Assessing Greenland Ice Sheet Albedo and Mass Balance Variability Using In-Situ Data, Spaceborne Observations and Regional Model Outputs

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ASSESSING GREENLAND ICE SHEET ALBEDO AND MASS BALANCE VARIABILITY USING IN-SITU DATA, SPACEBORNE OBSERVATIONS AND REGIONAL MODEL OUTPUTS

by

PATRICK MICHAEL ALEXANDER

A dissertation submitted to the Graduate Faculty in Earth and Environmental Science in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

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Abstract

ASSESSING GREENLAND ICE SHEET ALBEDO AND MASS BALANCE VARIABILITY USING IN-SITU DATA, SPACEBORNE OBSERVATIONS AND REGIONAL MODEL OUTPUTS

by

Patrick Michael Alexander

Advisor: Professor Marco Tedesco

In this dissertation, I present a series of studies that further our understanding of processes responsible for variations in the mass balance of the Greenland ice sheet, and assess our ability to model them. The Greenland ice sheet will likely contribute to sea level rise in a future warmer climate, and it is important to be able to predict future changes in sea level. I perform assessments of (1) spatiotemporal variations in Greenland ice sheet albedo, a key parameter that modulates the mass and energy balance at the ice sheet surface, and (2) spatiotemporal variations in Greenland ice sheet mass balance. Both studies make use of model results, and spaceborne remote sensing estimates, and one makes use of in situ measurements, to assess the observed quantities.

The first topic is addressed using satellite data, in situ observations, and results from the Modèle Atmosphérique Régionale (MAR), a regional climate model that simulates the ice sheet surface, and the atmosphere above. I find that MAR reproduces spatial variations in albedo captured by remote sensing and in situ observations, but overestimates albedo by up to 0.1 at low elevations, due to overestimated bare-ice albedo. This can significantly impact the simulated ice sheet surface mass balance. Declining trends in albedo over 2000-2012 are captured by MAR, satellite data, and in situ observations at low elevations. At high elevations, discrepancies between satellite data and in situ observations limit the ability to draw conclusions regarding
albedo trends. Discrepancies between modeled and observed mean albedo and trends at low elevations may partially be accounted for by the presence of surface impurities, which are not accounted for by MAR. We also identify discrepancies between satellite albedo products in spatial variations in albedo north of 70°N, limiting our ability to draw conclusions for this region.

In the second portion of this work I compare MAR surface mass balance estimates combined with dynamic mass changes from the Ice Sheet System Model (ISSM) with satellite-derived estimates of mass change from the Gravity Recovery and Climate Experiment (GRACE). I find that the models underestimate mass loss at low elevations, and capture the timing of the GRACE seasonal cycle. There are discrepancies between the modeled and observed seasonal cycles at smaller spatial scales, suggesting the need for further study of mass balance processes not fully captured by ISSM or MAR. The studies collectively provide information that will allow for improvement of models used to simulate future changes in Greenland ice sheet mass.

I have also included a series of studies that I contributed to as part of my work for this dissertation. These include (1) a study investigating the processes responsible for trends in Greenland Ice Sheet albedo and predictions future albedo changes, (2) an investigation of processes responsible for record melting during the year 2012, and (3) a study of the role of surface lake drainage events in Greenland ice sheet motion.
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For my parents, Paula and Robert Alexander
In memory of my grandmother, Ida Stone, who nurtured my love for Mother Earth

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Chapter 1

Introduction

1.1. Background

For millions of years the Earth’s global climate has changed in response to natural fluctuations in Earth’s orbital cycle and tectonic processes (Zachos et al. 2001). Through changes in global temperatures, as well as patterns of atmospheric and oceanic circulation, this natural variability has led to the periodic expansion and contraction of ice-covered areas (Rahmstorf 2002; Broecker and Denton 1990). The present period can be thought of as a transition period in global climate, in which the anthropogenic release of carbon dioxide has led to increases in global temperature (Hartmann et al. 2013), and an energy imbalance, in which the Earth is receiving more energy than it is releasing into space (Hansen et al. 2011). Global temperatures are projected to increase further in coming centuries and subsequent changes in climate will likely result in the loss of mass from the Greenland and Antarctic Ice Sheets (GrIS and AIS), the largest glaciated areas on the Earth today, leading to global sea level rise and changing global climate patterns (Church et al. 2013).

Our ability to predict future changes in the Earth’s ice sheets is important for understanding changes in global climate as well as the societal impacts of climate change. Loss of ice from land areas will lead to changes in global sea level, impacting the infrastructure for coastal communities worldwide (Church et al. 2013). Snow and ice cover in northern latitudes influences temperature and climate patterns by reflecting a relatively large percentage of incoming solar radiation. Loss of snow and ice cover can dramatically reduce surface albedo in
what is known as the “ice-albedo feedback”, leading to increased absorbed solar radiation, and in turn, amplified warming and changes in atmospheric circulation (Serreze et al. 2009, 2011). Addition of freshwater into the oceans through melting ice can also result in changes in ocean circulation (Rahmstorf 2002). Long-term changes in snow and ice cover at the poles can also be thought of as an early indicator of climate change, particularly in the Arctic, where temperatures are increasing at a faster rate relative to the rest of the Earth, and changes in snow and ice cover occur dramatically at large spatial scales (Vaughan et al. 2013).

In this work, I focus on simulations and observations of changes in the mass of the GrIS, in particular the simulation of processes that have not been extensively evaluated or are not well understood. My focus has been to draw insight into these processes, rather than to focus solely on assessment of model simulations or satellite results. Specifically I have conducted an evaluation of observed and simulated GrIS albedo, and simulated spatiotemporal variations in GrIS mass balance. This work is unique because it combines model results, in situ observations, and satellite data to reveal information about GrIS processes that could not be obtained through any single method. This work has revealed model biases and observations of differences between satellite products, model results, and in situ observations and will lead to improved simulations of current and future GrIS mass balance.

**1.2. Greenland Ice Sheet Mass Balance**

Within the past decade, the GrIS has experienced changes consistent with a response to a warmer climate, including record melt extent and duration in three of the last ten years (2007, 2010, 2012 as shown by Tedesco et al. 2008, 2011, 2013; Nghiem et al. 2012). During an extreme event in 2012, nearly the entire ice sheet surface experienced melting, a phenomenon that had not occurred at high elevations since 1867 (Nghiem et al. 2012). At least three
independent techniques have confirmed that the GrIS has been losing mass during the past decades (Shepherd et al. 2012; Rignot et al. 2011; van den Broeke et al. 2009), at an estimated rate of \(-142 \pm 49 \text{ Gt/yr}\) for the 1992-2011 period (Shepherd et al. 2012), which is equivalent to roughly \(7\pm2 \text{ mm/yr}\) of sea level rise. These changes are a result of increasing mass loss from the ice sheet surface (Fettweis et al. 2013a; Ettema et al. 2009) and accelerating flow of GrIS glaciers into the ocean (Rignot et al. 2011).

Changes in temperatures at the ice sheet surface have been linked to anthropogenic global warming (Hanna et al. 2008), as well as changes in patterns of atmospheric circulation over the ice sheet (Fettweis et al. 2013), which may or may not be influenced global temperature changes. Acceleration in glacial flow is in part associated with lubrication of the GrIS bed resulting from increased production of surface meltwater, which reaches the bed through vertical channels (Zwally et al. 2011). This relationship has been recently revealed to be more complex, with changes in meltwater production leading to acceleration or deceleration of the ice depending on the season (Sundal et al. 2011). It has also been proposed that warmer ocean temperatures associated with global warming can lead to acceleration of glacial flow (Rignot et al. 2012). Regardless of the relative contribution of different factors to the present day changes, they are ultimately a response to increased temperatures, which are projected to increase over the GrIS in response to the anthropogenic release of carbon dioxide within this century (Kirtman et al. 2013).

In this context, it is important to understand the processes responsible for changes in the mass of snow and ice from the ice sheet surface, as well as the processes responsible for changes in dynamic motion of the ice. Knowledge of such processes also allows for more accurate simulations of future changes in ice sheet mass. At the fundamental level, the rate of mass change of an entire ice sheet or glacier over time can be defined by the “mass balance” \((MB = dM/dt)\), defined by the equation \(MB = SMB + EMB + BMB + D\), where \(SMB\) is the mass balance
at the ice sheet surface, $EMB$ is the englacial mass balance, or the mass balance within the ice sheet, $BMB$ is the basal mass balance, or the mass balance at the ice sheet base, and $D$ represents discharge, loss of mass through the dynamic flow of ice into the sea. Often, the $EMB$ and $BMB$ terms are ignored as they are though to represent a small contribution to $MB$ and the equation is often expressed as $MB = SMB + D$ (Cuffey and Paterson, 2011).

Three methods can be used to measure changes in GrIS MB over time. First, since 2003 it has been possible to estimate changes in ice sheet mass using data from the Gravity Recovery and Climate Experiment (GRACE; e.g. Luthcke et al. 2013; Velicogna and Wahr 2006). Changes in the distance between two co-orbiting satellites can be used to estimate spatial and temporal variations in the Earth’s gravity field, which can then be converted into spatiotemporal variations in mass. A second method makes use of laser altimetry measurements to estimate annual changes in the volume of the ice sheet, which are combined with simulations of ice sheet density to derive changes in mass (e.g. Zwally et al. 2011; Li and Zwally 2011). Finally, climate-model simulations of $SMB$ can be combined with satellite radar-derived estimates of $D$ to estimate overall changes in mass (e.g. van den Broeke et al. 2009). While these methods can be used to evaluate current changes in mass with varying degrees of accuracy, advances in our ability to measure and simulate current and future changes in the two components of MB are essential for producing accurate estimates of sea level rise in the future.

1.2.1. The Surface Mass Balance

The Surface Mass Balance or SMB is the balance between surface accumulation and ablation, and can be expressed by the equation $SMB = P - R - S + BS$, where $P$ is the total precipitation (snow + rain), $R$ represents liquid runoff from the surface, $S$ is the net sublimation minus deposition, and $BS$ represents blowing snow, the net deposition or removal of snow due to
wind. The surface energy balance \( SEB = SW_{\downarrow}(1-\alpha) + LW_{\text{net}} + SH + LH \), where \( SW_{\downarrow} \) represents incoming shortwave radiation from the sun, \( LW_{\text{net}} \) is the net longwave radiation, \( SH \) and \( LH \) are sensible and latent heat fluxes respectively, and \( \alpha \) is the surface albedo or reflectivity) is responsible for determining \( R \), which is the primary means of mass loss for the GrIS. The surface albedo \( \alpha \) plays a particularly important role in modulating the amount of absorbed shortwave radiation, and hence the energy available for surface melting.

As a result of the need for simulating changes in ice sheet mass, numerous studies have attempted to quantify changes in GrIS SMB at varying levels of complexity. Some studies used available weather station observations and energy balance models, or more complex snow models to simulate changes in mass (e.g. Oerlemans 1991; van de Wal and Oerlemans 1994; Mernild et al. 2009). Others have used reanalysis products, global scale simulations of climate that assimilate available observational data, to estimate GrIS SMB (e.g. Hanna et al. 2002, 2006, 2008). These studies generally refine reanalysis temperature estimates to a higher spatial resolution through statistical downscaling, and estimate runoff using positive degree-day models, which make use of empirically derived relationships between temperature and runoff (e.g. Janssens and Huybrechts 2000).

In recent years, Regional Climate Models (RCMs) have been used to simulate current and future changes in mass at the GrIS surface (e.g. Fettweis et al. 2013a; Ettema et al. 2009; Box et al. 2006; Franco et al. 2013). RCMs solve equations of atmospheric dynamics, mass and energy balance, and surface-atmosphere interactions for multiple three-dimensional grid cells, and are forced at the lateral boundaries by climate reanalysis data. RCMs can simulate accumulation and ablation processes continuously at high spatial and temporal resolutions, which is essential
for accurately simulating ablation, which occurs within a narrow band along the GrIS margin (Box et al. 2006). There is a fairly large disagreement between different RCMs regarding GrIS SMB (Vernon et al. 2013; Rae et al. 2012). These differences result from different means of representing physical processes in different models, as well as differences in the representation of the extent of the GrIS (Vernon et al. 2013). It is also difficult to validate simulated SMB directly, as there are relatively few areas on the GrIS where direct measurements of SMB are available. These include estimates from ice cores of annual net accumulation in areas where there the ice sheet gains mass from year to year (e.g. Vernon et al. 2013) and measurements of SMB along a transect of stations in the western ablation zone where the ice sheet loses mass on average (the Kangerlussuaq Transect; van de Wal et al. 2012).

1.2.2. The Dynamic Mass Balance

The dynamic component of ice sheet mass balance, also referred to as ice discharge, balances the net accumulation of snow at the center of the ice sheet through the flow of glaciers into the ocean. Until the mid 1990s, ice dynamics were thought to vary on timescales of hundreds to thousands of years, but since then, studies that make use of satellite and airborne radar data to measure ice velocities have revealed that large variations in glacier flow can take place on timescales of days to years (Joughin et al. 2010; Howat et al. 2007; Goldstein et al. 1993).

Simulations of dynamic ice motions are generally accomplished through Ice Sheet Models (ISMs), which solve the thermal and mechanical equations of fluid dynamics of ice, subject to forcing by the SMB or climate parameters at the ice surface (e.g. Larour et al. 2012; Robinson et al. 2011; Huybrechts et al. 2011; Ridley et al. 2005; Quiquet et al. 2012). These models are generally employed to study long-term changes in ice dynamics, and they are not well suited to capturing variability in ice flow at shorter timescales (Schlegel et al. 2013), likely
because findings regarding variability in glacial flow at sub-century timescales are relatively recent, and have yet to be accounted for in ISMs. These recent findings, however, highlight a need for improved simulations of short-timescale variability, especially given the need for projections of changes in GrIS MB within the coming century.

1.3. Problems and Objectives

1.3.1. Objective 1: Spatiotemporal variability of Greenland Ice Sheet Albedo

This dissertation addresses two challenges to our ability to simulate the magnitude and variability of the GrIS MB. First, we address a key parameter in the simulation of SMB, the surface albedo, which is the fraction of incoming solar radiation reflected at the Earth’s surface. Potential biases in albedo are likely to have an important influence on a model’s simulation of the SMB, because of the role of albedo in feedbacks at the ice sheet surface (Box et al. 2012). Warmer conditions generally lead to processes at the GrIS surface that reduce surface albedo, including increases in snow grain size, exposure of relatively dark bare ice beneath snow in low elevation areas, and the formation of streams, rivers, and lakes (Tedesco et al. 2008; Box et al. 2012; Moustafa et al. 2014). Lower albedo results in a darker surface, leading to increased absorbed solar radiation and in turn, amplified melting. Observational studies suggest that surface albedo plays an important role in the surface energy balance of the GrIS, especially in locations where there is considerable melting during summer months (van den Broeke et al. 2011; Box et al. 2012). Modeling studies also identify albedo as a key factor in RCM simulations of SMB; differences in albedo parameterizations can lead to large differences in simulated SMB (Rae et al. 2012; Vernon et al. 2013; Lefebre et al. 2003). Despite its importance in determining SMB, a systematic study of spatial and temporal variations in GrIS albedo using multiple measurements and modeling techniques had not been conducted prior to
the work presented here. To our knowledge, only one study (Fettweis et al. 2005) has evaluated RCM-simulated albedo against satellite data, but the comparison was made difficult by contamination of the satellite data by the presence of clouds.

The first objective of this work is to evaluate the spatiotemporal variability of GrIS albedo using available satellite, in situ observations and the simulations of a state of the art RCM, the Modèle Atmosphérique Régionale (MAR). This objective fulfils the dual purpose of (1) identifying biases in simulated spatiotemporal variations in albedo, with the ultimate goal of improving a simulation of GrIS SMB through a better representation of the surface energy balance, and (2) developing an improved understanding of spatiotemporal variations in GrIS albedo, with the ultimate goal of understanding how the impact of changes in albedo on SMB, now and in the future.

This objective is addressed through two studies. In Chapter 2, I provide an evaluation of spatiotemporal variability of GrIS albedo from two satellite products from the Moderate Resolution Imaging Spectroradiometer (MODIS) and in situ observations from automatic weather stations (AWS). Observed spatiotemporal variations in albedo are compared with simulated MAR variability. Through comparison of SMB simulated by two different versions of MAR, I show that biases in model-simulated albedo can significantly impact simulated SMB. I also identify discrepancies between the MODIS albedo products that limit our understanding of spatial variations in GrIS albedo at high elevations. In Appendix A, I present a second study, which I assisted in designing, and to which I contributed processed satellite data. The study examines current and projected trends in ice sheet albedo, and the role of concentration of surface impurities in low elevation areas, bare ice exposure, and snow grain growth in these trends. The study characterizes the processes responsible for recent trends in ice sheet albedo, revealing that
deposition of surface impurities has a small affect on albedo trends, while the processes mentioned above have more substantial impact.

1.3.2. Objective 2: Spatiotemporal Variability of Greenland Ice Sheet Mass Balance

The second objective of this work is to evaluate spatiotemporal variations in GrIS mass simulated by the combined results of the MAR RCM and the Ice Sheet System Model (ISSM; Larour et al. 2012) against satellite data. Several studies have utilized observations of ice sheet mass change (e.g. from GRACE) in conjunction with observations of ice discharge as a means of evaluating large scale SMB simulated by RCMs (e.g. van den Broeke et al. 2009; Rignot et al. 2011). However, it is unclear whether RCMs and ISSM can capture spatiotemporal variations in GrIS SMB on seasonal or interannual scales. The ability to capture such variations is indicative of the ability of RCMs and ISMs to capture processes that may contribute to future changes in mass, which the models must be able to project. The MB simulated by the combined results of RCMs and ISMs has not been evaluated against observations of mass change from satellite data; and no studies to our knowledge have investigated variations in the seasonal cycle of GrIS mass balance. Additionally, as discussed above, our understanding of short-term variations MB is limited due to a poor understanding of englacial and subglacial processes, such as meltwater storage, and a relatively poor understanding of short-term changes in ice dynamics.

In order to address the problem of a lack of model validation, and poor understanding of processes that contribute to MB variability, the second objective of this work has the sub-goals of (1) evaluating the combined MAR and ISSM simulated MB for the first time against observations on annual and seasonal scales and (2) identifying whether processes not generally accounted for by RCMs or ISMs (such as storage of liquid water within the GrIS and hydrology-induced glacial acceleration) may play a substantial role in variations in GrIS MB at the timescales examined.
To address this objective, Chapter 3 provides a comparison between satellite-derived mass changes from GRACE, available at a temporal resolution of 10 days and a spatial resolution of ~100 km, and MAR and ISSM simulated mass changes. I spatially filter model results generated by the ISSM team to provide a fair comparison with GRACE estimates, and identify spatial differences in 10-year trends, and the timing of the seasonal cycle of mass change. The analysis reveals a general agreement between the models and GRACE with respect to long term changes in mass and the seasonal cycle of mass change, but also reveals regional differences that may indicate processes not captured by either MAR or ISSM.

The objectives addressed here represent small but necessary steps towards developing our understanding of GrIS MB and the ability to predict future changes in it. A discussion of main conclusions, limitations, and potential future studies is provided in Chapter 4. In the Appendix, I also include three studies (in addition to Appendix A) to which I contributed model and satellite data and assessment as part of my dissertation work. Two of them (in Appendices D and E) discuss changes observed and modeled on the Greenland ice sheet during 2012, a year in which record melting occurred. The last (Appendix F) discusses observations of two lake drainage events and the ice motions associated with them, which have implications for the role of surface meltwater production in determining ice velocities. I assisted in collecting the ice velocity measurements and observed the drainage of these lakes during a field-trip to the Greenland Ice Sheet in 2011. The different studies that comprise this dissertation represent work that was carried out over a course of five years. Therefore, I have made use of multiple versions of the MAR RCM. In Appendix G, I provide a brief discussion of differences in albedo and SMB between different versions of the MAR model.
Chapter 2


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2.1. Introduction

Over the past decade, the Greenland Ice Sheet (GrIS) has simultaneously experienced accelerating mass loss (van den Broeke et al. 2009; Rignot et al. 2011) and records for the extent and duration of melting (Tedesco et al. 2008, 2011, 2013a; Nghiem et al. 2012). Increased melt over Greenland has been associated with both changes in temperature and an amplifying ice-albedo feedback: increased melting and bare ice exposure reduce surface albedo, thereby increasing the amount of absorbed solar radiation and, in turn, further amplifying melting (Box et al. 2012; Tedesco et al. 2011). Recent studies (van den Broeke et al. 2011; Vernon et al. 2013) also indicate that albedo plays an essential role in the GrIS surface energy balance, and consequently, the surface mass balance (SMB) of those regions where considerable melting occurs. Because of the impact of albedo on the surface energy balance, it is crucial to assess the performance of models that simulate albedo over the GrIS and the quality of albedo estimates from remote sensing or in situ observations. These assessments are pivotal for improving our
understanding of the physical processes leading to accelerating mass loss, and for improving projections for the next decades.

Several studies that have investigated GrIS albedo trends and variability have primarily relied on satellite measurements, particularly those collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) (e.g. Stroeve et al. 2005, 2006, 2013; Box et al. 2012). Remote sensing measurements can capture changes at large spatial scales and for long periods, continuously (with the exception of cases when the surface is obscured by clouds). Previous studies have found MODIS albedo products to agree reasonably well with in situ data, especially with regards to capturing the seasonal albedo cycle and mean seasonal values in regions where variability is small (Stroeve et al. 2005, 2006, 2013), but lower accuracy at high solar zenith angles has been identified (Stroeve et al. 2005, 2006), limiting the periods and locations for which these data can be used. Nevertheless, given their relatively high temporal and spatial resolution, these products are useful for evaluating albedo derived from regional climate models (RCMs). RCMs are an important tool for estimating both current and future changes in the GrIS SMB (Box and Rinke 2003; Box et al. 2006; Ettema et al. 2009; Fettweis et al. 2007, 2011b; Rae et al. 2012; Tedesco and Fettweis 2012), and the surface albedo schemes employed by these models have a substantial impact on their simulation of the SMB (Rae et al. 2012; van Angelen et al. 2012; Lefebre et al. 2005; Franco et al. 2012).

In this paper, we report the results of an assessment of GrIS albedo spatio-temporal variability and trends for the period 2000-2013. To our knowledge, this is the first time that a multi-tool integrated assessment of albedo over Greenland is presented. We use (1) data from two remote sensing products from the Moderate Resolution Imaging Spectroradiometer (MODIS), the MOD10A1 daily albedo product (Hall et al. 2012) and MCD43A3 16 day albedo product (Schaaf et al. 2002), (2) in situ albedo data from the Greenland Climate Network (GC-Net; Steffen et al.
1996) and Kangerlussuaq-Transect (Van de Wal et al. 2005), and (3) outputs from two versions (v2.0 and v3.2) of the Modèle Atmosphérique Régionale (Fettweis et al. 2013a,b). In order to carry out comparisons between products, MODIS data have been regridded to the MAR model grid and in some instances daily data have been averaged over 16 day periods when necessary. The role of potential errors associated with differences in spectral range between satellite and in situ data and cloud cover have been considered and corrected for when possible.

2.2. Data and Methods

2.2.1. The MAR model

The Modèle Atmosphérique Régionale (Gallée and Schayes 1994; Gallée 1997; Lefebre et al. 2003), abbreviated MAR, is a coupled land-atmosphere regional climate model featuring the atmospheric model described by Gallée and Shayes (1994) and the Soil Ice Snow Vegetation Atmosphere Transfer scheme (SISVAT) surface model. SISVAT incorporates the multilayer snow model Crocus (Brun et al. 1992), which simulates fluxes of mass and energy between snow layers, and reproduces snow grain properties and their effect on surface albedo. The model setup used here is described in detail by (Fettweis 2007). We primarily use a recent version of MAR (v3.2), which features changes to the albedo scheme relative to previous versions (v1 and v2), detailed in Section 2.2.2, but also examine differences between MAR v3.2 and a previous version, MAR v2.0. MAR v3.2 (v2.0) has been run at a 25 km horizontal resolution for the period 1958-2013 (1958-2012). Both model versions are forced at the lateral boundaries and ocean surface and initialized with 6-hourly reanalysis outputs from the European Centre for Medium-Range Weather Forecasts (ECMWF), using the ERA-40 reanalysis (Uppala et al. 2005) for the period 1958-1978 and the ERA-Interim reanalysis (Dee et al. 2011) for the period 1979-present. Here we focus on the 2000-2013 period for comparison with satellite data. The MAR v3.2 ice
sheet mask (which gives the fraction covered by ice for each grid box) and surface elevation are defined using the Greenland digital elevation model of Bamber et al. (2013). MAR v2.0 uses the elevation model of Bamber et al. (2001), and the land surface classification mask from Jason Box (sites.google.com/site/jboxgreenland/datasets).

In MAR v3.2, in contrast with MAR v2.0, sub-grid scale parameterizations make it possible to have fractions of different land cover types within a single grid box. Quantities are computed for the sectors within each grid box and a weighted average of these quantities is used to represent the average value for a grid box.

For the reader’s convenience, we show the mean September 2000 - August 2013 SMB from MAR v3.2 in Figure 2.1, along with the equilibrium line dividing positive and negative SMB, together with the locations of the weather stations used in this study. In this study, areas below the mean 2000-2013 equilibrium line as defined by MAR are collectively referred to as the “ablation area”, while areas above this line are referred to as the “accumulation area”.

2.2.2. The MAR albedo scheme

The basis for the MAR albedo scheme is described in detail by Brun et al. (1992) and Lefebre (2003). MAR snow albedo ($\alpha$) depends on the optical diameter of snow grains ($d$), which is in turn a function of other snow grain properties, such as grain size, sphericity and dendricity. In the model, the sphericity, dendricity, and size of snow grains are a function of snowpack temperature, temperature gradient, and liquid water content. Albedo is defined in MAR for three spectral intervals:
Figure 2.1. MAR v3.2 mean September 2000 - August 2013 SMB (mWE/yr) and locations of all GC-Net and K-Transect weather stations. Pixels not defined as 100% ice covered in MAR are masked out. The bold dotted black line shows the mean equilibrium line (where the mean SMB is 0). The K-transect stations (S5, S6, S9, S10) are colored red, while GC-Net stations are black. Stations in grey are GC-Net stations that have not been used in this study. Other contour lines indicate elevation in meters above sea level. The inset shows individual stations near the west coast ablation zone.
Interval 1, visible (0.3 – 0.8 µm):
\[ \alpha_1 = \max(0.94, 0.96 - 1.58\sqrt{d}) \]  
(2.1)

Interval 2, near infrared (0.8 – 1.5 µm):
\[ \alpha_2 = 0.95 - 15.4\sqrt{d} \]  
(2.2)

Interval 3, far infrared (1.5 – 2.8 µm):
\[ \alpha_3 = 364 \cdot \min(d, 0.0023) - 32.31\sqrt{d} + 0.88 \]  
(2.3)

where \( \alpha_1, \alpha_2, \) and \( \alpha_3 \) are wavelength dependent albedo values. The integrated snow albedo \( (\alpha_s) \) for the range 0.3 to 2.8 µm is a weighted average of albedo over these intervals based on solar irradiance fractions:
\[ \alpha_s = 0.580\alpha_1 + 0.320\alpha_2 + 0.1\alpha_3 \]  
(2.4)

The minimum albedo of snow is set to 0.65. In MAR v2.0, bare ice albedo was simply assigned a fixed value. In MAR v3.2 (the version primarily used here), bare ice albedo is a function of accumulated surface water following the parameterizations of Lefebre (2003), described below. In the case of bare ice (which occurs in MAR when the surface snow density is greater than 920 kg m\(^{-3}\)) ice albedo \( (\alpha_I) \) is given by:
\[ \alpha_I = \alpha_{I,\text{min}} + (\alpha_{I,\text{max}} - \alpha_{I,\text{min}})e^{-\left(\frac{M_{\text{SW}}(t)}{K}\right)} \]  
(2.5)

where \( \alpha_{I,\text{min}} \) and \( \alpha_{I,\text{max}} \) are the minimum and maximum bare ice albedo, \( K \) is a scale factor (set to 200 kg/m\(^2\)), and \( M_{\text{SW}}(t) \) is the time-dependent accumulated amount of excessive surface meltwater before runoff (in kg m\(^2\)). According to the parameterization of (Zuo and Oerlemans 1996), there is delay in MAR v3.2 between the production of meltwater and evacuation towards the oceans (Lefebre et al. 2003), in order to account for the reduction of bare ice albedo due to the
presence of surface water. The ice surface albedo ($\alpha_I$) will therefore be lower if the melt rate is higher, asymptotically approaching the minimum bare ice albedo.

Additionally, to ensure temporal continuity in simulated albedo, values of albedo between the maximum bare ice and minimum snow albedo are possible when the surface (or near-surface) snow density lies between 830 and 920 kg m$^{-3}$. In this case (which corresponds to the presence of firn), albedo ($\alpha_I$) is a function of density as follows (Lefebre et al. 2003):

$$\alpha_I = \alpha_{I,\text{max}} + (\alpha_{S,\text{min}} - \alpha_{I,\text{max}}) \left( \frac{\rho_I - 920\,\text{kg}\,\text{m}^{-3}}{\rho_C - 920\,\text{kg}\,\text{m}^{-3}} \right)$$

(2.6)

where $\alpha_{S,\text{min}}$ is the minimum albedo of snow, $\rho_I$ is the density of the upper firn layer, and $\rho_C$ is the density at which pores within firn close off (830 kg m$^{-3}$). For the reader’s convenience, Table 2.1 provides the range of possible albedo values for ice, firn, and snow in MAR v2.0 and v3.2.

In cases where there is a snowpack with a thickness of <10 cm overlaying ice or firn (with a density greater than 830 kg m$^{-3}$), excluding the case of ice lenses, albedo is interpolated between the ice albedo and the surface snow albedo as a linear function of snowpack thickness, to produce an “integrated” surface albedo of snow, ice and water ($\alpha_{SI}$):

$$\alpha_{SI} = \alpha_I + \alpha_S \left( \frac{H_s}{0.1} \right)$$

(2.7)

where $H_s$ is the snowpack height in meters. In cases where a snowpack thicker than 0.1 m lies above ice, or there is bare ice at the surface, $\alpha_{SI}$ is simply set equal to the snow albedo ($\alpha_S$), or bare-ice albedo ($\alpha_I$), respectively.

**Table 2.1** Range of possible albedo values for different surface types in MAR v2.0 and v3.2.

<table>
<thead>
<tr>
<th>Surface Type</th>
<th>MAR v2.0</th>
<th>MAR v3.2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare Ice</td>
<td>0.45</td>
<td>0.45 to 0.55</td>
</tr>
<tr>
<td>Firn</td>
<td>0.45 to 0.65</td>
<td>0.55 to 0.65</td>
</tr>
<tr>
<td>Snow</td>
<td>&gt;0.65</td>
<td>&gt;0.65</td>
</tr>
</tbody>
</table>
2.2.3. Satellite-derived albedo

We use the daily MODIS albedo product (MOD10A1, Version-5) distributed by the National Snow and Ice Data Center (Hall et al. 2012; available at http://nsidc.org/data/mod10a1.html), available for the period March 2000 - present, and the 16-day (MCD43A3, Version-5) product from Boston University (Schaaf et al. 2002; available at https://lpdaac.usgs.gov), available for the same period.

The MOD10A1 Version-5 product contains daily albedo (0.3 - 3 µm) based on the “best” daily MODIS observation, defined as the observation that covers the greatest percentage of a grid cell. Corrections are also applied to account for anisotropic scattering, for the influence of the atmosphere on surface albedo, and for the limited spectral range of MODIS bands (Klein and Stroeve 2002; Stroeve et al. 2006). Here we use MODIS data from the TERRA satellite, as MODIS data from the AQUA satellite are less reliable due to an instrument failure in the near infrared band (Stroeve et al. 2006; Box et al. 2012).

The MCD43A3 Version-5 product makes use of all atmospherically-corrected MODIS reflectance measurements over 16-day periods to provide an integrated albedo measurement every 8 days. A semi-empirical bidirectional reflectance function (BRDF) model is used to compute bi-hemispherical reflectance as a function of these reflectance measurements (Schaaf et al. 2002). The MCD43A3 product contains, in addition to albedo values for each MODIS instrument band, “shortwave” albedo values calculated over a wavelength interval of 0.3-5.0 µm and “visible” albedo values for the 0.3-0.7 µm interval, calculated using the BRDF parameters. Here we primarily make use of “shortwave” MCD43A3 albedo, as its wavelength interval is consistent with those of MAR and MOD10A1, but briefly consider “visible” albedo as well. The MCD43A3 product provides, over each wavelength interval, an integrated diffuse White Sky
Albedo (WSA) and a direct Black Sky Albedo (BSA) for a specific viewing geometry (from above when the local solar zenith angle is at a maximum). A linear combination of WSA and BSA can be used to compute the true “blue-sky albedo”. Stroeve et al. (2005) suggest that there is little difference between BSA and WSA for typical summer midday solar zenith angles over Greenland. Simulation of blue-sky albedo requires models or observations of aerosol optical depth (e.g. Stroeve et al. 2013) that are not available for this study and therefore, the following results consider BSA only.

Both MODIS products provide quality flags indicating “good quality” vs. “other quality” data. In the case of MCD43A3, “other quality” data are produced using a “backup” algorithm. When few observations are available, the backup algorithm is used to scale an archetypal BRDF function that is based on past observations (Schaaf et al. 2002). In order to understand the influence of data quality on our results, we present results for both “all quality” as well as “good quality” data.

2.2.4. Weather station data

We use Automatic Weather Station (AWS) data from two sources, the Greenland Climate Network (GC-Net; Steffen et al. 1996) and the Kangerlussuaq Transect (K-Transect; Van de Wal et al. 2005). The locations of the weather stations are shown in Figure 2.1, and a list of the weather stations used and their period of coverage is provided in Table 2.2. We use all available GC-Net and K-transect June-July-August (JJA) data within the period 2000-2012 for comparison with MODIS and MAR albedo. (GC-Net data for the summer of 2013 were not yet available when data analysis for this study was conducted.) We follow a procedure similar to that employed by Stroeve et al. (2005) to generate albedo timeseries’ from GC-Net and K-Transect data. Mean daily albedo was computed as the sum of daily incident shortwave (SW) radiation
Table 2.2 GC-Net and K-Transect weather stations used in this study and years of coverage.

