. Mass loss ≥ 2018 measured mass balance does not occur in any of the simulations in our natural world ensemble, while there is a 0 – 1.4% chance of occurring with anthropogenic forcing (Figs. 4.3a & 4.4). The mass loss measured at Rolleston Glacier in both 2011 and 2018 has a <0.1 – 0.2% chance of occurring in the natural world, while similar or greater mass-loss years for Rolleston Glacier have a 1.4 – 5.8% (in 2011) and 0.2 – 2.8% (in 2018) chance of occurring in a climate with anthropogenic forcing (Figs. 4.3b & 4.4).

By comparing the probability of measured mass loss occurring in the present world with the probability of measured mass loss occurring in the natural world, we calculate the increase in likelihood of extreme mass loss occurring due to human influence (Fig. 4.4). In 2011, measured mass loss at Brewster Glacier was at least 10 times ($>90\%$ confidence level), and on average 30 times, more likely to occur in a climate influenced by anthropogenic forcing (Fig. 4.4). Measured mass loss at Rolleston Glacier in 2011 was at least 14 times ($>90\%$ confidence level), and on average 42 times, more likely to occur with anthropogenic forcing (Fig. 4.4). The mass loss measured at Rolleston Glacier in 2018 is on average 15 times more likely to occur with human influence (Fig. 4.4). Simulations show that the

Figure 4.3: Annual mass-balance probability distributions for Brewster Glacier (a) and Rolleston Glacier (b), and annual snowline probability distributions for Brewster Glacier (c) and Rolleston Glacier (d), for natural (nat.; black) and present world (pres.; red) ensembles for CMIP5 (solid) and CESM (dashed). Measured 2011 and 2018 mass balances and snowlines are marked with dashed lines. Axes on (c) and (d) are different, due to differences in glacier size and elevation range. Note that simulated snowlines below the minimum glacier elevation are set to the minimum glacier elevation, and those above the maximum glacier elevation are set to the maximum glacier elevation.

mass loss measured at Brewster Glacier in 2018 could not have occurred without anthropogenic influence ($>90\%$ confidence level) (Fig. 4.4).

Snowline measurements from Brewster and Rolleston Glaciers also show a higher probability of extreme mass loss occurring in the present climate compared with the natural climate (Fig. 4.3c,d), with mean increases in the calculated likelihood of 5 – 8 times for 2011 and 2018 (Fig. 4.4). However, for both glaciers there is a larger increase in calculated likelihoods of mass loss attributed to anthropogenic forcing when mass-balance measurements, compared with snowline measurements, are used (Fig. 4.4). For example, considering mass loss at Brewster Glacier in 2018, measured mass balance could not have occurred without anthropogenic influence, while the high-elevation snowline was only 7 times more likely to occur

Figure 4.4: Top: Probabilities of extreme mass loss occurring in natural and present worlds, and the increase in likelihood. Values highlighted in red are discussed in detail in the text. Mean values are presented, with the 90% confidence level (5th – 95th percentile confidence intervals) shown in parentheses. Bottom: The increase in likelihood of glacier mass loss occurring in the present world compared with the natural world. Error bars show the 5th - 95th percentile confidence intervals. Arrows indicate an increase in likelihood of over 50 times within the 90% confidence level. Hatching for 2018 Brewster Glacier mass balance indicates that for all scenarios, the measured mass loss could not have occurred in the natural world. Note the y axis starts at 1, corresponding to no change in likelihood.

with anthropogenic influence (Fig. 4.4).

