Improving Greenland surface mass balance estimates through the assimilation of MODIS albedo: a case study along the K-transect

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Key Points:

- A data assimilation technique was used to improve the simulated estimation of the surface mass balance of the Greenland ice sheet along the K-transect stations.
- A particle batch smoother technique was used to condition the prior estimates of surface mass balance on MODIS-derived albedo.
- Results show that data assimilation techniques can be used to reduce uncertainty of the modeled surface mass balance estimates.

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Abstract

Estimating the Greenland Ice Sheet (GrIS) surface mass balance (SMB) is an important component of current and future projections of sea level rise. Given the lack of in situ information, imperfect models, and under-utilized remote sensing data, it is critical to combine the available observations with a physically based model to better characterize the spatial and temporal variation of the GrIS SMB. This work proposes a data assimilation framework that yields SMB estimates that benefit from a state-of-the-art snowpack model (Crocus) and a 16-day albedo product. Comparison of our results against in-situ SMB measurements from the Kangerlussuaq transect shows that assimilation of 16-day albedo product reduces the root mean square error (RMSE) of the posterior estimates of SMB from 1240 millimeter water equivalent (mmWE/yr) to 230 mmWE/yr and reduces the bias from 1140 mmWE/yr to -20 mmWE/yr.

Plain Language Summary

Diagnosing the surface mass balance (SMB) of the Greenland Ice Sheet (GrIS) is a critical objective, which, despite its importance, continues to contain large uncertainties from significant errors in modeled precipitation as well as errors related to sub-grid process representation. This work uses a data assimilation framework (which has not been used in estimations of the GrIS SMB) and a satellite-derived 16-day albedo product to improve the estimates of the SMB on the southern Greenland ice sheet. We used the K-transect point-scale SMB measurements to validate our results over the 2009-2010 hydrological year. The data assimilation technique (i.e., particle batch smoother) reduces the spatial root mean square error of SMB over the K-transect stations by 82% from 1240 millimeter water equivalent (mmWE)

to 231 mmWE and bias of the estimates by 98% from 1142 mmWE to -20 mmWE. It was shown that this methodology has the potential to resolve the spatial variability of the surface processes along the K-transect stations and surface albedo which is not resolved by the model at a resolution of 25km. The modularity of the algorithm makes it possible to combine nearly any land surface model with different satellite-based or ground-based measurements.

1 Introduction and Background

The Greenland ice sheet (GrIS) is losing mass through ice discharge from outlet glaciers and surface processes (e.g. meltwater runoff, sublimation, and evaporation). Enderlin et al., (2014) showed that contribution of ice discharge to the total GrIS mass loss has been reduced from 58% during 2000-2005 to 36% during 2005-2009 and 32% between 2009 and 2012. More recently, van den Broeke et al. (2016) showed that surface processes, particularly meltwater, are more important than ice dynamic processes in recent GIS mass changes. Despite the importance of surface mass loss, estimates of GrIS SMB from different methodologies contain significant uncertainties mainly because of the complexities of the ice sheet surface dynamics and nonlinearities of underlying surface mass loss mechanisms.

Given the limitations of observation-based methods (i.e., in situ and remote sensing retrievals), spatially and temporally continuous estimates of surface mass loss fluxes generally require physically based numerical modelling. Some recent efforts (e.g. Larour et al. 2014; Navari et al. 2016) have taken advantage of both models and remotely sensed measurements by combining these two data streams to construct reanalysis estimates of surface mass loss fluxes. In this approach, measurements can be optimally merged with a model using data assimilation techniques, which have proven to be a more robust alternative to deterministic modelling approaches (Margulis et al. 2015).

In this work, a satellite-derived 16-day albedo product is used to update a priori snow/ice model estimates to generate reanalysis estimates of the GrIS SMB and associated spatial variability along the Kangerlussuaq transect (K-transect) stations in west Greenland over 2009-2010. Specifically, we aim to answer the following questions: (1) How much does the ice sheet lose mass through surface processes along the K-transect stations? (2) How do posterior estimates (conditioned on remotely-sensed albedo) compare with the simulation-only estimates and in-situ SMB measurements in the K-transect stations? (3) What is the spatial variability of the SMB along the K-transect?