<table>
<thead>
<tr>
<th>Station Name</th>
<th>Coverage Period</th>
<th>Excluded data</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ablation Area</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JAR 1 (GC-Net)</td>
<td>2000-2012</td>
<td></td>
</tr>
<tr>
<td>JAR 3 (GC-Net)</td>
<td>2000-2003</td>
<td></td>
</tr>
<tr>
<td>S5 (K-Transect)</td>
<td>2004-2012</td>
<td></td>
</tr>
<tr>
<td>S6 (K-Transect)</td>
<td>2004-2012</td>
<td></td>
</tr>
<tr>
<td>S9 (K-Transect)</td>
<td>2004-2012</td>
<td></td>
</tr>
<tr>
<td>Peterman ELA (GC-Net)</td>
<td>2012</td>
<td>2003, 2005</td>
</tr>
<tr>
<td>Peterman Glacier (GC-Net)</td>
<td>Not Used</td>
<td>2002-2005</td>
</tr>
<tr>
<td><strong>Accumulation Area, North of 70°N</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Summit (GC-Net)</td>
<td>2000-2012</td>
<td></td>
</tr>
<tr>
<td>NEEM (GC-Net)</td>
<td>2006-2012</td>
<td></td>
</tr>
<tr>
<td>NASA-U (GC-Net)</td>
<td>Not Used</td>
<td>2003-2012</td>
</tr>
<tr>
<td><strong>Accumulation Area, South of 70°N</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KULU (GC-Net)</td>
<td>2000</td>
<td></td>
</tr>
<tr>
<td>S10 (K-Transect)</td>
<td>2010-2012</td>
<td></td>
</tr>
<tr>
<td>Crawford Point 1 (GC-Net)</td>
<td>2000-2004</td>
<td>2005-2010</td>
</tr>
<tr>
<td>Crawford Point 2 (GC-Net)</td>
<td>2000</td>
<td></td>
</tr>
<tr>
<td>Dye-2 (GC-Net)</td>
<td>2000-2012</td>
<td></td>
</tr>
<tr>
<td>South Dome (GC-Net)</td>
<td>2003-2012</td>
<td></td>
</tr>
<tr>
<td>KAR (GC-Net)</td>
<td>2000, 2001</td>
<td></td>
</tr>
<tr>
<td>Aurora (GC-Net)</td>
<td>Not Used</td>
<td></td>
</tr>
</tbody>
</table>
divided by the sum of daily outgoing SW radiative flux. Instances where hourly upward SW radiative flux exceeded downward SW radiative flux were excluded. Upward and downward hourly radiative fluxes were excluded when downward fluxes were smaller than 250 W/m$^2$ to reduce the impact of relative errors on measured albedo, especially during cases of low incident radiation. (We investigated the sensitivity of our results to this threshold, and did not find a considerable effect on the results). Data from several locations and time periods were excluded from this analysis. These stations are included in Table 2.2. In particular, measured albedo at Swiss Camp for the year 2012 appeared to be unrealistically high relative to previous years and was excluded (mean measured JJA albedo for 2012 was 0.99, 3.5 standard deviations above the mean 2000-2011 value of 0.64). Measured albedo at Crawford Point-2 undergoes a step change after 2004 (mean albedo is $0.81 \pm 0.03$ for 2000-2004 and $0.90 \pm 0.04$ for 2005-2010) and therefore we excluded data after 2004, as was done by Stroeve et al. (2013). At the stations NASA-U and NGRIP, leveling errors produce a low bias in upward radiation for all years (Stroeve et al. 2013) resulting in measured albedo values that are unrealistically low for snow outside of the ablation area ($0.30 \pm 0.01$ at NASA-U and $0.33\pm0.01$ at NGRIP), and are therefore excluded. At the Peterman Glacier and Peterman ELA, missing MODIS data prevented us from including all weather station data in this analysis.

2.2.5. Methods of analysis

2.4.2.1. Corrections to MAR albedo

Snow albedo is generally higher during cloudy conditions due to the masking of a portion of the incoming solar spectrum by clouds (Greuell and Konzelman 1994). Both MAR v3.2 and
MAR v2.0 account for this factor by applying a correction to the integrated surface albedo ($\alpha_{SI}$) as a function of cloud fraction, following Greuell and Konzelman (1994):

$$\alpha_{CL} = \alpha_{SI} + 0.05(n - 0.5)$$

(2.8)

where $n$ is the cloud fraction computed by MAR, and $\alpha_{CL}$ is the cloud-corrected albedo. Satellite data can only provide cloud-free measurements, and therefore we re-correct MAR surface albedo to produce estimates of cloud-free surface albedo. We use this particular technique rather than excluding pixels from MAR because MAR does not necessarily replicate the actual cloud fraction observed by MODIS. The correction applied here reverses the correction applied in MAR, then corrects albedo for the case where there is a cloud fraction of 0:

$$\alpha_{MAR, clear-sky} = \alpha_{MAR, daily} - 0.05(n_{MAR, daily} - 0.5) - 0.025$$

(2.9)

In this case $\alpha_{MAR, daily}$ is the daily mean MAR albedo, $n_{MAR, daily}$ is the daily mean cloud fraction from MAR, and $\alpha_{MAR, clear-sky}$ is the daily mean clear-sky albedo. All analyses with MAR results are conducted using $\alpha_{MAR, clear-sky}$.

2.4.2.2. Aggregation of MODIS data to the MAR grid

For the purpose of comparing model results and satellite data, MODIS albedo products are re-gridded to the MAR 25 km resolution grid from the original 463 m spatial resolution at which they are distributed. Re-gridded values contain the median value of all the MODIS values falling within a MAR grid box. When comparing satellite datasets and satellite data against model results, we restrict our analysis to the GrIS. For all comparisons including MAR v3.2 results, areas where the MAR sub-grid level ice cover percentage is less than 100% are excluded. For all comparisons including MAR v2.0 results, the same mask from MAR v3.2 is used, except
that pixels classified as 100% ice covered in MAR v3.2, but classified as non-ice-covered in MAR 2.0 are also excluded from the analysis.

2.4.2.3. Comparisons at in situ stations

Comparisons at in situ stations are conducted between weather station data and data or outputs from the MODIS or MAR grid box that encompasses the in situ station. In this case we use the original (463x463m) MODIS grid box containing the station rather than the MODIS data aggregated to the encompassing 25x25 km MAR grid box to reduce potential errors associated with spatial variations of albedo. In cases where an in situ station is contained within a MAR grid box classified as less than 100% ice-covered in MAR v3.2, we compare in situ data to MAR v3.2 data from the ice-covered sector of that grid box rather than data from the entire grid box.

As in the case of the original MAR albedo outputs, in situ measurements also include measurements made during cloudy conditions while MODIS albedo data do not. Given a lack of available measurements, we do not explicitly correct in situ data for the presence of clouds in this study, but only consider data where coincident satellite and in situ measurements are available. Stroeve et al. (2013) applied a correction to GC-Net data using a radiative transfer model, but found that the correction did not significantly impact their results.

2.4.2.4. Spectral differences

The GC-Net LI-COR sensors are sensitive within the 0.4-1.1µm band, and K-Transect data are collected in the 0.3-2.8 µm band. The GC-Net bands are narrower than the MOD10A1 interval of 0.3-3µm and the MCD43 shortwave albedo interval of 0.3-5µm, and the interval of 0.3-2.8µm over which albedo is calculated in the MAR model. GC-Net incoming and outgoing radiation values are calibrated to represent radiation for a spectral interval of 0.28 to 2.8 µm
(Wang and Zender 2010). However, because snow has a high spectral reflectance over the 0.3 to 1.1 µm interval, and a much lower reflectance above 1.1 µm, measured albedo over the smaller interval will be higher for snow-covered areas (Stroeve et al. 2005). Stroeve et al. (2005) compared albedo derived with GC-Net LI-COR pyranometers to measurements from pyranometers with a larger spectral range, and found that the smaller wavelength interval results in a positive albedo bias of between 0.04 and 0.09, for GC-Net data relative to MODIS albedo, depending on the location and time period (Stroeve et al. 2005). This bias does not apply to K-Transect measurements, as the spectral sensitivity is comparable to the sensitivity of MODIS sensors. Because this bias may be smaller or larger depending on multiple factors, we do not apply any correction here, but provide an indication of spatial variability of this bias in Section 2.4.2.1 by comparing MCD43A3 visible albedo (0.3 – 0.7 µm) with MCD43A3 shortwave (0.3-5.0 µm) albedo.

2.4.2.5. Calculation of bias, correlation, and trends

In the following analysis, we focus on the JJA period because MODIS data are less reliable during other months, when solar zenith angles are high, as discussed by Box et al. (2012), and because this is the period when surface albedo has the largest impact on SMB.

In order to compare spatial variations in albedo we calculated the mean 2000-2013 JJA MOD10A1, shortwave MCD43A3 BSA albedo, and MAR clear-sky albedo using all available measurements or model outputs over the specified period, excluding cases where greater than 25% of data were missing for a given pixel. When differences between datasets or between satellite data and model results are calculated, we only use measurements or results that overlap in time and space, to avoid the possibility of biases introduced by missing data. The mean difference between two samples for a given grid box was deemed to be statistically significant if
the p-value for a two-sample Student’s t-test was smaller than 0.05. Unless otherwise specified, we use only “good quality” MODIS data in comparisons.

In some cases, observational data or model results have been spatially averaged or aggregated within the ablation and accumulation areas defined using MAR v3.2 or v2.0. The ablation (accumulation) area is defined as the area that experienced a net loss (gain) of mass over the 2000-2013 period as simulated by either version of the model.

For analyses of temporal variability, we consider daily variability, for which MOD10A1 data, in situ values, and MAR outputs are available, as well as variability over 16-day MCD43A3 periods. In the case of the analysis of 16-day data, MOD10A1, MAR, and in situ daily data are averaged to produce a value for each overlapping MCD43A3 16-day period. We examine the correlation between daily satellite data and between satellite data and model results using Pearson’s coefficient of determination ($r^2$).

To compare the distribution of ablation area albedo for satellite data and MAR model outputs, we produced frequency histograms for ablation area albedo using a bin width of 0.0099. Parameters for the best fit of a bimodal distribution to the histograms were obtained using the maximum likelihood estimation function in MATLAB, assuming a bimodal normal distribution for the fit.

Box et al. (2012) investigated changes in GrIS albedo using the MOD10A1 albedo product, finding that between 2000 and 2012, surface albedo decreased over almost the entire ice sheet. Here, we build on the analysis of Box et al. (2012) and extend the analysis to include MCD43A3, MAR v3.2 and in situ JJA data for the period 2000-2013. Trends in albedo have been obtained by performing linear regression on 16-day albedo values for satellite products, in situ data, and model outputs, excluding albedo values outside of the JJA period. We have also computed trends for annual JJA average values. A trend was determined to be statistically
Figure 2.2. Mean 2000-2013 June, July, August (JJA) albedo (unitless) for (a) the MCD43A3 BSA shortwave product (on the MAR grid), (b) the MOD10A1 product (on the MAR grid), and (c) MAR v3.2 clear-sky albedo. Only good quality MODIS data are used here.
different from 0 if the p-value for a Student’s t-test was smaller than 0.05. For in situ stations, only stations with a record of at least 9 years of data are included in the analysis, and only trends for albedo from the encompassing MAR v3.2 (25x25 km) grid box and MODIS (463x463m) grid boxes over the same range of years are considered.

2.3. Results

2.3.1. Albedo spatial variability

MAR v3.2 and the two MODIS datasets show coherent spatial patterns of JJA mean 2000-2013 albedo (Figure 2.2) that are consistent with previous studies (e.g. Box et al. 2012), with low-elevation areas in the ablation area dominated by lower albedo values (<0.7 on average, Table 2.3) due to the presence of meltwater and bare ice, and high elevation areas by relatively higher albedo (>0.74). The most obvious discrepancy between the satellite products occurs north of 70°N, where the MOD10A1 daily product exhibits an increase in albedo with latitude, while MCD43A3 points to the opposite. The difference between the two satellite products (Figure 2.3a) is statistically significant (at the 95% confidence level) above 70°N, reaching ~0.08 (for albedo ranging between 0 and 1) at the highest latitudes.

<table>
<thead>
<tr>
<th>Locations</th>
<th>MOD10A1</th>
<th>MCD43A3 BSA Shortwave</th>
<th>MAR Clear Sky</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ice-Sheet wide</td>
<td>0.77 ± 0.04</td>
<td>0.73 ± 0.04</td>
<td>0.75 ± 0.03</td>
</tr>
<tr>
<td>Ablation Area</td>
<td>0.68 ± 0.07</td>
<td>0.63 ± 0.07</td>
<td>0.68 ± 0.07</td>
</tr>
<tr>
<td>Accumulation Area</td>
<td>0.80 ± 0.03</td>
<td>0.75 ± 0.03</td>
<td>0.77 ± 0.02</td>
</tr>
<tr>
<td>Acc. Area (N. of 70°N)</td>
<td>0.80 ± 0.03</td>
<td>0.75 ± 0.03</td>
<td>0.77 ± 0.02</td>
</tr>
<tr>
<td>Acc. Area (S. of 70°N)</td>
<td>0.78 ± 0.03</td>
<td>0.77 ± 0.03</td>
<td>0.77 ± 0.02</td>
</tr>
</tbody>
</table>
The pattern of differences between MAR v3.2 and the two satellite products (Figure 2.3b and c) appears to vary with both elevation and latitude, while the difference between the two satellite products varies primarily with latitude (Figure 2.3a). Because any systematic biases in the satellite products are likely to be relatively consistent across space (at least as a function of longitude), it is likely that MAR v3.2 biases contribute to some of the elevational differences seen in Figure 2.3 (b and c). Within the accumulation area south of 70°N, MAR v3.2 albedo (0.77 on average) is comparable to MODIS albedo (average of 0.78 for MOD10A1 and 0.77 for MCD43A3). At low elevation areas, especially along the west coast ablation area, MAR v3.2 overestimates albedo (up to ~0.1) relative to both satellite products. The mean ablation area albedo from MOD10A1 (0.68 ± 0.07) is identical to MAR mean ablation area albedo (Table 2.3), despite the large positive bias in MAR albedo within the west coast ablation area that can be seen in Figure 2.3. This is likely a result of a positive bias for MOD10A1 at high latitudes, as will be discussed further below. For areas north of 70°N, the discrepancy between satellite products makes it impossible to determine the magnitude and direction of MAR biases.

MAR v3.2, MOD10A1 and MCD43A3 mean 2000-2013 JJA albedo values show a similar logarithmic dependence of albedo with elevation (Figure 2.4a); below 2000 m, albedo increases relatively rapidly with elevation (both MAR and the MODIS products show a statistically significant albedo increase of ~0.01 to ~0.02 per 100 m increase in elevation), while above 2000 m, the change is smaller (no statistically significant increase for MAR, and an increase of ~0.002 to ~0.003 per 100 m for both MODIS products). The discrepancies between MODIS products north of 70°N are evident in Figure 2.4b: MCD43A3 decreases with latitude while MOD10A1 increases, and MAR v3.2 shows little change.

For in situ stations in the ablation area (Table 2.4), in situ mean albedo (0.56 ± 0.08) is higher than coincident average MOD10A1 (0.51 ± 0.09) and MCD43A3 (0.50 ± 0.07) albedo
Figure 2.3. Mean difference in JJA albedo (unitless) for the 2000-2013 period: (a) MCD43A3 BSA shortwave minus MOD10A1 (b) MAR v3.2 clear-sky minus MOD10A1, and (c) MAR v3.2 clear-sky minus MCD43A3. In each case, only coincident data for each of the two datasets being compared is used. MAR grid boxes where the difference is not statistically significant at the 95% confidence level are marked with a grey “x”.
Figure 2.4. (a) Mean 2000-2013 JJA MOD10A1, MCD43A3 BSA shortwave (SW), and MAR v3.2 clear sky GrIS albedo (unitless) as a function of elevation divided into 150 m elevation bands. Error bars indicate standard deviation within each elevation band. (b) The same as (a) but for albedo as a function of latitude, divided into 2° Latitude bands. “Good qual.” indicates results obtained by only using “good quality” MODIS data. “All qual.” indicates that all available MODIS observations have been used.
Table 2.4. Same as Table 2.3, but for the average of 16 day data for all in situ stations within each region.

<table>
<thead>
<tr>
<th>Locations</th>
<th>MOD10A1</th>
<th>MCD43A3 BSA Shortwave</th>
<th>MAR Cloud-Corrected</th>
<th>In Situ</th>
</tr>
</thead>
<tbody>
<tr>
<td>All stations</td>
<td>0.69 ± 0.06</td>
<td>0.67 ± 0.04</td>
<td>0.70 ± 0.04</td>
<td>0.74 ± 0.05</td>
</tr>
<tr>
<td>Ablation Area</td>
<td>0.51 ± 0.09</td>
<td>0.50 ± 0.07</td>
<td>0.57 ± 0.06</td>
<td>0.56 ± 0.08</td>
</tr>
<tr>
<td>Accumulation Area</td>
<td>0.79 ± 0.04</td>
<td>0.77 ± 0.02</td>
<td>0.76 ± 0.02</td>
<td>0.82 ± 0.03</td>
</tr>
<tr>
<td>Acc. Area (N. of 70°N)</td>
<td>0.82 ± 0.04</td>
<td>0.75 ± 0.02</td>
<td>0.78 ± 0.01</td>
<td>0.83 ± 0.02</td>
</tr>
<tr>
<td>Acc. Area (S. of 70°N)</td>
<td>0.77 ± 0.04</td>
<td>0.78 ± 0.03</td>
<td>0.75 ± 0.03</td>
<td>0.81 ± 0.03</td>
</tr>
</tbody>
</table>

values, and is comparable with MAR v3.2 clear sky mean albedo for sectors classified as ice-covered (0.57 ± 0.07). Within the accumulation area, in situ albedo is larger by 0.01 to 0.06 relative to MAR and the MODIS products (Table 2.4). These results appear to be consistent with a positive bias in GC-Net measurements identified by Stroeve et al. (2005). However, we also find that the difference between in situ and satellite albedo is larger at K-Transect stations (+0.08) than at GC-Net sites (+0.04), and K-Transect data are not expected to exhibit the positive bias. It is likely that the high spatial variability of ablation area albedo contributes to the differences. Data from in situ stations may be positively biased relative to satellite data because of a bias introduced by station locations: locations are not chosen to be within streams, lakes, or crevasses, which have a lower albedo. In the accumulation zone, a lack of variation in surface features likely leads to smaller spatial variations in albedo.

Mean 2000-2012 JJA albedo values for ablation area GC-Net stations with a record of at least 7 years does not appear to exhibit a clear variation with latitude when compared with satellite data and model results (Figure 2.5). GC-Net albedo at stations north of 70°N is on average larger by 0.02 relative to stations south of 70°N (Table 2.4), suggesting that GC-Net albedo does not confirm the decrease in albedo with latitude indicated by MCD43A3. MOD10A1 accumulation area measurements are comparable (within 0.01 for aggregated station
data) to uncorrected GC-Net data north of 70°N (Figure 2.5, Table 2.4). This suggests that the MOD10A1 may also be positively biased north of 70°N.

It appears possible from Figure 2.5 that the bias at GC-Net sites (between 0.04 and 0.09 Stroeve et al. 2005) could increase with latitude, rendering corrected GC-Net mean 2000-2013 albedo comparable to MCD43A3 albedo. In order to indicate how the GC-Net albedo bias is likely to vary spatially, the mean difference between MCD43A3 visible BSA (for the interval 0.3-0.7 µm) and MCD43A3 shortwave BSA (for the interval 0.3-5.0 µm) was computed (Figure 2.6). The difference is larger than the biases observed by Stroeve et al. (2005) at GC-Net stations likely because the MCD43A3 visible wavelength interval is smaller than that for GC-Net stations. The difference does not vary with latitude, but is rather lowest in the ablation area, where bare ice is exposed during summer months, is largest in regions where melting occurs, but bare ice exposure is infrequent, and is relatively small at high elevations.

The spatial variability of the difference appears to be associated with the differences in spectral albedo between different materials. Because ice does not exhibit the spectral dependence of albedo that snow does (Hall and Martinec 1985), the difference between MCD43A3 visible and shortwave albedo is lower in the ablation area, where bare ice is exposed during summer. In locations where melting occurs, snow grains tend to be larger because of constructive metamorphism, reducing reflectance mostly in the near infrared band (Wiscombe and Warren 1980), resulting in a larger difference between visible and near infrared reflectance. This suggests that in situ albedo values do not exhibit the decrease of albedo with latitude suggested by MCD43A3.
Figure 2.5. 2000-2012 mean JJA albedo (unitless) for the MAR accumulation zone vs. latitude, for MOD10A1, MCD43A3 BSA shortwave, MAR v3.2 clear-sky, and GC-Net station data (black circles) for stations with a record spanning at least 7 years of the 2000-2012 period. Only MODIS data flagged as “good quality” are used here. The error bars for GC-Net stations indicate the range of corrections to GC-Net data (between 0.04 and 0.09) employed by Stroeve et al. (2005).
Figure 2.6. MCD43A3 BSA visible (0.3–0.7 μm) minus MCD43A3 BSA shortwave (0.3–5 μm) 2000-2013 JJA mean albedo (unitless) on the MAR grid. Areas not defined as 100% ice covered in MAR v3.2 are excluded.
Figure 2.7. Standard deviation of JJA albedo (unitless) (2000-2013) for (a) MCD43A3 shortwave BSA (b) MAR v3.2 clear sky 16 day averages (c) MOD10A1 16 day averages (d) MAR v3.2 clear sky daily, and (e) MOD10A1 daily.
2.3.2. Albedo temporal variability

The standard deviation of an albedo time-series provides information on the magnitude of its temporal variability. Within the low elevation ablation area of the ice sheet, both MAR and the MODIS products exhibit a relatively high standard deviation for the 2000-2013 period (0.07 on average for 16 day periods; Figure 2.7, Table 2.3). At high elevations, variability is smaller (0.02 to 0.03 on average for 16 day periods). The MCD43A3 and MOD10A1 products show similar spatial patterns of standard deviation when the daily product is averaged over 16 day MODIS periods (Figure 2.7a and c). Table 2.3 suggests that MAR v3.2 ablation area temporal variability is identical to MODIS variability on average, but Figure 2.7 shows that there are locations, particularly within the west coast ablation area, where MODIS variability is considerably higher. MAR v3.2 albedo variability in low elevation areas reaches a maximum of 0.09, while MODIS variability for the same regions is 0.15 at maximum. At a daily temporal resolution, MOD10A1 daily variability in the ablation area (0.17 maximum, 0.07 on average) is considerably larger than the variability of MAR v3.2 albedo (0.12 maximum, 0.04 on average). As will be discussed in Section 2.4.2, this may be the result of a positive bias in bare-ice albedo from MAR, but may also be associated with errors introduced by cloud artifacts in the MOD10A1 product. For the accumulation area, the standard deviation of albedo for MAR and MODIS generally falls within the 16-day uncertainty of 0.04 for MCD43A3 high-quality albedo and daily uncertainty of 0.067 for MOD10A1 albedo estimated by Stroeve et al. (2005, 2006). This limits the comparison among MAR and the MODIS products for high elevations.

For areas south of 70°N and in the ablation area north of 70°N, the two MODIS products are highly correlated (for MCD43A3 16 day periods, $r^2 > 0.5$), but in the accumulation area north of 70°N this correlation decreases (Figure 2.8a). Poor correlation in this area is likely a result of
Figure 2.8. Coefficients of determination ($r^2$ values) for the 2000-2013 period during JJA for (a) MOD10A1 (averaged to 16 day periods) vs. MCD43A3 BSA shortwave (b) MAR v3.2 clear sky (16 day data) vs. MCD43A3 BSA shortwave, (c) MAR v3.2 clear sky (16 day data) vs. MOD10A1 (16 day data), and (d) MAR v3.2 clear sky (daily) vs. MOD10A1 (daily). MAR grid boxes where the correlation is not statistically significant are marked with a grey “x”.
the low standard deviation of albedo, which falls within the uncertainty range for MODIS. Maps of the coefficient of determination between MAR and MODIS (Figure 2.8b and c) indicate that MAR v3.2 captures more than 50% of the ablation area variability detected by satellite products for 16 day periods and more than 25% for daily periods. It is, however, important to note that the daily variability from MOD10A1 is partially driven by cloud artifacts retained in the MOD10A1 product (Box et al. 2012). Again, in the accumulation area, it is difficult to draw any conclusions regarding correlation, as the variability in albedo is smaller than the assumed uncertainty for the MODIS products.

### 2.3.3. Albedo spatio-temporal variability

Further insights into the consistency of spatio-temporal variations in albedo between MODIS products and between MAR and MODIS products can be drawn from scatter plots for all MCD43A3 vs. MOD10A1 2000-2013 JJA albedo values (Figure 2.9a) and MAR vs. MODIS values (Figure 2.9b-d). Figure 2.9a indicates that MCD43A3 albedo is lower (by 0.03 on average) compared to MOD10A1 albedo, consistent with the significant difference between the products at high latitudes seen in Figure 2.3a. There is a fairly good correlation between MCD43A3 and MOD10A1 ($r^2 = 0.66$) and the slope of the best linear fit (0.83) is close to 1.

When MAR is compared with MCD43A3 and MOD10A1 over 16 day periods (Figure 2.9b and c), the correlation between MAR and satellite data is as good or better than the correlation between MOD10A1 and MCD43A3 ($r^2 = 0.66$ vs. MOD10A1 and 0.81 vs. MCD43A3). However, there is less agreement about the 1 : 1 line; a linear fit reveals a slope of 0.58 for MAR vs. MCD43A3 and 0.51 for MAR vs. MOD10A1. MAR overestimates low values of albedo (below 0.6) relative to satellite data, which is consistent with the apparent positive MAR bias in the ablation area seen in Figure 2.3b and c. On a daily basis, there is a poor
Figure 2.9. Scatter plots for 2000-2013 JJA albedo for (a) MOD10A1 (16 day averaged) vs. MCD43A3 BSA shortwave albedo (unitless) (b) MAR v3.2 clear-sky (16 day) vs. MCD43A3 BSA shortwave albedo, (c) MAR v3.2 clear-sky (16 day) vs. MOD10A1 (16 day) albedo, and (d) MAR v3.2 clear-sky vs. MOD10A1 (daily) albedo. Black points indicate ablation zone locations, while blue points indicate locations within the accumulation zone as defined using MAR v3.2. A solid black line indicates the 1:1 line, and dashed red lines indicate the best linear fit.
agreement between MAR and MOD10A1 (Figure 2.9d, $r^2=0.35$), consistent with the poor correlations observed in Figure 2.8d. (Note that MOD10A1 albedo is only accurate to two decimal places, resulting in the apparent vertical lines in Figure 2.8d.)

Scatter plots of 2000-2012 JJA albedo values for both satellite products and MAR v3.2 vs. all weather station measurements (Figure 2.10) indicate a strong correlation between in situ data and the two satellite products over 16 day periods (Figure 2.10a and b; $r^2 = 0.80$ for MOD10A1, $r^2=0.81$ for MCD43A3), as well as a good agreement about the 1 : 1 line (slope = 0.95 for MOD10A1 and 0.88 for MCD43A3). MAR agrees reasonably well with in situ data, but the correlation is lower ($r^2 = 0.78$), and the slope (0.66) is further from 1. Again, it appears that MAR also overestimates low albedo values relative to in situ measurements, in consistency with Figure 2.9b and c.

On a daily basis, MOD10A1 albedo exhibits a nearly 1 : 1 relationship with daily in situ albedo (Figure 2.10d; slope = 0.99), although there is increased scatter ($r^2=0.75$) due to higher variability on daily timescales (Figure 2.7). Similarly, when MAR is compared with daily in situ measurements, the correlation is lower relative to the 16 day comparison ($r^2=0.74$), while the slope of the best fit line does not change substantially (slope = 0.65).

In situ and satellite data and MAR v3.2 outputs all indicate that spatiotemporal variability of albedo is higher in the ablation area (where the standard deviation of albedo is ~0.13) than in the accumulation area (standard deviation of ~0.04). This is to be expected, given that the ablation area undergoes a substantial seasonal cycle in melting.

### 2.3.4. MAR v3.2 vs. MAR v2.0 albedo

In order to further examine some of the discrepancies between MAR and observations, we find it useful to examine differences between MAR v3.2 and MAR v2.0, which has been
Figure 2.10. Scatter plots of 2000-2012 JJA mean albedo [unitless] vs. automatic weather station (GC-Net and K-Transect) albedo: (a) MOD10A1 16 day averages vs. 16 day in situ (b) MCD43A3 BSA shortwave vs. 16 day in-situ (c) MAR v3.2 clear sky 16 day vs. 16 day in situ (d) MOD10A1 vs. in situ (daily) and (e) MAR v3.2 vs. in situ (daily). As for Figure 2.9, blue points indicate locations within the accumulation zone as defined using MAR v3.2.
validated against satellite and in situ data (e.g. Fettweis et al. 2005, 2011b) and used for making future projections (Fettweis et al. 2013a; Tedesco and Fettweis 2012). A major difference between MAR v3.2 and MAR v2.0 is in the scheme for calculating the albedo of bare ice; MAR v2.0 bare ice albedo is set to 0.45, while in MAR v3.2, it ranges between 0.45 and 0.55 as a function of surface melt (Table 2.1).

Scatter plots for MAR vs. MODIS 2000-2012 JJA albedo in the ablation area, along with frequency histograms and best fit curves of the distribution (Figure 2.11) suggest that there is a bimodal distribution of ablation area albedo, which we attribute to the presence of two main surface types, ice (and firn) and snow. Pixels classified by MAR as having bare ice (or firn, surface density > 830 kg m\(^{-3}\)) for at least 8 days of each 16 day period coincide with one of the peaks in the bimodal distributions (Figure 2.11).

There are differences in the observed distributions, however. MAR v2.0 exhibits a clustering of albedo values above 0.65 and below 0.55 (Figure 2.11a). MCD43A3 exhibits an overlap in the distribution of the two modes, and there is a wider range of low albedo values (\(\sigma=0.10\) for MCD43A3 and 0.05 for MAR for the best fit of the lower albedo peak; Table 2.5). The MAR v3.2 distribution exhibits a slightly wider range of low albedo values (\(\sigma=0.06\) for the low albedo peak) with a mean that is positively shifted relative to MAR v2.0 (\(\mu=0.61\) vs. 0.50) (Figure 2.11b). MOD10A1 does not appear to exhibit a bimodal distribution with two distinct peaks, but the best-fit curve agrees qualitatively with the observed distribution (Figure 2.11c). The higher uncertainty and therefore increased variability for the MOD10A1 product (Figure 2.6; Stroeve et al. 2006) may possibly mask the two peaks of the distribution. Indeed, the best-fit bimodal distribution from MOD10A1 has a higher standard deviation of albedo for the higher albedo peak (\(\sigma = 0.06\) for MOD10A1 vs. 0.04 for MCD43A3; Table 2.5).
Figure 2.11. Scatter plots and histograms for JJA 2000-2012 albedo [unitless] within the MAR v3.2-defined GrIS ablation zone, for (a) MAR v2.0 clear sky (16 day avg.) vs. MCD43A3 BSA shortwave. (b) The same as (a), but for MAR v3.2. (c) The same as (a) but for MOD10A1 albedo (averaged to 16 day periods). (d) The same as (c) but for MAR v3.2. Points where there is snow or firm (surface snowpack density > 830 kg/m$^3$) for more than 8 days of a 16 day period are shown in red. Light blue curves show the best fit to each distribution obtained using maximum likelihood estimation.
Figure 2.12. (a) MAR v3.2 clear-sky minus MAR v2.0 clear-sky mean JJA albedo (b) MAR clear-sky v2.0 minus MOD10A1 2000-2012 mean JJA albedo, (c) MAR clear-sky v2.0 minus MCD43A3 BSA shortwave 2000-2012 mean JJA albedo, and (d) MAR v3.2 minus MAR v2.0 mean JJA SMB (mWE/yr) for the same period. Note that in the ablation area, where net SMB is negative (Figure 2.1), a positive SMB bias indicates a net mass loss that is reduced in magnitude. Grid boxes where differences are not significant at the 95% confidence level are marked with a black “x”.
Table 2.5. Mean and standard deviation for the best fit to the distributions of ablation area albedo shown in Figure 2.12 (assuming that the appropriate distribution is a combination of two normal distributions).

<table>
<thead>
<tr>
<th></th>
<th>MOD10A1</th>
<th>MCD43A3</th>
<th>MAR v2.0</th>
<th>MAR v3.2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>BSA Shortwave</td>
<td>Cloud-Corrected</td>
<td>Cloud-Corrected</td>
</tr>
<tr>
<td>First Mode (Ice)</td>
<td>0.57 ± 0.10</td>
<td>0.55 ± 0.10</td>
<td>0.50 ± 0.05</td>
<td>0.61 ± 0.06</td>
</tr>
<tr>
<td>Second Mode (Snow)</td>
<td>0.73 ± 0.06</td>
<td>0.71 ± 0.04</td>
<td>0.74 ± 0.04</td>
<td>0.74 ± 0.03</td>
</tr>
</tbody>
</table>

Table 2.6. Trends (and 95% confidence intervals) in JJA albedo (fraction per decade) at GC-Net and K-Transect weather stations and the nearest MOD10A1, MCD43A3, and MAR pixels. In this case, MODIS data flagged as “other quality” have been included. Only 16 day periods when coincident estimates are available for all datasets have been used. Values in bold indicate trends significant at the 95% confidence level.

<table>
<thead>
<tr>
<th>Ablation Zone</th>
<th>Period</th>
<th>MCD43A3</th>
<th>MOD10A1</th>
<th>MAR clear-sky</th>
<th>In Situ</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>BSA Shortwave</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Swiss Camp (GC)</td>
<td>2000-2011</td>
<td>-0.15 ± 0.05</td>
<td>-0.15 ± 0.06</td>
<td>-0.05 ± 0.03</td>
<td>-0.06 ± 0.03</td>
</tr>
<tr>
<td>JAR 1 (GC-Net)</td>
<td>2000-2012</td>
<td>-0.19 ± 0.06</td>
<td>-0.21 ± 0.07</td>
<td>-0.07 ± 0.03</td>
<td>-0.22 ± 0.03</td>
</tr>
<tr>
<td>JAR 2 (GC-Net)</td>
<td>2000-2012</td>
<td>-0.06 ± 0.02</td>
<td>-0.08 ± 0.03</td>
<td>-0.04 ± 0.02</td>
<td>&lt;0.01 ± 0.02</td>
</tr>
<tr>
<td>S5 (K-Transect)</td>
<td>2004-2012</td>
<td>-0.05 ± 0.03</td>
<td>-0.09 ± 0.04</td>
<td>-0.04 ± 0.04</td>
<td>-0.08 ± 0.04</td>
</tr>
<tr>
<td>S6 (K-Transect)</td>
<td>2004-2012</td>
<td>-0.13 ± 0.07</td>
<td>-0.19 ± 0.08</td>
<td>-0.08 ± 0.06</td>
<td>-0.14 ± 0.06</td>
</tr>
<tr>
<td>S9 (K-Transect)</td>
<td>2004-2012</td>
<td>-0.15 ± 0.05</td>
<td>-0.17 ± 0.06</td>
<td>-0.12 ± 0.05</td>
<td>-0.25 ± 0.05</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Accumulation Zone, North of 70°N</th>
<th>Period</th>
<th>MCD43A3</th>
<th>MOD10A1</th>
<th>MAR clear-sky</th>
<th>In Situ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Humboldt (GC)</td>
<td>2002-2011</td>
<td>-0.01 ± 0.02</td>
<td>-0.05 ± 0.02</td>
<td>-0.02 ± 0.01</td>
<td>&lt;0.01 ± 0.01</td>
</tr>
<tr>
<td>Summit (GC-Net)</td>
<td>2000-2012</td>
<td>-0.02 ± 0.02</td>
<td>-0.04 ± 0.02</td>
<td>&lt;0.01 ± &lt;0.01</td>
<td>&lt;0.01 ± &lt;0.01</td>
</tr>
<tr>
<td>Tunu N (GC-Net)</td>
<td>2000-2012</td>
<td>-0.03 ± 0.01</td>
<td>-0.05 ± 0.02</td>
<td>-0.01 ± 0.01</td>
<td>&lt;0.01 ± 0.01</td>
</tr>
<tr>
<td>NASA-E (GC-Net)</td>
<td>2000-2011</td>
<td>-0.02 ± 0.01</td>
<td>-0.05 ± 0.02</td>
<td>&lt;0.01 ± 0.01</td>
<td>-0.03 ± 0.01</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Accumulation Zone, South of 70°N</th>
<th>Period</th>
<th>MCD43A3</th>
<th>MOD10A1</th>
<th>MAR clear-sky</th>
<th>In Situ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dye-2 (GC-Net)</td>
<td>2000-2012</td>
<td>-0.05 ± 0.01</td>
<td>-0.07 ± 0.02</td>
<td>-0.01 ± 0.01</td>
<td>-0.01 ± 0.01</td>
</tr>
<tr>
<td>Saddle (GC-Net)</td>
<td>2000-2012</td>
<td>-0.03 ± 0.01</td>
<td>-0.05 ± 0.02</td>
<td>-0.01 ± 0.01</td>
<td>-0.01 ± 0.01</td>
</tr>
<tr>
<td>South Dome (GC)</td>
<td>2003-2012</td>
<td>-0.04 ± 0.01</td>
<td>-0.06 ± 0.02</td>
<td>-0.01 ± 0.01</td>
<td>-0.08 ± 0.01</td>
</tr>
<tr>
<td>NASA SE (GC)</td>
<td>2000-2012</td>
<td>-0.04 ± 0.01</td>
<td>-0.07 ± 0.02</td>
<td>-0.02 ± 0.01</td>
<td>&lt;0.01 ± 0.01</td>
</tr>
</tbody>
</table>
We compare MAR v2.0 mean 2000-2012 clear-sky JJA albedo with albedo from MAR v3.2 and MODIS in Figure 2.12 (a-c.) MAR v3.2 albedo is significantly larger in the ablation area compared with MAR v2.0 (Figure 2.12a). Rather than being positively biased relative to MODIS (as is the case for MAR v3.2 as shown in Figure 2.3), MAR v2.0 albedo is either negatively biased or is not significantly different from MODIS data (Figure 2.12b and c). The difference in albedo scheme is the major difference between MAR v3.2 and MAR v2.0, and it results in a significant difference in SMB (Figure 2.12d). The average ablation area JJA SMB for MAR v3.2 is higher by 0.53 mWE yr⁻¹ compared with the average for MAR v2.0, a considerable fraction (roughly 25%) of the mean ablation area JJA SMB from MAR v3.2, which is on average -2.02 mWE/yr for the period 2000-2013. This highlights the importance of a model’s albedo scheme in determining the ablation rate and size of the ablation area (van Angelen et al. 2012).

