The pattern of anthropogenic signal emergence in Greenland Ice Sheet surface mass balance

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Abstract: Surface mass balance (SMB) trends influence observed Greenland Ice Sheet (GrIS) mass loss, but the component of these trends related to anthropogenic forcing is unclear. Here we study the simulated spatial pattern of emergence of an anthropogenically derived GrIS SMB signal between 1850 and 2100 using the Community Earth System Model. We find emergence timing heterogeneity, with a bimodal structure reflecting interior snowfall increases against a background of low SMB variability, and peripheral surface melting increases against a backdrop of high SMB variability. We also find a nonemerging intermediate region. We conclude that (1) a bimodal pattern of GrIS SMB change will unambiguously reflect the impact of anthropogenic forcing; (2) present-day peripheral and interior SMB trends likely have an underlying anthropogenically forced component; (3) local emergence occurs well before emergence of a spatially integrated signal; and (4) the GrIS summit region may be an ideal location for monitoring regional/global climate change.

1. Introduction

The Greenland Ice Sheet (GrIS) is often considered a bellwether of global anthropogenically forced and polar-amplified climate change [Serreze and Barry, 2011; Stocker et al., 2013]. Currently, the GrIS is losing mass at an increasing pace [Shepherd et al., 2012], primarily because of surface melt and runoff [Enderlin et al., 2014]. Several studies suggest that recent Greenland and Arctic climate trends are inconsistent with natural climate variability [Hanna et al., 2008; Andres and Peltier, 2013; Fyfe et al., 2013]. It is not yet clear, however, to what extent current GrIS surface mass balance (SMB) trends are related to anthropogenic climate change [Bamber and Aspinall, 2013], given the short length of remotely sensed/isitu records and high GrIS SMB variability [Wouters et al., 2013]. Also, it is not clear where or when a robust signal of anthropogenic forcing in GrIS surface conditions will first appear (and by extension, where monitoring efforts should be focused). Improved understanding of the spatiotemporal signal of anthropogenically forced climate change in GrIS SMB is therefore needed, particularly in light of the potential for climate change, via SMB, to affect GrIS stability [Robinson et al., 2012] and long-term sea level rise.

The separation of GrIS SMB trends into contributions from anthropogenic climate change and natural variability can potentially be addressed with coupled ice sheet/climate models. However, until recently such models were considered unsuitable for calculating ice sheet SMB because of surface biases, insufficient resolution, and lack of explicitly simulated ice/snow surface processes [van den Broeke et al., 2008]. Here we use the first global climate model with a realistic simulation of GrIS surface processes [Vizcaíno et al., 2013] to directly address, for the first time, the pattern and timing of anthropogenic signal emergence in GrIS SMB. Previous modeling studies have focused on anthropogenic signal emergence in, for example, surface air temperatures [Mahlstein et al., 2011; Hawkins and Sutton, 2012]. These studies highlighted the role of natural variability in determining the spatial pattern of anthropogenic signal emergence and also explored the physical mechanisms controlling variability, signal magnitude, and emergence timing. Motivated by these works, we use a similar approach to generate emergence criteria for GrIS SMB, assess the timing and pattern of anthropogenic signal emergence in the simulated GrIS SMB over the 20th and 21st centuries, and interpret this emergence in the context of background variability and long-term trends.

2. Methods

We use the Community Earth System Model (CESM) [Hurrell et al., 2013], which includes the Community Atmosphere Model (CAM) and Community Land Model (CLM) at 0.9° latitude/1.25° longitude resolution and
the Parallel Ocean Program (POP) and Los Alamos sea ice models at 1° resolution. A critical model feature is inclusion of unbias-corrected SMB calculations performed with an energy balance model that explicitly accounts for surface melt and snow/ice processes such as albedo evolution and refreezing. All SMB processes in CLM are coupled to the evolving state of CAM and thus to the broader climate system. To capture fine-scale features, SMB calculations are first carried out in CLM over multiple elevation classes, then remapped during run time to the present-day GrIS topography at 5 km resolution. This procedure is summarized and described in detail in previous studies [Lipscomb et al., 2013; Fyke et al., 2014]. We note that the simulation described here uses static GrIS topography, which neglects the impact of ice geometry changes on SMB. Offline sensitivity tests show that by 2100, the CESM-derived decrease in SMB is ~5% greater due to the elevation-SMB feedback [Edwards et al., 2014] if topography evolves. However, the impact of the resulting ablation area expansion on our emergence-based results would be limited, given that large projected 21st century GrIS elevation changes are confined to the margin edges [Lipscomb et al., 2013].