2 Models and Method

2.1 Regional climate model and snow physical model

We used meteorological outputs from the regional climate model Modèle Atmosphérique Régional (MAR; Gallée and Schayes (1994)) and a stand-alone version of surface mass/energy balance snow physical model Crocus (Brun et al. 1989, 1992) in the data assimilation framework in this study. Aside from the modifications listed below, the model setup and initialization are similar to those used in our previous work (Navari et al. 2016) in which nominal forcing from MAR (version 2, Fettweis et al. 2013) at 25km resolution was used to run Crocus offline for 2009-2010 over the GrIS. We used an ensemble batch smoother data assimilation approach to evaluate the feasibility of generating a reanalysis estimate of the GrIS surface mass fluxes via combining remotely sensed ice surface temperature measurements with a priori estimate from Crocus. Navari et al. (2016) showed that the DA methodology is able to generate posterior estimates of the surface mass fluxes that are in good agreement with the synthetic true estimates.

2.2 Snow model adaptation

Albedo parameterization

The original Crocus albedo parameterization has been described in Brun et al. (1992). Crocus computes snow albedo for three spectral ranges including the visible range (0.3-0.8µm), and two near infrared ranges (i.e. 0.8-1.5µm and 1.5-2.8 µm). As MAR uses a modified version of Crocus snow and ice albedo as described in Lefebre et al. (2003) and Alexander et al. (2014), the original Crocus albedo module was modified here to be more consistent with MAR. The reader is referred to the supporting information (Text S1) for a detailed discussion on modification of the albedo module in Crocus.

2.3 Method (Particle Batch Smoother algorithm)

A Particle Batch Smoother (PBS: Margulis et al. 2015) framework is implemented to assimilate satellite-derived 16-day albedo with prior states to generate posterior state and flux estimates. Unlike commonly used filtering methods, in which states are sequentially updated when a measurement becomes available (e.g., Dumont et al. 2012; Charrois et al. 2016), PBS updates the states in a single step using all measurements in the assimilation window (i.e. one year). By construct, the method provides a historical reanalysis, where state and flux estimates benefit from *all* measurements within the assimilation window. Note that, both the sequential and batch smoother data assimilation techniques use all observations. For a more detailed discussion about the methodology, see the supporting information (Text S2).

3 Study Site and Data

3.1 Study site

The focus of this work is on K-transect stations. Since 1990, SMB measurements (conducted in late August every year) have been carried out at eight locations on the southern Greenland ice sheet, near the town of Kangerlussuaq at different elevations. Among the stations, seven stations (S4, S5, SHR, S6, S7, S8, S9) are located in the ablation zone where the annual surface mass balance is negative and one station (S10) is located in the percolation zone where melt occurs but annual SMB remains positive (van de Wal et al., 2012). Figure 1 shows the location of the K-transect stations and the different GrIS mass balance zones and in-situ SMB measurements at these stations for year 2009-2010 are listed in Table 1. The ablation zone is defined as the region of the GrIS where the annual surface mass balance is negative. The dry snow zone is defined as the region where the mean annual temperature is less than -25^{o} C (based on Crocus model output). The area between the ablation zone and the dry snow zone is considered the percolation zone.

3.2 Data

3.2.1 Satellite-derived albedo data

Albedo plays an important role in controlling the surface mass and energy exchange between the GrIS and atmosphere (van den Broeke et al. 2011; Vernon et al. 2013). Many studies have investigated the impact of the positive ice-albedo feedback and suggested that this mechanism is likely responsible for extensive melt in recent years (e.g., Box et al. 2012, Tedesco et al. 2011, 2016). Given the large impact of albedo on GrIS mass and energy balance, it is critical to extract information contained in satellite-derived albedo measurements to improve the SMB estimates of the GrIS.