2.3.5. Greenland Ice Sheet albedo trends

MAR v3.2, MCD43A3, and MOD10A1 consistently agree that there has been a significant decrease in albedo within the ablation area over 2000-2013, and that the largest decreases in albedo have occurred below 2000 m a.s.l. (Figures 2.13 and 2.14). MCD43A3 shows a decrease of up to -0.1 per decade for pixels in the ablation area, as does MOD10A1 (both products show a decrease of -0.06 per decade for the entire area). MAR v3.2 agrees with these trends, but the overall magnitude is smaller (-0.03 per decade for the entire area).

Within the accumulation area, MAR v3.2 disagrees with the two MODIS products as to the direction and magnitude of trends. MCD43A3 shows a decrease of -0.03 per decade on average, and MOD10A1 trends are somewhat larger (-0.04 per decade on average), while for MAR v3.2, trends are generally not statistically significant at the 95% level for grid boxes above 2500 m a.s.l., and are slightly positive in some high-elevation areas.
**Figure 2.13.** JJA mean albedo trends (2000-2013) in units of fraction per decade for (a) MCD43A3 BSA shortwave albedo, (b) MOD10A1 albedo, and (c) MAR clear-sky albedo. Grid boxes where trends are not significant at the 95% confidence level are marked with a black “x”.
Figure 2.14. Mean annual JJA ice sheet albedo (solid lines) simulated by MAR v3.2 (clear-sky) (blue), MOD10A1 (black) and MCD43A3 BSA shortwave (orange) for 2000-2013 and best linear fit (dashed lines) for (a) the entire ice sheet, (b) the accumulation zone, and (c) the ablation zone defined with MAR v3.2. The trends shown are statistically significant at the 95% confidence level for the MODIS products, but are not statistically significant for MAR. Shaded areas show annual JJA standard deviation of albedo for 16 day periods from each dataset. Note that the y-axis interval is the same for all graphs, but is shifted by 0.1 for (c).
For locations within the GrIS ablation area, trends at GC-Net stations with a record of at least 9 years are consistent with significant decreases in albedo indicated by MODIS and MAR the periods covered (2000-2012 or 2004-2012; Table 2.6). The magnitude of the trends varies between MAR v3.2, MODIS and in situ data at individual stations. These differences can be attributed in part to the high spatio-temporal variability of albedo within the ablation area. This can potentially lead to trends at a weather station that are substantially different from trends within a 500 m MODIS grid box containing the location of that weather station. At higher elevations, this factor is less important as there is less spatio-temporal variability in albedo (Figures 2.9 and 2.10). Within the accumulation area, trends at weather stations are generally within ±0.01 per decade of MAR trends; they are generally not statistically significant and are close to zero, unlike MODIS estimates, which show trends ranging between -0.01 and -0.07 per decade (Table 2.6).

2.4. Discussion

2.4.1. Albedo properties of the Greenland Ice Sheet common to all observations and model results

The results presented above highlight certain features of Greenland ice sheet albedo variability that are common to in situ, satellite data, and model results. MAR, MODIS and in situ data capture general spatial patterns of low albedo in the ablation area, which increases with increasing elevation below ~2000 m and is relatively insensitive to elevation at higher elevations (Figures 2.2 and 2.4a, Table 2.4). This spatial variability is consistent with the presence of meltwater and bare ice exposure at low elevations, which are a function of surface air temperatures, and therefore elevation (Tedesco et al. 2011; Fettweis et al. 2011b). Bare ice in the ablation area is often covered with dust, further reducing low elevation albedo (Bøggild et al. 2010; Wientjes and Oerlemans 2010). At high-elevation areas that are permanently snow
covered, particularly at northern sites, melting is infrequent (Ngheim et al. 2012; Tedesco et al. 2011) and albedo variability is primarily associated with accumulation, subsequent dry snow grain size metamorphism (Wiscombe and Warren 1980), and possibly impurities (Dumont et al. 2014). Low elevation melting and bare ice exposure during warm summer months reduces surface albedo relative to snow albedo, resulting in a seasonal cycle that increases local variability. As Figure 2.7 and Tables 2.3 and 2.4 show, there is higher variability in ablation area albedo (where the mean standard deviation of albedo at in situ stations ranges between ±0.06 and ±0.09) relative to the accumulation area (where standard deviations range between ±0.02 and ±0.04).

As noted in Section 2.3.5, MAR, MODIS, and in situ data agree that there has been a significant decline in ablation area albedo between 2000 and 2013. These trends in surface albedo are associated with increased melting and bare ice exposure resulting in a declining ablation area SMB, captured by models (Fettweis et al. 2011b; Ettema et al. 2009) and in situ observations (van de Wal et al. 2012). Increased melting has been linked to higher regional atmospheric air temperatures, associated with atmospheric circulation changes (Fettweis et al. 2013b; Häkkinen et al. 2014).

2.4.2. Insights from differences between datasets

2.4.2.6. Variation of albedo with latitude

Results from Section 2.3.1 indicate that above 70°N, MOD10A1 shows an increase in albedo with latitude, MCD43A3 exhibits a decrease, MAR shows little change, and there is also a small increase with latitude at local weather stations (Figures 2.2, 2.4b, 2.5, and Table 2.4). The increase with latitude at local stations is likely unaffected by differences in spectral range between MODIS and in situ sensors (Figure 2.6).
Theoretically, snow albedo is expected to increase with increasing solar zenith angle, particularly for high solar zenith angles (Wiscombe and Warren 1980) and therefore will increase slightly with latitude at high latitudes, as long as other factors do not contribute to lower albedo values. Wang and Zender (2010) compared 16 day MCD43C3 albedo with GC-Net measurements and suggest that the MCD43C3 product is unrealistic at higher latitudes, in particular for solar zenith angles > 55°. (The MCD43C3 product differs from the MCD43A3 product used here only in its grid.) Schaaf et al. (2011) and Stroeve et al. (2013) suggest that the findings of Wang and Zender (2010) are inaccurate, partially because they did not separate results for high- vs. low-quality albedo. We have considered this in our study: results for all MCD43A3 data are shown along with good quality MCD43A3 data in Figure 2.4b. While the use of only good quality data increases MCD43A3 albedo above 70°N, it does not fundamentally change the dependency of MCD43A3 albedo on latitude. For MOD10A1, excluding low quality data has little effect on the binned values.

It should also be noted that the MOD10A1 product, to the contrary, may be positively biased above 70°N, given that it is comparable with uncorrected GC-Net data, which are likely positively biased (Figure 2.5). We do not have a reasonable explanation for this potential bias, but as noted by Box et al. (2012), the MOD10A1 product contains artifacts that have not been removed during quality control, even for “good quality” data. The in situ observations of Konzelmann and Ohmura (1995) also suggest that values of albedo above 0.84 are unrealistic for snow under clear-sky conditions. Part of the reason for discrepancies in the latitudinal dependence of albedo may be associated with biases resulting from viewing geometry or sun angle, which vary with latitude, making it difficult to draw conclusions from the various observational datasets as to “true” variations in albedo with latitude.
2.4.2.7. Differences between MAR v3.2, MAR v2.0 and observations

The major difference between MAR v3.2 albedo and observed albedo is an overall positive bias in the ablation area. This bias can be seen most clearly as a difference of ~0.1 between MAR v3.2 and the two MODIS products along the west coast ablation area in Figure 2.3b and c, and in a difference between MAR v3.2 and both MODIS products of 0.06 at in situ stations (with low elevation stations mostly located in the west coast ablation area). Mean ablation area albedo from local stations is also comparable with coincident MAR v3.2 albedo (Table 2.4), but local station measurements are likely positively biased, further confirming a positive MAR bias in this area.

Scatter plots of ablation area albedo appear to confirm this: when MAR v3.2 is compared with both MODIS data and in situ measurements (Figures 2.9b, c and 2.10c) the result is a best fit line with a slope smaller than one. Additionally in the same area where MAR v3.2 appears positively biased in the west coast ablation area, MODIS exhibits relatively high variability compared with MAR v3.2 (as discussed in Section 2.3.2; Figure 2.7).

Biases in MAR ablation area albedo are related to its ability to capture the observed bimodal distribution in ablation area albedo (Figure 2.11) associated with two main surface types, ice and snow. The positive bias from MAR v3.2, as well as the relatively low modeled variability in the ablation area is the result of the albedo values set for bare ice in MAR v3.2 (Table 2.1) that may be too high on average. MAR v2.0 albedo, by contrast, which has a fixed bare ice albedo of 0.45, generally exhibits a negative bias in most portions of the ablation zone. A bare ice albedo that is too high will also lead to a smaller difference between the albedo values of melting snow and bare ice, reducing temporal variations in ablation area albedo, resulting in the relatively low variability from MAR v3.2 (Figure 2.7).
An examination of Figure 2.11 indicates that the low albedo peak for MAR v3.2 is closer to being normally distributed compared with the peak for MAR v2.0, and therefore better matches the distribution from MCD43A3. However, the MAR v3.2 parameterization overestimates the bare ice albedo, as already discussed, and still does not fully capture the variability in the low albedo peak for MODIS albedo (σ=0.06 for MAR v3.2 and σ=0.10 for both MODIS products). The results suggest that although MAR v3.2 appears to correct a low albedo bias present in MAR v2.0, and introduces a somewhat more realistic distribution of albedo in the ablation area, it also introduces a positive albedo bias, particularly along the west coast ablation zone, which is rich in impurities.

MAR albedo is only a function of accumulated meltwater and does not explicitly take into account the presence of dust, surface lakes and surface streams, including the West Greenland “dark zone” (van de Wal and Oerlemans 1994; Wientjes and Oerlemans 2010), which reduces bare ice albedo and likely introduces increased ablation area albedo variability. Assigning a wider range of MAR albedo values for bare ice (which has been implemented in most recent release of MAR, v3.4) may improve its representation of the distribution of bare ice albedo, but may not necessarily improve its ability to capture the spatial distribution of ablation area albedo. This could potentially be achieved through the inclusion of an explicit representation of dust and sub-grid-scale hydrology in the model.

2.4.2.8. Discrepancies in accumulation area trends

As noted in Section 2.3.5, there is a discrepancy between the satellite products, in situ data, and model results regarding albedo trends in the accumulation area of the ice sheet. MOD10A1 and MCD43A3 show significant decreases in accumulation area albedo (-0.04 to -
0.03 per decade) while MAR v3.2 trends are generally not statistically significant, and in situ trends are generally small (not larger than -0.01 per decade) or not significant.

A possible explanation for this discrepancy is that MODIS trends are negatively biased as a result of declining instrument sensitivity of the MODIS sensors (Wang et al. 2012). In particular, a larger degradation has been observed for the MODIS Terra satellite (Wang et al. 2012). The MCD43A3 product uses data from both the Terra and Aqua satellites, while MOD10A1 only uses data from Terra. This could potentially explain the larger trends for MOD10A1 relative to MCD43A3 (Table 2.6, Figure 2.13). Box et al. (2012) conclude that declining instrument sensitivity does not substantially affect GrIS albedo trends, because they find larger trends in GC-Net data relative to MOD10A1 for 70% of cases where trends are deemed to be significant. We do not find JJA GC-Net trends larger than those of MODIS, except within the ablation area, with high local variability, in contrast to the findings of Box et al. (2012). The analysis performed here is somewhat different from that employed by Box et al. (2012). Differences in trends may result from the fact that here we have focused on trends for the entire JJA period rather than on monthly trends, and calculate trends for 16 day albedo values rather than calculating a monthly albedo from integrated fluxes over a 1-month period, as was done by Box et al. (2012). We also investigated the possibility that the smaller spectral interval of GC-Net data influences trends by comparing MCD43A3 visible vs. shortwave albedo trends, but did not find the trends to be significantly different from each other. We are not able to confirm that the larger trends from MODIS are associated with declining instrument sensitivity, as this analysis is outside the scope of this study. However, the findings of this study seem consistent with this possibility and this is suggested as a topic for future research.

2.5. Conclusions
We have examined spatio-temporal variability and trends in GrIS albedo using in situ measurements, satellite products obtained from MODIS data, and outputs of a regional climate model (MAR v3.2). The results presented here reveal areas of agreement as well as discrepancies between observational and model estimates of GrIS albedo spatio-temporal variability. Examining local measurements, satellite data, and model results concurrently reveals information about the GrIS albedo and potential biases that would not be revealed by examining the observational datasets or model results individually.

The results presented here show that albedo varies spatially as a function primarily of surface properties, in particular melting and bare-ice exposure in the ablation area. These factors are also associated with temporal variations in albedo, resulting in high variability in low elevation regions. The differences in variations with latitude indicated by satellite products appear likely to be a function of inaccuracies associated with the products themselves, rather than a record of actual variations in surface albedo, particularly as the two products are derived from the same MODIS sensors.

Both satellite products and MAR model outputs (for v2.0 and v3.2) suggest that there is a bimodal distribution of surface albedo within the ablation area of the ice sheet. Based on model results, we infer that this distribution is associated with the presence of two primary surface types within the ablation area, snow and bare ice. The model’s inability to capture the full range of low elevation albedo leads to inaccuracies in the representation of spatiotemporal variations in albedo, which can substantially impact the representation of SMB. The MAR version examined here (v3.2) appears to better represent the full range of bare-ice albedo in the ablation area relative to a previous version (v2.0), but a lower minimum bare ice albedo value (as is implemented in the next version of MAR, v3.4), may produce results that are more consistent with observations. [See Appendix G for a comparison of MAR v3.5.1 albedo and other versions of MAR.] Even so, it
may be necessary to account for the presence of impurities and sub-grid scale hydrology in order to fully capture spatial variations in albedo.

The analysis performed here indicates a statistically significant decrease in ablation area albedo over the period 2000-2013 that is consistent with previous studies (Box et al. 2012; Tedesco et al. 2011, 2013a; Stroeve et al. 2013). This decrease is consistent with a coincident decline in ablation area SMB recorded by both models and observations (e.g. Fettweis et al. 2011b; Ettema et al. 2009). Our results are inconclusive regarding high elevation trends in albedo; we observe inconsistencies between satellite-derived trends and trends obtained from in situ measurements and MAR v3.2 results. We are therefore unable to confirm previously reported decreases in surface albedo at high elevations.

Future research should be directed towards understanding the reasons for discrepancies between satellite products, in situ data and model results, in order to better understand changes in GrIS albedo. This includes resolving discrepancies regarding high-elevation trends, and discrepancies in mean satellite-derived surface albedo at high latitudes. Models such as MAR appear to be effective at capturing surface albedo, but refinements are necessary for representation of surface albedo in low elevation areas. In particular, the representation of bare ice albedo is critical. Sensitivity studies, such as those performed by van Angelen et al. (2012) of the impact of surface albedo on SMB variability, may help to quantify the accuracy with which surface albedo must be modeled for a given region. Analysis of spatiotemporal variations in albedo across different spatial scales (including at a higher spatial resolution than has been examined here) may also become increasingly important as models operate at higher spatial resolutions, and as we seek to understand the GrIS surface mass and energy budget in greater detail. Given the strong relationship between surface albedo and SMB, these future studies are
crucial for efforts aiming at estimating and predicting the impact of current and future climate change on GrIS SMB.

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Chapter 3

Greenland ice sheet high-resolution mass balance variability from model simulations and GRACE (2003-2012)

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This chapter is in preparation for submission to a scientific journal.

3.1. Introduction

The Earth’s ice sheets represent substantial reservoirs of water stored in the form of ice; the Greenland and Antarctic Ice Sheets contain enough frozen water to raise sea levels by about 70 meters on average if they were to melt completely (Alley et al. 2005), with the Greenland ice sheet in particular able to contribute approximately 7 meters to mean global sea level rise (Ridley et al. 2005). Predictions of future rising temperatures associated with anthropogenic carbon dioxide emissions (e.g. Kirtman et al. 2013) have prompted studies of the ice sheets’ contribution to current and future sea level changes. The Greenland Ice Sheet (GrIS), in particular, is estimated to have lost mass at an average rate of $-142 \pm 49$ Gt/yr between 1992 and 2011 (Shepherd et al. 2012), contributing roughly $7\pm2$ mm/yr to sea level rise. A portion of this mass loss is associated with melting at the ice sheet surface: a relatively warm climate experienced over the GrIS during the past decade has led to multiple records in GrIS melt extent and duration (Tedesco et al. 2008, 2011, 2013a; Nghiem et al. 2012) leading to increased runoff that more than compensates for smaller increases in precipitation (van den Broeke et al. 2009; Ettema et al. 2009; Fettweis et al. 2013b). The other portion of GrIS mass loss is associated with an acceleration of outlet glaciers (Rignot et al. 2011). The speedup of glaciers has been attributed
to warming oceans (Rignot et al. 2012) and lubrication of the ice sheet bed from meltwater generated at the surface, and channeled from the surface to the bed by vertical conduits, allowing glaciers to slide more easily (Zwally et al. 2002). This second factor has been shown to be complex: increases in runoff from the surface can result in more efficient elimination of meltwater at the bed, actually decreasing glacier velocities (Sundal et al. 2011). Thus, the overall impact of meltwater lubrication on long-term changes in dynamics is not well understood.

While previous studies have generally focused on decadal trends in ice sheet mass (e.g. Shepherd et al. 2012; Rignot et al. 2011), seasonal variations, and variability at smaller spatial scales have been not been explored extensively. The overall GrIS mass balance (MB) or \( \frac{dM}{dt} \), the rate of ice sheet mass change, is generally considered to consist of two components, the Surface Mass Balance (SMB, i.e. the balance between accumulation and ablation at the ice sheet surface), and ice discharge (D), such that MB = SMB - D. Simulations of SMB at high spatial and temporal resolutions (e.g. daily temporal resolution and <25 km spatial resolution) are conducted by Regional Climate Models (RCMs; e.g. Fettweis et al. 2013a; Ettema et al. 2009), and D can be simulated by Ice Sheet Models (ISMs) (e.g. Larour et al. 2012; Quiquet et al. 2012; Robinson et al. 2011; Huybrechts et al. 2011), which simulate glacial flow subject to SMB forcing. While RCMs can simulate SMB at high resolution, there are few observations available that allow simulated SMB to be directly evaluated, leading to a relatively wide range of RCM SMB estimates (Vernon et al. 2013; Rae et al. 2012). Also ISMs are generally used for long-term estimates of ice volume change, and are not as effective at capturing short-term (i.e. interannual or seasonal) fluctuations in mass (Schlegel et al. 2013). While simulated SMB combined with measured discharge has been compared with estimates of large-scale mass changes over the GrIS derived from satellite-derived estimates (van den Broeke et al. 2009; Rignot et al. 2011), and generally agree with these estimates, the combined results of RCMs and ISMs have not been
evaluated against satellite estimates. Such an evaluation is important, given that RCMs and ISMs are currently the best tools available for predicting future changes in GrIS mass.

At shorter timescales, and at smaller spatial scales, poorly understood processes not accounted for by ISMs or RCMs may play particularly important role in mass changes. These include time-variable and spatially variable ice flow associated in part with basal lubrication and ice-ocean dynamics, and englacial storage and release of liquid water. The full MB for a fixed control volume on the ice sheet can be expressed as follows (after Cuffey and Paterson 2011):

\[
MB = SMB + EMB + BMB + DMB
\]

(3.1)

where EMB is the englacial mass balance, BMB is the basal mass balance, and DMB is the mass balance associated with dynamic flow.

While few studies have attempted to calculate the EMB or BMB for the GrIS, numerous studies have identified seasonal variations in glacial flow (e.g. Moon et al. 2014; Joughin et al. 2014, 2008; Howat et al. 2010; Bartholomew et al. 2010), and local variations in flow associated with lake drainage events or summer melting (e.g. Das et al. 2008; Tedesco et al. 2013b; Hoffman et al. 2011), which are not accounted for by ice sheet models. Ice sheet hydrology may contribute to changes in EMB and BMB. For example, an observational study by Rennermalm et al. (2013) suggests that within one catchment along the GrIS coast, up to 50% of runoff generated at the surface may have been stored within the ice over multiple seasons, suggesting a positive EMB for that catchment over multiple years. Water can also be stored at or near the surface of the ice sheet, within supraglacial lakes, or within firn aquifers, which were recently discovered to be persist during winter over large portions of the southwest and southeast GrIS margins (Forster et al. 2013; Koenig et al. 2014). While the amount of water stored within supraglacial lakes is likely small relative to the overall MB (Smith et al. 2015), the amount of water stored within the firn aquifers or englacially is unknown. Most of the above processes are not accounted for by
either RCMs or ISMs. In a warmer climate, more meltwater production and runoff is expected (Fettweis et al. 2013), suggesting that such processes will play an increasingly important role in future GrIS mass balance (Chu 2014).

Cognizant of the potential role of such processes in GrIS MB, and the need for evaluation of the combined results of ISMs and RCMs, we conduct a comparison between satellite-derived mass changes from the Gravity Recovery and Climate Experiment ((GRACE; Luthcke et al. 2013)), modeled DMB from the Ice Sheet System Model (ISSM; Larour et al. 2012) and SMB from the Modèle Atmosphérique Régionale (MAR; e.g. Fettweis et al. 2013a) for the period 2003-2013. The analysis is conducted at a relatively high spatial and temporal resolution (100 km and 10 days respectively). We aggregate model results to the GRACE grid and spatially and temporally filter the aggregated outputs in order to match inherent spatial attenuation of the GRACE product. After filtering model outputs, we compare spatial patterns of simulated and satellite-derived mean annual mass balance, the mean annual seasonal cycle of mass change, and the spatial distribution of the timing of the seasonal cycle. This analysis has two purposes: (1) to evaluate spatiotemporal variations in mass simulated using the combined results of an RCM and ISM applied over the Greenland ice sheet, and (2) through this comparison, to reveal any discrepancies between simulated and observed mass changes not accounted for by the simulations.

3.2. Data and Methods

3.2.1. GRACE data

We use the iterated global GRACE solution of Luthcke et al. (2013), which utilizes a mass concentration (mascon) approach to derive spatially and temporally distributed changes in the mass of land ice, at a 1 arc-degree (~100 km) spatial resolution and 10-day temporal
resolution. GRACE mass change estimates are provided for ~100x100 km “mascon” regions, on what is essentially an equal area grid (shown in Figure 3.1). All GRACE solutions are ultimately derived from k-band range and range rate (KBRR) data for two co-orbiting satellites roughly 220 km apart (Tapley et al. 2004). In one approach (e.g. that used by Velicogna and Wahr 2006), a set of Stokes coefficients or spherical harmonic fields provided by GRACE processing centers are spatially filtered and used to estimate spatial and temporal variations in mass using equations of spherical harmonics. The Luthcke et al. (2013) solution differs from other solutions in that changes in mass on an equal area grid of mascons are estimated and used to simulate KBRR observations. Through iteration, the residuals between the simulated and observed KBRR are minimized and unrealistic large changes in mass are also avoided by attempting to minimize overall spatially distributed mass changes. The approach minimizes the loss of signal associated processing GRACE data, and detailed error estimates, accounting for various steps in processing are provided. As described by Luthcke et al. (2013), various corrections are applied during the processing of GRACE data to attempt to isolate the signal associated with land-ice changes. In particular, the static gravity field, orbital parameters, ocean and earth tides, terrestrial water storage, variations in mass associated with atmospheric and ocean circulation, and glacial isostatic adjustment are simulated by various models, and these simulated changes are used to correct GRACE-estimated mass change. The errors associated with each of these simulations are included in calculations of error for each GRACE mascon. The GRACE mascons are distributed at a resolution that is higher than the fundamental spatial resolution of GRACE (Luthcke et al. 2006), so that there is “leakage” of mass into and out of each mascon. This results in a spatial “smoothing” effect such that the change in mass for the area represented by a mascon is distributed over a radius of roughly 600 km from the mascon center (Luthcke et al. 2013). As a result, we must spatially filter model data to allow a fair
Figure 3.1. Grid of mascons over the GrIS for the GRACE solution of Luthcke et al. (2013). The constraint regions of Luthcke et al. (2013) are also identified: areas below 2000 m in elevation are shaded red, while areas above 2000 m in elevation are shaded blue.
comparison with the GRACE data. The details of this process are described further in Section 3.2.4.

3.2.2. The MAR RCM

The MAR RCM (Gallée and Schayes 1994; Gallée 1997; Lefebre et al. 2003) is a coupled surface-atmosphere RCM that has been applied over the GrIS to simulate current and future changes in SMB (e.g. Fettweis et al. 2013a; Franco et al. 2013). The atmospheric portion of MAR is described by Gallée and Schayes (1994), while the land surface model is the Soil Ice Snow Vegetation Atmosphere Transfer scheme (SISVAT), containing the Crocus snow model (Brun et al. 1992). The model is forced at the lateral boundaries with reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF). We use model outputs from two versions of the MAR model, MAR v2.0 for the period 2000-2010, with the model setup described by Fettweis (2007), and MAR v3.5, the latest version of MAR, for the period 2003-2012. MAR v3.5 features an updated albedo scheme also present in MAR v3.2, and the possibility of having fractional ice cover within a grid box (as described by Alexander et al. 2014). The major difference between MAR v3.5 and MAR v3.2, is the use of a new lower limit on bare ice albedo in low elevation areas (of 0.4 rather than 0.45, as suggested by the study of Alexander et al. 2014). Both MAR v3.5 and MAR v2.0 are forced at the lateral boundaries by the ERA-Interim reanalysis (Dee et al. 2011) beginning in 1979, and are run at a 25 km spatial resolution (as shown in Figure 3.2a). In order to force ISSM, MAR data for 1979-2012 are first spatially interpolated onto a 5 km grid, using the method of Franco et al. (2012) to correct for vertical gradients in SMB.
3.2.3. The Ice Sheet System Model

The Ice Sheet System Model (ISSM; Larour et al. 2012) is a thermo-mechanical ice sheet model that simulates ice flow in response to forcing from surface mass balance. The model solves equations for conservation of mass, momentum, and energy, in conjunction with constitutive equations for ice properties and boundary conditions. It has the capability of incorporating multiple approximations to the Full Stokes (FS) ice flow equations in different regions. The model is implemented on a finite element mesh, which can be refined anisotropically to allow for a higher resolution in areas of high observed surface velocities. Inversion methods are used to derive constitutive properties such as ice rigidity and basal friction, by iteratively minimizing differences between radar-derived observed and modeled ice velocities (Morlighem et al. 2010; Larour et al. 2012).

In this study, ISSM has been run over the entire GrIS, following the model configuration of Schlegel et al. (2013), which uses a 2D Shelfy-Stream Approximation (SSA) to the FS equations (MacAyeal 1989) in order to increase computational efficiency (as described by Larour et al. 2012). Aside from the inversion methods used to perform initialization of parameters for ice properties, the model is forced only by SMB at the surface, subject to the boundary conditions described by Larour et al. (2012). The GrIS simulation consists of an anisotropic mesh, which ranges in spatial resolution from 1 km to 15 km, consisting of 73,320 elements. The MAR v3.5 mean SMB for the period 1979-1988, interpolated to a 5 km resolution, and subsequently onto the ISSM mesh, is used to spin up ISSM until the model reaches steady-state equilibrium, i.e. the change in GrIS mass over time is negligible. Once the model reaches steady-state, MAR SMB for the period 2003-2013 is used to force ISSM at a daily temporal resolution. We evaluate the ISSM spin-up by comparing the ISSM ice thickness at steady-state to the ice thickness obtained from the 5 km spatial resolution Digital Elevation Model (DEM) of Bamber et al. (2001). The
DEM of Bamber et al. (2001) is spatially interpolated onto the 10 km grid on which ISSM data are provided using bilinear interpolation.

3.2.4. Methods of Comparison

2.6.2.9. Spatial Aggregation

MAR v3.5 and ISSM daily outputs for the period 2003-2012 were spatially aggregated into GRACE mascons (shown in Figure 3.1; average 2003-2012 MAR v3.5 and ISSM outputs are shown in Figure 3.2). In the case of ISSM data, ISSM dynamic thickness changes (ice thickness change associated only with dynamic motion of ice) on the anisotropic mesh were first interpolated onto a 10 km equal area grid, converted into mass changes using the density of ice (917 kg/m$^3$) and then aggregated to the nearest GRACE mascon to produce timeseries of DMB for each mascon. In the case of MAR data, MAR SMB at a 25 km resolution were aggregated to the nearest GRACE mascon. The sum of mass change simulated by each model was then calculated for each GRACE mascon. Over the oceans, all mass changes predicted by MAR (likely associated with accumulation over sea ice) were set to zero, as such accumulation does not result in changes in mass due to the presence of isostatic adjustment of sea ice over the oceans. MAR SMB over land areas was included when aggregating MAR data into GRACE mascons. Snow accumulation and melt over GrIS land areas are not corrected for in GRACE data, and therefore must be included in the comparison. A map of average surface mass balance for the period 2003-2010 for MAR v2.0 (MAR v3.2) data aggregated into GRACE mascons is provided in Figure 3.3a (Figure C.1a).
Figure 3.2. (a) MAR v3.5 average specific Surface Mass Balance (SMB, kg km\(^{-2}\) yr\(^{-1}\)) for 2003-2012 on the MAR 25 km grid, for the GrIS and periphery (contours show elevation above sea level) and (b) ISSM average specific Dynamic Mass Balance (DMB, kg kg km\(^{-2}\) yr\(^{-1}\)) for the same period on the ISSM mesh.
Figure 3.3 Average MAR v2.0 SMB (Gt yr\(^{-1}\)) for the period 2003-2010: (a) averaged onto GRACE mascons with no filtering, (b) filtered using the resolution operator from GRACE processing, (c) filtered using a Gaussian approximation to GRACE filtering in space and time. (d) The difference between (a) and (b). Note the difference in the color scale for (d).
2.6.2.10. Spatial and Temporal Filtering Using GRACE equations

In order to conduct a fair comparison with GRACE at a high resolution, model results must be spatially and temporally filtered to account for spatial and temporal attenuation of the GRACE signal, associated with the “leakage” of mass changes from each mascon into nearby mascons in space and time (Luthcke et al. 2013). Luthcke et al. (2013) use a Gauss-Newton (GN) procedure to adjust an equivalent height of water within each mascon to produce perturbations in the GRACE spherical harmonic fields or Stokes coefficients. The partial derivatives of the Stokes coefficients with respect to the equivalent water height, and the partial derivatives of the KBRR observations with respect to the Stokes coefficients are then used to determine the change in KBRR observations associated with a change in equivalent water height. The GN procedure iteratively adjusts equivalent water height within all mascons to minimize the residuals between the KBRR observations and the simulated KBRR values. The final GRACE solution for a given mascon is not the “true” mascon state, but differs from it due to “leakage” between mascons and the presence of noise in the solution. The relationship between the true mascon state \( h_k \) and the updated mascon state \( \hat{h}_{k+1} \) is given by Equation 8 of Luthcke et al. (2013), expressed as three equations below:

\[
\hat{h}_{k+1} = Rh_k + Ke
\]  

where \( e \) represents added noise, and \( R \) is referred to as the resolution operator, as it serves the function of “smoothing” the true mascon state \( h_k \) in space and time. \( K \) and \( R \) are in turn expressed by:

\[
K = \left(L^T A^T W A L + \mu P_{ss} \right)^{-1} L^T A^T W
\]
\[ R = KAL \tag{3.4} \]

where \( L \) represents the partial derivatives of the Stokes coefficients with respect to the mascon state, \( A \) represents the partial derivatives of the KBRR observations with respect to the Stokes coefficients, and \( W \) is a data weight matrix that accounts for orbital parameters and corrections for processes not related to ice sheet mass changes (e.g. isostatic adjustments, tides, etc.). \( P_{hh} \) is a regularization matrix, which constrains the solution so that differences in mass change between mascons closer together are minimized (Sabaka et al. 2010). Constraint regions for the GrIS are also defined (Figure 3.1) such that the constraint does not apply across the boundaries of the constraint region. Thus, for the GrIS, changes in mass above 2000 m in elevation, where the MB is generally positive, can occur independently of changes in mass below 2000 m in the GRACE solution.

In order to spatially filter MAR data to match GRACE, we applied the resolution matrix to the aggregated MAR v2.0 data, using Equation 1, taking the aggregated MAR v2.0 on GRACE mascons as the “true” mascon states \( h_k \), and ignoring the added noise term \( e \). The resulting updated mascon states \( \hat{h}_{k+1} \) are MAR v2.0 data spatially and temporally filtered to match GRACE. The effect of spatial smoothing on the MAR v2.0 aggregated data, along with the impact of different constraint regions above and below 2000 m in elevation, can be seen in Figure 3.3b, which shows the mean 2000-2010 MAR v2.0 data filtered using the resolution matrix.

Unfortunately, the methods discussed above, hereafter referred to as “GRACE filtering” are computationally expensive and time consuming to perform. We only filtered MAR v2.0 data using GRACE filtering, as this was the only MAR dataset available when the GRACE filtering procedure was applied. To filter MAR v3.5 and ISSM data, we employ an approximation to the GRACE filtering procedure, which is described further below.
A Gaussian approximation to GRACE filtering

As discussed by Luthcke et al. (2013), the leakage associated with individual GRACE mascons is roughly equivalent to a spatial Gaussian filter with a radius of 300 km, with the mascons within a 600 km radius accounting for almost 100% of the mass changes within a mascon. To allow for spatial filtering of MAR v3.5 and ISSM outputs, we developed an approximation to the GRACE filtering using a Gaussian filter. The Gaussian function can be expressed as a function of distance from the center of the distribution (x-µ) and a standard deviation (σ) as:

\[ g(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \]  \hspace{1cm} (3.5)

We used a gaussian function to weight the data for all surrounding mascons (j) as a function of radial distance from a central mascon (i). In this case, x-µ is replaced by the distance from a central location to another mascon \( r_{ij} \), and a discrete approximation to the Gaussian is used, as follows:

\[ g(r_{ij}) = e^{-\frac{(r_{ij}-\mu)^2}{2\sigma^2}} \]  \hspace{1cm} (3.6)

\[ w(r_{ij}) = \frac{g(r_{ij})}{\sum_{j \neq i} g(r_{ij})} \]  \hspace{1cm} (3.7)

The weight, \( w \), assigned to a given mascon, \( j \), at a distance \( r_{ij} \) from mascon \( i \), is given by the value of the Gaussian function at that mascon divided by the sum of all Gaussian values surrounding mascon \( i \). The weights for mascons \( j \) surrounding a central mascon \( i \) are then used to create a weighted average of surrounding mascon values. A different \( \sigma_i \) value is chosen for each mascon.
Additionally, we must account for the constraint regions discussed in the previous section, which for the GrIS, includes areas above and below 2000 m in elevation (Luthcke et al. 2013), as the leakage across such constraint regions is minimized. For a given mascon within a constraint region (mascon \( i \)), weights for mascons outside of the constraint region were multiplied by a leakage parameter, \( \lambda_j \), which was set to 1 within the constraint region, and a fixed value between 0 and 1 outside of the constraint region. Accounting for these constraints, Equations 3.6 and 3.7 become:

\[
g(r_{ij}) = e^{-\frac{1}{2} \left( \frac{r_{ij}}{\sigma_i} \right)^2} \tag{3.8}
\]

\[
w(r_{ij}) = \frac{g(r_{ij})\lambda_{ij}}{\sum_{j \neq i} g(r_{ij})\lambda_{ij}} \tag{3.9}
\]

Where \( \lambda_{ij} \) for mascon \( i \) is set equal to 1 within the constraint region, and equal to a constant value between 0 and 1 for all mascons \( j \) outside of the constraint region. Finally, we added a time component to the filtering procedure, as the regularization matrix (\( P_{hh} \)) discussed in Section 3.3.4.2 also includes a temporal component (Sabaka et al. 2010). After applying the spatial filter described by Equations 3.8 and 3.9, timeseries of cumulative mass from MAR v2.0 were interpolated onto GRACE time-intervals. We then applied the same Gaussian filter of Equations 3.6 and 3.7 to the cumulative mass timeseries for each mascon, replacing the radius \( r_{ij} \) with the temporal radius \( \Delta t_{t0t1} \):

\[
g(\Delta t_{t0t1}) = e^{-\frac{1}{2} \left( \frac{\Delta t_{t0t1}}{\sigma_{\text{temp}}} \right)^2} \tag{3.10}
\]

\[
w(\Delta t_{t0t1}) = \frac{g(\Delta t_{t0t1})}{\sum_{t=1}^n g(\Delta t_{t0t1})} \tag{3.11}
\]
We applied this filter to the MAR v2.0 data to which the GRACE filtering was applied, and compared the resulting cumulative mass timeseries’ from each mascon to the GRACE-filtered timeseries. We iteratively adjusted the values of $\sigma_i$, $\sigma_{\text{time}}$, and $\lambda_{ij}$, for each mascon $i$ to minimize the root mean squared error (RMSE) between the Gaussian-filtered and GRACE-filtered cumulative mass timeseries. Initially, fixed values of $\sigma_i$, $\sigma_{\text{time}}$, and $\lambda_{ij}$ were used for all mascons $i$, but it was found that by varying the values of these parameters for each mascon $i$, the errors were reduced. We also set $\lambda_{ij}$ equal to zero outside of Greenland as defined by the GRACE mascons, as this improved the agreement with the GRACE-filtered results. Values of $\sigma_i$ were varied at 10 km increments over a range of 1 to 600 km, while values of $\sigma_{\text{time}}$ ranged between 1 and 91 days at increments of 5 days, and $\lambda_{ij}$ ranged between 0 and 1 at increments of 0.01. We also tried larger values of $\sigma_i$ beyond the indicated range at larger increments, but did not find a reduction in RMSE for values larger than 600 km. We also performed a version of this procedure in which temporal filtering was not applied, in order to evaluate the impact of temporal filtering.