The dampened likelihood calculated with snowlines highlights that snowlines are not a perfect proxy for mass balance, and underlines the importance of continuing to measure mass balance directly. Snowlines are subject to small-scale processes, including avalanches, and other processes not captured in the mass-balance model used here. Extreme mass-loss years at Brewster Glacier have snowlines within 8 ± 5 m elevation of each other, but differences in measured mass balance of almost 0.5 m w.e. (28%) (Fig. 4.1), reflecting previous work that shows the re-

relationship between snowlines and mass balance is not linear (Cullen et al., 2017). Furthermore, the 2011 snowline at Rolleston Glacier is higher (indicating more mass loss) than the 2018 snowline, while the measured mass balance shows higher mass loss in 2018 by ~ 0.4 m w.e. (20%) (Fig. 4.1). Additionally, picking snowlines is subjective, leading to unquantified uncertainty associated with manually identifying the snowline from photographs (Vargo et al., 2017). While these results show limitations of snowlines as a mass-balance proxy, snowlines do provide an estimate of inter-annual mass-balance changes that can be used for attribution of glacier mass loss (Fig. 4.4) for glaciers where field-based measurements are not available.

	Measurement	Natural		Current		Likelihood	
		CMIP5	CESM	CMIP5	CESM	CMIP5	CESM
Brewster mass balance	-1728 mm w.e. ('11)	0% (0%)	<0.1% (0-0.3%)	3.8% (0.6-8.8%)	1.8% (0.3-4.1%)	only occurs in present	12 (1-inf)
	-2217 mm w.e. ('18)	0% (0%)	0% (0%)	0.9% (0-3.8%)	0.1% (0-0.9%)	only occurs in present	only occurs in present
Rolleston mass balance	-2039 mm w.e. ('11)	<0.1% (0-0.4%)	0% (0%)	5.0% (1.3-10.0%)	2.7% (0.6-5.3%)	28 (7-inf)	only occurs in present
	-2456 mm w.e. ('18)	<0.1% (0-0.4%)	0% (0%)	2.2% (0-5.6%)	0.7% (0-2.4%)	12 (0-inf)	only occurs in present
Brewster ELA	2303 m ('11)	0.3% (0-1%)	<0.1% (0-0.3%)	2.2% (0-5.6%)	0.4% (0-1.8%)	9 (0-inf)	3 (0-inf)
	2311 m ('18)	0.3% (0-1%)	<0.1% (0-0.3%)	1.9% (0-5.6%)	0.4% (0-1.8%)	8 (0-inf)	3 (0-inf)
Rolleston ELA	1857 m ('11)	10% (7-13%)	8% (6-11%)	55% (44-66%)	48% (41-56%)	5 (4-8)	6 (4-8)
	1847 m ('18)	12% (9-16%)	11% (8-13%)	60% (49-71%)	55% (47-62%)	5 (4-7)	5 (4-7)
Glenmary ELA	2297 m ('11)	14% (11-17%)	13% (10-17%)	36% (26-47%)	36% (29-43%)	3 (2-4)	3 (2-4)
	2327 m ('18)	7% (5-9%)	5% (3-7%)	21% (13-31%)	20% (14-26%)	3 (2-5)	4 (2-7)
Ridge ELA	2436 m ('11)	3% (2-5%)	2% (1-3%)	17% (9-26%)	10% (6-15%)	6 (3-12)	8 (3-21)
	2434 m ('18)	3% (2-5%)	2% (1-3%)	18% (10-26%)	11% (6-16%)	6 (3-11)	9 (3-22)
Vertebrae 12 ELA	2094 m ('11)	0% (0-1%)	0% (0-1%)	10% (4-18%)	5% (2-8%)	33 (6-inf)	18 (3-inf)
	2086 m ('18)	1% (0-1%)	0% (0-1%)	12% (6-19%)	6% (3-9%)	33 (7-inf)	18 (4-inf)
S. Cameron ELA	2395 m ('11)	15% (11-18%)	15% (12-19%)	51% (41-63%)	52% (44-59%)	4 (3-5)	3 (3-4)
	2426 m ('18)	10% (7-13%)	9% (7-12%)	44% (33-55%)	43% (36-50%)	4 (3-6)	5 (3-7)
Thurneyson ELA	2125 m ('11)	7% (5-10%)	4% (3-6%)	27% (18-37%)	26% (20-33%)	4 (2-6)	6 (4-11)
	2232 m ('18)	1% (0-2%)	0% (0-1%)	4% (1-9%)	3% (1-5%)	7 (1-31)	12 (2-64)
Vertebrae 25 ELA	>2002 m ('11)	1% (0-2%)	1% (0-2%)	17% (9-26%)	10% (6-15%)	28 (8-140)	22 (5-119)
	>2002 m ('18)	1% (0-2%)	1% (0-2%)	17% (9-26%)	10% (6-15%)	28 (8-140)	22 (5-119)
Salisbury ELA	not measured	N/A	N/A	N/A	N/A	N/A	N/A
	1967 m ('18)	3% (2-5%)	1% (0-3%)	32% (22-42%)	22% (16-29%)	10 (5-19)	20 (8-52)
Chancellor ELA	>1836 m ('11)	0% (0%)	0% (0%)	1% (0-3%)	0% (0-2%)	(0-inf)	1 (0-inf)
	>1836 m ('18)	0% (0%)	0% (0%)	1% (0-3%)	0% (0-2%)	(0-inf)	1 (0-inf)
Park Pass ELA	2040 m ('11)	4% (2-6%)	2% (1-4%)	23% (14-33%)	26% (20-33%)	7 (3-13)	7 (5-11)
	1966 m ('18)	8% (6-11%)	6% (4-8%)	37% (27-48%)	41% (34-49%)	5 (3-7)	14 (7-30)