The albedo product used in the reanalysis estimate proposed in this work is the MODIS 16-day composite (MCD43B3) dataset available online at https://lpdaac.usgs.gov/. The MCD43B3 product is a high quality combined product using MODIS data from both the NASA Terra and Aqua satellites to provide 1-km albedo. The product algorithm uses atmospherically corrected, cloud-cleared MODIS reflectance data measured over 16-day periods to generate an integrated albedo measurement every eight days (i.e., this product is produced every 8 days with 16 days of acquisition). Using partition coefficients for direct beam and diffuse radiation (Allen et al. 2006), we linearly combined directional hemispherical reflectance (black-sky albedo) and bi-hemispherical reflectance (white-sky albedo) at local solar noon to obtain the true blue-sky albedo which better represents the model generated albedo. Stroeve et al. (2005, 2006) suggested that the quality of albedo products decrease under the condition where the solar zenith angle is larger than 70º. To account for this quality control step, solar zenith angle was computed for all stations over the simulation period and all the observations corresponding to solar zenith angles larger than 70º were removed from the dataset, which accounts for 50% of the dataset. In addition, an aggregation operator was used to map the 16-day albedo from the measurement space of 1 km to the MAR model resolution of 25 km. Figures 2a-d show the albedo map for day of year (DOY) 129, 161, 193, and 225. As can be seen, there is a significant variation in albedo along the K-transect stations. On DOY 129 and 162 (May 9 and June 11) albedo gradually increases with elevation (Figure 2a-b). On DOY 193 and 225 (July 12 and Aug 13), the albedo maps show different patterns (Figure 2c-d). Albedo is higher in the margin of the ice sheet where the first 3 K-transect stations (i.e., S4, S5, and SHR) are located and decreases around -49º longitude and then gradually increases. The irregular variations around -49º are likely driven by snow and ice impurities (e.g., dust, black carbon, and organic material) this area is also called the dark zone (Wientjes et al. 2011). When snow from previous accumulation season covers the impurities, there is a smooth transition between high and low albedo along the K-transect stations (Figure 2a-b). With the advancing melt season, winter snow cover gradually disappears and bare ice with impurities become exposed (Figure 2c-d). Impurities and biological material significantly reduce the albedo and increase the absorbed solar radiation and consequently enhance the magnitude of the snow/ice melt. The albedo gradient (Figure 2) shows an apparent correlation with in-situ SMB measurements at the K-transect stations (Table 1). Therefore, it is reasonable to expect that, MODIS based albedo data would provide useful information for constraining modeled SMB estimates. Previous works by Dumont et al. (2012) and Charrois et al. (2016) showed successful application of albedo within assimilation frameworks.

3.2.2 Model input data

The snow/ice model (Crocus), applied in this study, uses the meteorological data from the hourly MAR output for the years 2009 and 2010 and is run at the same spatial resolution of the MAR data (i.e., 25 km).. Here, the nominal forcings from MAR integration (i.e., precipitation, short wave, long wave, and air temperature) were perturbed to generate the ensemble of meteorological forcing variables. The perturbed MAR based hourly forcings were used as input to the Crocus to generate prior estimates of mass fluxes which are the main components of reanalysis estimates of SMB. For a more detailed discussion about the input data and perturbation technique, the reader is referred to Navari et al. (2016).

4 Experimental design

The model setup and open loop simulation are very similar to that explained in Navari et al. (2016). Hence, for brevity, only the key points are repeated here. In order to adjust the initial states of the snow/ice model to quasi-stationary conditions, a one-year model spin-up was performed with Crocus initialized by MAR, which has been properly spun-up and run from 1979 to 2009. Snow processes in the GrIS ablation zone are very similar to those of seasonal snow, therefore, the spin-up period does not affect the simulation results over the ablation zone. However, in the percolation zone the melt water affects the firn structure and density, which will carry over from one year to the next. Therefore, for a longer simulation it might be more accurate to use a longer spin-up period. A data assimilation analysis was performed for the two-year period from January 2009 through December 2010. The years 2009 and 2010 were chosen because the hydrological year 2009-2010 was characterized by an extreme negative SMB of 2.6 standard deviations below the 1958-2009 average (Tedesco et al. 2011). Moreover, the ice surface temperature (IST) record also shows that the GrIS has experienced a large positive IST anomaly in summer 2010 (Hall et al. 2013).