Average Gaussian-filtered MAR v2.0 SMB for the period 2003-2013 is shown in Figure 3.3c. The Gaussian filtered MAR v2.0 patterns of SMB are similar to those of the GRACE-filtered results. The range of differences between the GRACE-filtered and Gaussian-filtered results (Figure 3.3d) is an order of magnitude smaller than the average SMB values (-0.2 to 0.2 vs. -2 to 5 Gt), although in some regions where trends in SMB are small, the differences are a large percentage of the average SMB. Optimal values for $\sigma_i$, $\sigma_{\text{time}}$, and $\lambda_{ij}$ and the RMSE for the Gaussian vs. the GRACE-filtered MAR v2.0 data are shown in Appendix C (Figure C.2). Further discussion of the impacts of filtering on the results is provided in Section 2.6.2.13.
2.6.2.12. Application of Gaussian filters and seasonal cycle analysis

Following the choice of the optimal Gaussian filter, we applied the chosen filter to MAR v3.5 and ISSM data forced by MAR v3.5, aggregated to the GRACE grid. Spatial filtering was conducted first at a daily temporal resolution. Filtered cumulative mass timeseries for each mascon were then interpolated onto GRACE time steps, and temporal filtering was performed. We then summed the timeseries of cumulative mass change from MAR v3.5 and ISSM, and compared them with GRACE.

We examined differences between the modeled and GRACE seasonal cycles of cumulative mass change by first interpolating filtered cumulative model and GRACE timeseries to a daily temporal resolution, removing linear trends from the timeseries for each mascon, and averaging the data for a given day of the year across all available years. This was performed for the GrIS-wide timeseries, as well as for individual mascons and GrIS sub-regions. The timing of maximum and minimum peaks in the seasonal cycle were determined for the model data and compared among datasets.

GRACE data from Luthcke et al. (2013) include estimates of the error associated with the timeseries of cumulative mass change for each mascon. When examining aggregated data, we summed the error for all mascons. The error for a given day for the GRACE seasonal cycle was determined to be the total GRACE error for the cumulative timeseries divided by $\sqrt{n}$, where $n$ was the number of years being averaged. Errors in the GRACE timeseries lead to errors in the timing of the seasonal cycle. To account for these errors, we performed 1,000 Monte Carlo simulations with the GRACE seasonal data, assuming that the errors in the timeseries were normally distributed. For each of these simulations, the local maximum and minimum peaks in the seasonal cycle were determined, allowing us to generate a distribution of dates for maximum
and minimum mass in the annual cycle. If the model peaks fell outside of the 95% confidence interval for this distribution, the timing of the GRACE and model peaks was deemed to differ.

2.6.2.13. Effect of filtering on seasonal variations in mass

As we are interested in examining seasonal variations in mass, in addition to the spatial variability of 10-year trends in mass, we examined the impact of spatial and temporal filtering on the cumulative timeseries of GrIS-wide mass changes. While it is not possible to compare GRACE directly to MAR, given that GRACE also records the effects of changes in DMB, a comparison of de-trended timeseries of cumulative mass can be performed, if it is assumed that seasonal variations in ice discharge are small relative to those of SMB. A comparison of de-trended MAR v2.0 and GRACE cumulative timeseries for the GrIS over 2003-2010 (Figure 3.4), suggests that this is a reasonable assumption for the entire ice sheet. Fluctuations in mass, coinciding with net loss of mass during summer months, and net gain of mass during winter months, are captured by both GRACE and MAR v2.0. The MAR v2.0 and GRACE timeseries roughly agree as to the seasonal timing of fluctuations in mass. In general, unfiltered MAR v2.0 data exhibit a seasonal cycle with a larger amplitude relative to GRACE (~600 vs. 400 Gt), while the amplitude of fluctuations in GRACE-filtered MAR v2.0 data is similar to those of GRACE. Spatially Gaussian-filtered MAR v2.0 data (to which no temporal filter is applied) exhibit a cumulative timeseries nearly identical to that of the unfiltered MAR v2.0 data, indicating that the spatial Gaussian filter does not substantially change GrIS-wide fluctuations in mass, but mainly redistributes them across the ice sheet. These results indicate that temporal filtering is necessary to reproduce the amplitude of fluctuations in the GRACE-filtered MAR data.

The average seasonal cycle of cumulative mass change in Figure 3.5a confirms a larger amplitude of mass fluctuations for unfiltered and spatially Gaussian-filtered MAR v2.0 results (of
Figure 3.4. Detrended timeseries of cumulative GrIS-wide mass change, for GRACE, MAR v2.0 (unfiltered), MAR 2.0 (GRACE-filtered), and MAR v2.0 (Gaussian Filtered). In this case a temporal filter has not been applied in the case of Gaussian filtering. The pink shading indicates the range of error for the GRACE timeseries.
Figure 3.5. Average seasonal cycle of 2003-2010 GrIS-wide de-trended cumulative mass change for GRACE, unfiltered MAR v2.0 data, GRACE-filtered MAR v2.0 data, and Gaussian-filtered MAR v2.0 data, for (a) the case where no temporal Gaussian filtering is applied, and (b) the case where it is applied. Vertical dashed lines indicate the timing of peaks of maximum and minimum mass in the cycle. Red horizontal error bars indicate the error in the timing of the GRACE cycle, with bold error bars indicating 50% of the GRACE distribution, and thin red lines indicating 95% of the distribution.
Table 3.1 | Timing of maximum and minimum peaks in the seasonal cycle of GrIS-wide detrended cumulative mass change for GRACE and MAR v2.0 for the 2003-2010 period. For GRACE, the median value and bounds for the 95% confidence interval of the distribution after accounting for uncertainty in GRACE are listed.

<table>
<thead>
<tr>
<th></th>
<th>GRACE (Median and 95% CI)</th>
<th>MAR v2.0 Unfiltered</th>
<th>MAR v2.0 GRACE-Filtered</th>
<th>MAR v2.0 Gaussian-Filtered</th>
<th>MAR v2.0 Gaussian-Filtered (w/Time Filtering)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Maximum (2.5% Bound)</strong></td>
<td>March 28</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Maximum</strong></td>
<td>April 26</td>
<td>May 19</td>
<td>May 9</td>
<td>May 19</td>
<td>April 29</td>
</tr>
<tr>
<td><strong>Maximum (97.5% Bound)</strong></td>
<td>May 27</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Minimum (2.5% Bound)</strong></td>
<td>August 29</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Minimum</strong></td>
<td>September 16</td>
<td>September 8</td>
<td>September 9</td>
<td>September 8</td>
<td>September 21</td>
</tr>
<tr>
<td><strong>Minimum (97.5% Bound)</strong></td>
<td>October 9</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

524 and 500 Gt respectively) relative to GRACE (287 ± 30 Gt), and a closer agreement between the amplitudes of GRACE-filtered MAR v2.0 data (339 Gt) and GRACE. On average, during summer periods of net ablation, GRACE begins losing mass earlier (by 25 days), and starts gaining mass later (by 8 days) as compared with MAR v2.0 unfiltered data (Table 3.1). GRACE-filtering changes the timing of the start of mass loss such that the simulated mass loss begins about 13 days after that of GRACE. In all cases, however, the timing of peak mass loss from MAR v2.0 falls within the 95% confidence bounds on maximum and minimum dates for GRACE.

When temporal Gaussian filtering is applied to the MAR v2.0 data, the amplitude of the seasonal cycle is reduced (to 351 Gt), resulting in a better agreement with GRACE and with the GRACE-filtered MAR v2.0 data (Figure 3.5b). The timing of peaks in maximum and minimum mass are also changed, with the temporally Gaussian-filtered MAR v2.0 data exhibiting a longer period of mass loss (145 days) relative to that of the GRACE-filtered MAR v2.0 data (123 days), resulting in the filtered seasonal cycle peaks occurring within 5 days of GRACE peaks. Thus, while the temporal Gaussian-filtering improves the agreement between the Gaussian-filtered
MAR v2.0 timeseries and the GRACE-filtered timeseries in terms of amplitude, the temporal filtering lengthens the period of net ablation. For both methods of Gaussian filtering, the timing of the peaks for filtered MAR v2.0 data fall within the 95% confidence bounds on the timing of the GRACE seasonal cycle. In our analysis of ISSM and MAR v3.5 outputs, we have chosen to focus on results obtained with temporal Gaussian filtering applied, as it results in reduced errors relative to the GRACE filtering method. We consider this to be a conservative approach, as the filter brings the timing of the seasonal cycle closer to that of GRACE. Where the timing of the filtered cycle disagrees with GRACE, we can confirm a difference in the seasonal cycle, but where it agrees, we cannot confirm a difference.

3.3. Results

3.3.1. Trends and spatial differences in modeled vs. measured mean MB

We first examine timeseries of cumulative mass as simulated by MAR v3.5, ISSM, and GRACE over the 2003-2012 period, as shown in Figure 3.6. MAR v3.5 cumulative SMB shows a net accumulation of mass over Greenland (of 236 Gt yr\(^{-1}\) on average), which varies seasonally in response to melting. ISSM exhibits a net loss of mass (-418 Gt yr\(^{-1}\) on average), with little seasonal variability relative to the long-term trend (although there is a small seasonal cycle in dynamic changes driven by the SMB cycle). Together, ISSM and MAR v3.5 results produce a net loss of mass over 2003-2012, although the trend in simulated mass loss (-166 Gt yr\(^{-1}\)) is smaller in magnitude than that of GRACE (-218 Gt yr\(^{-1}\)).

There are also spatial differences between GRACE MB and simulated MB from MAR v3.5 and ISSM, as shown in Figure 3.7. Figures 3.7a and b show the impact of spatial filtering on average 2003-2013 MAR SMB and ISSM DMB respectively. Spatial filtering removes the signal of net negative SMB in some low-lying areas simulated by MAR (e.g. Figure 3.2 and
Figure 3.6. Cumulative GrIS mass change for the 2003-2013 period from GRACE, MAR SMB, ISSM DMB, and the combined results of MAR v3.5 + ISSM. Pink shading surrounding the GRACE timeseries indicates the estimated error associated with the GRACE solution.
Figure 3.7. Average 2003-2012 mass balance (Gt) for MAR, ISSM and GRACE. Gaussian spatial and temporal filtering has been applied to MAR and ISSM outputs. (a) SMB from MAR, (b) Dynamic mass change from ISSM, (c) The sum of (a) and (b), giving the mean MB. GRACE mean MB is shown in (d), and (e) depicts the difference between modeled MB (c) and GRACE MB (d).
Figure C.1a), resulting in a near-zero or positive SMB for areas south of \(\sim 80^\circ\)N. This is in contrast with MAR v2.0 (Figure 3.3b), which exhibits a more negative SMB in areas below 2000 m, particularly along the west coast of the GrIS. [A comparison between MAR v2.0 and MAR v3.5 SMB is also provided in Appendix G] ISSM DMB generally complements MAR SMB; wherever there is high accumulation, the ice diverges more rapidly. Thus in areas above 2000 m, ISSM mass loss is relatively high, balancing the strongly positive SMB from MAR. There is a smaller mass loss from low elevation areas (below 2000 m): although mass is lost from outlet glaciers, some is gained from flow emanating from higher elevations. The spatial filtering preserves the complementary nature of SMB and DMB, which can also be observed at a higher spatial resolution and without filtering (Figure 3.2; Figure C.1).

When MAR SMB and ISSM DMB are combined, they indicate a net mass loss over the 2003-2012 period (Figure 3.7c), which is mainly concentrated in areas below 2000 m in elevation, which is also true of the mean GRACE MB (Figure 3.7d). However, as can be seen from a comparison between Figures 3.7c and d, and a map of modeled minus GRACE MB in Figure 3.7e, mass loss from GRACE is larger in magnitude along the ice sheet boundaries (by up to \(\sim 2.5\) Gt yr\(^{-1}\) per mascon). In some high elevation areas north of \(80^\circ\)N, GRACE also indicates a net gain in mass, while the model results do not. These differences are smaller, on the order of 1 or 2 Gt, compared with those along the coast. The differences between simulated and GRACE MB may be due to a modeled MAR v3.5 SMB that is too high below 2000 m in elevation, or alternately, to simulated velocities that are too slow in ISSM A positive bias in SMB at low elevations will result in a reduced gradient of SMB between high and low elevations, which will also serve to reduce the net discharge simulated by ISSM. It is also possible that ISSM does not capture a long-term acceleration of outlet glaciers due to warm ocean waters. A comparison of ice thicknesses from ISSM forced by MAR v3.5 and remote-sensing-derived thicknesses from
Bamber et al. (2001) suggests that there are substantial differences between observed ice thicknesses and ISSM-simulated ice thicknesses at the end of the ISSM spinup period (Figure 3.8). In particular, the ice thickness is underestimated in central northern Greenland, but overestimated along the coast and in southern Greenland. In these areas, ISSM may be flowing too slowly, resulting in a dynamic accumulation of mass that should be leaving the ice sheet. It is difficult to determine if these differences are a result of errors in the ISSM model, errors in the MAR v3.5 SMB forcing, or errors associated with the assumption that during the spin-up period, the ice sheet is in steady state.

3.3.2. Seasonal mass changes from MAR, ISSM, and GRACE

The average seasonal cycle of filtered cumulative MAR v3.5 + ISSM for the 2003 through 2012 period agrees well with that of GRACE, as shown in Figure 3.10a and Table 3.1. (It can also be seen in Figure C.3 and Table C.1 that the timing of cycles for MAR v3.5 and MAR v2.0 are similar in both the filtered and unfiltered case, in spite of some differences in amplitude. Thus the Gaussian filtering affects MAR v3.5 and MAR v2.0 results similarly.) The amount of mass loss during the period of net ablation is similar for MAR v3.5 + ISSM (317 Gt) and GRACE (355±32 Gt). The dates of simulated maximum and minimum mass fall within the range of uncertainty for these dates from GRACE. Because it is possible that differences in modeled and GRACE trends alter the timing of the seasonal cycle, we also show the seasonal cycle for the de-trended timeseries in Figure 3.10b and Table 3.2. For the de-trended seasonal cycle, the timing of the seasonal maximum occurs roughly 1 month before the maximum peak from the original seasonal cycle, and the timing of the seasonal minimum occurs roughly 1 week earlier for both MAR v3.5 + ISSM and GRACE. In either case, the model timing for the filtered model data falls within the range of dates from GRACE, and therefore we cannot
Figure 3.8 Thickness difference between ISSM forced with MAR v3.5 outputs on 1 January 2003 and the thicknesses obtained from the 5 km DEM from Bamber et al. (2001).
Figure 3.10. (a) The mean 2003-2012 seasonal cycle of GrIS cumulative mass change from GRACE and MAR v3.5 + ISSM. (b) The same as (a) for the case when the timeseries from all mascons are de-trended.
Table 3.2. Same as Table 3.1, but for GRACE and MAR v3.5 + ISSM, for the period 2003-2012.

<table>
<thead>
<tr>
<th></th>
<th>MAR v3.5 + ISSM</th>
<th>GRACE (Median and 95% CI)</th>
<th>GRACE (Detrended) (Median and 95% CI)</th>
<th>MAR v3.5 + ISSM (Detrended)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Maximum</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2.5% Bound)</td>
<td></td>
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<td>March 21</td>
<td></td>
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<tr>
<td>Maximum</td>
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<tr>
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<td></td>
<td>April 21</td>
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<td></td>
</tr>
<tr>
<td><strong>Minimum</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2.5 % Bound)</td>
<td></td>
<td>September 16</td>
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<td></td>
</tr>
<tr>
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<td>October 2</td>
<td>October 4</td>
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</tr>
<tr>
<td>(97.5% Bound)</td>
<td></td>
<td>November 28</td>
<td>October 9</td>
<td></td>
</tr>
</tbody>
</table>

confirm any difference in the Greenland-wide seasonal cycle of mass change.

3.3.3. Spatial variability in the seasonal cycle from MAR, ISSM, and GRACE

Maps of the timing of peaks in the seasonal cycle of de-trended cumulative mass change from GRACE (Figure 3.11) suggest that the timing of in seasonal cycle peaks is spatially variable. Maps of the median GRACE date for the maximum and minimum peaks (Figures 3.11a and d) show that in some locations (e.g. northwest Greenland), GRACE suggests that mass loss can begin as early as November 1, where in other areas it can begin as late as July 1 (for an area in north Greenland). The range of possible dates suggested by 95% of the GRACE distribution is fairly large, spanning the full Nov 1 to July 1 period in some locations in northern Greenland (Figures 3.11b, c, e and f), but some of the spatial differences in seasonal timing are preserved even with these large ranges. The GRACE data suggest that the period of net mass loss begins in late winter and ends in early summer in the northwestern portion of the ice sheet, while in most other parts of the ice sheet, mass loss begins in early or late spring, and mass begins to increase again beginning in late autumn. The period of summer mass loss over most of the ice sheet is consistent with what would be expected, given the cycle of climate forcing (warm conditions
leading to increased melt), but the timing of the cycle in the northwest suggests that other processes may be responsible for seasonal variability in that region.

MAR v3.5 + ISSM suggest a more uniform pattern of timing in seasonal cycle peaks (Figures 3.12a, b), consistent with the SMB forcing. The models suggest that mass loss begins in late spring and early summer (between March and June) without much spatial variability across the ice sheet, and mass gain commences in late summer and early fall (between September and November), with the period of mass loss ending ~1 month later for mascons below 2000 m in elevation relative to those above 2000 m in elevation. These results are consistent with what would be expected given warmer temperatures at lower elevations and a longer period available for melting. For many mascons in the Northwest, the modeled cycle maximum and minimum peaks can occur up to 3 months after and 2 months before the GRACE peaks (Figures 3.11c, d), with differences of ~1 month being quite common. Given the relatively large uncertainty in the timing of the GRACE peaks, the model peaks often fall within the distribution of peaks from GRACE. For most mascons, the timing of seasonal minimum falls within 95% of the distribution from GRACE, with the exception of six mascons at high elevations along the southeast coast. Along the northwest coast, the timing of the seasonal maximum occurs in May according to the models, roughly one or two months after the 95% confidence limit on the timing of maximum mass from GRACE, and more than three months after the median peak from GRACE. Despite the large uncertainty in the GRACE timing, the timing of GRACE peaks tends to be clustered in groups, suggesting that the spatial variations in GRACE timing are not random, but may be reflective of seasonal variations in mass not captured by the models.
Figure 3.11. Timing of peaks in the average 2003-2013 seasonal cycle of detrended cumulative mass from GRACE. (a) Dates of maximum mass for each mascon from the median of the distribution from GRACE (b) the 2.5% limit on the distribution of maximum mass dates, and (c) the 97.5% limit. (d) Dates of minimum mass for each mascon, and (e) the 2.5% and (f) 97.5% limits.
Figure 3.12. Timing in peaks of the seasonal cycle of de-trended cumulative MB simulated by MAR v3.5 + ISSM. (a) The timing of the maximum peak for each mascon, and (b) the timing of the minimum peak for each mascon. The number of days between MAR v3.5 + ISSM and the GRACE median dates for the cycle maximum and cycle minimum are shown in (c) and (d) respectively. For (c) and (d) red colors indicate that the model date occurs later than that of GRACE, and blue colors indicate an earlier date. ‘x’ marks indicate where the modeled peak falls outside of the 95 percentile range of dates for the GRACE peak shown in Figure 3.11.
3.3.4. The average seasonal cycle within ice sheet sub-regions

In order to further examine discrepancies at regional scales, we created eight sub-regions of the GrIS based on the median timing of the maximum and minimum peaks of the average detrended annual cycle from GRACE (Figures 3.11a and b). Mascons were grouped together if the timing of their maximum and minimum peaks were within 30 days of each other. The eight sub-regions are shown in Figure 3.13a, along with the average seasonal cycle from four of these sub-regions (Figure 3.13b-e). The average cycles for other regions are provided in Figures C.4a-d. The average GRACE seasonal cycle for Region 1 (Figure 3.13b), which falls within the area of significant differences in the timing of the maximum of the seasonal cycle (as shown in Figure 3.12c) significantly differs in its timing from the MAR v3.5 + ISSM cycle. GRACE results suggest that the period of net mass loss begins no later than mid-February, while the models suggest that it begins in mid-April. For Region 6 (Figure 3.13e), also in the region of significant differences for individual mascons (Figure 3.12c), the maximum modeled mass occurs in early May (although the ice sheet does not appear to start losing a substantial amount of mass until July), while the GRACE peak occurs in early November. The entire modeled cycle appears to be offset by three months relative to GRACE in this region, although seasonal mass changes are relatively small (on the order of 5 Gt). For Regions 4 and 5 (Figure 3.13c and d), the model maximum and minimum peaks fall within the distribution for GRACE peaks. For Regions 2, 7 and 8 (Figure C.4a, c, and d) the cycles are similar to those of Regions 1 and 6. For Region 3 (Figure C.4b), the cycle is similar to the cycle of Region 4, except for a sharp peak in mass in early July, which leads the GRACE peak to occur after the peak from the models.

Dividing the GrIS into high and low elevation areas (above and below 2000 m in elevation) also produces differences in the seasonal cycle (Figure 3.14). For areas below 2000 m in elevation (Figure 3.14a), there is a good agreement between the GRACE and simulated
Figure 3.13. (a) GrIS regions defined based on the timing of peaks in the average cycle of detrended cumulative mass change from GRACE. Also shown is the average seasonal cycle from MAR v3.5 + ISSM and GRACE for selected regions: (b) Region 1, (c) Region 4, (d) Region 5, and (e) Region 6.
Figure 3.14. Same as Figure 3.10, but for (a) regions below 2000 m in elevation, and (b) regions above 2000 m in elevation.
seasonal cycles; the timing of MAR v3.5 + ISSM maximum and minimum peaks fall within the distribution of peaks for GRACE. For areas higher than 2000 m in elevation (Figure 3.14b), the period of simulated net mass loss is shortened relative to that of GRACE. The good agreement between cycles at low elevations and the poor agreement at higher elevations suggests that the timing of ablation and accumulation at low elevations is well captured by MAR v3.5 + ISSM.

The differences in the GRACE and modeled seasonal cycles within individual regions seem unlikely to be caused by errors in the simulated timing of surface ablation, as they occur either during times of the year when melting does not occur at the surface (i.e. the ‘early’ start to the period of net mass loss in the northeast from November through February), or in areas where the net ablation due to melting is small (i.e. above 2000 m in elevation). The results therefore suggest that the observed changes may be associated with errors in seasonal accumulation from MAR v3.5, or the inability of ISSM to capture large seasonal fluctuations in ice velocity. These processes are difficult to validate, and therefore it is difficult to determine which processes are most responsible for the observed differences. However, we provide some discussion of these factors in the following section.

3.4. Discussion and Conclusions

The above results show several areas of agreement as well as areas of disagreement between MAR v3.5 + ISSM and GRACE Greenland mass balance from the mascon solution of Luthcke et al. (2013). We have shown that in order to compare spatial and temporal variations in GrIS mass from RCM and ISM results and GRACE at a relatively high spatial and temporal resolution, it is necessary to spatially and temporally filter the model data. We have developed a Gaussian approximation to the GRACE resolution operator, which accurately captures the effect of the GRACE solution on spatial variations in mean MB, and the amplitude of seasonal
variations in mass. We experimented with different versions of this filtering procedure, in which we apply and do not apply temporal filtering. When we do not apply temporal filtering, there are significant differences between the modeled and GRACE seasonal cycles, suggesting that the models do not fully capture the seasonal cycle of mass change observed by GRACE. However, GRACE processing does include a temporal component, such that for a given point in time, changes in mass from the GRACE solution are influenced by mass changes that may actually be occurring later than or earlier than the given point in time (Sabaka et al. 2010). We have therefore also implemented a temporal Gaussian filter in an attempt to reproduce this effect. The Gaussian temporal filtering does not completely capture the seasonal cycle of mass changes obtained using the GRACE resolution operator in that it extends the period of mass loss simulated by the models further than the expanded period obtained from GRACE filtering. As the filter brings the timing of the Greenland-wide cycle of mass changes closer to that of GRACE, in cases where it disagrees with the Greenland-wide cycle, differences in the timing of the modeled and GRACE cycle are likely.

When this filter is applied to MAR v3.5 + ISSM results, spatial patterns of MB for the 2003-2012 period are similar to those of GRACE in that there is an observed net loss of mass from areas below 2000 m in elevation. However, the models tend to underestimate the magnitude of this mass loss, resulting in an underestimation of annual mass loss by 57 Gt yr\(^{-1}\) (with a trend of -182 Gt yr\(^{-1}\) as compared with -239 Gt yr\(^{-1}\) from GRACE). This difference is either due to an overestimation of SMB from MAR v3.5 in low elevation areas, which could also result in slower flow from ISSM due to a reduced SMB gradient between high- and low-elevation areas, or to intrinsic errors in ice flow from ISSM (suggested by the comparison of Figure 3.8) A preliminary comparison at in situ stations suggests that MAR v3.5 SMB may
actually be too negative in low elevation areas (X. Fettweis, Personal Communication), but it is
difficult to draw conclusions from the limited number of observations available.

We examined the mean seasonal cycles of de-trended cumulative mass change from
GRACE and MAR v3.5 + ISSM as a means of examining the ability of the models to capture
mass changes at a relatively high spatial and temporal resolution. On a Greenland-wide scale,
there is a good agreement between modeled and measured seasonal cycles, with the timing of
modeled peaks coinciding with a range of estimates for the timing of GRACE peaks derived from
GRACE errors. On the scale of individual mascons, there is considerable variability in the
timing of the seasonal cycle as represented by GRACE, while model results suggest a more
uniform timing across Greenland. While some of this variability is likely due to GRACE errors,
other variations likely reflect real differences in the seasonal variability within different regions,
particularly as the differences are not random, but spatially clustered. In particular, in
northwestern Greenland, the simulated period of mass loss is shorter than that of GRACE, and
the timing of the simulated maximum in the seasonal cycle occurs up to three months after the
GRACE peak in some areas.

Spatial differences in the seasonal cycle may result from various factors including (1)
underestimation or overestimation of accumulation and ablation by MAR v3.5, (2) inability of
ISSM to capture seasonal variations in ice sheet motion, (3) cycles of water storage and release,
and (4) errors in the GRACE solution. We have attempted to account for the last factor by
considering the impact of errors of the GRACE solution estimated by Luthcke et al. (2013) on the
timing of the seasonal cycle, and by filtering our model results to match GRACE. However, as
GRACE does not provide direct observations of mass changes, and different methods of
processing can produce somewhat different mass change solutions (Shepherd et al., 2012), it is
possible that some of the observed discrepancies may be due to errors not considered in this
solution. Of the other factors, the two that seem most likely to cause the observed discrepancies are errors in MAR v3.5 accumulation, and seasonal variations in ice sheet motion not captured by ISSM.

For areas below 2000 m in elevation, we do not find evidence that factors such as water storage and release as indicated by Rennermalm (2013), and observed on glaciers in locations outside of Greenland (Jansson et al. 2003) play a role in mass balance variability on seasonal timescales. In other words, the assumption that that is generally made, that EMB and BMB are negligible, appears to be valid. It is possible that these processes lead to changes in mass on shorter timescales that we cannot observe given the uncertainties in GRACE results and filtering, and that they play a role in interannual variations in mass, which we do not explore in detail in this study. The models appear to capture the timing and magnitude of seasonal fluctuations fairly well, but long-term trends in mass loss (primarily at elevations below 2000 m) are underestimated. This suggests either an overestimation of low elevation SMB from MAR v3.5, or an underestimation of D from ISSM (which can also be a consequence of errors in the SMB forcing from MAR v3.5).

Discrepancies at between models and GRACE at high elevations and in northwest Greenland are potentially a result of errors in seasonal variations in velocity from ISSM and errors in accumulation from MAR. The “early” loss of mass in northwest Greenland is unlikely to be associated with melting, because it occurs during winter months, but rather with DMB exceeding SMB, either due to periods of low accumulation or surges in ice motion. Accumulation is difficult to validate over the GrIS as few observations are available, and not much can be said about this factor. It is possible that the large peak in mass present in the GRACE data in early march at high elevations (Figure 3.14b and Figures C.4c,d ) suggests that MAR v3.5 may be missing some heavy accumulation events during this time of year, although
there is no previous assessment of MAR that suggests that this is the case. Although data on seasonal velocities are not available for the entire GrIS, various studies have indicated seasonal variations in the flow of GrIS glaciers occur, particularly in association with meltwater that reaches the ice sheet bed (e.g. Joughin et al. 2008), as well as interactions between ocean circulation and ice at calving fronts (Howat et al. 2010). Using GPS measurements for west coast GrIS glaciers, Ahlstrøm et al. (2013) showed that the glaciers examined underwent seasonal cycles in velocity, with several glaciers showing a decline in velocity in late summer associated with increased efficiency of subglacial drainage systems. Moon et al. (2014) present the most comprehensive evaluation of seasonal velocity cycles to date, identifying three types of seasonal cycles in velocity, one in which glaciers accelerate as a result of meltwater generated at the surface reaching the GrIS bed, another in which they accelerate and then decelerate in response to the evolution of the subglacial drainage system, and a third in which fluctuations are more likely associated with ice-ocean interactions. Different glaciers exhibit different patterns of flow variability, and may transition between different patterns in different years. Seasonal variations in flow are generally represent ~10-20% of mean annual velocities. However, it is unclear how these variations in flow contribute to seasonal fluctuations in ice sheet discharge, as different glaciers have different widths and thicknesses and may exhibit seasonal fluctuations that offset each other. A study examining how these variations in flow affect ice discharge would be useful for evaluating ISMs such as ISSM, which do not currently take into account the influence of these processes.

Further studies are also needed to understand the impact of temporal variations in mass on the observations presented here, i.e. whether they are associated with processes that reoccur from year-to-year, or whether isolated events influence the timing of the seasonal cycle. In addition, future studies are needed to validate RCM accumulation against observed ice thickness changes,
such as those from airborne and spaceborne radar instruments, or to evaluate simulated precipitation, to better understand how model biases in accumulation impact simulated MB and cycles of cumulative MB. In summary, it appears that MAR v3.5 and ISSM simulate Greenland-wide fluctuations in mass and general spatial variability fairly well, considering that the processes mentioned above are not considered. At smaller spatial scales, however, such processes may become increasingly important. It is possible that if seasonal variations in GrIS mass are examined at higher spatial and temporal resolutions, with reduced errors, further discrepancies between modeled and measured cycles will be observed. As the ice sheet changes in the future, such processes could potentially become more important to GrIS-wide changes in mass, and therefore they need to be better understood.

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Chapter 4

Conclusions

4.1. Overview

The two preceding studies provide comparisons between simulated and observed processes over the GrIS, with the goal of furthering our understanding of those processes that contribute to variations in the mass of the GrIS and which are not fully understood, or have not yet been explored. In Chapter 2, I investigated spatial and temporal variations in GrIS albedo, a quantity that plays an important role in GrIS surface mass balance through its modulation of the absorbed solar radiation, by means of satellite data, in-situ observations, and outputs of the MAR regional climate model. The main purposes were a) characterizing spatiotemporal variations in GrIS albedo and b) evaluating the simulation of these variations from MAR. In Chapter 3, I turned to a larger scale evaluation of the combined Greenland mass balance simulated by MAR and the ISSM ice sheet model, with the purpose of evaluating the results from these two models against spaceborne estimates of GrIS mass changes for the first time. In this context, I also studied the potential role of processes not simulated by either model in GrIS mass changes, especially their impact on the seasonal scale. These studies together help to advance our understanding of and ability to model the GrIS mass balance. In the first case, the study identifies a bias in low-elevation albedo from the MAR model, which will spur the development of an improved MAR albedo scheme for improved SMB estimates. It also identifies consistencies and discrepancies between observational products (e.g. variations in albedo with respect to latitude, and differences in trends), which have previously been ignored or have gone unnoticed. The study indicates the need for future research to account for errors in various products, and to better characterize...
spatiotemporal variations in GrIS albedo. In the second study, I reveal potential discrepancies between models and spaceborne estimates of mass balance, both in terms of 10-year trends, and seasonal variability in the timing of mass change on a sub-GrIS-wide scale. This work indicates a need for further evaluation of modeled ice dynamics and SMB against additional satellite and in situ measurements. I show that unexplored processes involved in mass balance variability may need to be considered in model projections of future mass change.

4.2. Conclusions regarding modeled and measured Greenland ice sheet albedo

The study presented in Chapter 2 shows consistencies in spatial patterns of mean summertime albedo from two satellite products from the MODIS sensor, in situ measurements, and MAR over the 2000-2012 period. The model is able to capture spatial variations in albedo associated with elevation, with low elevation areas exhibiting lower albedo values (associated with melting and bare ice exposure during summer months). The analysis revealed a discrepancy in summer average albedo of up to ~0.1 between the 16-day and daily MODIS products north of 70°N. Here, the 16-day MODIS product suggests a gradual decrease in albedo with latitude above 70°N while the 10-day product points to an increase and, lastly, MAR and in-situ observations suggest little change. Given larger uncertainties on spaceborne albedo estimates in these areas associated with relatively high solar zenith angles, it is difficult to draw any conclusions regarding these variations, although the decrease in albedo from the 16-day product appears to be unrealistic and related to a geometric artifact.

A key finding of the study presented in Chapter 2 is the identification of a positive bias of ~0.1 in MAR v3.2 mean albedo in the ablation area (e.g., where annual mass loss exceeds mass gain). We attribute this bias to an overestimated bare-ice albedo in version 3.2 of the MAR model. MAR v3.2 includes a new scheme for bare-ice albedo that simulates the influence of the
presence surface meltwater on variations in bare ice albedo. While we find that MAR v3.2 better represents the distribution of albedo in the ablation zone relative to the previous version MAR v2.0, the resulting values of bare ice albedo are often overestimated relative to satellite data. This albedo difference contributes to a significant difference in SMB between the v3.2 and v2.0 versions. In Appendix G, we include MAR v3.5 in this comparison, showing that MAR v3.5 albedo is higher than that of MAR v3.2, resulting in a larger difference in ablation area SMB between MAR v3.5 and MAR v2.0. It is not clear why MAR v3.5 albedo is higher than MAR v3.2 albedo, as the bare ice albedo minimum for MAR v3.5 has been lowered relative to MAR v3.2. Other factors, such as differences in precipitation, may contribute to this discrepancy. These results suggest that further refinements to the MAR bare-ice albedo scheme may be necessary, including the incorporation of surface impurities.