Table 4.1: The percentage of years with equal or lower mass balance, and equal or higher snowlines, for individual glaciers in a natural world and the present world, as well as the change in likelihood (ratio of present percentages to natural percentages) for each glacier. The 5th – 95th percentile confidence intervals are shown in parentheses.

Both direct mass-balance measurements and snowline observations from Brewster and Rolleston Glaciers consistently show that extreme mass loss is more likely to occur with anthropogenic forcing. We therefore apply the same analysis to nine glaciers where only snowline measurements are available. All nine of the glaciers show an increase in probability (Fig. 4.5), and resulting increase in likelihood (Fig. 4.4), of extreme mass loss occurring with anthropogenic forcing. The difference in annual snowline probability distributions (Fig. 4.5) are largely influenced by differences in glacier size and elevation range. Snowlines from seven of the nine glaciers indicate that extreme mass loss in 2011 and 2018 was 3 – 11 times more likely to occur with anthropogenic forcing (Fig. 4.4). For the additional two glaciers, mean increases in likelihood are 20– 25 times (Fig. 4.4). Results from Brewster and Rolleston Glaciers, showing that likelihoods of mass loss due to anthropogenic forcing is dampened when using snowlines compared with mass balance (Fig. 4.4), suggest that if measured mass balance was available for the additional glaciers, increases in likelihoods of extreme mass loss occurring with anthropogenic forcings would be even higher.

4.4 Discussion and Conclusions

Changes in glacier mass balance depend on changes in accumulation and melt, which are largely driven by temperature and precipitation variations (Oerlemans, 2010). Previous work has shown that New Zealand glacier mass balance is largely influenced by sea surface temperature, with precipitation being less important in driving mass changes (Mackintosh et al., 2017). In our experiment setup, the differences between natural and present worlds are adjusted climate model temperature and precipitation. In this adjusted climate, averaged for the 11 glacier domains, present world temperatures are 1.0°C ($0.4 - 1.7^{\circ}\text{C}$ across ensemble members) higher than natural world temperatures (Fig. 4.6). This difference in adjusted temperature between pre-industrial climate and the present is equal to the change in measured New Zealand temperatures over the last century of $+1.00 \pm 0.25^{\circ}\text{C}$ (Mullan et al., 2010). The adjusted climate also shows increasing precipitation in the present world in 45 of the 50 climate models (Fig. 4.6). In our mass-balance calculation, precipitation only influences accumulation, with increasing precipitation leading to either more positive mass balance when temperatures are below 0°C , or no change in mass balance if temperatures are not below 0°C (Oerlemans, 2001). Therefore, it is the temperature increase in the present world simulations, not precipitation, that drives the increase in likelihood of extreme annual mass loss occurring with anthropogenic forcing.