The measurement error standard deviation dictates how much measurements are trusted relative to the prior estimate of the state variable in the assimilation step. The measurement error standard deviation at the simulation grid resolution (i.e. 25 km) depends (among other factors) on sensor spatial resolution and accuracy. Stroeve et al., (2005) compare the MODIS 16-day albedo measurements with in-situ measurements at the Greenland Climate Network (GC-Net) stations and report a root mean square error (RMSE) of 0.07. Alexander et al., (2014) compared the 16-day albedo product with the GC-Net and K-transect in-situ measurements and report a RMSE of 0.09. However, the range of RMSE error ranges from 0.12 for the S5 station to 0.03 for S10 station. Here, we chose to use white Gaussian measurement errors with a standard deviation of 0.05. We have also run the simulation with a measurement error standard deviation of 0.1. The results (not shown) indicate that the bias and RMSE increase by 40% and 60% respectively.

5 Results

For illustration, representative individual pixels are presented, which allow for an understanding of how the PBS algorithm works. Figure 3a-b shows the time series of prior estimates of albedo, satellite-derived 16-day albedo observations, and posterior estimates of albedo for the year 2010 at the model computational grid cells co-located with the S6-S7 and S9 stations (see Figure S1 in the SI for other stations). The prior estimates are those before assimilation of albedo and posterior estimates are estimates after assimilation of the 16-day albedo product. Both the prior and posterior provide statistical information, which can be used to evaluate the accuracy of the estimates. The median represents the central tendency of estimates and the interquartile range (IQR) can be used to describe the variability of the estimates around the median.

As shown in Figure 3a, the ensemble median of the prior estimates of albedo at the above-mentioned grid cells are higher than the observations over the entire period and the ensemble spread of the prior estimates is very large (i.e, IQR ranges from around 0.4 to 0.85). For the grid cell co-located with the S6 and S7 stations (Figure 3a) the observed albedo decreases from about 0.8 to 0.3 during early May to late July and remains about 0.3 until late August before starting to increase. The median posterior estimate drops from 0.8 to 0.4 in early May to early June and then remains about 0.4 until late August before starting to increase during the accumulation season. The 16-day albedo shows significantly low values due to the snow melt and presence of the liquid water in the snowpack at the beginning of melt season and the exposure of bare ice and surface impurities later in the melt season. This indicates that the satellite sensor is able to capture the evolution of snow processes during the melt season. In addition, it shows that the Crocus albedo module cannot properly model the evolution of albedo due to both errors in the forcing data (e.g. winter accumulation driving the appearance of low albedo zones) and overestimation of the bare ice albedo in Crocus which is a constant value over the whole ice sheet. The PBS actually uses this signal (i.e., the difference between observation and model) to update the prior estimates. Figure 3b shows a similar pattern for grid cells co-located with the S9 station where on average the prior estimates do not simulate appearance of bare ice or dark firn. However, as can be seen by moving toward the higher elevation (from S6 to S9) both the simulated and observed albedo increase. In the grid cell co-located with the S9 station more than 50% of the ensemble members do not show melt; therefore the median of the ensemble remains very high during the summer (Figure 3b). The lower bound of IQR indicates that at least 25% of the ensemble members show considerable melt and cause bare ice with low albedo to become exposed.

As show in Figures 3a-b, by construct, the posterior albedo is closer to the observations. The PBS heavily weights ensemble members that closely fit the observations, while those very far from the observations have reduced weights, which consequently decreases the uncertainty of the posterior estimates. Note that the 2009 time series has not been shown because the melt season for the measurement year 2009-2010 (i.e., September 1st, 2009 to August 31st, 2010) takes place in summer 2010 only.

Figure 3c shows the reanalysis estimates of SMB relative to the prior estimates and in-situ observations at the K-transect stations in the measurement year 2009-2010. The PBS extracts the implicit information contained in albedo measurements to update the prior estimates of SMB at each computational grid cell. Posterior SMB for grid cells covering the K-transect stations were computed by applying the posterior weights to the prior SMB from the Crocus simulations. Then the posterior SMB values from September 1st, 2009 to August 31st, 2010 were compared against the open-loop and in-situ measurements.