We also find that satellite data, in-situ measurements, and MAR results all indicate that the ablation area of the GrIS has darkened over the 2003-2012 period, with MAR suggesting smaller overall trends in this area. Within high elevation areas, MODIS data suggest a decline in albedo that is not confirmed by MAR or available in-situ observations. This may be partially explained by a decline in sensitivity of the MODIS sensor due to sensor degradation, but we cannot confirm this, and our results are inconclusive. After the publication of the study presented in Chapter 2, Dumont et al. (2014) published results to suggest that the observed darkening at higher elevations from MODIS is the result of increased atmospheric deposition of impurities on the icesheet surface. This finding is consistent with the discrepancy between MODIS and MAR trends, as MAR does not simulate the effects of deposition of impurities on the ice sheet surface. The finding cannot explain the relatively small trends from in situ stations that we observe at high elevations (although admittedly, we only have data from four stations with a long enough record to observe trends). In the study presented in Appendix A, we argue that the effects of impurities
are difficult to discern as the impact of the impurity concentrations on albedo falls within the range of uncertainties in satellite measurements.

In Appendix A, we also further examine the role of various factors in changes in GrIS albedo, including changes in snow grain size, exposure of bare ice and concentration of impurities at the ice sheet surface. We find that in the ablation area, the concentration of impurities left behind after melting of snow and ice likely plays an important role in the decline in albedo in these areas, in addition to increased bare ice exposure and snow grain size metamorphism. The MAR model does not capture the concentration of impurities at the ice sheet surface, which can explain both its overestimation of mean bare ice albedo along the western margin of the GrIS, and its underestimated trends relative to MODIS in this region.

4.3. Conclusions regarding modeled and measured Greenland ice sheet mass variations

In Chapter 3, we evaluate results from the MAR v3.5 SMB and ISSM DMB against estimates of GrIS mass change from the GRACE solution of Luthcke et al. (2013), at a high spatial and temporal resolution (100 km and 10 days respectively). We show that in order to compare GRACE and model estimates at these resolutions, it is necessary to conduct spatial and temporal filtering of model data to match the spatial leakage inherent in the GRACE solution.

When we evaluate spatial variations in filtered average MB from MAR v3.5 and ISSM relative to GRACE, we observe a general agreement between the models and GRACE, with a pattern of relatively uniform mass loss below 2000 m in elevation, and relatively small mass loss, or increases in mass above 2000 m in elevation. However, MAR v3.5 + ISSM tend to underestimate the magnitude of mass loss present in GRACE. This underestimation of mass loss is potentially a result of overestimated SMB at low elevations from MAR v3.5 which also can lead to a reduced loss of mass from ISSM, although we cannot confirm this hypothesis. The
comparison of Appendix G shows that MAR v3.5 ablation area SMB is high relative to previous versions of MAR, which supports the hypothesis that MAR v3.5 SMB is overestimated. However, an independent preliminary comparison with in situ measurements along the K-Transect (X. Fettweis, personal communication) suggests the opposite, that MAR v3.5 underestimates SMB at K-Transect stations. Further evaluation with spatially distributed SMB estimates is therefore necessary.

A comparison of the average seasonal cycles of cumulative GrIS mass from models and GRACE suggest that the models capture the timing and magnitude of the GRACE seasonal cycle on a Greenland-wide scale, but on the scale of individual mascons, and subregions of the ice sheet, we identify discrepancies between the modeled and observed seasonal cycles. In particular the northwestern portion of the ice sheet exhibits a net loss of mass during winter months, which the models do not capture.

The reasons for discrepancies between MAR v3.5 + ISSM and GRACE are not clear, but given that the discrepancies are largely associated with the maximum peak in the average cycle of mass changes, and that they tend to occur at higher elevations, suggest that they may result from either biases in seasonal accumulation from the MAR v3.5 model, or the inability of ISSM to capture seasonal cycles of ice sheet discharge.

4.4. Limitations

It was necessary to overcome many difficulties inherent to the investigative nature of this work and I developed several analytical and scientific tools to address such difficulties. Yet, various limitations were encountered in addressing the original objectives of this work. These limitations were generally associated with imperfections in observational data, or their absence. In general, there are few in situ measurements from the Greenland ice sheet, and this limited the
ability to validate satellite and model data. In the case of the evaluation of GrIS albedo variability, we are limited by discrepancies between the two MODIS albedo products with regard to spatial and temporal variations in albedo. Part of these discrepancies may result from instrument errors, for example the decline in the sensitivity of MODIS sensors (particularly on the Terra satellite) discussed by Wang et al. (2012). The MCD43A3 16-day albedo product uses data from two MODIS sensors (on the Terra and Aqua satellites), and therefore errors in trends may be reduced for this product relative to the MOD10A1 daily product, for which we used data from MODIS Terra. The MCD43A3 product appears to produce unrealistic changes in albedo with latitude, perhaps as a result of the algorithms used to calculate albedo from raw observations. These discrepancies limited our ability to draw definitive conclusions regarding trends and spatial variations in albedo in some locations. Contamination or missing satellite data due to the presence of clouds is always an obstacle when using remote sensing data to measure surface albedo. Errors in the MOD10A1 daily product associated with the presence of clouds reduce our ability to evaluate daily variations in albedo as simulated by MAR.

Additionally, we were limited by differences between the spectral range of in situ measurements and satellite and model results, which results in an unknown positive bias for in situ locations relative to satellite data. This prevented us from directly evaluating mean satellite albedo against in situ measurements. In the ablation area, in particular, it is also particularly difficult to use in situ measurements to evaluate satellite data or model results, given that albedo exhibits high spatial variability, limiting our ability to compare point measurements to larger scale model or satellite data.

Finally, we were able to show that simulated albedo from the MAR model has a substantial impact on simulated SMB, and that correcting errors in simulated bare ice in albedo will significantly change simulated SMB. However, we cannot validate simulated SMB at high
spatial and temporal resolutions, given a lack of available SMB measurements. Therefore, our results cannot confirm whether improvements to the albedo scheme actually improve simulated SMB relative to observations.

Our comparison between GRACE and MAR v3.5 + ISSM simulated mass change serves as a means of indirectly evaluating SMB simulated by MAR. In fact, comparing MAR v2.0 + ISSM results with GRACE may help us to understand the errors in MB that may be associated with SMB, given that MAR v2.0 SMB is lower than MAR v3.5 SMB. However, in this comparison we cannot separately evaluate MAR and ISSM to identify where each of the models contributes to discrepancies with GRACE.

Our comparison with GRACE is also limited by several other factors, including the uncertainty of GRACE measurements (a product of the corrections that must be made for various factors such as tides, atmospheric variability, isostatic rebound, and orbital affects), which affects the timing of the GRACE seasonal cycle. The need to spatially filter model data in order to effectively compare it with GRACE introduces further errors associated with the ability of the filter to reproduce the mass changes indicated by the GRACE solution. We faced logistical challenges associated with the filtering procedure. Ideally we would have liked to have filtered MAR v3.5 and ISSM data using the resolution operator from GRACE, but the process is time consuming, computationally expensive and not easily reproducible. The Gaussian filter that was developed to approximate the GRACE solution reproduced its effects fairly well, but this procedure introduced additional uncertainties in the timing of the simulated seasonal cycle, limiting our ability to identify discrepancies in seasonal timing between models and GRACE except for regions where the cycles differed dramatically.

While we suggest that processes not captured by MAR or ISSM may be responsible for discrepancies between modeled and GRACE changes in mass balance, we are unable to identify
the relative contribution of these processes to the observed discrepancies, given the limited availability of observations of these processes at the scales necessary to evaluate their impact on regional scale mass changes. Including additional GRACE products in our analysis and results from other models may help us to better understand the extent to which the observed discrepancies are associated with the GRACE solution that was used, and the extent to which mass balance simulated by other models agree with GRACE.

4.5. Future Work

Much future work is needed to better understand and simulate processes responsible for spatiotemporal variations in the mass of the GrIS. Much of this work will likely address the challenges discussed in the previous section. For instance, we need to be able to independently validate the components of mass balance (the SMB and DMB) simulated by models. Since ISMs and RCMs currently operate independently from one another, we need to be able to evaluate them independently as well, and to be able to understand processes that are poorly represented in models, and are poorly understood.

For evaluation of GrIS SMB, much work has been done to evaluate the timing and spatial extent of melting (e.g. Fettweis et al., 2011; Tedesco et al., 2007, 2011), but validation of the volume of simulated runoff at the ice sheet surface, and measurements of actual runoff from the ice sheet have only been carried out by a handful of studies (e.g. Rennermalm et al., 2010; Smith et al., 2014). Future studies need to better quantify the amount of runoff generated at the ice sheet surface, as well as how much reaches the oceans. The recent discovery of unknown aquifers storing large quantities of water during winter months below the ice sheet surface (Forster et al., 2013) indicates a need for a better understanding of ice sheet hydrology. When these processes are better understood, they can then be incorporated into models.
Accumulation at the ice sheet surface is also difficult to validate, and more observations or estimates of surface accumulation are needed for validation of models. RADAR measurements (e.g. from NASA’s airborne Operation Ice Bridge mission) can be used to estimate ice sheet thickness changes. Combining such changes with simulated densities can produce estimates of surface mass change that can then be used to evaluate annual accumulation from RCMs. Simulated densities also need to be evaluated against observations to confirm their accuracy. These techniques cannot capture seasonal accumulation, for which new techniques may need to be developed.

Surface albedo plays a crucial role in the simulated (and actual) SMB. Our results show that capturing spatial and temporal variations in surface albedo, particularly those associated with surface impurities over bare ice areas, can be crucial in the simulation of SMB. The melt-induced accumulation of surface impurities needs to be better understood and quantified, and subsequently implemented in models.

In the case of dynamic mass balance, observations of annual GrIS discharge are available from satellite measurements. Ice velocities are now available for various glaciers at sub-annual timescales (Moon et al., 2014). Calculation of seasonal discharge from glacier thicknesses and velocities will help reveal how such seasonal variations in discharge influence seasonal variations in ice sheet mass. ISMs need to incorporate the influence of processes such as meltwater at the GrIS bed-ice interface, and ice-ocean interactions, to better capture these seasonal fluctuations.

Finally, none of these advances can take place without additional in situ observations, which are needed to calibrate, validate, and evaluate remote sensing measurements and model results. The field expeditions necessary to carry out these in situ observations have the fortunate side effect of inspiring young scientists to appreciate the beauty of the GrIS and to continue to study its potential impact on humanity in the future.
Appendix

Appendix A

Warming-driven darkening of the Greenland ice sheet


This chapter is in preparation for submission to The Cryosphere

The surface energy balance and meltwater production of the Greenland ice sheet (GIS) are modulated by snow and ice albedo through the amount of absorbed solar radiation. Here we show, using a combination of satellite data (Liang et al. 2013) and model outputs (Tedesco et al. 2013a; Fettweis et al. 2005, 2013a), that summer albedo over the GIS decreased at a rate of 0.019/decade between 1996 and 2012 because of increasing near-surface temperatures and enhanced melting promoting snow grain growth, the expansion of bare ice areas and the accumulation of light-absorbing impurities (Warren 1982; Dumont et al. 2014; Doherty et al. 2013). Neither models nor observations suggest trends in impurities in the atmosphere over Greenland, suggesting that their apparent increase at the surface is related to the exposure of a ‘dark band’ of dirty ice (Wientjes et al. 2011; Wientjes and Oerlemans 2010; Bøggild et al. 2010) and melt consolidation (Doherty et al. 2013). Albedo projections through the end of the century obtained under different warming scenarios (Moss et al. 2010; Meinshausen et al. 2011) consistently point to a continued darkening, with anomalies down to -0.07 by 2100 (with respect to year 2000) driven solely by a warming climate. The projected darkening is likely underestimated because of known underestimates in projected melting (Fettweis et al. 2013a; Tedesco and Fettweis 2012) and because the model albedo scheme does not include light-absorbing impurities, which itself has a positive feedback to melting, grain growth and darkening.
The contribution to sea-level rise by mass loss from Greenland is projected to exceed 20 cm by the end of this century (Rignot et al. 2011), with the past two decades being characterized by increased melting (Nghiem et al. 2012; Tedesco et al. 2011, 2014) and total mass loss (Shepherd et al. 2012). Remarkably, the summer of 2012 set new records for surface melt extent (Nghiem et al. 2012) and duration (Tedesco et al. 2013a), and a record 570 ±100 Gt in total mass loss, doubling the average annual loss rate of 260 ±100 Gt for the 2003–2012 period (Tedesco et al. 2014). Variations in snow and ice albedo are driven by snow grain metamorphosis and by the presence of light-absorbing impurities (i.e., impurities thereafter) on their surfaces, playing a decisive role in surface meltwater production (Tedesco et al. 2011). Warming and melting/refreezing cycles catalyse grain growth, decreasing albedo in the near-infrared region (Warren 1982). The increased absorbed solar radiation following the albedo reduction promotes additional grain growth, further reducing albedo and accelerating melting. The presence of surface impurities such as soot (e.g., black carbon, BC), dust, and organic matter reduces albedo as well, but mostly in the visible and ultraviolet regions (Warren 1982). Such impurities are added through dry and wet deposition, and their mixing ratios are further enhanced through sublimation and melt-consolidation (Dumont et al. 2014). Once layers of snow or firn are removed through ablation, the exposure of bare ice and water bodies will also reduce albedo (Tedesco et al. 2011).

We hypothesise that the GIS surface albedo has been decreasing (i.e., ‘darkening’) during summer since the mid 1990s as a consequence of increased warming, with enhanced melting leading to persistently and extensively to larger surface snow grains, the expansion of areas where bare ice is exposed, and the accumulation of impurities at the surface. To test this
hypothesis, we analysed the time series of mean summer (June-July-August, JJA) broadband albedos (0.3 – 3 μm) retrieved from the Global Land Surface Satellite product (GLASS; Methods) for the 1981 – 2012 period (when data are available; Figure A.1a) together with outputs of the Modèle Atmosphérique Régionale (MAR) regional climate model (Fettweis et al. 2005, 2013a; Tedesco and Fettweis 2012; Tedesco et al. 2011; Methods, Appendix B).

The GLASS albedo product points to a sustained darkening of the surface of the GIS starting in 1996, with the albedo declining at a rate of -0.019±0.04/decade (p<0.01) for 1996-2012. Over the same period, MAR-simulated near-surface temperature increased at a rate of +0.74±0.5°C/decade (Figure A.1b, p<0.05), consistently with enhanced surface melting (Fettweis et al. 2013a). MAR simulations of broadband albedo α (0.3 – 2.8 μm, Equation B.1) suggest an albedo decline at the rate of -0.01±0.005/decade (p<0.01), half as much darkening as retrieved from GLASS. There is no statistically significant trend in albedo or temperature for 1981-1996 (Figure A.1). MAR simulations also point to positive trends between 1996 and 2012 in summer surface grain size (radius, +0.12±0.03 mm/decade, p<0.01, Figure A.1c) and the extent of regions along the west margin of the ice sheet where bare ice is exposed during summer (+380±190 km²/decade, p<0.01, Figure A.1d). According to MAR, summer snowfall in the 1996-2012 period was not sufficiently different from the long-term average to offset the impact of enhanced melting and increasing temperatures on albedo.

Darkening observed from space is more pronounced at lower elevations in southwest Greenland, with values down to -0.20±0.07/decade (Figure A.1a, note that the color bar goes down to -0.06/decade for graphical purposes) where trends in both grain size (Figure A.1c) and the number of summer days when bare ice is exposed (Figure A.1d) reach values as high as +1.0±0.3 mm/decade and +20±3 days/decade.
Figure A.1. Mean summer standardized values plotted as time series for a) GLASS (0.3 – 3 \( \mu \)m) albedo, together with b) surface temperature, c) surface grain size (effective radius of optically “equivalent” sphere) and d) bare ice exposed area simulated by MAR. Trends for the periods 1981 – 1996 and 1996 – 2012 are reported in each plot. The baseline 1981 – 2012 period is used to compute standardized anomalies, obtained from the subtraction of the mean and dividing by the standard deviation of the values in the time series. All trends are computed from JJA averaged values over ice-covered areas only, not tundra. Maps of JJA trends (per decade) from 1996 to 2012, when darkening began to occur, are also reported for a) GLASS albedo, b) number of days when surface temperature exceed 0°C, c) surface grain size and d) number of days when bare ice is exposed. Regions where trends are not statistically significant at a 95 % level are shown as grey-hatched areas. White regions over the ice sheet indicate areas where no trend occurred or were not viewed by the satellite.
Inter-annual variability in the JJA GLASS albedo is captured by MAR albedo simulations, with the latter explaining up to 90% (de-trended) of the spaceborne-derived albedo variations. Mean summer values of surface grain size and bare ice extent simulated by MAR explain, respectively, 54% (grain size) and 65% (bare ice) of the inter-annual variability of GLASS albedo. When linearly combined, grain size, bare ice extent and snowfall explain ~85% of the GLASS inter-annual variability, with the influence of new snowfall alone explaining only 44% of the same quantity.

Albedo trends are underestimated by MAR when compared to GLASS, with the largest differences occurring along the southwest margin of the ice sheet (Figure A.2), where a “dark band” composed of outcropping layers of ice containing large concentrations of impurities has been identified (Wientjes et al. 2011; Wientjes and Oerlemans 2010; Figure B.1a,b) and where the number of days when surface temperature has been exceeding 0°C has been increasing (Figure A.1b). Albedos in this area are as low as 0.30 (Figure B.1c), lower than that of bare ice (i.e., 0.45) and consistent with in-situ measured values of dirty ice (Wientjes and Oerlemans 2010; Bøggild et al. 2010). As MAR does not account for the effects of impurities in snow and ice, the underestimated darkening by MAR relative to GLASS is consistent with an increase in the mixing ratios of impurities in this region. However, quantifying the contribution of surface impurities to GLASS albedo trends is a challenging task because of the relatively low impurity concentrations measured over Greenland (Doherty et al. 2010) and because of known limitations related to remote sensing estimates of impurities from space (Warren 2013).
Figure A.2. Differences between spaceborne measured and model-simulated albedo trends and albedo simulated trends in different spectral regions. a) Difference between the MAR and GLASS trends (albedo change per decade), with positive values indicating those regions where MAR has less darkening than GLASS, and vice versa. Maps of JJA mean albedo trends (1996 – 2012) simulated by MAR for b) visible and c) near-infrared wavelengths.
MAR simulations of albedo in different spectral bands (Equations B.1-B.4) point to consistent trends in the visible (0.3 – 0.8 µm; -0.009±0.005/decade, p<0.05) and near-infrared (0.8 – 1.5 µm; -0.010±0.004/decade, p<0.05) bands (Figure A.3a), but a much smaller and not statistically significant trend in the shortwave infrared band (1.5 – 2.8 µm, -0.003±0.004/decade, p>0.1). Because the GLASS product does not provide visible albedo, we estimate the visible component of the GLASS albedo values by subtracting the near-infrared and shortwave infrared albedo values computed with MAR from the GLASS broadband values, following the MAR albedo scheme (Equation B.1). To evaluate the robustness of the resulting visible GLASS albedo trends, we compared anomalies (with respect to year 2000) in GLASS visible albedo with those from the MODIS MCD43A3 product (Stroeve et al. 2013), containing also the visible albedo (Figure A.3b). The GLASS-estimated and MODIS visible albedo anomalies are highly consistent, with a mean absolute error of 0.0055 and a standard deviation of 0.0053.

As MAR does not account for the presence of surface impurities, and because the impact of impurities is mostly in the UV and visible portion of the spectrum, we suggest that the difference of -0.017/decade between the MAR and GLASS visible albedo trends can be attributed to increasing mixing ratios of impurities in the GIS surface snow. This could be due to a combination of increased exposure of dirty ice with ablation (Wientjes et al. 2011; Wientjes and Oerlemans 2010), to enhanced melt consolidation with warming (Dumont et al. 2014), or to increased deposition of impurities from the atmosphere. In the absence of in-situ, spatially distributed measurements to separate these processes, we analysed trends of modelled and in-situ measured aerosol optical depth (AOD) and modelled deposition fluxes for BC, dust and organic matter over Greenland (Appendix B). Our analysis did not reveal any significant trend in AOD for several sites around the GIS (Figures B.3-B.5, Table B.2). Modelled deposition of impurities
Figure A.3. Time series of modelled and measured mean summer (JJA) albedo anomalies (with respect to year 2000) in different spectral bands. a) Visible, near-infrared and shortwave-infrared albedo values simulated by MAR; b) as in a) but for the visible albedo only from MAR, MODIS (obtained from the product MCD43) and GLASS. Note that the vertical axis scale in (b) is different from that in (a).
to the snow surface also did not show a trend, though the model may fail to capture trends in locally lofted dust, particularly in regions where glacial retreat leaves newly-exposed silt (Dumont et al. 2014).

We also analysed trends in the number of fires in North America and Eurasia as estimated from satellite observations (Figure B.6), because smoke from forest fires has been identified as a source of impurities over Greenland (Stohl et al. 2006; Hegg et al. 2009). Again we did not identify any statistically significant trend, and the years when surface melting was extreme (i.e., 2012) were unexceptional with respect to the number of fires. The absence of trends in AOD and in the number of forest fires in source regions for the GIS suggests that any trends in aerosol deposition likely played a smaller role than did enhancement in surface snow impurity mixing ratios due to melting and thus exposure of old dirty layers from previous years. However, in the absence of in-situ measurements, it is not possible to separate the contribution of each to the observed darkening. Outside of this “dark band” region, an increase in the deposition of impurities is not needed to account for the observed darkening: as noted above, changes in grain size, bare ice extent and snowfall alone explain ~ 85 % of the inter-annual variability in GLASS summertime albedo.

To estimate how much darkening could be caused by the projected warming over Greenland (Fettweis et al. 2013a; Tedesco and Fettweis 2012), we simulated albedo anomalies through the end of the century by forcing MAR with the outputs of three Earth System Models (ESMs) under two different CO₂ future scenarios (Methods). The first scenario corresponds to an increase of the atmospheric greenhouse gas concentration to a level of 850 ppm CO₂ (RCP45); the second scenario increases CO₂ equivalent to > 1370 ppm 2100 (RCP85) (Moss et al. 2010; Meinshausen et al. 2011). All simulations consistently point to darkening accelerating through
the end of the century (Figure A.4), with albedo anomalies (relative to year 2000) as large as -0.07 by the end of the century. The magnitude of such anomalies by 2100, however, is likely going to be larger than projected by our simulations, because (a) the model likely underestimates grain size growth as it tends to underestimate melting when forced with the ESMs (Fettweis et al. 2013a; Tedesco and Fettweis 2012); (b) the modelled albedo does not account for the direct impact of surface impurities on the surface; and (c) the MAR albedo scheme does not enhance surface snow mixing ratios with melt and does not include the indirect effect of impurities on grain growth. As a first step in quantifying the impact of this last process, we modified the MAR albedo scheme to include the effect of a constant mixing ratio of impurities of the order of that measured in Greenland, so we could assess the impact of impurities on grain size growth (Figure B.2, Table A.1). Our results confirm that grain growth is accelerated in the presence of impurities, with grains in the case of dirty snow being up to 15-20 % larger than those in pure snow during the melt periods following new accumulation and 1-2 % larger over the summer season on average. As these simulations did not include the effects of enhanced impurities with melt and sublimation, these likely represent lower bounds on the enhancement in grain growth due to the presence of impurities.

Our results indicate that a darkening of the GIS associated with increasing temperatures and enhanced melting occurred between 1996 and 2012, promoted by extensively and persistently increased surface snow grain size, by the expansion and persistency of the areas of exposed bare ice and by the increased surface impurity concentration associated with the appearance of dirty ice and consolidation with snowmelt. In a model that only accounts for the effects of warming on snow grain size and melting, darkening is projected to continue as a consequence of continued climate warming. Calculated trends in future darkening would be even greater if they accounted for the presence of surface impurities, and the associated feedbacks.
Figure A.4. Projections of broadband albedo anomaly (with respect to year 2000) averaged over the whole GIS for 1990-2012 from MAR simulations and GLASS retrievals (black and red lines, respectively), and as projected by 2100. Future projections are simulated with MAR forced at its boundaries with the outputs of three ESMs under two warming scenarios, with the first scenario (RCP45) corresponding to an increase in the atmospheric greenhouse gas concentration to a level of 850 ppm CO$_2$ equivalent by 2100 and the second (RCP85) to > 1370 ppm CO$_2$. The top and the bottom of the coloured area plots represent the results concerning the RCP45 (bottom) and RCP85 (top) scenarios. Semi-transparent colours are used to allow view of the overlapping data. Dark green corresponds to the case where MIROC5 and CANESM2 results overlap and brown to the case when the results from the three ESMs overlap.
In this regard, understanding those processes driving albedo changes and quantifying future darkening of the GIS are crucial tasks for reducing uncertainties on projected estimates of total mass balance and, consequently, sea-level rise.

Methods.

The GLASS albedo product is derived from a combination of data from the Advanced Very High Resolution Radiometer (AVHRR) and the MODerate resolution Imaging Spectroradiometer (MODIS) (Liang et al. 2013). Shortwave broadband albedo (0.3 – 3 μm) is provided every eight days at a spatial resolution of 0.05° (~6 km in latitude) for the period 1981 - 2012. GLASS albedo data with a resolution of 1 km is also available from 2000 to 2012 but it is not here used for consistency with the data available before 2000. A description of the GLASS retrieval process and available products can be found in (Liang et al. 2013) and references therein. A comparison between GLASS and in-situ albedo measurements over Greenland is given in Appendix B. Several efforts have been made to make the AVHRR and MODIS products consistent within the GLASS product, including the use of the same surface albedo spectra to train the regression and the use of a temporal filter and climatological background data to fill data gaps. Monthly averaged albedos from GLASS-AVHRR and GLASS-MODIS were cross-compared over Greenland in (He et al. 2013) for months where there was overlap (July 2000, 2003, and 2004), revealing consistency in GLASS retrieved albedo from the two sensors. The GLASS analysis provides retrievals of both black-sky albedo (i.e., albedo in the absence of a diffuse component of the incident radiation) and white-sky albedo (albedo in the absence of a direct component, with an isotropic diffuse component). The actual albedo is a value interpolated between these two according to the fraction of diffuse sunlight, which is a function of the aerosol optical depth. In
the absence of the full information needed to properly re-construct the actual albedo, here we use in our analysis the black-sky albedo, because we focus mostly on retrieved albedo under clear-sky conditions. Our analysis using the white-sky albedo (not shown here) is fully consistent with the results obtained using the black-sky albedo.

The 16-day MODIS MCD43A3 albedo product is distributed by Boston University, available at https://lpdaac.usgs.gov/. The product makes use of all atmospherically corrected MODIS reflectance measurements over 16-day periods to provide an averaged albedo every 8 days. A semi-empirical bidirectional reflectance function (BRDF) model is used to compute bi-hemispherical reflectance as a function of these reflectance measurements (Schaaf et al. 2002). The MCD43A3 product contains, in addition to albedo values for each MODIS instrument band, “shortwave” albedo values calculated over a wavelength interval of 0.3-5.0 µm and “visible” albedo values for the 0.3-0.7 µm interval, calculated using the BRDF parameters.

Simulations of surface quantities over the GIS are performed using the Modèle Atmosphérique Régionale (MAR) (Tedesco et al. 2013b; Fettweis et al. 2005, 2013a; Tedesco and Fettweis 2012). MAR is a modular, non-hydrostatic, and compressible atmospheric model that uses the sigma-vertical coordinate to better simulate airflow over complex terrain and the Soil Ice Snow Vegetation Atmosphere Transfer scheme (SISVAT) surface model. The MAR model has been presented and assessed over Greenland in several studies (Tedesco et al. 2013b; Fettweis et al. 2005; Vernon et al. 2013; Rae et al. 2012; van Angelen et al. 2012), with recent work specifically focusing on assessing simulated albedo over Greenland (Alexander et al. 2014). The snow model in MAR, the CROCUS model (Brun et al. 1992), calculates albedo for snow and ice as a function of snow grain properties (Equations B.1 – B.4), which in turn are dependent on energy and mass fluxes within the snowpack. The model configuration used here has 25 terrain-
following sigma layers between the Earth’s surface and the 5-hPa-model top. The spatial configuration of the model uses the 25-km horizontal computational domain over Greenland described in Fettweis et al. (2005), and temporal configuration for the runs from 1981 to the present. The lateral boundary conditions and lower boundary conditions are prescribed from meteorological fields modelled by the global European Centre for Medium-Range Weather Forecasts (ECMWF) Interim Reanalysis (ERA-Interim). The sea surface temperature and the sea-ice cover are also prescribed in the model using reanalysis data. The atmospheric model within MAR interacts with the CROCUS model, which provides the state of the snowpack and associated quantities (e.g., albedo, grain size). We refer to Fettweis et al. (2005) and Tedesco et al. (2011) for a more detailed description of the MAR version used here as well as its set-up. No nudging or interactive nesting was used in any of the experiments.

Future projections of albedo over the GIS are calculated using MAR forced with the outputs of three different ESMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5), driven by two radiative forcing scenarios (Moss et al. 2010) over the 1980 – 2100 period. The three ESMs used are the second generation of the Canadian Earth System Model (CanESM2), the Norwegian Community Earth System Model (NorESM1) and the Model for Interdisciplinary Research on Climate (MIROC5) of the University of Tokyo, Japan. More information is available in Fettweis et al. (2013a) and Tedesco and Fettweis (2012).

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GISS) for providing the outputs of GISS modelE of the AeroCom phase II project and to Marie Dumont, Eric Brun and Samuel Morin for the data used in Figure A.5. Konrad Steffen research group is acknowledged for providing GC-Net data. We thank Tao He at the University of Maryland, College Park, for the discussion on the GLASS product. The authors thank Stephen Warren for providing suggestions and guidance during the preparation of the manuscript.

Author contributions

MT conceived the study, processed and interpreted all data and wrote the manuscript. PA and JS supported the analysis of GLASS and MODIS data. PA provided MODIS and MAR data and helped with their analysis. XF generated MAR outputs. SD provided feedback on the discussion of the impact and evolution of surface impurities and considerably contributed to editing the manuscript. All authors contributed to the review of the final draft of the manuscript.
Appendix B

Supplemental Material for Appendix A

We first describe the MAR albedo scheme and how its different spectral components are computed within the MAR model from the values of optical grain size and the values of albedo measured by GLASS along the ‘dark band’. Then we discuss the results concerning the sensitivity experiment of grain size growth when modifying the visible albedo to simulate the presence of a constant concentration of impurities as well as the trends of modelled and measured AOD. We finally report the assessment of the GLASS product and the potential impact of MODIS sensor degradation on our results.

B.1 Supplementary Methods

B.1.1 The MAR albedo scheme

The original MAR albedo scheme is reported in (Alexander et al. 2014; Brun et al. 1992). Surface albedo is a function of the optical properties of snow, the presence of bare ice, whether snow is overlying ice (and whether ice lenses are present), and the presence of clouds. The broadband albedo ($\alpha_s$, 0.3 – 2.8 $\mu$m) of snow has a lower bound of 0.65 and is a weighted sum of the albedo in three spectral bands, $\alpha_1$, $\alpha_2$ and $\alpha_3$, which are functions of the optical diameter of snow grains ($d$, see below for computation of $d$ within MAR), as given in (Brun et al. 1992):

$$\alpha_s = 0.580\alpha_1 + 0.320\alpha_2 + 0.1\alpha_3$$  \hspace{1cm} (B.1)

$$\alpha_1 = \max(0.94, 0.96 – 1.58 \sqrt{d}) \text{, (0.3 – 0.8 $\mu$m)}$$  \hspace{1cm} (B.2)

$$\alpha_2 = 0.95 – 15.4 \sqrt{d}, \text{ (0.8 – 1.5 $\mu$m)}$$  \hspace{1cm} (B.3)
\[ \alpha_3 = 364 \times \min(d, 0.0023) - 32.31 \sqrt{d} + 0.88, \ (1.5 - 2.8 \ \mu m) \]  
(B.4)

The optical diameter \( (d) \) is in turn a function of snow grain properties and it evolves as described in (Bøggild et al. 2010).

Albedo values for bare ice are a function of the accumulated surface meltwater preceding runoff and a minimum (\( \alpha_{i,\text{min}} \)) and maximum (\( \alpha_{i,\text{max}} \)) bare ice value:

\[ \alpha_i = \alpha_{i,\text{min}} + (\alpha_{i,\text{max}} - \alpha_{i,\text{min}}) e^{-M_{\text{SW}(i)}/K} \]  
(B.5)

Where here \( \alpha_{i,\text{min}} \) is set to 0.4, \( \alpha_{i,\text{max}} \) is set to 0.55, \( K \) is a scale factor set to 200 kg m\(^{-2}\), and \( M_{\text{SW}(i)} \) is the time-dependent accumulated excess surface meltwater before runoff (in kg m\(^{-2}\)). In the case where snow density ranges between 830 and 920 kg m\(^{-3}\), albedo values fall between the maximum value for bare ice (\( \alpha_{i,\text{max}} = 0.55 \)) and the minimum value for snow (\( \alpha_{s,\text{min}} = 0.65 \)) as a function of density:

\[ \alpha_i = \alpha_{i,\text{max}} + \left( \alpha_{s,\text{max}} - \alpha_{i,\text{max}} \right) \left( \frac{\rho_i - 920 \text{ kg} \ m^{-3}}{\rho_C - 920 \text{ kg} \ m^{-3}} \right) \]  
(B.6)

where \( \rho_i \) is the density of the upper firn layer and \( \rho_C = 830 \text{ kg} \ m^{-3} \). When a snowpack exceeding 10 cm is overlying ice or a layer with a density exceeding 830 kg m\(^{-3}\), albedo is a vertically averaged value of snow albedo (\( \alpha_s \)) and ice albedo (\( \alpha_i \)). However, when snowpack exceeds 10 cm, the value is set \( \alpha_s \).
The presence of clouds can increase snow albedo due to the dampening of a portion of the incoming solar spectrum (Greuell and Konzelman 1994), in which case $\alpha_{SI}$ is corrected based on the cloud fraction (n) produced by MAR.

Figure B.1 shows the spatial distribution of MAR and GLASS mean JJA albedo for year 2010 over an area centred on the dark band in southwest Greenland, as well as a time series of mean albedo for the area in the region identified by the black rectangle in Figure B.1b. The black line in Figure B.1c shows the spatially averaged albedo, with the top and the bottom of the grey area indicating, respectively, the maximum and minimum albedo within that area. Note that only pixels containing 100 % of ice sheet (i.e. coloured areas in Figures B.1a and B.1b) are included in the calculation shown in Figure B.1c. Mean summer albedo from GLASS over this region shows a decrease from ~ 0.6 to ~ 0.45 between 2005 and 2012. Minimum albedo across all years is ~0.4, but dips close to 0.3 in 2010, a value consistent with dirty bare ice, as shown in previous studies (Wientjes et al. 2011; Wientjes and Oerlemans 2010; Bøggild et al. 2010). To test the hypothesis on whether differences between the modelled and measured albedo could be partially due to using a set value of 0.4 for bare ice albedo in MAR, we performed simulations using an albedo for bare ice as low as 0.3. Simulations using either 0.3 or 0.4 for bare ice albedo did not show any considerable differences over the dark band region, suggesting that the choice of bare ice albedo in MAR is likely not the reason for the discrepancy. Therefore, we suggest that the discrepancy between modelled and measured albedo along the dark band is due to the spatial and temporal distribution of high concentrations of impurities (and eventually associated organic matter) in the snow and ice in this region, not captured by the model.
Figure B.1. a) MAR and b) GLASS mean JJA albedo for year 2010 over an area including the dark band together with c) time series of mean albedo for the ice covered areas in the black rectangle. The black line in c) shows the spatially averaged albedo, where the top and the bottom of the grey area indicate, respectively, the maximum and minimum albedo within the black box in b).
B.2 Supplementary discussions

B.2.1 Assessment of the impact of surface impurities on grain size growth.