We provide a framework for calculating the influence of natural and anthro-

Figure 4.5: Annual snowline probability distributions in natural (nat; black) and present (pres; red) climate ensembles for CMIP5 (solid) and CESM (dashed), ordered in decreasing glacier elevation range from a) through i). Measured 2011 and 2018 snowlines are marked with dashed lines, with blue shading indicating snowlines over the top of the glacier that can only be quantified as over the maximum glacier elevation. Note that axes are different, due to differences in glacier size and elevation range.

pogenic forcing on annual glacier mass loss or mass gain at a regional scale. This framework can be replicated elsewhere, for glaciers with direct or proxy mass-balance records. For attribution of mass change over a single year, this framework only requires climate data, and short-term mass-balance data for calibration of the mass-balance model. It can therefore be applied to glaciers worldwide, instead of being limited to glaciers with long-term mass-balance records that are largely in the Northern Hemisphere (Fig. 4.1).

Our results show that extreme annual glacier mass loss is much more likely to occur with anthropogenic forcing. In one case, extreme mass loss is entirely attributed to anthropogenic forcing, and would not have occurred in the natural world. The increase in likelihood of mass loss occurring with anthropogenic influence is driven by modern temperatures $\sim 1^\circ\text{C}$ above pre-industrial levels (Mullan

Figure 4.6: Temperature (top; °C) and precipitation (bottom; %) climate anomalies for present GCM scenarios compared with natural GCM scenarios. For each model or CESM ensemble member, values are averaged for all 11 glaciers.

et al., 2010), highlighting the connection between warming caused by humans and large annual ice loss. As global temperatures continue to rise to 1.5°C or more above pre-industrial levels over the coming decades (Masson-Delmotte et al., 2018), both the frequency and magnitude of extreme annual mass loss will likely increase, along with the associated anthropogenic signal. This work highlights the value of field-based and remote monitoring of glacier mass balance and high-elevation mountain climate for attribution of glacier mass changes.

Chapter 5

Synthesis

The primary aim of this thesis was to quantify modern changes in New Zealand glaciers and to investigate the drivers of those changes. We first developed a method to quantitatively measure New Zealand glacier length and ELA changes from historic images. The newly developed ELA chronology shows several years of extreme mass loss occurring in the past decade (2009 – 2018). We then investigated the climate drivers of extreme glacier mass-loss years, and the influence of anthropogenic forcing on extreme mass-loss years. The following section summarizes findings in the context of the original objectives, details the contribution these findings have made, and finishes with an outlook to future work.

5.1 Objectives

1. Develop a method to quantitatively measure glacier changes from historic and modern images using photogrammetry techniques. Revisit the historic EoSS images, and use the developed method to generate a) chronologies of quantitatively measured snowline elevations and, b) new chronologies of glacier length changes.

We established a new method for quantitatively measuring glacier changes from historic images. The method uses modern georeferenced images and structure from motion photogrammetry in addition to the historic images. We establish this method by initially applying it to Brewster Glacier, generating annual length and ELA records (1981 – 2017). We find that Brewster Glacier’s terminus retreated 365 ± 12 m between 1981 and 2017. The retreat was largely continuous, suggesting that Brewster retreat has been dominantly forced by 20th century warming, as the glacier responds too slowly to reflect decadal scale climate variability. Brewster

Glacier's ELA record shows pronounced interannual variability, with lower ELAs occurring 1981 – the mid 2000s, and the highest ELAs occurring since 2008.

2. Use reanalysis data to identify the climatic drivers of extreme glacier mass-loss years, and use event attribution methods to calculate the anthropogenic signal on the identified drivers of extreme glacier mass loss.