At the margin of the ice sheet where the computational grid cell is co-located with the S5 and SHR stations, the PBS improves estimates of SMB relative to the open-loop estimates. The red and blue error bar in Figure 3c represents the uncertainty (IQR) of the SMB estimates for the prior and posterior estimates. Observed SMB at both S5 and SHR stations falls within the uncertainty range of the posterior estimates and the uncertainty of the posterior estimates are clearly smaller than that of the prior estimates. The albedo assimilation provides superior estimates of the SMB at the grid cell that is co-located with S6 and S7 stations. SMB estimates from the assimilation of albedo at the grid cell co-located with the S8 station matches the in-situ measurement. The PBS substantially reduces the uncertainty of the posterior estimates and increases the confidence in model estimates. At the grid cell that encompasses the S9 station the PBS significantly improves the estimate. While the prior estimates show a positive SMB (i.e., accumulation) without appearance of low albedo snowpack in summer, the PBS shows a significant mass loss. However, it slightly underestimates the in-situ SMB measurement. The posterior SMB estimates at the grid-cell co-located with the S10 station matches the measured SMB. Figure 3c also shows the variability of the SMB along the K-transect stations in the ablation and percolation zones. It is evident that most of the surface mass losses take place in the relatively narrow ablation zone areas. Table 1 shows the SMB in mmWE estimates from the open loop and posterior simulation, and in-situ measurement. It should be noted that mmWE and kg/m2 are used interchangeably as the SMB unit.

6 Discussion and Conclusion

In this work a PBS data assimilation methodology was implemented to assimilate the MODIS 16-day albedo product with the a priori estimates of SMB provided by the Crocus snowpack model. Crocus is applied at the MAR regional climate model grid-cell co-located with the K-transect stations for 2009 and 2010. We showed that the PBS is able to reproduce the observed K-transect SMB given the uncertain forcing data from MAR. Grid-scale comparison between the PBS estimates, open loop simulation estimates and in-situ measurements demonstrates the advantages of assimilating the 16-day albedo measurements.

It was hypothesized that the modeled SMB is biased due to the complexities of the surface ice/snow spatial variability, the presence of impurities and nonlinearities of underlying surface mass loss mechanisms. We used the K-transect point-scale SMB measurements to evaluate our results over the 2009-2010 hydrological year. It was shown that the PBS was able to overcome the prior SMB bias by using the information contained in the 16-day albedo to optimally select relevant ensemble members. The PBS significantly reduced the bias by using ensemble members that pass near the observations and weighting them heavily, thereby fitting the observations within the expected measurement error.

A successful application of PBS also depends on prior estimates of the assimilated variable (i.e., 16-day albedo). In other words, if the dynamic range of the prior estimate of albedo is significantly biased or shows unrealistically low bias that does not cover the measurements, then the PBS will fail to find a robust fit, usually by heavily weighting a small number of replicates at the extreme tail of the distribution that are close to the measurements. This was the main reason for increasing the upper limit of the ice-albedo from 0.45 to 0.55 in this study (See Text S1 in the supporting information). This change allows some ensemble members to be able to mimic the integrated observed albedo at 25 km resolution and also adequately covers the measurements.

The results from the assimilation of the 16-day albedo product are promising and estimates from the albedo assimilation capture the evolution of SMB at K-transect stations. The PBS reduces the spatial RMSE of SMB over the K-transect stations by 82% from 1240 mmWE/yr to 231 mmWE/yr and bias of the estimates by 98% from 1142 mmWE/yr to -20 mmWE/yr knowing that the mean K-transect SMB has been -2600 mmWE/yr (see Table 1). However, results from this work are based on a single year experiment and the PBS provided good results for this extreme negative SMB year. We acknowledged that a more robust evaluation of the methodology needs multiple years of evaluation. Finally, it should be noted that point scale measurements may not be adequate to represent a model grid cell of 25 km.

It was shown that assimilating remote sensing data into a snow model is an effective methodology to reduce error and uncertainty in SMB estimates. It was also shown that, this methodology has the potential to resolve the spatial variability of the surface processes along the K-transect stations and surface albedo which is not resolved by the model at a resolution of 25 km. Extending the methodology to the entire GrIS and evaluating the feasibility of directly updating the MAR SMB will be the focus of our future work.

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Table 1: In-situ SMB measurements at the K-transect stations, and the prior and posterior Crocus SMB estimates at the MAR grid cells co-located with the K-transect stations for the measurement year 2009-2010 in mmWE/yr.