Light-absorbing impurities in snow indirectly affect snow grain size by absorbing sunlight, warming the snowpack, and accelerating snow grain size growth. We studied the magnitude of this “indirect effect” of impurities on snow grain size, and therefore albedo, by modifying the albedo scheme within MAR. Specifically, we reduced the visible component of the albedo, $\alpha_1$ in Equation B.2, by between -0.01 and -0.05 to simulate the effects of impurities. This was, in turn, used in Equation B.1 to compute the broadband albedo. The value of -0.05 was selected because it represents the maximum estimated albedo decrease for BC concentrations measured in the cold snow and percolation zones of the GIS (Doherty et al. 2010). The value of -0.05 used in our simulations for each iteration of MAR likely overestimates the effect of impurities on grain size at the beginning of the melting season, but underestimates the effect during the melting season when impurities tend to concentrate at the snow surface (Dumont et al. 2014). In addition, higher concentrations of impurities are present along the margins of the ice sheet because of their proximity to local sources of dust and the proliferation of algae and microorganisms on the ice surface, so the effect of impurities on grain size is likely larger there.

We specifically focus our discussion on the results over an area of 100 x 100 km$^2$ centred at Swiss Camp, one of the Greenland Climate Network stations (Steffen and Box 2001) for summer 2012. Figure B.2a shows daily broadband albedo simulated by MAR, with and without the imposed albedo reductions of 0.01, 0.03 and 0.05 in the visible albedo. The differences in broadband albedo between the default case and the cases simulating dirty snow are relatively constant and equal to the imposed albedo reduction, until the end of May, when substantial melting begins (Tedesco et al. 2013a). After this, all cases show broadband albedo lowered by an
Figure B.2. a) Daily broadband albedo and b) grain size simulated by MAR over a 100 x 100 km$^2$ area centred at Swiss Camp obtained when MAR simulated visible-band albedo is reduced by 0.01, 0.03 and 0.05 to simulate the effects of light-absorbing impurities in snow. The default value refers to the albedo calculated for impurity-free snow (Eq. S2). Bars at the bottom of plot a) (right-hand y-axis) gives the difference between the albedo of pure snow (“default”) and that when visible albedo is reduced (i.e., dirty snow).
Table B.1 Mean, standard deviation and maximum absolute difference of the difference between grain size in the case of pure snow and in the case of snow with impurities that reduce visible-band albedo by 0.01, 0.03 and 0.05. The difference is expressed as a percentage relative to the grain size value obtained in the case of pure snow.

<table>
<thead>
<tr>
<th>Grain size difference [%] (pure − dirty snow)</th>
<th>Δα</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>-0.01</td>
</tr>
<tr>
<td>Mean</td>
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</tr>
<tr>
<td>Standard deviation</td>
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</tr>
<tr>
<td>Maximum absolute difference</td>
<td>20.3</td>
</tr>
</tbody>
</table>

Table B.2 June-July-August mean and standard deviation of measured aerosol optical depth (AOD) at 550 nm at the three sites of Thule, Ittoqqortoormiit and Kangerlussuaq of the AERONET network (AERONET web site, http://aeronet.gsfc.nasa.gov, 2013).

<table>
<thead>
<tr>
<th>Station</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thule</td>
<td>0.042±0.010</td>
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<td>N/A</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ittoqqortoormiit</td>
<td>N/A</td>
<td>0.040±0.017</td>
<td>N/A</td>
<td>0.051±0.012</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kangerlussuaq</td>
<td></td>
<td></td>
<td>0.093±0.020</td>
<td></td>
<td>0.088±0.017</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year</td>
<td>2007</td>
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<td>2009</td>
<td>2010</td>
<td>2011</td>
<td>2012</td>
<td>2013</td>
</tr>
</tbody>
</table>
amount as low as the imposed albedo reduction. The presence of new snowfall during the first week of June increases albedo temporarily, with the “dirty snow” case (albedo reduction of 0.05) showing the fastest return to reduced albedo after the new snowfall. This can be explained by the accelerated metamorphism induced by the increased absorbed solar radiation (Figure B.2b), which is due to the reduced albedo in the visible region (i.e. the presence of absorbing impurities). A similar behaviour is simulated for the precipitation events occurring during the second week of August, though in this case the minimum albedo values obtained in the different cases are dependent on the introduced negative albedo anomaly (i.e. snow impurity content). This is in contrast to the behaviour during the snowfall event in the month of July when there is persistent melting; here, all cases show similar albedo values.

We performed a linear regression between the grain sizes simulated for clean snow and for snow with the three imposed reductions in visible-band simulating the presence of light-absorbing impurities. These regressions had slopes of 1.0099 ($R^2 = 0.92$, -0.01 bias), 1.0037 ($R^2 = 0.91$, -0.03 bias) and 1.0094 ($R^2 = 0.9$, -0.05 bias) when considering all grain sizes. The slope between grain sizes in dirty vs. clean snow increase to 1.0529 ($R^2 = 0.89$, -0.01 bias), 1.0656 ($R^2 = 0.9$, -0.03 bias) and 1.0676 ($R^2 = 0.89$, -0.05 bias) when considering only cases where grain size is less than 0.6 mm. This value was selected based on an analysis of the temporal evolution of grain size (Figure B.2b) as characterizing the presence of persistent melting. The percentage difference between simulated grain sizes in clean pure versus dirty snow (Table B.1) indicates that grain sizes are typically only about 1 % larger for dirty snow typical of the GIS dry snow and percolation zones, though these differences can be as high as 15 – 20 % during the period of snow metamorphosis and melting following new snowfall.
B.2.2 Trends in AOD of impurities and forest fires

Aerosol optical depth (AOD) is a measure of the total extinction (omni-directional scattering + absorption) of sunlight as it passes through the atmosphere, and so is related to atmospheric aerosol abundance. In the absence of in-situ measurements of trends in impurities concentrations over Greenland, we studied the trends in AOD in aerosol models and from retrievals using ground-based measurements at several locations around the GIS. In the models, we are able to examine trends in total AOD as well as in aerosol components: black carbon, dust and organic matter. These are used to quantify trends in the amount of these impurities over the Greenland ice sheet. In addition, we examined trends in modelled deposition fluxes of these species to the Greenland ice sheet.

The Aerosol Comparisons between Observations and Models (AEROCOM) project is an open international initiative aimed at understanding the global aerosol and its impact on climate (Samset et al. 2014; Myhre et al. 2013; Jiao et al. 2014; Tsigaridis et al. 2014). The project combines a large number of observations and outputs from more than fourteen global models to test, document and compare state-of-the-art modelling of the global aerosol. We plot standardized (i.e., subtracting the mean and dividing by the standard deviation) deposition fluxes of BC, dust and organic aerosols (OA) from the GISS modelE contribution to the AeroCom phase II series of model runs (http://aerocom.met.no/aerocomhome.html). The runs used here use the Coupled Model Intercomparison Project Phase 5 (CMIP5) decadal emission data, which are interpolated annually. The analysis of the AEROCOM data shows no statistically significant trend in deposition fluxes at the two locations of Kangerlussuaq (Figure B.3) and Summit (Figure B.4) for all months and aerosol components (BC, dust and organic matter). These two sites were selected as representative of the ablation (Kangerlussuaq) and dry snow (Summit) zones. Over longer periods, other studies (Stone et al. 2014) also indicate that since the 1980s, atmospheric
Figure B.3. AEROCOM standardized deposition fluxes for BC, dust and organic aerosol Kangerlussuaq for a) June, b) July and c) August (1981 – 2008).
Figure B.4. Same as Fig. S3 but for Summit station.
concentrations of BC measured at surface stations in the Arctic have decreased, with variations attributed to changes in both anthropogenic and natural aerosol and aerosol precursor emissions.

Mean summer values of AOD (550 nm) measured at three AERONET Greenland sites of Thule (northwest Greenland; 77°28′00″N, 69°13′50″W), Ittoqqortoormiit (east-central Greenland), and Kangerlussuaq (southwest Greenland; 67°00′31″N, 50°41′21″W) (http://aeronet.gsfc.nasa.gov) during the period 2007 – 2013 (with the starting year ranging between 2007 and 2009, depending on the site) are reported in Table B.2, together with the relative standard deviations. The values are consistent with those reported in (Dumont et al. 2014) and none of the stations show statistically significant trends. The two sites in western Greenland, Thule and Kangerlussuaq, have consistent temporal variations, and the most outstanding feature of both is a peak in 2009.

Our analysis above indicates no trend in either AOD or deposition fluxes of aerosols over the GIS. A recent analysis (Dumont et al. 2014), however, concluded that dust deposition has been increasing over much of the GIS and that this is driving lowered albedo across the ice sheet. Here we compare AOD trends from the model used in (Dumont et al. 2014) (the Monitoring Atmospheric Composition and Climate, or MACC, model) with that from the Goddard Chemistry Aerosol Radiation and Transport (GOCART; Figure B.5) model. The GOCART model simulates major tropospheric aerosol components, including sulphate, dust, black carbon (BC), organic carbon (OC), and sea-salt aerosols using assimilated meteorological fields of the Goddard Earth Observing System Data Assimilation System (GEOS DAS), generated by the Goddard Global Modeling and Assimilation Office. The model has a horizontal resolution of 1°x1°. AOD at 550nm is compared for dust, organic matter and black carbon for the domain bounded by 75 to 80°N and 30 to 50° W. The analysis of AOD does not point to any significant trend on
component AODs, with the exception of dust for GOCART. The models don’t capture trends in exposed silt/dust as Greenland glaciers have receded, and therefore we would not expect to capture trends in dust from this source. Moreover, the dramatic difference between MACC and GOCART suggests that more work is required to better understand the reliability of such models when applied over Greenland. We, therefore, cannot exclude increased deposition at the margins of the ice sheet (as already pointed out through the exposure of a ‘dark’ zone), but we also point to the fact that increased deposition is not needed to explain the observed albedo reduction, in view of melt consolidation of impurities at the surface.

We use the MODIS monthly active fire products produced by the TERRA (MOD14CMH) and AQUA sensors (MYD14CMH) generated at 0.5° spatial resolution (Climate Modelling Grid, CMG) to study trends in the number of fires over North America and Eurasia, as fires in these two regions likely contribute to the amount of soot deposited to the Greenland ice sheet (Hegg et al. 2009). The CMG fire products are gridded statistical summaries of fire pixel information and are distributed from the University of Maryland via anonymous ftp (http://www.fao.org/fileadmin/templates/gfims/docs/MODIS_Fire_Users_Guide_2.4.pdf). For convenience, the products are distributed in multiple, standard data formats. More information on the MOD14 products can be found at http://modis.gsfc.nasa.gov/data/dataprod/dataproducts.php?MOD_NUMBER=14. Figure B.6 shows the standardized (subtracting the mean and dividing by the standard deviation of the 2002 – 2012 period) cumulative number of fires detected over North America and Eurasia by the MOD14CMH and MYD14CMH GCM climatology products between 2002 and 2012. The MODIS fire products show high variability but no trend in the number of fires over the two areas 2002-2012, with a negative trend occurring between 2004 and 2011.
Figure B.5. May – June averaged aerosol optical depth at 550 nm for a) dust, b) organic matter, c) black carbon and d) total obtained from the GOCART model and from the MACC model (as in Dumont et al. 2014) for the domain bounded by 75 to 80°N and 30 to 50° W.
Figure B.6. Standardized cumulative number of fires detected over North America and Eurasia by the MOD14CMH and MYD14CMH GCM climatology products between 2002 and 2012.
B.2.3 Assessment of the GLASS product

Data collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) are used in the GLASS albedo retrieval for the period 2002 – 2012. Previous studies (Steffen and Box 2001) have shown that the MODIS TERRA sensor has been degrading at a pace that can be approximated by a second order polynomial, with the coefficients being spectrally dependent. Over Greenland, the impact of sensor degradation on albedo trends has been estimated at 0.0059/decade (Stroeve et al. 2013). This value is one order of magnitude smaller than the retrieved albedo trends for the period 1996 – 2012 over the whole GIS, but it is of the same order of magnitude as the albedo decrease expected from the concentrations of impurities measured in the dry snow and percolation zones of the GIS.

We complemented previous assessments of the impact of sensor degradation by assessing albedo trends over a relatively stable target located at Dome C, Antarctica. We also quantified the uncertainty in the GLASS retrieved albedo through comparisons with in-situ albedo observations in Greenland. Dome-C (75.1º S, 123.5º E) on the Antarctic plateau is ideal for calibration studies because of its surface spatial uniformity and temporal stability [http://calvalportal.ceos.org/c/document_library/get_file?uuid=9a7eadf7-7ca5-492a-98fa-22012274be9b&groupId=10136]. With no surface melting, small annual accumulation, and minimal influence from atmospheric aerosol (because of the elevation), this location is indeed optimal for performing vicarious calibration of remote sensing products (Loeb 1997; Masonis and Warren 2001). Trends, p-values and standard deviations of monthly summer austral albedo at Dome-C are reported in Table B.3. None of the monthly trends during the AVHRR period (1981-2002) are statistically significant. However, the trends become statistically significant during the 2000 – 2012 period, with the months of October and November being significant at a 99 % level.
Table B.3 Trends [/decade], p-value and standard deviation of the monthly albedo 1981 – 2002 (AVHRR) and 2002 – 2012 (MODIS) for Dome-C, Antarctica.

<table>
<thead>
<tr>
<th></th>
<th>Trend [/decade]</th>
<th>p-value</th>
<th>Sigma</th>
</tr>
</thead>
<tbody>
<tr>
<td>1981-2000*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>October</td>
<td>0.0023±0.0043</td>
<td>0.273</td>
<td>0.0049</td>
</tr>
<tr>
<td>November</td>
<td>0.0023±0.0055</td>
<td>0.378</td>
<td>0.0067</td>
</tr>
<tr>
<td>December</td>
<td>0.0015±0.0047</td>
<td>0.506</td>
<td>0.0056</td>
</tr>
<tr>
<td>January</td>
<td>0.0036±0.0043</td>
<td>0.091</td>
<td>0.0055</td>
</tr>
<tr>
<td>2000-2012</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>October</td>
<td>-0.0070±0.0052</td>
<td>0.013</td>
<td>0.0041</td>
</tr>
<tr>
<td>November</td>
<td>-0.0062±0.0054</td>
<td>0.012</td>
<td>0.0067</td>
</tr>
<tr>
<td>December</td>
<td>-0.0073±0.0083</td>
<td>0.076</td>
<td>0.0056</td>
</tr>
<tr>
<td>January**</td>
<td>-0.0068±0.0079</td>
<td>0.081</td>
<td>0.0047</td>
</tr>
<tr>
<td>1981 - 1996</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>October</td>
<td>0.0044±0.0062</td>
<td>0.0052</td>
<td>0.147</td>
</tr>
<tr>
<td>November</td>
<td>0.0038±0.0081</td>
<td>0.0067</td>
<td>0.33</td>
</tr>
<tr>
<td>December</td>
<td>0.0024±0.0071</td>
<td>0.0055</td>
<td>0.453</td>
</tr>
<tr>
<td>1996-2012</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>October</td>
<td>-0.007±0.003</td>
<td>&lt;0.01</td>
<td>0.0045</td>
</tr>
<tr>
<td>November</td>
<td>-0.022±0.0045</td>
<td>&lt;0.01</td>
<td>0.0119</td>
</tr>
<tr>
<td>December</td>
<td>-0.0182±0.0071</td>
<td>&lt;0.01</td>
<td>0.0112</td>
</tr>
</tbody>
</table>

*1994 data is not available for the selected period

** 2000 data was not available
Table B.4 Comparison between GLASS retrieved albedo and GC-NET in-situ albedo measurements, for monthly- and seasonally-averaged albedos at twelve surface stations on the Greenland ice sheet.

<table>
<thead>
<tr>
<th></th>
<th>June</th>
<th>July</th>
<th>August</th>
<th>JJA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>rmse [%]</td>
<td>rmsep [%]</td>
<td>slope</td>
<td># of years</td>
</tr>
<tr>
<td>Swiss</td>
<td>0.12</td>
<td>19.60</td>
<td>-0.22</td>
<td>11</td>
</tr>
<tr>
<td>CP</td>
<td>0.07</td>
<td>8.72</td>
<td>0.12</td>
<td>12</td>
</tr>
<tr>
<td>Humboldt</td>
<td>0.08</td>
<td>10.38</td>
<td>-0.16</td>
<td>8</td>
</tr>
<tr>
<td>Summit</td>
<td>0.01</td>
<td>1.45</td>
<td>0.85</td>
<td>15</td>
</tr>
<tr>
<td>TunuN</td>
<td>0.05</td>
<td>6.72</td>
<td>-0.66</td>
<td>15</td>
</tr>
<tr>
<td>Dye-2</td>
<td>0.02</td>
<td>2.58</td>
<td>0.57</td>
<td>14</td>
</tr>
<tr>
<td>Jar1</td>
<td>0.06</td>
<td>8.45</td>
<td>0.68</td>
<td>13</td>
</tr>
<tr>
<td>Saddle</td>
<td>0.01</td>
<td>1.28</td>
<td>0.94</td>
<td>14</td>
</tr>
<tr>
<td>NASAE</td>
<td>0.03</td>
<td>4.23</td>
<td>0.46</td>
<td>14</td>
</tr>
<tr>
<td>NASA SE</td>
<td>0.02</td>
<td>2.76</td>
<td>0.59</td>
<td>13</td>
</tr>
<tr>
<td>JAR2</td>
<td>0.06</td>
<td>12.27</td>
<td>0.20</td>
<td>11</td>
</tr>
<tr>
<td>Mean</td>
<td>0.048</td>
<td>7.13</td>
<td>0.0455</td>
<td>6.99</td>
</tr>
</tbody>
</table>
Figure B.7. Time series of monthly averaged albedo values from the GLASS product (symbols) and simulated by MAR (lines) at Dome-C.
and December at a 90% level. Variability in albedo, as measured by standard deviation, is similar for AVHRR and MODIS. Since in-situ long-term albedo measurements are not available at Dome-C, we compared albedo values obtained from GLASS at Dome-C with those generated by the MAR model for the pixel containing Dome C for the period 2001–2011 (when MAR outputs over Antarctica are available to us, Figure B.7). MAR also does not simulate statistically significant trends in albedo for the 2001–2011 period, suggesting that the trends detected from the GLASS product might be due to sensor degradation or to long-term surface changes that are not captured by the model. The trends identified over Dome-C are of the same order of magnitude of those reported in previous studies (Stroeve et al. 2013).

Table B.4 shows the results of the comparison between monthly GLASS albedo and in-situ values measured by automatic weather stations of the Greenland climate network (GC-Net; Steffen and Box 2001), including root mean square error (RMSE), the percentage RMSE, and the slope of a linear fit between GLASS and in-situ measured albedos for 12 stations with in-situ measurements. The number of available years used for the statistics is also reported for each station. We considered only stations for which at least 10 years were available for the analysis in one of the months. The mean value of the RMSE for all stations ranges between 0.044±0.0026 in July and 0.048±0.034 in June, with values as high as 0.15 for station JAR1 in August and as low as 0.01 for Summit and Saddle stations in June. These results are consistent with the findings reported in Alexander et al. (2014) concerning the assessment of the MODIS albedo products over the Greenland.
## Appendix C

**Supplemental Material for Chapter 3**

**Table C.1** Same as Table 3.1, but for GRACE, MAR v3.5, and MAR v.20, for the period 2003-2010. "Filtered" indicates that Gaussian temporal and spatial filtering was applied.

<table>
<thead>
<tr>
<th></th>
<th>GRACE (Detrended) (Median and 95% CI)</th>
<th>MAR v3.5 (Unfiltered)</th>
<th>MAR v2.0 (Unfiltered)</th>
<th>MAR v3.5 (Filtered)</th>
<th>MAR v2.0 (Filtered)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Maximum</strong></td>
<td>March 28</td>
<td>April 26</td>
<td>May 22</td>
<td>May 19</td>
<td>April 29</td>
</tr>
<tr>
<td><strong>(2.5% Bound)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Maximum</strong></td>
<td>May 27</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>(97.5% Bound)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Minimum</strong></td>
<td>August 29</td>
<td></td>
<td></td>
<td>September 1</td>
<td>September 21</td>
</tr>
<tr>
<td><strong>(2.5% Bound)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Minimum</strong></td>
<td>September 16</td>
<td>September 1</td>
<td>September 8</td>
<td>September 21</td>
<td>September 21</td>
</tr>
<tr>
<td><strong>(97.5% Bound)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Minimum</strong></td>
<td>October 9</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>(97.5% Bound)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure C.1. Unfiltered modeled SMB and DMB for the 2003-2012 period as simulated by (a) MAR v3.5 and (b) ISSM forced by MAR v3.5.
Figure C.2. Optimal values of parameters used in spatial and temporal Gaussian filtering of MAR v3.5 and ISSM data: (a) $\sigma_i$ (km), (b) $\sigma_{\text{time}}$ (days), and (c) $\lambda_{ij}$ (unitless). (d) RMSE (Gt) for GRACE-filtered vs. Gaussian-filtered MAR v.2.0 data (2003-2010).
Figure C.3. Average seasonal cycles of de-trended cumulative mass change for filtered and unfiltered data for MAR v2.0 and MAR v3.5 for the period 2003-2010, along with the GRACE detrended cycle as shown in Figure 3.5. Error bars and vertical lines are as described in Figure 3.5.
Figure C.4. Same as Figure 3.13b-e, but additional regions shown in Figure 3.13a: (a) Region 2, (b) Region 3, (c) Region 7, (d) Region 8.
Appendix D

Evidence and analysis of 2012 Greenland records from spaceborne observations, a regional climate model, and reanalysis data

M. Tedesco, X. Fettweis, T. Mote, J. Wahr, P. Alexander, J. E. Box, and B. Wouters

The content of this appendix also appeared in The Cryosphere, 7, 615-630, doi: 10.5194/tc-7-615-2013

D.1 Abstract

A combined analysis of remote sensing observations, regional climate model (RCM) outputs and reanalysis data over the Greenland ice sheet provides evidence that multiple records were set during summer 2012. Melt extent was the largest in the satellite era (extending up to ~ 97 % of the ice sheet) and melting lasted up to ~ 2 months longer than the 1979 – 2011 mean. Model results indicate that near surface temperature was ~3 standard deviations (σ) above the 1958-2011 mean, while surface mass balance (SMB) was ~ 3σ below the mean and runoff was 3.9 σ above the mean over the same period. Albedo, exposure of bare ice and surface mass balance also set new records, as did the total mass balance with summer and annual mass changes of, respectively, -627 Gt and -574 Gt, 2σ below the 2003 – 2012 mean. We identify persistent anticyclonic conditions over Greenland associated with anomalies in the North Atlantic Oscillation (NAO), changes in surface conditions (e.g., albedo, surface temperature) and preconditioning of surface properties from recent extreme melting as major driving mechanisms for the 2012 records. Less positive if not increasingly negative SMB will likely occur should these characteristics persist.

D.2 Introduction
During the past decade, surface melting over the Greenland Ice Sheet (GrIS) has been increasing (e.g. Hanna et al. 2008; Fettweis et al. 2013b; Mote 2007; Tedesco et al. 2008, 2011), with results from regional climate models, *in situ* observations and satellite data revealing accelerating ice sheet mass loss (van den Broeke et al. 2009; Rignot et al. 2011). Melting is responsible for summer meltwater production over the GrIS, which ultimately translates into runoff to the surrounding ocean. Aside from the direct impact of increased runoff on the surface mass balance (SMB) of the GrIS, changes in the meltwater production affect supraglacial, englacial and subglacial processes. Persistent and enhanced melting can lead to reduced surface albedo (because of snow grain size metamorphism or bare ice exposure, for example) and, consequently, to increased absorbed solar radiation (which further enhances melting). The existence of supraglacial lakes, whose formation is driven by meltwater production, increases the ice ablation rate relative to that of bare ice at the surface (e.g. Tedesco et al. 2012). Moreover, rates of meltwater production play a key role in modulating the opening and persistence of surface-to-bedrock connections (e.g., hydro-fracturing, e.g., Weertman 1973; van der Veen 2007; Catania et al. 2008), which are associated with ice sheet velocity spatio-temporal gradients and, therefore, can impact the total GrIS mass balance. Given the complex and nonlinear nature of the mechanisms linking melting to other surface and sub-surface processes, it is crucial to adopt a multidisciplinary approach in which multiple tools are used to identify different aspects of extreme events and their drivers. This enables the limitations of any single method to be overcome, providing a more comprehensive understanding of the phenomenon under observation.

Here we combine results obtained from the analysis of spaceborne remote sensing data, the outputs of a Regional Climate Model (RCM) and reanalysis data to show evidence that multiple
records were set during the summer of 2012 over the GrIS, and to investigate the driving mechanisms. In particular, for the summer of 2012, new records were set for melt extent and duration derived from passive microwave remote sensing (1979 – 2012), satellite-derived snow/ice surface temperature and albedo (2000 – 2012), RCM-derived surface mass balance, bare ice exposure, runoff and near-surface temperature (1958-2012), and total mass balance derived from gravimetric satellite measurements (2002 – 2012). In many cases, the new records were exceeding the mean by values between 2 and 4 standard deviations. In Section D.2, we describe the data and methods employed; in Section D.3 we discuss the records associated with each data set examined; lastly in Section D.4, we investigate the drivers of the records; conclusions follow in Section D.5.

D.3 Methods and Data

D.3.1 Melt extent and duration from passive microwave data

Wet snow can be mapped at large spatial scales and high temporal resolution from spaceborne measurements collected in the microwave region of the electromagnetic spectrum. As the liquid water content (LWC) within the snowpack increases, so does the absorption as a consequence of the increase of the imaginary part of snow permittivity. In the case of passive microwave sensors this has the consequence of suddenly and considerably increasing the recorded microwave brightness temperature \( T_b \) (e.g. Tedesco 2007). Microwave sensors can also detect sub-surface liquid water, which can occur when the surface is frozen and, therefore, cannot be detected with thermal sensors.

We use data collected by the Scanning Multichannel Microwave Radiometer (SMMR) and by the Special Sensor Microwave Imager (SSM/I). SMMR was a five-frequency instrument on the Nimbus-7 satellite. It had dual-polarized, horizontal (H) and vertical (V), channels at 6.63,
10.69, 18.0, 21.0, and 37.0 GHz (Gloerson et al. 1984). The first SSM/I sensor was launched aboard the DMSP F-8 mission in 1987 (Hollinger et al. 1987). A series of SSM/I sensors on subsequent DMSP satellites has provided a continuous data stream since then. Sensors on the F-8, F-11, F-13, and F-17 platforms are used for the data used here. The SSM/I sensor has seven channels at four frequencies. The 19.4, 37.0, and 85.5 GHz frequencies are dual polarized (H and V); the 22.2 GHz frequency has only a single vertically polarized channel. For simplicity, the channels are sometimes denoted as simply 19H, 19V, 22V, 37H, 37V, 85V and 85H. The SSM/I sensor was replaced by the Special Sensor Microwave Imager /Sounder (SSMIS) sensor with the launch of F-16 in 2003. The SSMIS sensor has the same 19.4, 22.2, and 37.0 GHz channels of SSM/I. However, the 85.5 GHz channels on SSM/I are replaced with 91.0 GHz channels on SSMIS. This does not affect the melt detection, as this frequency is not used in the algorithms considered here.

The National Snow and Ice Data Center (NSIDC) processes and combines swath brightness temperature data from Remote Sensing Systems, Inc. (RSS) (http://www.ssmi.com). The NSIDC distributes SMMR, SSM/I and SSMIS as gridded daily products, distributed in a polar stereographic projection and the Equal Area Earth Scalable (EASE) projection with a 25 km spatial resolution. Near-real-time DMSP SSMIS Daily Polar Gridded Brightness Temperatures (http://nsidc.org/data) and EASE-Grid brightness temperatures (http://nsidc.org/data/docs/daac/nsidc) are also available through NSIDC and are used here for the analysis reported in the following for the 2012 season. Though near-real time data did not go through the same processing as fully processed data, the difference between the two data sets is generally small (on the order of 1-2 K at most, but below that on average based on a comparison performed by the authors using data from previous years over Greenland). Because of the strong
impact of LWC on recorded brightness temperatures (e.g. increase of the order of tens of K, up to 100 K in some cases, when moving from dry to wet snow conditions, e.g. Tedesco 2007), we assume that the use of near-real time brightness temperatures does not impact the results discussed in the following for the 2012 melting season.

Changes in melt duration and extent over the Greenland and Antarctic ice sheets have been mapped using the seasonal change in emissivity and thresholds computed through the aid of electromagnetic models (Mote and Anderson 1995; Mote 2007; Tedesco 2009), the frequency dependence of emissivity, such as the cross polarized gradient ratio (XPGR, e.g. Abdalati and Steffen; Steffen et al. 2004), the diurnal change in emissivity (e.g. Tedesco 2007) and fixed threshold coefficients (e.g. Zwally and Fiegles 1994). Here, we use the algorithms reported by Mote and Anderson (1995) and Tedesco (2009), as they are based on a similar concept (e.g., when the LWC within the snowpack is assumed to exceed a certain threshold). The algorithm of Mote and Anderson (1995) is a dynamic threshold algorithm (DTA) based on a simple microwave-emission model, which is used to simulate 37 GHz horizontally polarized brightness temperatures associated with 1% liquid water content across the Greenland ice sheet (Mote 2007). The other approach is based on Tedesco (2009) and assumes a fixed value of LWC to compute the brightness temperature threshold (still from an electromagnetic model) above which melt is assumed to be occurring. This approach is conceptually similar to the one originally proposed by Zwally and Fiegles (1994), producing coefficients that are similar to those produced in that approach but that are spatially and temporally dynamically computed.

D.3.2 MODIS albedo and surface temperature

The Moderate-resolution Imaging Spectroradiometer (MODIS) on board the Terra and Aqua satellites (http://modis.gsfc.nasa.gov/) records data in 36 spectral bands between 0.4 and
14.4 μm. MODIS thermal infrared observations allow estimates of land surface temperature (LST) under cloud-free conditions at a 1 km horizontal spatial resolution. In particular, the MODIS MOD11A1 data product (http://www.icess.ucsb.edu/modis/) makes use of daily averaged LST retrievals from swath data using bands 31 (11 μm) and 32 (12 μm) (Wan et al. 2002; Wan 2008). The root mean square error (RMSE) of the MOD11A1 product with respect to independent in-situ observations has been estimated to be 1°C (Wan 2008), with higher RMS errors (>1°C) found over Greenland (Hall et al. 2008b,a; Koenig and Hall 2010).

Surface albedo retrievals from the NASA Terra platform MODIS sensor beginning 5 March 2000 are available from the NSIDC (Hall et al. 2011). The daily MOD10A1 product is used in this study instead of other available products, such as the MODIS MOD43 (http://modis.gsfc.nasa.gov/data/dataprod/) or MCD43 8-day (http://www-modis.bu.edu/brdf/userguide/intro.html) products, in order to increase temporal resolution. After collection, the data are interpolated to a 5 km EASE grid. Stroeve et al. (2006) showed that the MOD10A1 product captures the albedo seasonal cycle, but exhibits more temporal variability than recorded by in-situ observations. A dominant component of this assessed error might be the failure of the MODIS data product to completely remove cloud effects. Another problem might be the presence of spuriously low values, for example below 0.4 in the accumulation area, where albedo is not observed by pyranometers at the surface to drop below 0.7. In this study, we follow the approach reported by Box et al. (2012), in which 11-day running statistics are here used to identify and reject values that exceed 2 standard deviations from an 11-day average. To prevent rejecting potentially valid cases, data within 0.04 of the median are not rejected. June–August (JJA or summer) seasonal averages are then generated from monthly averages of the daily filtered and smoothed data. Only data from the Terra MODIS instrument is used in this study, to reduce
computational burdens, and given an Aqua MODIS instrument near infrared (channel 6) failure (Hall et al. 2008b) that reduces the cloud detection capability.

D.3.3 The MAR regional climate model

MAR is a 3-D coupled atmosphere-land surface model that predicts the evolution of the coupled land-atmosphere system (subject to land-atmosphere feedbacks) in response to radiative forcing from the sun, and known or projected atmospheric forcing applied at the model’s lateral boundaries. The atmospheric portion of MAR is coupled to the 1-D surface-vegetation-atmosphere transfer scheme SISVAT (Soil Ice Snow Vegetation Atmosphere Transfer; Gallée and Schayes 1994; De Ridder and Gallée 1998), which simulates surface properties and the exchange of mass and energy between the surface and the atmosphere. SISVAT incorporates an interactive snow model based on the CROCUS model (Brun et al. 1992), a 1-D layered energy and mass balance model of the snowpack capable of simulating up to 20 snow and ice layers. CROCUS is more sophisticated with respect to snow models used by most RCMs (e.g. Rae et al. 2012) in that it is a physically-based model capable of simulating the evolution of snow properties, such as grain sizes and shapes, in response to energy and mass changes within the snowpack, and their influence on surface albedo. CROCUS also incorporates a water balance module that takes into account the refreezing of meltwater, a turbulence module, and a snow/ice discretization module (Brun et al. 1992).

MAR has been used to simulate long-term changes in the GrIS SMB and surface melt extent (Fettweis et al. 2005, 2011a; Tedesco et al. 2008, 2011) using ERA-40 (1958–1978) and ERA-INTERIM reanalysis (1979–2012) (Dee et al. 2011) as forcing every 6 hours at the MAR lateral boundaries. Validation has been performed through comparison with ground
measurements (e.g. Lefebre et al. 2003; Gallée et al. 2005; Lefebre et al. 2005), and satellite data (e.g. Fettweis et al. 2005, 2011a; Tedesco et al. 2011). These studies have demonstrated the validity of the model for accurately simulating climate changes (Fettweis et al. 2013b; Franco et al. 2013) and capturing feedback mechanisms, including surface air temperatures, specific humidity, wind speed, surface albedo, melting, and radiative fluxes over Greenland.

Specifically, comparisons with weather station data from the Greenland Climate Network (GC-Net; Steffen et al. 1996) reveal that MAR captures annual surface temperatures within ~1-2°C (Fettweis et al. 2011a; Box et al. 2012). The lack of available SMB measurements limits the degree to which model SMB estimates can be assessed. When compared with annual SMB measurements (1990-2008) at the GrIS ablation zone K-Transect (van de Wal et al. 2012), MAR exhibits an RMSE of 24% of simulated SMB (the best of four models), but is less accurate (RMSE of 46%) when compared with ice core estimates over the centre of the ice sheet (Vernon et al. 2013). Another comparison with available ice core estimates suggests MAR overestimates SMB by 20-25% over the ice sheet accumulation zone (Rae et al. 2012). Despite limitations associated with a lack of available observations, these studies suggest that relative changes in SMB predicted by MAR and other models should be emphasized rather than the absolute value of SMB estimates, which is sufficient for the purposes of this study. Here, MAR is run at a 25 km resolution (though outputs can be used to estimate the SMB at a higher resolution, e.g. Franco et al. 2012) with the specific model setup discussed by Fettweis (2007) and with adjustments to the albedo scheme as noted by Fettweis et al. (2011). Only the first 10m of snow/ice are resolved in the snow model. Ice is added at the bottom of the snowpack if its height is lower than 8 m (Franco et al. 2013). The refreezing scheme is described in Reijmer et
al. (2012). Initialization of the snow model follows Fettweis et al. (2005) and Lefebre et al. (2005), where further details can be found.

**D.3.4 GRACE**

The Gravity Recovery and Climate Experiment (GRACE) satellite mission has been providing monthly solutions for the earth’s global gravity field since its launch in spring of 2002. These solutions can be used to determine time variations in the gravity field, which provide information on month-to-month variations in the earth’s mass distribution (e.g. Tapley et al. 2004; Wahr et al. 2004). Here, we use monthly GRACE gravity fields from April, 2002, through September, 2012, generated and made publicly available by the Center for Space Research (CSR) at the University of Texas (http://podaac.jpl.nasa.gov/), to solve for temporal changes in the total mass of the Greenland ice sheet. CSR’s Release 4 fields were used for months prior to March 2003, and Release 5 fields were used for all months thereafter. Each monthly field consists of a set of spherical harmonic geoid coefficients up to degree and order 60. We replace the GRACE $C_{20}$ coefficients with $C_{20}$ coefficients inferred from satellite laser ranging (Cheng and Tapley 2004), and we include degree-one coefficients computed as described by Swenson et al. (2008)(coefficients provided by S. Swenson). We use model results from A, et al. (2013) to remove contributions from glacial isostatic adjustment (GIA): the earth's viscoelastic response to past ice mass variability. Those GIA results were computed for a compressible, spherically symmetric Earth, and were based on the global ICE-5G model and VM2 viscosity profile of Peltier (2004).