The CESM-simulated GrIS SMB has been comprehensively validated against 475 in situ observations, remotely sensed data, and SMB calculated by a high-resolution regional atmospheric climate model (RACMO2) [Vizcaíno et al., 2013]. In addition, we also compared simulated SMB variability against variability derived from observed SMB time series in the ablation and accumulation areas. These comparisons (summarized in the supporting information) demonstrate CESM's ability to simulate recent GrIS SMB magnitude, spatial distribution, and variability. Along with the ability to simulate future GrIS SMB evolution without bias corrections, this makes CESM an ideal tool for exploring anthropogenic signal emergence. We examined the emergence of an anthropogenic signal in GrIS SMB in a 1850–2100 simulation [Vizcaíno et al., 2013, 2014] that was initialized from a multicentury preindustrial control run followed by a 100 year spin-up simulation with SMB calculations enabled. From this steady state, the model was integrated forward under historical forcing from 1850 to 2005 and Representative concentration pathway 8.5 (RCP8.5) emission scenario forcing from 2006 to 2100. RCP8.5 is the most extreme Intergovernmental Panel on Climate Change scenario but is already being exceeded by current emission trends [Sanford et al., 2014].

To assess emergence timing at each point, we adopted a signal-to-noise methodology [Hawkins and Sutton, 2012]. In this approach the anthropogenic signal $S$ is considered emerged if the ratio of the magnitude of $S$ to the magnitude of background natural variability ($N$, the noise) exceeds some threshold. We adopted $S/N > 1$ as our primary threshold and addressed the sensitivity of our results to this choice by repeating the analysis with a stricter $S/N > 2$ threshold and a statistical t test approach [Mahlstein et al., 2011]. Alternative emergence detection methods (for example, a median/quantile-based approach) could provide additional statistical benefits. However, based on our findings (section 3), we suggest that other methods would yield qualitatively similar results given the physical mechanisms underpinning GrIS SMB emergence signal. The signal $S$ was determined using a smoothed SMB time series at each point, where the SMB value at year $y$ was calculated as a backward looking moving average of the previous 30 years of SMB values. This approach mimics the climatological data available to a hypothetical observer at year $y$. $N$ was defined at each point as the ±1 standard deviation spread about the mean 1850–1950 SMB, with this long control period chosen to sufficiently characterize background variability. We ensured that the control period did not entirely overlap with the periods used to calculate emergence dates for our default emergence threshold definition and also verified that changing the control period did not qualitatively affect the main results. The standard deviation used to determine $N$ was computed after first detrending each pointwise SMB time series using empirical mode decomposition. The anthropogenic signal was considered emerged when the moving average SMB time series migrated permanently outside the ±1 standard deviation spread in the control state. Importantly, to exclude spurious emergence dates arising from climate variability, neither grid points displaying emergence dates after 2085 (i.e., within half of the 30 year analysis period from the end of the simulation) nor grid points experiencing only temporary emergence prior to 2085 were considered emerged. These choices did not critically affect our main conclusions.

Use of the single available SMB-enabled coupled CESM simulation to estimate emergence timing does not allow for assessments of emergence timing uncertainty related to regional internal climate variability [Hawkins and Sutton, 2012; Deser et al., 2012]. Depending on the phasing, simulated decadal variability could drive emergence sooner or later than in the case of no internal variability. For example, the Atlantic Meridional Oscillation appears to influence GrIS climate with a dominant ~20 year quasiperiodicity [Chylek et al., 2012], which could potentially lead to GrIS SMB emergence time uncertainty of about the same magnitude. However, robustly assessing this uncertainty is difficult without an ensemble of simulations.
Figure 1. (a) GrIS SMB emergence regions: red region emerges downward from the control SMB state due to increased melting, blue region emerges upward from the control SMB state due to increased snowfall, and grey region does not exhibit emergence (based on the $S/N > 1$ criterion). Circles correspond to locations of representative SMB time series shown in Figure 2. (b) Cumulative GrIS area emerged, with colors representing regions as in Figure 1a. (c) Emergence-year spatial distribution.

[e.g., Deser et al., 2012]. Similarly, gauging emergence timing uncertainty related to signal/noise biases associated with intrinsic model structural design is difficult without similar analyses by other climate models [Tebaldi and Knutti, 2007]. Bearing in mind these two sources of uncertainty, as well as basic parameter and boundary/initial condition uncertainty, our results should be interpreted as estimated projections that are subject to further uncertainty quantification as more SMB-enabled CESM ensemble members become available, and more climate models explicitly simulate GrIS SMB.