	MAR grid cell/K-transect stations						
	S5	SHR	S6	S7	S8	S9	S10
In-situ measurement	-5120	-4390	-2950	-2990	-1930	-1010	200
Open loop	-3390		-1740		-470	260	280
Posterior	-4660		-3010		-1890	-1300	200

Note: the in-situ measurements adapted from van de Wal et al., (2012)

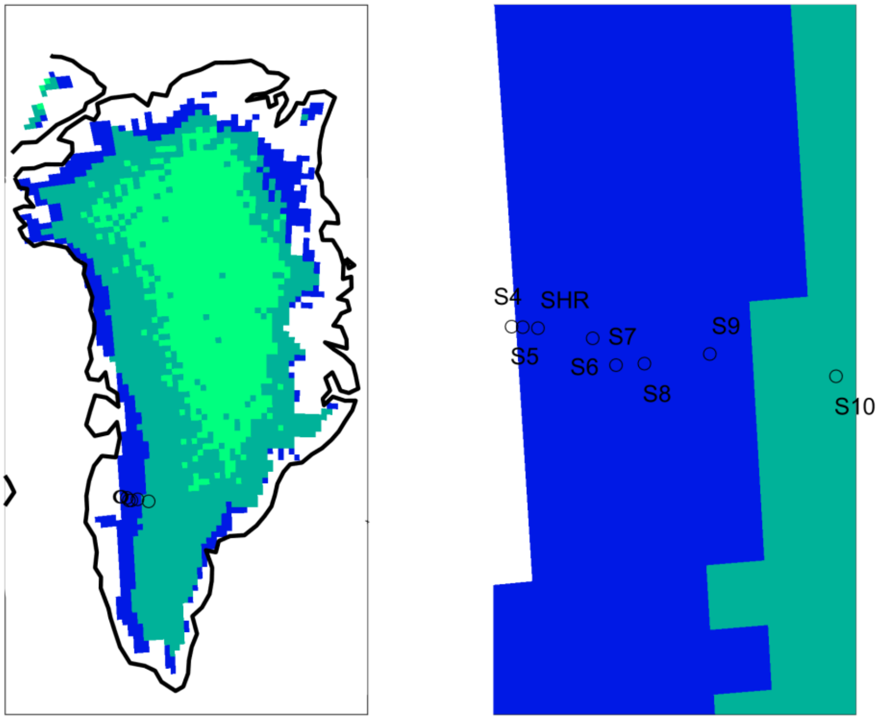

Figure1: The Greenland ice sheet mask from MAR (filled area) at resolution of 25km, including the ablation zone (blue), the percolation zone (dark green), and the dry snow zone (bright green) based on an offline Crocus simulation for the year 2010. The black circles show the location of the K-transect stations.

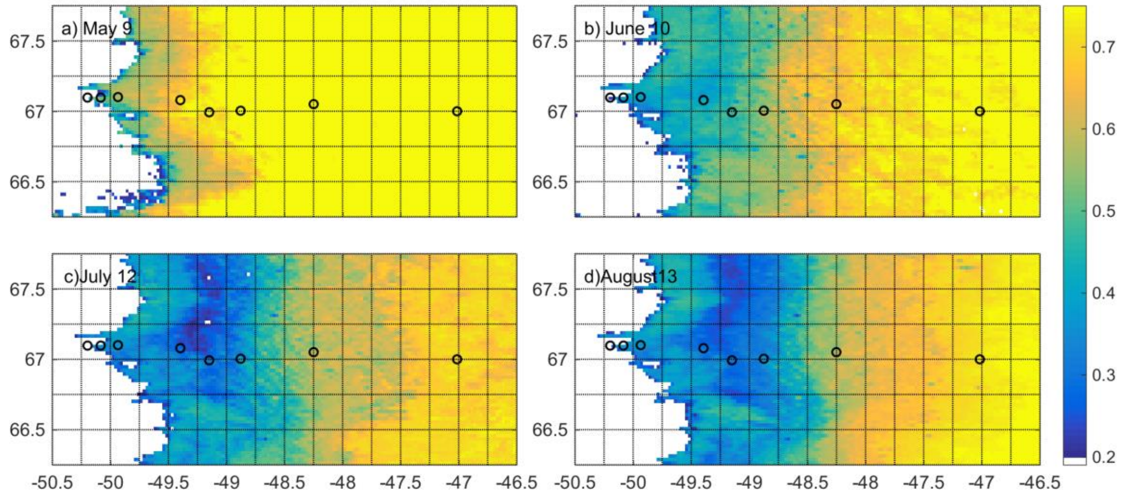

Figure 2: The 2010 16-day albedo map for day of year (a) 129, (b) 161, (c) 193, and (d) 225. The black circles show the location of the K-transect stations S4, S5, SHR, S6, S7, S8, and S9, S10 respectively from left to right. The dark blue areas in c-d represent the Greenland dark zone with very low albedo.