We compute the temporal mean of the monthly fields and subtract that mean from each field, so that the residuals represent the monthly departures from the mean. We convolve each monthly
residual field with a Greenland averaging kernel, as described by Velicogna and Wahr (2006), to obtain an estimate of Greenland mass-per-area in units of cm of water averaged over the ice sheet. Like any filtering process, this convolution has the potential of causing a loss of signal. To correct for this, we follow Velicogna and Wahr (2006) and determine a scaling factor by applying this analysis procedure to several simulated, but plausible, ice loss patterns. We multiply each monthly mass-per-area estimate by this scaling factor to obtain variations in the total mass of the ice sheet (in Gt) about its temporal average.

D.4 Results

D.4.1 Surface temperature

Figure D.1a shows the map of 2012 JJA near-surface air temperature (3m) anomalies (1958 – 2011 baseline) from MAR, indicating largely positive anomalies (up to 4 – 5 °C) over the entire GrIS. Surface temperature anomalies are extreme at high elevations, especially in the north and south regions, where melting lasted longer than previous years (see next section). Over the GrIS, anomalies at relatively low elevations closer to the coast are ~ 0°C. This is a consequence of the fact that melting generally occurs there every year for most of the summer and, therefore, near-surface air temperature is already close to the melting point for most of the season. Figure D.1b shows the mean JJA LST estimated by MODIS averaged over the entire Greenland ice sheet for the period 2000 – 2012. The JJA ice-sheet-wide MODIS LST increased 3.4 °C between years 2000 and 2012, from an average value of ~ -9°C in 2000 to -5.6°C in 2012, with a linear fit suggesting an increase of +2.1 ± 0.7 °C over the last 13 years. The MAR model (respectively, ERA-INTERIM) suggests an increase of + 1.3 (1.1)°C of the JJA near-surface temperature for the period 2000 - 2012. Knowing that observations were assimilated in ERA-INTERIM and that the trend of the near-surface temperatures should be higher than the surface temperature limited
Figure D.1. a) 2012 JJA surface temperature anomaly (1958 – 2011 baseline) simulated by MAR. Hatched areas indicate regions were the anomaly was above two standard deviations from the mean. b) Annual JJA mean surface temperature from MODIS averaged over the entire Greenland ice sheet for the period 2000 – 2012.
to 0°C, this suggests that MODIS could overestimate the trends. This is likely a consequence of sensor changes in the MODIS-based timeseries (Box et al. 2012). Nevertheless, the 2012 JJA average GrIS near-surface temperature simulated by MAR was the warmest since 1958, with an anomaly of +2.6°C (i.e., 2.9 times the standard deviation over 1958-2011). Finally, some coastal weather stations recorded JJA 2012 as the warmest JJA period since the beginning of the observations (more than 100 yr) according to Hanna et al. (2013). We note that while MODIS provides estimates of the actual snow/ice surface temperature, the near-surface air temperature represents the air temperature at 3 m above the surface.

D.4.2 Melting from passive microwave spaceborne data

GrIS melting in 2012 set a new record, according to results obtained from spaceborne microwave data (Tedesco 2009; Mote and Anderson 1995). Nearly the entire 2012 summer experienced above-normal melt extent across the ice sheet (Figure D.2a), with 79 of 92 days in JJA with melt extent greater than average. The only multiple-day periods with below-average melt extent occurred between 10-24 May and at the end of August. Apart from a period around mid-June, more extensive melt than average persisted from 27 May through 22 July and throughout much of August 2012. The area covered by melting was larger in 2012 than for any other year in the microwave satellite era (1979 – 2012), and 2012 was the first year within the satellite era when nearly the entire ice sheet experienced melt (Figure D.2b,c). The melt extent on Greenland reached a one-day record during the period 11-12 July, when at least 97% of the ice sheet underwent melt (Nghiem et al. 2012). The Nghiem et al. (2012) work was based on multiple satellite products; the individual product following Mote and Anderson (1995) produced a maximum single-day melt extent of 90 % on 11 July, compared to 23 % on average for 11 July, and >97% over the period of 11-13 July. The previous maximum melt extent was 77% on 28
Figure D.2.  a) Melt extent (as a percentage of the Greenland ice sheet) time series derived from spaceborne passive microwave observations using the algorithm in Tedesco (2009) in 2012 (red), in 2011 (blue), 2010 (green, being the previous record) and for the 1981 – 2010 mean (black). b) Maximum melt extent for the period 1979 – 2012 using the algorithm in Mote and Anderson (1995), denoted as TM and in Tedesco (2009), denoted as MT. c) Daily simulated GrIS melt extent (in % of the ice sheet area) from January through December for 1979 through 2012 from passive microwave based on the algorithm given in Mote and Anderson (1995).
Figure D.3. Average melt onset date (day of year) by elevation bands from passive microwave data using the algorithm in Mote and Anderson (1995).
Table D.1 Melt onset trend in days·decade$^{-1}$ for different elevation bands derived from passive microwave data using the approach by Mote and Anderson (1995).

<table>
<thead>
<tr>
<th>Elevation band</th>
<th>Days/decade</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 400 m</td>
<td>-11.59±0.015</td>
</tr>
<tr>
<td>400 – 800 m</td>
<td>-9.27±0.010</td>
</tr>
<tr>
<td>800 – 1200 m</td>
<td>-9.83±0.012</td>
</tr>
<tr>
<td>1200 – 1600 m</td>
<td>-7.31±0.012</td>
</tr>
<tr>
<td>1600 – 2000 m</td>
<td>-4.93±0.012</td>
</tr>
<tr>
<td>2000 – 2400 m</td>
<td>-4.49±0.015</td>
</tr>
<tr>
<td>2400 – 2800 m</td>
<td>-2.65±0.015</td>
</tr>
</tbody>
</table>

June 2002, but three days in summer 2012 exceeded the 2002 maximum. The melt extent exceeded 60% of the ice sheet a total of 10 days in 2012, compared to three days in 2002; only one other year (2005) had even a single day of melt extent exceeding 60% of the ice sheet. The updated 1979-2012 trend for melt extent is 22,337±24 km$^2$ yr$^{-1}$ (1.3 % yr$^{-1}$) following Mote and Anderson (1995) and 20,325±22 km$^2$ yr$^{-1}$ (1.19 % yr$^{-1}$) following Tedesco (2009).

In 2012, melting started more than two weeks earlier than average along large bands of the ice sheet below 1200 m a.s.l. An analysis updated through summer 2012 indicates that areas below 2400 m a.s.l. have experienced increasingly earlier melt onset dates since 1979, with the greatest changes occurring at lower elevations (Figure D.3, Table D.1). According to results obtained using the algorithm of Mote and Anderson (1995), melt onset at the lowest elevations (< 400 m.a.s.l.) has been occurring 11.59 days earlier per decade ($r=0.78$, $p<0.01$). This implies that, on average, melting in 2012 started about one month earlier than it did 33 yr ago. At higher elevations, as expected, the trend of the melt onset is smaller, with melting starting on average 2.65 days earlier per decade ($r=0.23$, $p=0.24$) for areas above 2400 m and below 2800 m (areas above 2800 m are not considered here because they do not melt every year). As an example, a transect at 72° N in West Greenland had melt exceeding 60 days in JJA at elevations below 1700
m a.s.l., exceeding the 1981-2010 average by roughly 40 days between 1600 and 1800 m (Table D.2). The regression coefficient of the melt onset trend expressed as a function of elevation is 0.0368±0.0004 days m⁻¹ decade⁻¹ using Mote and Anderson (1995) and 0.0359 ± 0.04 days m⁻¹ decade⁻¹ using Tedesco (2009).

**Table D.2** Melt duration (in days) for JJA 2012 and the 1981-2010 average (days) for a transect in west Greenland at approximately 72°N using the algorithm in Mote and Anderson (1995).

<table>
<thead>
<tr>
<th>Latitude</th>
<th>Longitude</th>
<th>Elevation</th>
<th>2012</th>
<th>1981-2010</th>
<th>2012 departure</th>
</tr>
</thead>
<tbody>
<tr>
<td>72.122</td>
<td>-51.988</td>
<td>1685</td>
<td>64.0</td>
<td>25.6</td>
<td>38.5</td>
</tr>
<tr>
<td>72.148</td>
<td>-51.259</td>
<td>1739</td>
<td>56.0</td>
<td>14.7</td>
<td>41.3</td>
</tr>
<tr>
<td>72.171</td>
<td>-50.528</td>
<td>1961</td>
<td>43.0</td>
<td>9.0</td>
<td>33.9</td>
</tr>
<tr>
<td>72.191</td>
<td>-49.794</td>
<td>2080</td>
<td>33.0</td>
<td>6.6</td>
<td>26.4</td>
</tr>
<tr>
<td>72.208</td>
<td>-49.059</td>
<td>2220</td>
<td>21.0</td>
<td>5.7</td>
<td>15.3</td>
</tr>
<tr>
<td>72.223</td>
<td>-48.323</td>
<td>2325</td>
<td>15.0</td>
<td>4.7</td>
<td>10.3</td>
</tr>
<tr>
<td>72.234</td>
<td>-47.586</td>
<td>2460</td>
<td>10.0</td>
<td>3.1</td>
<td>6.9</td>
</tr>
<tr>
<td>72.243</td>
<td>-46.848</td>
<td>2547</td>
<td>7.0</td>
<td>2.0</td>
<td>5.0</td>
</tr>
<tr>
<td>72.249</td>
<td>-46.109</td>
<td>2641</td>
<td>6.0</td>
<td>1.2</td>
<td>4.8</td>
</tr>
<tr>
<td>72.252</td>
<td>-45.370</td>
<td>2714</td>
<td>5.0</td>
<td>0.7</td>
<td>4.2</td>
</tr>
<tr>
<td>72.252</td>
<td>-44.630</td>
<td>2770</td>
<td>5.0</td>
<td>0.8</td>
<td>4.1</td>
</tr>
<tr>
<td>72.249</td>
<td>-43.891</td>
<td>2846</td>
<td>5.0</td>
<td>0.6</td>
<td>4.4</td>
</tr>
<tr>
<td>72.243</td>
<td>-43.152</td>
<td>2887</td>
<td>4.0</td>
<td>0.0</td>
<td>4.0</td>
</tr>
<tr>
<td>72.234</td>
<td>-42.414</td>
<td>2969</td>
<td>4.0</td>
<td>0.0</td>
<td>4.0</td>
</tr>
<tr>
<td>72.223</td>
<td>-41.677</td>
<td>3001</td>
<td>5.0</td>
<td>0.0</td>
<td>5.0</td>
</tr>
<tr>
<td>72.208</td>
<td>-40.941</td>
<td>3064</td>
<td>4.0</td>
<td>0.0</td>
<td>4.0</td>
</tr>
</tbody>
</table>

In 2012, melting lasted longer than average for the majority of the areas subject to melting (Figures D.4a,b), up to 30 days longer than the 1981 – 2010 average for large areas of west Greenland below 2400 m a.s.l. For areas in northwest Greenland between 1400 and 2000 m a.s.l., melting lasted up to two months longer than average. The cumulative melting index, MI (e.g., defined as the number of melting days times the area subject to melting) set a new record in 2012. Figure D.4c shows the time series of the annual standardized melting index (SMI, the MI
minus its mean and divided by the standard deviation) obtained using the results from the two passive microwave algorithms. The new SMI record was ~ 2.5 standard deviations above the 1981 – 2010 mean (represented by the 0 value on the y axis in the SMI plot), while the previous record set in 2010 was ~ 1.2 standard deviations above the mean.

Because the use of microwave data does not allow one to estimate either LWC within the snowpack (or ice) or the amount of liquid water that refreezes after melting, it is difficult to translate the surface melting record detected by spaceborne microwave sensors into runoff and, ultimately, into surface mass balance. Moreover, to interpret the 2012 melting record in terms of surface mass balance, it is essential to know the mass that accumulated after the end of the previous melting season and to compute the net mass for the hydrological year (which here is defined starting on 1 September and ending on 31 August). Following this aim, the results of the regional climate model MAR are used here to complement those obtained from remote sensing and are reported in the following section.

**D.4.3 Surface Mass Balance**

The SMB simulated by MAR for the 2011-2012 hydrological year (from September 2011 through August 2012) is the lowest for the period 1958 – 2012 (Figure D.5a, ~ -400 Gt yr\(^{-1}\) anomaly), setting a new record for modeled SMB. The 2012 SMB value is 3 standard deviations below the 1958 – 2011 mean, exceeding by ~ 100 Gt yr\(^{-1}\) the previous record set in 2010 (~ -300 Gt yr\(^{-1}\) anomaly, Figure D.5a). According to MAR, the 2012 SMB record is driven by the record melt and the associated modelled runoff (~ 350 Gt yr\(^{-1}\), 3.9 standard deviations above the 1958 – 2011 average). The simulated winter snowfall over 2011- 2012 does not play a major role in setting the SMB record, because it is close to the 1958 – 2011 average. This is different from previous record melt summers (2007, 2008, 2010, 2011), when the low SMB anomaly was driven
Figure D.4. a) Melt duration (days) during June, July and August of 2012 from Mote and Anderson (1995) and b) departure from the 1981-2010 average. c) Standardized melting index (SMI) for the period 1979 – 2012 using the algorithm in Mote and Anderson (1995), denoted as TM and in Tedesco (2009), denoted as MT.
Figure D.5.  a) Barplot of annual time series of the GrIS SMB, snowfall and run-off anomalies integrated over the hydrological year simulated by MAR forced by ERA-40 over 1958-1978 and by ERA-INTERIM over 1979-2012. Units are Gt/yr and anomalies are given with respect to the 1958-2011 period. b) Daily time series of the cumulative SMB (Gt/yr) using January 1st as a reference for 2012 (dark blue), 2011 (light red) and 2010 (green) and for the 1958 – 2011 mean (50 % gray).
Figure D.6. a) 2011-2012 winter accumulation anomaly (in mmWE) simulated by MAR with respect to 1958-2011. b) 2012 SMB anomaly integrated over the hydrological year simulated by MAR with respect to 1958-2011. The 2011-2012 ELA (Equilibrium Line Altitude) is plotted as a red line and areas where the anomalies are at least twice the 1958-2011 standard deviation of MAR forced by ERA-INTERIM are hatched in black. c) Same as b) but for the JJA meltwater production. Only about 40-50% of this meltwater reaches the ocean by runoff. The ELA is plotted in blue here. d) Same as b) but for the JJA snowfall. e) Time series (in red) of the 2012 GrIS cumulative meltwater production simulated by MAR. The same simulation starting the 1st of May 2012 with the state of the snow pack from May 1997 is plotted in green for the purpose of a sensitivity analysis. The 1958-2011 mean simulated by MAR is plotted in black. The dark and light grey areas correspond to the 1958-2011 standard deviation and respectively 2 times the standard deviation of the GrIS MAR simulated values. Finally, the absolute daily maximum values over the considered period are plotted in blue.
by substantial contributions from both high runoff anomalies and reduced winter accumulation (Tedesco et al. 2011). Figure D.5b shows the daily time series of the cumulative SMB for 2010, 2011 and 2012, as well as for the 1958 – 2011 mean. The graph shows that the accumulated mass during winter in the case of 2010 was lower than that in 2011 and 2012 and highlights the relatively steep slope of the cumulative SMB starting around day 192 (10 July) 2012 (linear regression between day 192 and day 246 of -7.69±0.2 Gt yr\(^{-1}\) day\(^{-1}\), \(R^2 = 0.99\)) with respect to 2011 (-5.4±0.2 Gt yr\(^{-1}\) day\(^{-1}\)) and 2010 (-5.15±0.13 Gt yr\(^{-1}\) day\(^{-1}\)). Figure D.6b shows the map of SMB anomalies for the 2011-2012 hydrological year simulated by MAR. SMB was below the average over the entire ice sheet with relatively low values in the ablation zone of the west and southeast regions. Simulated meltwater production for June through August (JJA, Figure D.6c) was also above the average over the entire ice sheet, with relatively high values (e.g., between 200 and 400 mmWE yr\(^{-1}\)) at high elevations in south Greenland. Snowfall was considerably lower than normal in south Greenland for the JJA period of 2012 (Figure D.6d), as a result of abnormal anticyclonic conditions (discussed later). The relative lack of snowfall during summer (combined with sunnier than normal conditions resulting from the position of the anticyclone) was likely responsible for maintaining a low albedo during the entire summer in southern Greenland, further enhancing melting in this area. The reduced snowfall in the southeast is also due to the fact that a larger part of precipitation in the summer of 2012 fell as rain rather than as snow (not shown here), due to warmer conditions.

D.4.4 Albedo

MODIS results indicate that the ice-sheet-wide average albedo for JJA 2012 was the lowest since MODIS began collecting data with a value of 0.684 (vs. a value of 0.750 in year
decreasing by 6.6% between 2000 and 2012 and with a linear fit suggesting a -6.4 ± 0.8% change. The degrading MODIS instrument sensitivity identified by Wang et al. (2012) introduces the possibility that the declining albedo trends may be erroneous. However, Box et al. (2012) discounted this problem through comparison of the MOD10A1 data with ground observations from sites distributed around the ice sheet and spanning 11 yr. Figure D.7 shows the MODIS JJA 2012 albedo anomaly map with respect to the 2000-2011 mean. Figure D.7b shows the 2012 JJA albedo anomaly (with respect to the 1979-2011 baseline) obtained from MAR. Differences between Figures D.7a and b can be attributed to the intrinsic differences between the two approaches, to the different baseline periods, and the spatial resolution of the two datasets. Nevertheless, both maps consistently indicate a decrease in albedo in 2012 with respect to previous years, especially along the southwest coast of Greenland. A preliminary analysis reveals an agreement between MAR and MODIS albedo of within 0.1, with a slight positive MAR bias of <0.1 over the center of the ice sheet. The time series of the 2012 albedo simulated by MAR, together with the 1958 – 2011 mean and the absolute daily minimum albedo over the 1958 – 2011 period, are plotted in Figure D.7e. MAR suggests that in 2012 the albedo over Greenland was below average, reaching new record low values in July and experiencing close-to-record values for most of August, with the exception of a short period at the beginning of August after a snowfall event.

D.4.5 Total mass change from GRACE

Results from GRACE reveal record 2012 GrIS mass loss, occurring in concert with the record observed and modeled surface temperature, albedo, and SMB anomalies indicated above. Figure D.8 shows the cumulative mass anomalies (CMA) from GRACE through September 2012
Figure D.7.  

a) JJA MODIS albedo anomaly map following Box et al. (2012) for 2012 (using the 2000 – 2011 mean). MODIS data are re-projected onto MAR grid for graphical consistency purposes. 

b) JJA MAR albedo anomaly map for 2012 (with respect to the 1958 – 2011 period). 

c) Same as Fig. D.6e but for albedo.
Figure D.8. Cumulative mass anomaly from GRACE updated through September 2012 (Gt).

over Greenland. The differences between the September and June CMA values and September through September are reported in Table D.3. The fixed period for the hydrological year allows changes in mass over the same length of time to be compared, but can also result in changes from one season being attributed to an adjacent season. GRACE did not deliver a June value in 2003 or 2011. For those years, we used the May value instead, but we modified that value by adding the average difference (13 ± 40 Gt, where ± 40 is a 2σ uncertainty estimate) between June and May for the 8 yr (2004-2010, and 2012) in which both values were given. The error on the summer CMA results are computed by smoothing the monthly CMA values, subtracting that difference from the unsmoothed values, and computing the 2σ scatter of the residuals. Figure D.8 and Table D.3 show that when compared with all years during 2003-2012, 2012 set new records in terms of summertime and annual mass loss, with a mass change between June and August of
Table D.3  Summer and annual mass changes from GRACE for the period 2003 – 2012.

<table>
<thead>
<tr>
<th>Year</th>
<th>Summer mass change [Gt]</th>
<th>Hydrological year</th>
<th>Annual mass change [Gt]</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>-335±91</td>
<td>2006 – 2007</td>
<td>-325±91</td>
</tr>
<tr>
<td>2008</td>
<td>-345±91</td>
<td>2008 – 2009</td>
<td>-218±89</td>
</tr>
<tr>
<td>2009</td>
<td>-383±91</td>
<td>2009 – 2010</td>
<td>-423±92</td>
</tr>
<tr>
<td>2010</td>
<td>-516±94</td>
<td>2010 – 2011</td>
<td>-319±91</td>
</tr>
<tr>
<td>2011</td>
<td>-435±122</td>
<td>2011 - 2012</td>
<td>-575±95</td>
</tr>
<tr>
<td>2012</td>
<td>-628±96</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

-628 ± 96 Gt, approximately 2σ below the 2003-2012 mean of -414 Gt. The previous record was set in 2010, with a summer CMA value of -516 ± 94 Gt, which lays ~ 0.8σ below the mean. The summer mass change values have been growing steadily more negative over the GRACE period of observation. The trend of those values during 2003-2012 is -29 ± 11 Gt yr⁻¹. That trend reduces to -20 ± 13 Gt yr⁻¹ if the summer of 2012 is excluded, which is a consequence of the fact that the 2012 summer mass loss was anomalously large, even after factoring in the steady increase in summer mass loss that has been occurring in recent years. In terms of annual loss (e.g. from mid-September to the successive mid-September) the 2012 loss was -575 ± 89 Gt (~ 2σ below the mean), also setting a new record, exceeding the previous record set in 2010 of -423 ± 89 Gt (~ 0.7σ below the mean). As shown by Sasgen et al. (2013), the 2012 mass balance anomaly is fully explained by anomalies in SMB and not likely in ice dynamics.

The uncertainties of the summer and yearly CMA results are computed by smoothing the monthly CMA values, subtracting that difference from the unsmoothed values, and computing the 2-sigma scatter of the residuals. For the summer 2003 and 2011 results, we also add the
uncertainty caused by using May values instead of June values. We add (in quadrature) this uncertainty determined by the scatter in the time series, to the uncertainty caused by errors in the scaling factor (see above), to obtain the total uncertainty.

D.5 Discussion

The analysis of both modeling and satellite data indicates that the 2012 melt season started at the end of May with a warm event that was not enough to completely remove the 2011 – 2012 winter accumulation in the ablation area, with the modeled bare ice exposed area remaining relatively low (See Figure D.9). From mid-June to the beginning of July, there was a succession of warm episodes that increased melting and decreased albedo, but large areas in the ablation area still remained covered by the winter snowpack. Around 10 July, an anticyclonic ridge inducing one of the warmest conditions over the past 50 yr contributed to the melting of most of the winter accumulation, exposing large bare ice regions in the ablation zone (seen as an increase in bare ice in Figure D.9). This event reduced the ice sheet albedo (Figure D.7) and induced the highest daily-modelled meltwater production in the past 50 yr (Figure D.6). A fourth melt event occurred at the end of July 2012, melting the fresh snow accumulated around 20 July and favouring the reduction in the albedo again. These two events have been recorded in the near-surface temperature at Summit (Nghiem et al. 2012). In general, the reduction of the albedo can be attributed to grain size metamorphism (e.g., constructive metamorphism reduces albedo through bounding of smaller grains) as well as bare ice exposure and ablation area melt water ponding. From Figure D.7 it is possible to observe that low negative albedo anomalies occur along the coastal areas corresponding to those regions where bare ice was exposed. In addition to the time series of the 2012 bare ice exposed area simulated by MAR, Figure D.9 shows the 1958 – 2011 mean and the absolute daily maximum bare ice area over 1958 – 2011. A comparison between
Figures D.9 and D.7 reveal a clear relationship between the MAR modelled albedo reduction for

**Figure D.9.** Same as Figure D.6e but for the daily bare ice extent (where the snow density is higher than 900 kg/m$^3$) in percentage of the GrIS area from MAR.
July and August and the simulated increase of the bare ice area exposed. This is the consequence of the increased melting on one side, but also of the reduced solid precipitation along southwest Greenland that characterized summer 2012 (as a consequence of the discussed anticyclonic, e.g. dry and warm, conditions).

In a synthetic sensitivity experiment, we tested the hypothesis that the simulated record of bare ice exposure might have been pre-conditioned by previous recent melting record years (e.g., 2010 and 2011). The removal of the seasonal accumulation from the previous years might indeed allow a premature exposure of bare ice, once the 2011–2012 winter accumulation melted in June 2012. We replaced MAR snowpack state variables for the top 10 meters (density, temperature, grain size, etc.) on 1 May 2012 with those from 1 May 1997 (when previous summers, in particular 1996, were particularly wet and cold). The results of those simulations obtained using the May 1997 snowpack conditions are reported as green lines in Figure D.6e, Figure D.7c and Figure D.9. Figure D.10 shows, as an example, the differences between the firn mean density and temperature in May 1997 (a,b) and May 2012 (c,d). The SMB rate in 1996 was one of the highest over the last two decades due to heavy snowfall and a cold summer. The bare ice extent during summer 2012 was larger than that in 1997 because it was inherited from the previous warm summers 2007-2011 when previous maxima of bare ice extent have been recorded (Box et al. 2012). The outputs indicate that with these new initial conditions for the snowpack (e.g., May 1997) the run-off rate (resp. meltwater production) is reduced by 20% (resp. by 10%) compared to the case when the original snow conditions from May 2012 were used. The decrease in run-off is greater because run-off of meltwater occurs mainly above the bare ice area. These results indicate that pre-conditioning of the snowpack from previous summers contributed in part to the record melt events of 2012.
Figure D.10. Mean density (kg/m$^3$, top figures) and mean snow temperature (°C, bottom figures) within the first two meters of snow simulated by MAR on 1 May 1997 (a,b) and 1 May 2012 (c,d).
Figure D.11. 700mb geopotential height (m) and wind anomaly for June, July and August 2012 from the NCEP/NCAR Reanalysis data.
Melting in 2012 was also considerably higher than normal along the western GrIS coast as a result of the enhanced warm southerly air advection associated with the abnormal persistence of anticyclonic circulation centred in south Greenland. Figure D.11 shows an anticyclonic-like anomaly at 700hPa in the geopotential height (Z700) for JJA 2012 occurring mainly over Greenland, which is not manifest over other regions of the Arctic, indicating a local pattern associated with the North Atlantic Oscillation (NAO). Following Fettweis et al. (2013b), we classified 16% of the JJA days for 2012 as low pressure-like days, 55% as anticyclonic days and 28% as day with a general circulation over Greenland similar to the JJA climatological mean. On average over the period 1958-2011, the NCEP-NCAR reanalysis data (Kalnay et al. 1996) shows that summer has, respectively, about 30±12 %, 20±10 % and 50±10% as low pressure like days, anticyclonic and normal days. The identified frequency of the JJA days classified as anticyclonic during summer 2012 is the highest in 50 years (compared with 2007: 40%, 2010: 33%, 2011: 47%). Figure 3 of Fettweis et al. (2013b) shows the corresponding 500hPa geopotential height for the three types of circulation as well as the temperature anomalies at 700hPa induced by these circulation types. As shown in that figure, the JJA run-off amount simulated by MAR (forced by the ECMWF reanalysis) is highly correlated with the JJA mean temperature at 700 hPa (T700) over Greenland. As for melt, T700 in summer 2012 was the highest in the previous 50 years. Daily analogues JJA circulations taken over 1961-1990 explain 55±5% of the T700 anomaly in 2012. We refer to Fettweis et al. (2013b) for more details about the analogue flows methodology and why 1961-1990 is chosen here as a baseline period. The analysis suggests that the abnormal anticyclonic conditions of summer 2012 explain at least 55% of this summer’s T700 anomaly, and ultimately surface melt. The remaining 45% might be, therefore, attributed to a more general long term warming occurring in the Arctic, as discussed by Fettweis et al. (2013b).
The persistent anomalous ridging over Greenland was associated with persistent and anomalously negative North Atlantic Oscillation (NAO) index values. The NAO is the leading mode of low frequency variability in the cool season across the north Atlantic and is a large-scale dipole in atmospheric mass between the subtropical high and the polar low. Negative NAO values are associated with higher pressure and temperature over Greenland (Thompson and Wallace 1998), surface melt extent (Mote 1998; Tedesco et al. 2011), and melt/runoff (Hanna et al. 2013). Negative NAO values have been persistent during summers since 2006, but the summer of 2012 featured the most negative NAO for the period 1950 – 2012 (Figure D.12), based on the NOAA Climate Prediction Center NAO index values (Barnston and Livezey 1987).

In addition to changes in the NAO, recent studies have pointed to persistent changes in early summer Arctic wind patterns for the past decade relative to previous decades, suggesting an enhancement of the so-called Arctic Dipole (AD), enhanced meridional flow across the Arctic for the period 2007 – 2012 and an increase in the Greenland Blocking Index (GBI, e.g., Overland et al. 2012). Should these large-scale atmospheric changes persist, conditions responsible for SMB loss in recent years, including a reduction of snowfall, increasing liquid precipitation and runoff, will also persist, likely leading to increasingly negative values of the SMB.

D.6 Conclusions

Relative to the beginning of the satellite record in 1979, melt in Greenland is now starting about one month earlier at low elevations, with the area subject to melt increasing over 1979-2012 at a rate of between ~ 20,000 and 22,000 km² yr⁻¹ (depending on the algorithm used). The amount and duration of melting at higher elevations has also been increasing, though at a slower rate. In this context, 2012 set new records in terms of melt extent (up to ~ 97 % of the entire ice
Figure D.12. North Atlantic Oscillation (NAO) index from NOAA Climate Prediction Center for June (blue), July (red), and August (green) for the period 1950-2012.
sheet) and duration (up to about two months above the 1979 – 2012 mean for some areas), albedo, modelled bare ice exposure, SMB and runoff, and overall mass loss. Measured mean JJA ice-sheet-wide albedo was the lowest since the MODIS instrument began collecting measurements in 2000. The 2012 SMB anomaly (1958 – 2011 baseline) was ~ -400 Gt yr\(^{-1}\) and the runoff anomaly was 350 Gt yr\(^{-1}\). The cumulative mass anomaly from GRACE indicates values of ~ -628 ± 96 Gt for the summer period and -575 ± 94 Gt for the 2011-12 hydrological year. These anomalies exceed the record anomalies of 2010, when SMB and runoff records were also set.

Large scale circulation patterns (e.g., NAO) and changes in local conditions (e.g. the snowpack heritage from previous summers) have acted in concert to increase SMB losses over previous years, through reduction of snowfall, increasing liquid precipitation and runoff. Premature and longer bare ice exposure was responsible, together with positive surface temperature anomalies, for the enhanced melting, which drove the SMB record in 2012. Anticyclonic conditions observed in recent years persisted in 2012, supporting more melting through the reduction of summer solid precipitation, persistent clear-sky conditions and the advection of warm air from the south, with the role played by the oceanic summer conditions around Greenland appearing to be negligible relative to the effects of the general circulation patterns (Hanna et al. 2013). Warmer temperatures lowered the albedo of snow-covered areas likely through a combination of grain-size metamorphism, bare-ice exposure, and meltwater ponding. Bare ice exposure was pre-conditioned by previous record melting years, through the removal of seasonal snowpack accumulated during the previous years. Should the trend continue for melting, there will be more bare ice exposed sooner and for longer periods, reducing surface albedo and leading to more absorbed solar energy.
Surface mass loss, together with losses from glacial flow, have been driving the recent records in terms of total mass loss identified through GRACE. Drainage basins along the southwest coast are projected to have the highest sensitivity of SMB to increasing temperatures during the 21st century (Tedesco and Fettweis 2012; Fettweis et al. 2013a). For these basins, the global temperature anomaly corresponding to a decrease of the SMB below the 1980 – 1999 average (when the ice sheet was near equilibrium) ranges between +0.60°C and +2.16°C (Tedesco and Fettweis 2012). These are also the basins where positive feedbacks associated with bare ice exposure are projected to be the strongest. Because the CMIP5 general circulation models, used to predict future climate changes, do not project changes of the general circulation in summer over Greenland through this century (Belleflamme et al. 2013; Fettweis et al. 2013a), their outputs do not account for the abnormal anticyclonic circulation resulting from negative NAO conditions that have been observed in recent years and that have been partially driving the enhanced melting and the observed records. Moreover, the MAR model and other RCMs, which have been used to project future SMB changes (e.g. Tedesco and Fettweis 2012), are not currently coupled with ice sheet flow models and, consequently, the impact of increased melting on ice dynamics is not accounted for. This suggests that the projected contribution to sea level rise under different warming scenarios might be underestimated (and the sensitivity to temperature changes might be higher) and points to the need for a synergic continuous monitoring of current changes using multiple tools (e.g., field observations, remote sensing, modelling) and interdisciplinary fields (e.g., a merging of glaciology, hydrology, atmospheric science) to improve future projections of the evolution of the GrIS.
D.7 Acknowledgements

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Appendix E

*Greenland Ice Sheet in State of the Climate 2012*


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The 2012 season in Greenland was characterized by the setting of new records in many of those quantities that were either measured on ground or estimated from remote sensing observations. The duration of melting at the surface of the ice sheet in summer 2012 was the longest since satellite observations began in 1979, and a rare, near-ice sheet-wide surface melt event was recorded by satellites for the first time. Surface air temperatures from long-term meteorological station records since 1873 were the warmest on record for the summer season along western Greenland. The lowest surface albedo observed in 13 years of satellite observations (2000-2012) was a consequence of a persistent feedback of enhanced surface melting and below normal summer snowfall. Field measurements along a transect on the western slope of the ice sheet revealed record-setting mass losses at high elevations also caused by low albedos, and satellite observations indicate new records in terms of summer and annual total mass loss.

Surface melting over the Greenland ice sheet set new records of melt extent and melt index (defined as the number of days on which melting occurred multiplied by the area where melting was detected) for the period 1979 - 2012, according to passive microwave observations (e.g. Tedesco 2007, 2009; Mote and Anderson 1995). Melt extent reached the breaking record
value of ~ 97% on July 11th and 12th (Figure E.1a, Nghiem et al. 2012). The record melt extent value in 2012 was nearly four times greater than the ~25% average melt extent that occurred in 1981-2010. The 2012 standardized melt index (SMI, defined as the melting index minus its average and divided by its standard deviation) was +2.4, almost twice the previous record of about +1.3 set in 2010 (Figure E.1b). According to satellite observations, melting in 2012 began about two weeks earlier than average at low elevations, lasting up to 140 days (20-40 days greater than the mean value) in some areas of southwest Greenland. 2012 anomalies for the number of melting days (defined as the number of melting days in 2012 minus the 1980-2010 average) were up to 27 days in the south and 45 days in the northwest. Areas in northwest Greenland between 1400 and 2000 m a.s.l. (where melting is negligible or sporadic) experienced melting nearly two months longer than the 1981-2010 reference period.

Surface air temperatures from Greenland long-term meteorological stations were characterized by record-setting warm summer months along the west and south of the island and at the ice sheet summit. Unusually cold months occurred much less frequently in space and time. The southeast Greenland station at Tasiilaq recorded the coldest month of June in its record beginning in 1895. The summer (JJA) surface temperature estimated by MODIS averaged over the entire Greenland ice sheet increased +3.4°C between years 2000 and 2012, from an average value of ~−9°C in 2000 to −5.6°C in 2012, with a linear fit suggesting an increase of +2.1±0.7 °C over the 13 last years (Tedesco et al. 2013a). Surface air temperatures at long-term meteorological stations were characterized by record-setting warm summer months, particularly in the west and south of the island and at high elevations. Also, the Greenland Climate Network (GC-Net) automatic weather station at Summit (3199 m above sea level) measured hourly-mean air temperatures above the freezing point for the first time since measurements began in 1996. The melt froze into an ice crust almost 2-cm thick at Summit; such a melt event is rare with the
Figure E.1.  a) Surface melt extent on the Greenland Ice Sheet detected by the SSM/I passive microwave sensor. b) Standardized melting index (SMI) for the period 1979–2012 using the algorithm in Tedesco (2009).
last significant one occurring in 1889 (Nguyen et al. 2012). Seasonally-averaged upper air temperature data available from twice-daily radiosonde observations show anomalous warmth throughout the troposphere in summer 2012 are consistent with an overall warming pattern near the surface between 850 and 1000 hPa. This recent warming trend is seen in the long-term air temperature reconstruction for the ice sheet, which also shows that mean annual air temperatures in all seasons are now higher than they have been since 1840 (Box et al. 2012).