We find that extreme glacier mass-loss years are associated with 1) positive air surface temperature anomalies over New Zealand, and 2) positive sea surface temperature and sea level pressure anomalies over the Tasman Sea. These positive anomalies are generally most pronounced in the ablation season (October – March). In particular, the three highest mass-loss years on record (2011, 2016, and 2018) are characterized by 2-month mean surface temperature anomalies between November and March of at least $+1.7^{\circ}\text{C}$. Comparison of the surface air temperature anomalies from two GCM ensembles shows a significant difference in the probability of extreme temperatures occurring in model simulations forced with anthropogenic influence, compared with simulations with natural forcings only. We find that surface air temperature anomalies of extreme mass-loss years had probabilities of 0 – $<1\%$ of occurring in a natural world, but probabilities of 1 – 10% of occurring with anthropogenic forcing.

3. Calculate the snowline elevations for highest glacier mass-loss years using the method developed in Chapter 2. Calculate the anthropogenic influence on these highest glacier mass-loss years using event attribution methods from Chapter 3, with the added step of modeling glacier mass balance and snowlines using an enhanced degree-day model.

We use the method developed in Chapter 2 to calculate snowline elevations for a subset of New Zealand glaciers for the two highest mass-loss years since 1977: 2011 and 2018. We use these snowline elevation measurements and existing mass-balance measurements in combination with event attribution methods, with the added step of simulating glacier mass balance. We find that both high mass-loss years were much more likely to occur with anthropogenic forcing, and the extreme mass loss measured at Brewster Glacier in 2018 would not have occurred without anthropogenic forcing. This increased likelihood is driven by present-day temperatures

$\sim 1.0^{\circ}\text{C}$ above the pre-industrial average, highlighting the connection between human-induced warming and extreme annual glacier mass loss. These results suggests that as warming continues and becomes more extreme, the anthropogenic influence on warming will increase further, and will lead to extreme glacier mass-loss years occurring more frequently and with more intensity.

5.2 Contributions and implications of this thesis

5.2.1 Measuring glacier change

Past and future changes in New Zealand glaciers have some of the highest uncertainties of any region globally (e.g. Gardner et al., 2013; Zemp et al., 2015; Huss and Hock, 2015; Zemp et al., 2019), highlighting the need for more measurements of New Zealand glacier change. The end-of-summer-snowline survey provides a rare record of >40 years of New Zealand glacier change. However, until now the output of this survey has only been the end-of-summer-snowline ELA record (Fig. 1.4), with qualitatively measured ELAs (Chinn, 1999; Willsman et al., 2018).

We provide a method that enables the measurement of past snowline and length changes with uncertainties of ~ 10 m from historic images. In addition to historic images, we show that using georeferenced modern images with precise timing enables ELA and terminus position measurements with uncertainties of <1 m. Future application of these methods to the >50 New Zealand glaciers photographed each year would result in a comprehensive, ongoing record of New Zealand glacier length and ELA changes. The ELA record can be used to better constrain changes in New Zealand glacier mass since ~ 1977 , and to better inform global studies. The ELA record can also be used to validate glacier models, as was done in Chapter 4. Finally, this method of measuring glacier change from historic photographs can be applied beyond New Zealand glaciers to measure past changes in any glacier, or landscape even, with historic images.

5.2.2 Climate drivers and anthropogenic influence of glacier mass loss

Extreme annual mass loss of New Zealand glaciers is becoming more prevalent, with the highest mass-loss years occurring in the past decade (2010 – 2019). We show a relationship between high positive surface air temperature anomalies and extreme mass loss of New Zealand glaciers. We also show that anthropogenic climate change had a substantial impact on the high temperatures that led to ex-

treme New Zealand glacier mass loss. Extreme mass-loss years are also occurring more often in recent decades for glaciers around the world (Fig. 1.1). As glaciers globally are largely driven by temperature (e.g. Oerlemans, 1994; Oerlemans and Reichert, 2000), it is likely that the increase in extreme glacier mass loss globally is linked with increasing temperatures (Stocker et al., 2013; Masson-Delmotte et al., 2018). Our results suggest that as temperatures continue to increase globally (Stocker et al., 2013; Masson-Delmotte et al., 2018) and extreme heat events occur more frequently (e.g. Easterling et al., 2000), the anthropogenic influence on warming will increase, and extreme mass loss of glaciers globally will become more common.