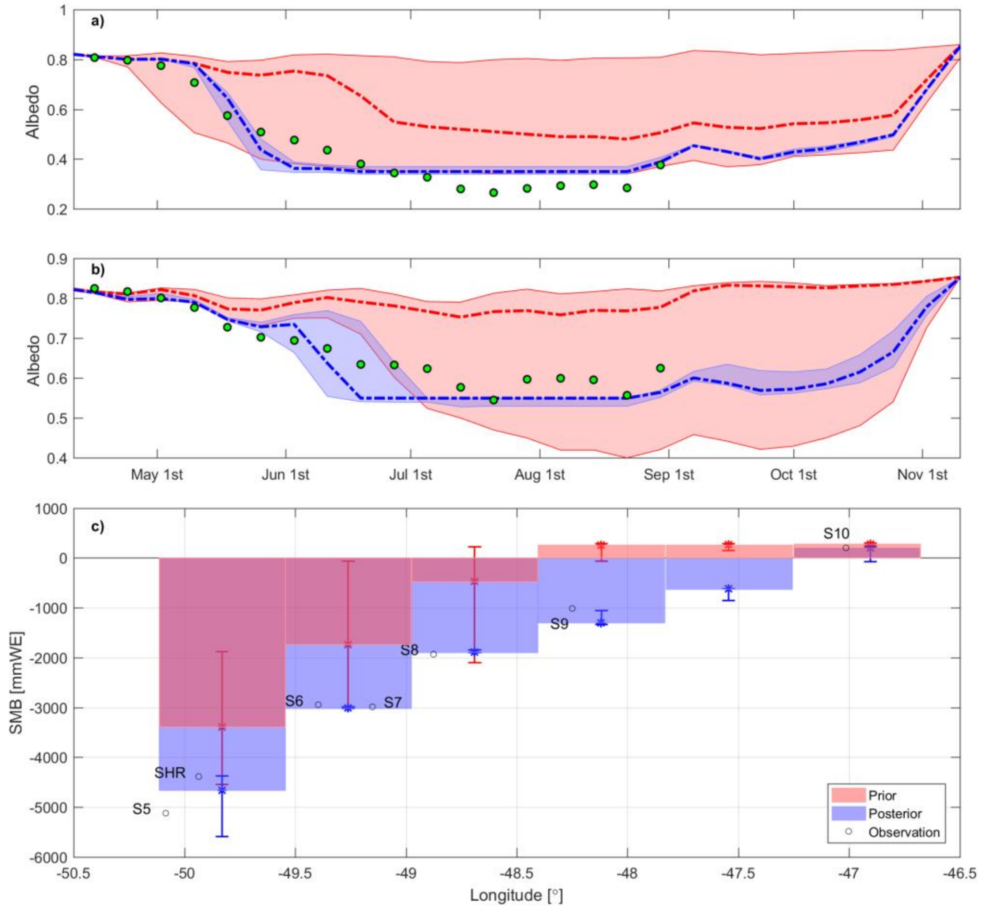

Figure 3: (a) Time series of albedo [-] for the grid cell co-located with the S6-S7 stations. The red and blue shaded areas represent the prior and the posterior uncertainty band (IQR) and the red and blue lines represent the median of the prior and the median of the posterior respectively. The green circles represent the satellite-derived 16-day albedo. (b) Similar to (a) but for the S9 station. (c) SMB (in mmWE/yr) at MAR grid cells co-located with the K-transect stations. The prior and posterior SMB estimates are shown by red and blue columns respectively and black circles represent the in-situ measurements. The error bars (IQR) represent the uncertainty of estimates. The width of the column represents dimension of the MAR computational grid cell and the height of the column represents SMB of the ice sheet at that location at the end of simulation (August 31st, 2010). The zero represents the surface of the ice sheet at the beginning of the simulation (September 1st, 2009)002E