Albedo estimated from spaceborne observations (MODIS) set a new record in 2012. Negative albedo anomalies were widespread across the ice sheet, but were particularly low along the western and northwestern margins in areas in particular in the upper ablation area, overlapping with those regions of extended melt duration. The albedo anomalies across the ice sheet in June-August 2012, when solar irradiance is highest are illustrated in Figure E.2a, together with the area-averaged albedo of the Greenland ice sheet during June-August each year of the period 2000-2012 (Figure E.2b).

Observations of surface mass balance along the K-Transect (located near Kangerlussuaq at 67°N between 340 m and 1500 m above sea level, a.s.l., Van de Wal et al. 2005) indicate that the equilibrium line altitude (ELA, e.g., the highest altitude at which winter snow survives) reached 2687 m a.s.l. (vs. a mean value of 1500 m a.s.l.) and was 3.7 times the standard deviation above the 21-year mean ELA value (van de Wal et al. 2012). K-transect data also show that the surface mass balance along in 2012 was the second lowest since measurements began in 1991. However, a weighted mass balance that includes a site that is above the former ELA indicates that the 2011-2012 mass balance year was the most negative in 22 years. At the highest elevation of 1847 m, almost 350 m higher than the previous ELA of 1500 m, the surface mass balance was estimated to be -74 cm water equivalent. Below 1500 m elevation, surface mass balance values decreased gradually to normal values near the ice margin.
Figure E.2.  a) Summer (JJA) albedo (reflectivity) anomaly in 2012 relative to the 2000-2011 reference period. Data were derived from MODIS observations. b) Area-averaged albedo of the Greenland ice sheet during June-August each year of the period 2000-2012. Data are derived from MODIS MOD10A1 observations. Figures are after Box et al. (2012b).
2012 set new records in terms of summertime and annual mass loss as estimated from the GRACE satellite mission (e.g., Velicogna and Wahr 2006), with a mass change between June and August of $-627 \pm 89$ Gt, 2 standard deviation below the 2003–2012 mean of $-414$ Gt (Figure E.3, Tedesco et al. 2013a). The previous record was set in 2010, with a summer cumulative mass anomaly value of $-516 \pm 89$ Gt, $\sim 0.8$ standard deviation below the mean. The trend of summer mass change values during 2003–2012 is $-29\pm11$ Gtyr$^{-1}$, reducing to $-20\pm13$ Gtyr$^{-1}$ if the summer of 2012 is excluded, a consequence of the 2012 large mass loss. Annual loss in 2012 (e.g. from mid-September to the successive mid-September) was $-575 \pm 89$ Gt ($\sim 2$ standard deviation below the mean), also setting a new record, exceeding the previous record set in 2010 of $-423 \pm 89$ Gt ($\sim 0.7$ standard deviation below the mean).

Daily surveys using cloud-free MODIS visible imagery (Box and Decker 2011; http://bprc.osu.edu/MODIS/) indicate that in the year prior to end of the 2012 melt season the marine-terminating glaciers collectively lost an area of 297 km$^2$. This is 174 km$^2$ greater than the average annual loss rate of the previous 11 years (132 km$^2$ yr$^{-1}$). Since 2000, the net area change of the forty widest marine-terminating glaciers is -1775 km$^2$. Glaciers in northernmost Greenland contributed to half of the net area change. In 2012, the six glaciers with the largest net area loss were Petermann (-141 km$^2$), 79 glacier (-27 km$^2$), Zachariae (-26 km$^2$), Steenstrup (-19 km$^2$), Steensby (-16 km$^2$, the greatest retreat since observations began in 2000) and Jakobshavn (-13 km$^2$). While the total area change was negative in 2012, four of forty glaciers did grow in area relative to the end of the 2011 melt season.
Figure E.3. Cumulative mass anomaly from GRACE updated through September 2012 (Gt).
Appendix F

Ice dynamic response to two modes of surface lake drainage on the Greenland ice sheet


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F.1 Abstract

Supraglacial lake drainage on the Greenland Ice Sheet opens surface to bed connections, reduces basal friction, and temporarily increases ice flow velocities by up to an order of magnitude. Existing field-based observations of lake drainages and their impact on ice dynamics are limited, and focus on one specific draining mechanism. Here, we report and analyse global positioning system measurements of ice velocity and elevation made at five locations surrounding two lakes that drained by different mechanisms and produced different dynamic responses. For the lake that drained slowly (>24 hours) by overtopping its basin, delivering water via a channel to a pre-existing moulin, speedup and uplift were less than half those associated with a lake that drained rapidly (~2 hours) through hydrofracturing and the creation of new moulins in the lake bottom. Our results suggest that the mode and associated rate of lake drainage govern the impact on ice dynamics.

F.2 Introduction

The ablation zone of the Greenland Ice Sheet (GrIS) accelerates each summer due to basal lubrication from surface meltwater that penetrates the ~1-km-thick ice (e.g., Zwally et al. 2002; van de Wal et al. 2008; Bartholomew et al. 2010; Hoffman et al. 2011). Basal sliding appears to be controlled by the rate of water delivery to the bed and the capacity of the subglacial drainage
system to accommodate it; rapid water delivery overwhelms the hydrologic system, leading to high subglacial water pressures, reduced basal friction and enhanced sliding, whereas slow delivery can be accommodated by gradual enlargement of the system, thereby lowering water pressures, increasing friction and reducing sliding (Bartholomaus et al. 2008; Schoof 2010; Pimentel and Flowers 2011).

The cumulation of hundreds of supraglacial lake drainage events on the GrIS each summer (e.g. Selmes et al. 2011; Liang et al. 2012; Howat et al. 2013) affects the seasonal speedup of the ice sheet in two key ways. First, by facilitating hydrofracturing (i.e., the propagation of water-filled cracks to the base of the ice sheet; Weertman 1973; van der Veen 2007; Krawczynski et al. 2009), lakes that drain rapidly may temporarily increase surface velocity five- to ten-fold as a direct result of the fracture opening (Doyle et al. 2013), and by overwhelming the capacity of the subglacial hydrologic system once the fracture reaches the bed, thereby reducing basal friction (Das et al. 2008; Pimentel and Flowers 2011). Second, by opening connections between the surface and the bed, surface water may continue to be delivered to the base of the ice sheet via moulins (Catania and Neumann 2010) where it may continue to reduce friction and enhance sliding through the remainder of the melt season. In this study, we define rapidly draining lakes as those that drain in the order of a few hours.

Although many lakes drain rapidly by hydrofracturing (e.g. Das et al. 2008; Doyle et al. 2013), others appear to drain more slowly by feeding supraglacial streams that, in turn, flow into moulins (Catania et al. 2008; Hoffman et al. 2011; Selmes et al. 2013). We define slowly draining lakes as those draining in less than two days but more than a few hours. The speed at which lakes drain, and therefore the rate at which water is delivered to the ice sheet bed, may be important not only for short-term ice dynamics, but also for velocities measured over longer-term (i.e. summer) timescales (Palmer et al. 2011). Using radar velocity data at a high spatial scale...
resolution, (Joughin et al. 2013) reveal a complex spatio-temporal pattern of 11-day ice velocity, with speedups associated with both fast and slow lake drainage events. However, the relative impact of slowly draining lakes on ice dynamics is yet to be isolated.

Here we report and analyse data collected in the summer of 2011 from five differential Global Positioning System (GPS) stations situated around two supraglacial lakes in the Paakitsoq region, West Greenland (Figure F.1), that drained within two days of one another through different mechanisms. The smaller of the two lakes (Lake Half Moon, ‘LHM’, 69.573 N, -49.805 E, maximum recorded depth, surface area and volume of ~ 1.6 m, 60,000 m² and 200,000 m³ respectively) drained slowly (>24 hours) via an overspill channel to an existing moulin when the water level rose high enough to breach the lowest point of the lake basin (‘overspill’ drainage). Drainage of the larger, deeper lake (Lake Ponting, ‘LP’, 69. 589 N, -49.783 E, maximum recorded depth, surface area and volume of ~5.2 m, 480,000 m² and 1,500,000 m³ respectively) was fast (~2 hours) and occurred through its bottom, following hydrofracturing (‘bottom’ drainage). We analyse and compare the impacts of the two different lake drainage modes on the dynamics of a ~16 km² area of the ice sheet surrounding the two lakes (Figure F.1).

F.3. Data and Methods

Water levels in the two lakes were measured every five minutes by pressure transducers (HOBO®), after correcting for elevation and for barometric pressure fluctuations, measured by a third pressure transducer located less than 1 km from the lakes. Further details of the approach are given by Tedesco et al. (2012). Water levels were converted to volumes using empirically derived depth-volume curves from surface topography data. For this, we used the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM), which has a nominal grid size of 30 m (http://asterweb.jpl.nasa.gov/gdem.asp).
This was smoothed with a 6 x 6 cell median filter to remove small-scale noise then re-sampled to a 100 m resolution using bilinear interpolation (Banwell et al. 2012). Knowing the topography of each lake also allows us to use the water level data to derive surface areas. Cumulative water volume curves were differenced to calculate net water discharge flowing to or from each lake at a five-minute temporal resolution. Uncertainty in calculated lake volumes due to error within the GDEM data was assessed by applying 1000 sets of Gaussian noise with a standard deviation of 13.8 m (MacFerrin 2011) to the raw GDEM data, then smoothing and interpolating the resultant DEM as above. The root mean square errors of sequential volume estimates in the cumulative volume curves were used to derive discharge errors.

The five GPS receivers were installed within 2 km of the two lakes, approximately along flowlines through LHM. Proceeding upglacier, receivers named R1 and R2 were located downstream of LHM and R3, R4, and R5 were positioned upglacier of the lake (Figure F.1). Antennas were mounted on aluminium poles drilled into the ice with a portable steam drill to a depth of 6 m. GPS data were logged every 15 seconds, and positions were determined by carrier-phase differential processing using TRACK software (Chen 1998) with the base station KAGA (25 km to the south) as a reference and final International GNSS Service satellite orbits. Each 15-second GPS time series was re-sampled to a six-minute interval, and a 1-hr moving average was then applied to reduce the sidereal noise, following the methods of Hoffman et al. (2011). The short filter width of 1 hour used here provides a pre-drainage velocity standard deviation ranging between 25 and 35 m yr$^{-1}$ (depending on the rover). Though noisier, a short filter allows for higher precision of the timing and magnitude of the high signal drainage events. The position data were used to generate velocity time-series averaged over 1-hour time windows and posted at six-minute intervals. The recorded peak speed during the drainage of the two lakes are at least
Figure F.1. Location of the lake pressure sensors and GPS receivers on the west margin of the GrIS. LANDSAT image (17 June 2011) overlaid with the annual mean ice velocity vectors from Joughin et al., 2010 and locations of the two pressure sensors (red squares) and five GPS receivers (coloured circles, R1 through R5) at Lake Half Moon (LHM) and Lake Ponting (LP). The location of Half Moon Moulin is shown as a yellow star.
four times greater than the pre-drainage speed standard deviation in the case of both drainage mechanisms.

F.4. Results

F.4.1 Overspill drainage of Lake Half Moon

Water pressure records indicate that LHM filled in less than three days, reaching a maximum depth of 1.6 m at our sensor at 22:10 (UTC) on 16 June 2011 (Figure F.2a) and a maximum estimated volume of ~ 200,000 m³ (Figure F.2b). Thereafter, the lake level began to decline slowly and at a declining rate, with an average net discharge of 1.4 ± 5.2 m³ s⁻¹ and a peak net discharge of 2.9 ± 6.5 m³ s⁻¹. The water pressure record ends 22 hours and 15 minutes later at 20:25 on 17 June 2011 when the lake level dropped below our sensor. From daily visual inspection of the lake, we know the lake level continued to drop very slowly until at least 26 June 2011 when we left the site. Water draining from LHM flowed in an existing channel incised into the ice surface to a moulin located ~700 m down glacier (Figure F.1). Initially, drainage was relatively rapid due to the observed removal of the previous winter’s snow from the channel via a series of slush flows. Drainage then declined at an exponential rate as the hydraulic head between the lake and the moulin dropped.

In association with the slow drainage of LHM, the ice velocity at our GPS stations increased from baseline values of ~90–100 m yr⁻¹ to a maximum of ~420 m yr⁻¹ (Figure F.3a), with flow trajectories remaining largely unaltered (Figure F.4) and velocities increasing in an east-west (downglacier) rather than a north-south (transverse) direction (Figure F.5a and b). The onset of the speedup began with the upglacier station R5 and proceeded downglacier. All stations started to accelerate before the lake level began to fall, with the acceleration of R5
Figure F.2. Time series of a) measured lake depths recorded by the pressure sensors resting on the lake bottoms and b) estimated lakes volumes. Blue and red lines refer, respectively, to the Lake HalfMoon (blue) and Lake Ponting (red) data.
Figure F.3. Dynamic response of the GPS receivers associated with the two lake drainage events. a,b) elevation (dashed lines) and horizontal speed (continuous lines) for the five receivers for two periods including the drainage of Lake Half Moon (a) and Lake Ponting (b). For convenience, the time series of the lake depth recorded by the pressure sensors are also reported. Blue shaded areas indicate the period when the drainage was recorded by the sensors in the lakes.
Figure F.4. Changing position of the GPS receivers over those periods including the two lake drainage events. East-west and south-north relative positions for the days 16 - 20 June 2011. Note the trajectories of flow are from right to left in this figure.
Figure F.5. North-south (a,c) and east-west (b,d) velocities (m/yr) estimated from GPS measurements collected during the drainage of Lake Halfmoon (a,b) and Lake Ponting (c,d). Note that scales on the y-axis are different for the four panels.
beginning ~3 hours before the onset of the lake level drop. Water was, however, observed to be entering the moulin at this time. The amplitude of the acceleration was highest for station R5 (a ~four-to-five-fold increase on the pre-drainage velocity), and decreased down glacier. After the level of LHM stabilized on 17 June and before drainage of LP began late on 19 June, velocities were ~160-170 m yr\(^{-1}\), over 50% above pre-drainage velocities (Figures F.3a, F.5a, F.5b). A gradual and uniform increase in elevation (~0.1 m over 45 hours) was recorded at all stations, beginning with initial speedup and continuing after completion of the drainage (Figure F.4a). We named this draining mechanism ‘overspill draining mechanism’ and a sketch is reported in Figure F.6.

**F.4.2 Bottom drainage of Lake Ponting**

Lake Ponting reached its maximum depth of 5.2 m at our sensor in six and half days at 14:35 on 19 June 2011 (Figure F.2a) and a maximum estimated volume of ~ 1,500,000 m\(^3\) (more than six times greater than the volume of LHM, Figure F.2b). In contrast to the relatively slow drainage of LHM, LP subsequently drained completely in two hours and ten minutes (Figure F.2), with an average net discharge of 166 ± 31 m\(^3\) s\(^{-1}\) and a peak net discharge of 586 ± 19 m\(^3\) s\(^{-1}\). Frames from a time-lapse sequence of the drainage are shown in Figure F.7 (a-f). The rapid increase in LP’s depth/volume seen at ~12:00 on 18 June 2011 was due to the overflow of an upstream lake into LP (Figure F.7g) and therefore the overall enlargement of LP’s catchment (Banwell et al. 2012).

Reconnaissance of the LP basin shortly after drainage revealed a recently formed northwest-southeast trending fracture (~600 m long, ranging from a few centimetres to several meters wide, Figure F.8a) that ran along the former lake bed, centred on what would have been its deepest part. Numerous ice blocks, several meters in size, lay close to the fracture (Figure
F.8b) and six moulins were found along it, ranging in size from a few meters to ~10 m in diameter (Figure F.8c). The blocks had been observed floating on the lake during the initial phase of the drainage, but before we had set up our time-lapse camera (Figure F.7). Overall, the evidence suggests that LP drained through its bottom by hydrofracture, that the ice blocks were plucked from the fracture, floated temporarily due to buoyancy and then became grounded nearby as the lake level dropped, and that the moulins were produced as water flow concentrated in places along the fracture during and immediately after the drainage event. We named this draining mechanism ‘bottom draining mechanism’ (Figure F.6).

Compared to the relatively slow drainage of LHM, the faster drainage of LP had a larger, more immediate impact on ice velocities and elevation (Figures F.3b) and displayed a more spatially variable ice dynamic response across our GPS station network (Figures F.4, F.5c, F.5d). In contrast to the velocity response following LHM drainage, downstream stations R1 and R2 responded first to LP drainage, and reached greater peak velocities of 1500-1600 m yr\(^{-1}\) (~ a ten-fold increase on pre-LP-drainage velocities and ~ a fifteen-fold increase on pre-LHM-drainage velocities, Figure F.3b, F.5d). The initial acceleration of station R1 followed the onset of LP drainage by 10 minutes, and was followed by acceleration of R2 ~20 minutes later. The remaining stations accelerated concurrently ~30 minutes after R2 accelerated, reaching peak velocities of 270 to 370 m yr\(^{-1}\). All stations reached peak velocities around 17:00 on 19 June 2011, fifteen minutes after LP finished draining. Unlike observations during the drainage of LHM, all stations temporarily changed flow direction to varying degrees towards the south during the drainage of LP (Figure F.4) and velocities showed a strong north-south (transverse) as well as an east-west (downglacier) component (Figure F.5 c, d). Rapid increases in elevation were recorded at all stations, peaking between 20:00 on 19 June and 01:00 on 20 June 2011.
Figure F.6. Schematic representation of the two types of lake drainage, “overspill-drainage” and “bottom-drainage” and their different dynamic responses.
Figure F.7. a) - f) Frames of the time-lapse photographic sequence of the Lake Ponting drainage  g) details of f) showing the blocks in Figure F.6b and the flow generated from the overspilling of a lake upstream Lake Ponting and responsible for the quick increase in lake depth before its drainage (see Figure F.2).
Figure F.8. Drainage features at the bottom of Lake Ponting a few hours after the drainage event. (a) Extensional fracture looking southeast towards the ice blocks. (b) Large ice blocks lying close to the fracture that had been plucked from it during lake drainage. (c) The largest of five moulins that lay on the fracture, looking southeast, with a diameter of ~ 10 m.
(Figure F.3b). Stations R1 and R2 reached maximum uplift of ~0.20 m, R3 and R5 reached maximum uplift of ~0.10 m, and peak uplift at R4 was ~0.05 m. Post-drainage velocities were on the order of 300-350 m yr$^{-1}$, nearly twice as high as pre-drainage velocities, which were already nearly twice as high as baseline velocities prior to LHM drainage.

**F.5. Discussion**

Through the opening of local surface-to-bed connections, the drainage of both LHM and LP caused increases in the local ice velocity, at least temporarily, from the relatively slow pre-drainage velocities. The drainage events also induced changes in vertical motion from downward movement associated with bed-parallel flow to upward movement. The evidence suggests, therefore, that in each case the surface water drained to and immediately exceeded the capacity of the subglacial drainage system (e.g. Hoffman et al. 2011). We interpret the evidence in terms of hydraulic jacking within basal cavities and increases in basal sliding. Fractures from elastic plates loaded from below typically produce radial fractures on the surface (the higher the stress, the greater the number of radial fractures) (Figure 1 of Beltaos 2002). We suggest that water-filled cavities forming beneath the ice sheet uplifted the ice and that the main northwest-southeast fracture which we observed at LP formed along the long-axis of this temporary water body. That velocities remained higher after each drainage event than before, suggests that the hydrologic system remained water filled and operated at higher pressure than before drainage, likely in response to the continued flow of water into the respective moulins. Peak velocities during both events occurred during the maximum uplift rate, shortly after lake drainage began, rather than when the capacity of the subglacial drainage system had reached a maximum, showing that changes in water storage are more important in driving velocity increases than the magnitudes of inputs (Iken 1981; Bartholomaus et al. 2008; Schoof 2010; Bartholomew et al. 2012), similar to
observations and modelling of valley glaciers during ‘spring events’ (Iken et al. 1983; Mair et al. 2003), and the drainage of other lakes on the GrIS (Das et al. 2008; Hoffman et al. 2011; Pimentel and Flowers 2011; Doyle et al. 2013).

The rapid drainage of LP generated a greater, but more spatially variable ice dynamic response across our GPS network than the slower drainage of LHM. During LP drainage, the speedup and uplift at R1 and R2 were about twice as large as those associated with LHM drainage, although the response at the other three stations was more muted and of similar magnitude to that which occurred during the drainage of LHM (Figures F.3, F.5). Even though the drainage of LHM occurred first, and therefore the water likely impinged on a lower capacity subglacial hydrologic system than existed when LP drained, the rapid drainage of LP still produced a larger ice dynamic impact.

Another difference between the two drainage events concerns the spatial pattern of displacement at each GPS receiver. The slow LHM drainage caused minor (<20°) adjustments in flow directions that were maintained subsequently through the rest of the GPS record (Figures F.4, F.5a and b). We interpret this in terms of lasting changes to the spatial distribution of basal friction caused initially by the first arrival of surface water to the bed, but maintained thereafter by continued input of water via the moulin. In contrast, the initial displacements of all receivers during the fast LP drainage show large deviations from their pre-event trajectories to the south, away from LP, with R1 and R2 moving in a transverse direction by ~0.1 m over the course of a few hours (Figures F.4, F.5c and d). A substantial fraction of this motion is subsequently recovered with northward motion. This is consistent with observations of Doyle et al. (2013) who interpreted this type of motion in terms of fracture opening and closing during and immediately after rapid lake drainage. Thus, a substantial component of the initial increased ice velocities
associated with the rapid drainage of LP is temporary, lateral displacement and not associated with increased longitudinal downglacier displacement. Thereafter, displacement is predominantly downglacier along trajectories that are slightly modified compared with those that existed previously (Figure F.4). As with the LHM drainage, we interpret this in terms of enduring changes to the spatial distribution of basal friction caused by the water from the lake drainage and continued input via the moulins.

Although the dynamic response to the slow LHM drainage was relatively uniform across the GPS network, there was some anomalous behaviour. The receivers began to accelerate prior to the initial drop in LHM water level. However, observations in the field showed that water was already entering the moulin prior to LHM attaining its peak water level at 22:10 (UTC) on 16 June 2011. We suggest that the receivers responded to the arrival of surface water at the bed at around 19:00 but that lake levels continued to rise up to 22:10 as water inputs to the lake exceeded the capacity of the snow-filled surface channel between the lake and the moulin to discharge the water.

That the acceleration began with the station furthest upglacier (R5) and proceeded downglacier past LHM is also puzzling. We considered the possibility that the receivers responded to a lake drainage event higher up on the ice sheet prior to the acceleration at R5, but an analysis of daily MODIS imagery shows no evidence for this. We suggest that despite its greater distance from the LHM moulin, R5 may have accelerated prior to R4 and R3, with R2 and R1 accelerating last because it lay closer to the flowline passing through the LHM moulin with the other receivers lying progressively further away from the flowline. This suggestion has some support from the dynamic response associated with LP drainage as outlined below.

The dynamic response to LP drainage is greatest for the receivers lying closest to the flowline passing through LP than for those lying further away, suggesting flow coupling between
the location where surface water reaches the bed and the surrounding ice has directional dependence. All five stations are approximately 2 km from LP (Figure F.1), yet stations R1 and R2, which lie on a flow line almost directly down glacier from LP, accelerate earlier and by greater amounts than the other stations (Figures F.3 through F.5). This suggests that the delayed, muted response of stations R3-R5 is caused by acceleration of the ice along the flow line dragging the adjacent ice by lateral shear stress coupling. Due to this directionally-dependent dynamic response, individual point observations of speedup associated with lake drainage (e.g. those using GPS) may show bias.

Our study has provided observational evidence for two discrete mechanisms of lake drainage, each with differing ice dynamic impacts. Thus, the assumption that all lake drainages are due to the previously well-described rapid bottom draining mechanism may result in an overestimation of the resultant ice dynamic effect at both short and seasonal time scales (because lakes that drain by the slower overspilling mechanism appear to have a more muted dynamic impact). In fact, previous studies have identified that rapid drainage is a small fraction of all drainages. In a study of supraglacial lakes detectable in MODIS imagery across the entire GrIS over five years, Selmes et al. (2011) found that only 13% of drainages occurred over less than two days, with the southwest and northeast regions of GrIS having higher rates of fast lake drainage than the rest of the ice sheet. Slow drainage, by contrast, accounted for 34% of lake drainage events over the same period (Selmes et al. 2013). Similarly, Liang et al. (2012) found that less than 20% of lakes drain faster than 0.5 km$^2$ d$^{-1}$ in a MODIS-based study in western Greenland. In an analysis of a network of nine GPS stations in western Greenland, Hoffman et al. (2011) were able to identify speedups associated with only 17% of lake drainages identified in the region from satellite imagery. Thus, the hydrofracture-induced rapid drainage mechanism appears to be relatively rare (Selmes et al. 2011; Liang et al. 2012) consistent with the
observation that lake drainage associated speedups account for <5% of all summer ice motion (Hoffman et al. 2011).

Slow draining lakes are unable to provide a rapid delivery of water to the ice sheet bed. Because the capacity of the subglacial hydrologic system adapts to steady inputs, slow drainage events theoretically will induce less sliding than pulsed inputs (Bartholomaus et al. 2008; Schoof 2010; Bartholomew et al. 2012), highlighting the importance of distinguishing between these two modes of surface lake drainage. Some lakes have different drainage speeds, and therefore presumably different modes, from year-to-year, and predicting which mode of drainage a particular lake will be subject to appears difficult. However, deeper lakes and those whose basins intersect extensional stress regimes in the ice would theoretically be more likely to experience hydrofracture and bottom drainage (e.g., Krawczynski et al. 2009).

F.6. Conclusions

Our measurements indicate that the impact of surface lake drainage on GrIS dynamics depends on the drainage mechanism (Figure F.6): either i) relatively slow (>24 hours) overspill drainage via an existing channel to an existing moulin; or ii) relatively rapid (~2 hours) bottom drainage via hydrofracture and the creation of new moulins. The overspill draining lake resulted in less speedup (four-to-five-fold vs. fifteen-fold compared to pre-drainage speeds) and uplift (0.1 m vs. 0.2 m) than the bottom draining lake, despite the fact that the overspill drainage occurred first, and therefore likely impinged on a lower capacity subglacial hydrologic system than existed after it drained. Due to the muted dynamic response associated with the overspill drainage mechanism, we caution against extrapolation of the dynamic response of draining by the previously-studied bottom-draining mechanism (e.g., Das et al. 2008; Doyle et al. 2013) to all lake drainages on the GrIS. Our observations also indicate spatially variable ice dynamic
responses, presumably due to differences in flow coupling in both the longitudinal and lateral directions. Care should be taken in interpreting point measurements of ice velocity associated with lake drainage, for example, by GPS receivers.

As evidence suggests that fast drainage events account for a relatively small percentage of total lake drainage events on the GrIS (e.g., Selmes et al. 2011; Liang et al. 2012), we suggest that the potential contribution of the slower drainage mechanism to seasonally averaged ice velocities may actually be higher than that associated with the rapid drainage mechanism. However, as both drainage mechanisms act to open up surface-to-bed connections (i.e. moulins), which can remain open for the rest of the melt season, both drainage mechanisms have the potential to enable diurnally varying meltwater inflow to access the bed for the remainder of the melt season (Banwell et al. 2013). It is this variability of water delivery to the bed, rather than the absolute magnitude, which is thought to have more of a significant influence on sliding speeds; thus the greater the number of open moulins the higher the potential for diurnal variations in velocities and overall summer enhancement of flow (Schoof 2010; Bartholomew et al. 2012).

F.7 Acknowledgements

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Appendix G

Comparison of Albedo and Surface Mass Balance Simulated by Different Versions of the MAR Regional Climate Model

In this Appendix, I provide a brief discussion of changes in simulated albedo and SMB that have occurred across different versions of the MAR model. Two versions of MAR, v3.2 and v2.0 are used in the analysis presented in Chapter 2. In Chapter 2 we discuss differences in simulated albedo and SMB between MAR v2.0 and MAR v3.2. The albedo of MAR versions 3.2 and 2.0 mainly differs as a result of the differences in the parameterization of bare-ice albedo. As noted in Section 2.2.2, bare ice albedo in MAR v2.0 is assigned a fixed value of 0.45, while in MAR v3.2, albedo ranges between 0.45 and 0.55 as a function of meltwater production at the ice sheet surface. This results in a substantial impact on SMB, as shown in Figure 2.12. MAR v3.5, used in Chapter 2, is similar to MAR v3.2, but albedo is set to range between 0.40 and 0.55. In MAR v3.5 a correction has also been applied to SMB, to correct for a positive accumulation bias identified by Vernon et al. (2013).

MAR v3.2 and v3.5 also differ from MAR v2.0 in their representation of areas where different surface types may be present within a MAR grid box. In MAR v3.2 it is possible to have a grid box fractionally covered by ice, while in MAR v2.0, each grid box is classified with a single surface type (e.g. ice, tundra, or ocean). This improved representation of sub-grid-scale variability may result in differences in SMB between MAR versions 3.2 and 3.5 for regions along the ice sheet margins that consist of different surface types.

Differences in mean JJA albedo between different MAR versions are shown in Figure G.1. It can be seen that MAR v3.5 albedo is similar to MAR v3.2 albedo. Both MAR v3.2 and
Figure G.1. Differences in mean 2000-2012 JJA cloud-corrected albedo, for (a) MAR v3.2 – MAR v2.0, (b) MAR v3.5 – MAR v2.0, and (c) MAR v3.5 – MAR v3.2. x-marks indicate grid boxes where the difference is not statistically significant at the 95% confidence level.
Figure G.2. Differences in mean 2000-2012 mean SMB (mWE yr\(^{-1}\)) from different MAR versions: (a) MAR v3.2 - MAR v2.0 JJA SMB, (b) MAR v3.5 - MAR v2.0 JJA SMB, (c) MAR v3.5 - MAR v3.2 JJA SMB, (d) MAR v3.2 - MAR v2.0 annual SMB, (e) MAR v3.5 - MAR v2.0 annual SMB, and (f) MAR v3.5 - MAR v3.2 annual SMB.
MAR v3.5 albedo are higher in the ablation areas relative to MAR v2.0, (0.61 ± 0.11 for MAR v2.0 and 0.66 ± 0.09 and 0.69 ± 0.08 for MAR v3.2 and v3.5 respectively; Table G.1) as a result of the differences in simulated bare ice albedo. MAR v3.5 albedo is generally higher than MAR v3.2 albedo in the ablation area, and differences are small in the accumulation area (Figure G.1c). It is not clear why this is, as minimum bare ice albedo in MAR v3.5.1 is set to be smaller than the value for MAR v3.2. It is possible that differences in snow accumulation account for this difference. Temporal variability of albedo, indicated by the standard deviation of albedo (Table G.1), is smaller in magnitude in MAR v3.2 and MAR v3.5, likely as a result of a smaller difference in albedo between snow and bare ice.

The impact of different albedo schemes on spatial patterns of SMB can be seen in Figure G.2. Over the icesheet, spatial differences in SMB coincide with spatial differences in albedo. The relatively high albedo of MAR v3.5 results in the highest SMB for the ablation area of the three model versions (-2.88 ± 3.27 mWe yr\(^{-1}\); Table G.2). The differences are most obvious when only JJA averages are shown (Figures G.2a-c), and are smaller when average values for the year are shown (Figures G.2d-f). This is partly a result of smaller magnitudes of SMB for the annual average (Table G.3), but is also a result the large impact of albedo differences during summer months.

The inclusion of sub-grid-scale ice cover in MAR versions 3.2 and 3.5 results in lower SMB along the periphery of the ice sheet (Figure G.2 and G.3), as these ice covered areas can now experience net annual loss. The differences along the periphery also exhibit high spatial variability (Figure G.2), in part as a result of the inclusion of these fractional ice covered areas.

The results presented in this Appendix show that MAR v3.5 shows relatively high albedo compared with MAR v2.0 and v3.2, especially in the ablation area. This is somewhat surprising,
Table G.1  Mean June July August (JJA) cloud-corrected albedo for the 2000-2012 period, from different versions of MAR, for the entire GrIS as defined by the pixels defined as 100% ice, using the mass balance areas defined in MAR v2.0.

<table>
<thead>
<tr>
<th>Locations</th>
<th>MAR v2.0</th>
<th>MAR v3.2</th>
<th>MAR v3.5.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ice-Sheet wide</td>
<td>0.78 ± 0.04</td>
<td>0.77 ± 0.04</td>
<td>0.78 ± 0.04</td>
</tr>
<tr>
<td>Ablation Area</td>
<td>0.61 ± 0.11</td>
<td>0.66 ± 0.09</td>
<td>0.69 ± 0.08</td>
</tr>
<tr>
<td>Accumulation Area</td>
<td>0.79 ± 0.04</td>
<td>0.78 ± 0.04</td>
<td>0.78 ± 0.03</td>
</tr>
</tbody>
</table>

Table G.2  Same as Table G.1, but for mean JJA MAR SMB (mWE yr⁻¹)

<table>
<thead>
<tr>
<th>Locations</th>
<th>MAR v2.0</th>
<th>MAR v3.2</th>
<th>MAR v3.5.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ice-Sheet wide</td>
<td>-0.14 ± 1.03</td>
<td>-0.07 ± 1.03</td>
<td>0.13 ± 1.00</td>
</tr>
<tr>
<td>Ablation Area</td>
<td>-4.73 ± 3.70</td>
<td>-3.92 ± 3.52</td>
<td>-2.88 ± 3.27</td>
</tr>
<tr>
<td>Accumulation Area</td>
<td>0.20 ± 0.89</td>
<td>0.21 ± 0.85</td>
<td>0.27 ± 0.88</td>
</tr>
<tr>
<td>Greenland Periphery</td>
<td>-0.69 ± 2.55</td>
<td>-1.98 ± 2.57</td>
<td>-1.79 ± 2.38</td>
</tr>
</tbody>
</table>

Table G.3  Same as Table G.2, but for mean annual MAR SMB (mWE yr⁻¹)

<table>
<thead>
<tr>
<th>Locations</th>
<th>MAR v2.0</th>
<th>MAR v3.2</th>
<th>MAR v3.5.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ice-Sheet wide</td>
<td>0.26 ± 0.91</td>
<td>0.25 ± 0.91</td>
<td>0.31 ± 0.88</td>
</tr>
<tr>
<td>Ablation Area</td>
<td>-0.81 ± 3.11</td>
<td>-0.67 ± 2.94</td>
<td>-0.26 ± 2.84</td>
</tr>
<tr>
<td>Accumulation Area</td>
<td>0.32 ± 0.52</td>
<td>0.32 ± 0.76</td>
<td>0.34 ± 0.77</td>
</tr>
<tr>
<td>Greenland Periphery</td>
<td>0.00 ± 1.73</td>
<td>-0.33 ± 2.05</td>
<td>-0.25 ± 1.95</td>
</tr>
</tbody>
</table>

as the minimum albedo for MAR v3.5.1 is lower than that of MAR v3.2. A preliminary comparison between K-Transect ablation measurements and MAR suggests that MAR v3.5 underestimates SMB in the ablation area (i.e. it predicts too much ablation relative to the observations; X. Fettweis, Personal Communication). The analysis also shows that the periphery of the ice sheet can play an important role in SMB if fractional ice-covered areas are included in the model. The analysis suggests the need for a more detailed sensitivity study of the impact of errors and biases in various factors on MAR-simulated SMB. In particular, it may also be necessary to model the presence of impurities to fully capture spatial variations in albedo indicated by satellite data as discussed in Chapter 2.


——, V. V. Salomonson, and G. A. Riggs, 2012: MODIS/Terra Snow Cover Daily L3 Global 500 m Grid, Version 5. [Tiles h15v02, h16v02, h17v02, h16v01, h17v02, h16v00, h17v00].