5.2.3 Anthropogenic influences on glacier mass loss

Previous studies attributing glacier change to anthropogenic forcing required long-term records of mass-balance measurements and did not accurately resolve annual changes (Fig. 1.5) (Marzeion et al., 2014). The most negative modeled mass-balance years (1990, 2000, and 2011; black line) are all more negative than simulated mass balance in the anthropogenic forcing scenarios (red shading) (Fig. 1.5) (Marzeion et al., 2014). We apply event attribution methods to calculate the anthropogenic influence on extreme glacier mass-loss years, which are occurring more often in recent decades (Fig. 1.1). We show event attribution methods can be used to calculate the anthropogenic influence on high glacier mass-loss years.

We provide a framework, which can be replicated elsewhere for other regions, that provides quantitative information with uncertainties on the impacts of anthropogenic climate change on the cryosphere. Having this formal and specific link between anthropogenic warming and glacier mass loss is critical, for application to extreme annual mass loss of other glaciers, and for settling public debate linking the reduction of glacier mass with human activities. The framework we provide enables the rapid assessment of ongoing glacier change, and will be useful for climate change assessments including Intergovernmental Panel on Climate Change reports.

5.3 Future work

In Chapter 2 we establish a method for measuring glacier change from historic images. This method involves using structure from motion photogrammetry and tens to hundreds of geotagged images of each glacier to generate high-resolution and high-accuracy DEMs and orthophotos for each glacier. The next steps in the snowline survey and New Zealand glacier monitoring should involve determining

the optimum data collection for this workflow, increasing the accuracy of these methods, quantifying errors for glaciers without ground control, and automating the workflow as much as possible. These steps will enable a more rapid and quantitative calculation for annual ELAs, which would currently take a single operator $\sim$ one year to process for 50 glaciers. This workflow will also enable the calculation of annual length and volume changes for each of the monitored glaciers. The attribution study in Chapter 4 of this thesis shows the value of establishing and continuing these records of Southern Hemisphere glacier change.

After completing Chapter 3, further investigation into the calculation of the 1990 snowline brought into question the accuracy of the 1990 estimate. Initial analysis of data from the 2019 snowline survey, based on the number of glaciers completely snow-free and the 2019 Brewster Glacier snowline elevation, suggests that 2019 is above the 90th percentile of extreme mass-loss years. Future work in developing a scientific article from this chapter should include a) replacing 1990 with the next highest mass-loss year in the snowline record, and b) further analysis of 2019 snowline data to confirm or deny this year as an extreme mass-loss year.

Comparison of monthly temperature anomalies from ERA-Interim (used in Chapter 3 to determine climate anomalies), GCMs (used for attribution), and VCSN can inform future additional analysis for Chapter 3. For all three data sets, monthly temperature anomalies from April 2006 – March 2017 were calculated relative to monthly climatology (April 1980 – March 2010). Anomalies were calculated as a spatial average for all grids that include glaciers on the South Island ($43 - 45^{\circ}\text{S}$, $167.5 - 171.5^{\circ}\text{E}$).

VCSN monthly temperature anomalies have a normal distribution, with a mean of 0.2°C , minimum of -2.2°C , and maximum of 2.6°C (Fig. 5.1). Comparatively, ERA-Interim anomalies have a mean of 0.3°C , but a much larger range with a minimum of -6.4°C and maximum of 8.8°C (Fig. 5.1). As VCSN is higher-resolution, specific to New Zealand, and has been tested for mountainous regions of New Zealand (Tait and Macara, 2014), it is likely that VCSN temperatures are more accurate than ERA-Interim. Therefore, future analysis of temperature anomalies of extreme glacier mass-loss years should include VCSN in the analysis. However, using ERA-Interim in the analysis is still useful, as VCSN only covers New Zealand, while ERA-Interim includes the entire globe, enabling the analysis of sea surface temperature and pressure anomalies around New Zealand.

Figure 5.1 also shows the distribution of general circulation model (GCM) monthly temperature anomalies for the 16 CMIP5 models and 34 ensemble members used for the attribution in Chapter 3. Anomalies are calculated from RCP 8.5 from April 2006 – March 2017, relative to Historical simulations from April 1975 – March 2004. This range was selected because historical simulations end

Figure 5.1: Distributions of monthly VCSN (blue), ERA-Interim (red), and GCM (yellow) temperature anomalies from April 2006 – March 2017, relative to April 1980 – March 2010 monthly climatology.

in 2005. GCM anomalies also show a normal distribution, with a mean of 0.4°C , minimum of -0.7°C , and maximum of 2.1°C . The distribution of GCM temperature anomalies is similar to the distribution of VCSN temperature anomalies, further suggesting that future analysis should include calculating climate anomalies for extreme glacier mass-loss years using VCSN temperatures, which should then be used as measured values for the attribution comparisons.

We have used records of New Zealand glacier change to establish that event attribution methods can be used to calculate the human influence on glacier mass loss (Chapter 4). Further attribution of extreme glacier mass-loss years for glaciers globally can be carried out for glaciers with measured mass-balance records, which are available for 41 glaciers (≥ 30 -year records) and 81 glaciers (≥ 10 -year records) (WGMS, 2018). Additionally, including future scenarios in attribution work will help to show how the anthropogenic influence on extreme glacier mass loss will increase as temperatures continue to rise.

5.4 Concluding statement

The primary aims of this thesis were to investigate 1) how New Zealand glaciers have changed in recent decades, 2) the climate drivers of those changes, and 3) the influence of humans on those changes. These aims are addressed by bringing together measurements of modern glacier change, climate analysis, glacier mass-balance modeling, and extreme event attribution.

Appendix A

Transformations

Determining the real world positions in the New Zealand Transverse Mercator (NZTM) projection from image (x, y) coordinates of snowlines and terminus positions, required several transformations. These transformations include from camera space to SfMP model space (T_{cm}) and from model space to world space (NZTM) (T_{mw}), as well as the inverses of both (T_{mc}) and (T_{wm}).

A.1 Camera model

The relationship between glacier features in the real world and pixels in an image is based on a standard ideal camera model (Ma et al., 2012). Using homogeneous coordinates, for an ideal camera:

$$\lambda \mathbf{x} = A P T_{wc} \mathbf{X} \quad (\text{A.1})$$

where λ is the scalar depth, $\mathbf{x} = [x, y, 1]^T$ is the pixel position, x and y are coordinates in the image plane (relative to the center of projection), and

$$A = \begin{bmatrix} f s_x & f s_\theta & o_x \\ 0 & f s_y & o_y \\ 0 & 0 & 1 \end{bmatrix}$$

is the interior camera parameter matrix, which combines the focal length matrix A_f with the scaling matrix A_s . In matrix A , $f s_x$ and $f s_y$ are the size of the focal length in horizontal and vertical pixels, $f s_\theta$ is the skew, and o_x and o_y are the center offsets calculated using the principal point. The projection matrix, P , is defined as

$$P = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

and the transformation (or exterior) matrix is defined as

$$T_{wc} = \begin{bmatrix} R_{wc} & \mathbf{t}_{wc} \\ 0 & 1 \end{bmatrix}$$

which is composed of a 3 by 3 rotation matrix R_{wc} , and 3 by 1 translation matrix $\mathbf{t}_{wc}$ in homogeneous coordinates. $\mathbf{X} = [X_1, X_2, X_3, 1]^T$ is a point in world coordinates. The transformation (T_{wc}) is a combination of (T_{wm}) and (T_{mc}).

A.2 Correcting lens distortion

Lens distortion is addressed by applying a correction to the projected image coordinate, following a method based on Heikkila and Silvén (1997). The total distortion is modelled as a combination of radial distortion and tangential (de-centering) distortion. After lens distortion is included, the new normalized point coordinate ($\mathbf{x}_d$) is defined as

$$\mathbf{x}_d = (1 + k_1 r^2 + k_2 r^4 + k_3 r^6) \mathbf{x}_n + \mathbf{x}_t \quad (\text{A.2})$$

where $r^2 = x^2 + y^2$ is the distance from the image center, k_1, k_2 and k_3 are the radial distortion parameters, $\mathbf{x}_n$ is the normalized image projection relative to the image center, and $\mathbf{x}_t$ is the tangential distortion vector defined as

$$\mathbf{x}_t = \begin{bmatrix} 2p_1 xy + p_2(r^2 + 2x^2) \\ p_1(r^2 + 2y^2) + p_2 xy \\ 0 \end{bmatrix} \quad (\text{A.3})$$

where p_1 and p_2 are the tangential distortion parameters. To do a back-projection from an image to the world, this correction needs to be reversed, but it is not possible to invert this analytically.

The steps to remove the distortion and unproject the points are as follows:

1. for an image point $\mathbf{x}$, normalize to calculate $\mathbf{x}_n$ by subtracting the principal

point (c), and dividing by the focal length (f), following:

$$\mathbf{x}_n = \begin{bmatrix} x_n = (x - c_x)/f_x \\ y_n = (y - c_y)/f_y \\ 1 \end{bmatrix} \quad (\text{A.4})$$

2. undo skew (α_c) by updating x_n (the x component of $\mathbf{x}_n$):

$$x_n \leftarrow (x_n - \alpha_c \cdot y_n) \quad (\text{A.5})$$

3. use a successive iteration scheme, starting with $\mathbf{x}_n$, to estimate undistorted normalized coordinate $\mathbf{x}_u$, which is then denormalized.

A.3 Back-projection

To quantify ELAs and terminus positions, we then complete a back-projection, calculating the position of pixels identified as the snowline and terminus in real-world coordinates (NZTM). The inputs include a DEM of the glacier surface, locations, interior and exterior camera parameters, and (x, y) image coordinates of snowlines and glacier outlines.

Following Ma et al. (2012), we return to equation A1, and substituting $\mathbf{x}_u$ for the undistorted pixel position $\mathbf{x}$, we get

$$\lambda \mathbf{x}_u = A P T_{wc} \mathbf{X} \quad (\text{A.6})$$

By considering P as $\begin{bmatrix} I_3, 0 \end{bmatrix}$, where

$$I_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

We rearrange to solve for $\mathbf{X}$,

$$T_{wc}^{-1} P^T A^{-1} \lambda \mathbf{x}_u I_3 = \mathbf{X} \quad (\text{A.7})$$

A.4 Calculate the scalar depth λ

Depth of a pixel in the image is calculated by intersecting a ray from the camera with a DEM where $h(x_w, y_w)$ is an arbitrary height defined by the DEM. A simple stepping scheme is used, where a test depth λ_T is increased in a stepwise fashion,

and after each step X_3 is calculated. If $X_3 > h(X_1, X_2)$ the the projected point is above the DEM elevation and another step is taken. If $X_3 < h(X_1, X_2)$ then the projected point is below the DEM, the test λ_T is too big. At this point the step size is halved, and the direction of stepping is reversed. This process of decreasing step sizes and reversing direction is continued until the xy error, that is the difference between the projected point (X_1, X_2) and the nearest DEM grid center is below a threshold, and the z error, that is the difference between the projected elevation X_3 and $h(X_1, X_2)$ is below a threshold.

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