3. Results

The spatial pattern of anthropogenic signal emergence arising from simulated SMB change is separable into three distinct regions (Figure 1a). Due to increasing SMB (Figures 2 (blue time series), 3, and 4a) an interior

Figure 2. Representative downward/upward emergent SMB time series (red/blue, corresponding to lower K-transect/Summit Camp locations), and nonemergent time series (grey, corresponding to Camp Century location). Thin time series are annual SMB and thick time series are 30 year moving average SMB; shaded horizontal bands represent 1850–1950 SMB ± 1 standard deviation. Thick vertical arrows are emergence times based on the $S/N > 1$ criterion for emergence; thin vertical arrows are emergence times based on a $t$ test (earlier) and an $S/N > 2$ criterion (later).
Figure 3. (a) Control state 1850–1950 GrIS mean surface mass balance. (b) End of 21st century GrIS mean surface mass balance. Thick black line represents the climatological equilibrium line altitude for each period, which delineates the ablation from the accumulation areas. Colored circles mark locations of example time series (main Figure 2).

region emerges upward from the control SMB state. This interior SMB increase arises from greater snowfall in the absence of significantly increased melting, a result common to other studies of GrIS SMB behavior in a warming climate [Fettweis et al., 2013a; Merz et al., 2013; Hawley et al., 2014]. Due to decreasing SMB (Figures 2 red time series, 3, and 4a), a second region emerges downward from the control SMB state in a broad ring around the GrIS periphery. This decrease occurs because of increased runoff in response to higher near-surface temperatures, enhanced incoming longwave radiation, less precipitation as snow, and a strong albedo feedback [Vizcaíno et al., 2014]. The peripheral SMB decrease dominates the spatially integrated SMB signal (which falls from 389 ± 99 Gt/yr during 1850–1950 to −17 ± 170 Gt/yr during 2071–2100 and coincides with a 190% ablation area increase; Figure 3) and is a response common to other studies [Fettweis et al., 2013a; van Angelen et al., 2013; Box, 2013]. Between these oppositely responding regions is a third region (Figure 2, grey time series) where an anthropogenic signal does not emerge before 2085, partially reflecting locally canceling ablation and accumulation increases.

Given the $S/N > 1$ emergence criterion, simulation completion at year 2100, exclusion of emergence dates after 2085 and use of RCP8.5 forcing, the mean simulated signal emergence year for the emergent regions is 2040 (standard deviation 24 years; Table 1). This is 14 years earlier than the emergence of the anthropogenic signal in the spatially integrated SMB time series [Vizcaíno et al., 2013, 2014], due to exclusion of nonemergent points in the point-by-point analysis and the impact of counteracting accumulation and melt increases on the spatially integrated SMB trend. In the downward emerging region, a small fraction of the ablation area (mainly in the northeast where variability is small and melting increases early) emerges in the second half of the twentieth century (Figure 1b). This downward emerging area covers less than 2% of the ice sheet until ~2000, after which it expands until the end of the simulation. The mean emergence year of this region is 2042 (Table 1). Interior upward emergence begins in the first decade of the 21st century (Figure 1b). The upward emerging region grows steadily until 2050, after which growth slows as melting advances up the ice sheet flanks. The mean emergence year in this region is 2038. By 2085, 75% of the ice
sheet area has emerged from the control SMB state, with interior emergence regions contributing 51% to this total emerged area and the margins contributing 49%. Figure 1c shows the spatial pattern of emergence times, which typically increase with elevation from the margin until the no-emergence region is reached. Interior of this region, emergence times become progressively earlier with increasing elevation and continentality. The resulting pattern is one of early emergence in the interior, surrounded by a ring of later or no emergence, and a second outer ring of early emergence. The interior and peripheral regions have similar emergence times. For example, both regions have initial emergence before 2014, >10% of both regions have emergence times before 2020, and by 2060, >50% of both regions have emerged.

The similarity between emergence times in the interior and on the margins is closely related to the characteristic spatial pattern of the signal-to-noise ratio (SNR, the ratio of the anthropogenic SMB change to natural SMB variability) over the ice sheet surface. Projected SMB changes are much larger in the ablation area than the accumulation area (Figure 4a). However, SMB variability is also much greater in the ablation area than the accumulation area (Figure 4b), because marginal melt processes are more variable than processes associated with interior accumulation [Fyke et al., 2014]. As a result, the spatial SNR pattern (Figure 4c) exhibits an interior maximum that depends on low variability and a peripheral maximum that depends on a large signal. This indicates that early interior and peripheral emergence times are enabled by low SMB variability and high SMB signal, respectively.

To test the sensitivity of our primary results to our default definition of emergence, we repeated the analysis with alternate criteria (section 2 and Table 1). A t test criterion, using a 95% significance level, predicts

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<th>Table 1. Summary of Emergence Time and Emergence Area Statistics</th>
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<td>Emergence Criterion</td>
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<td>Downward emerging area (% total emerged area)</td>
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*Bolded values are obtained with the default signal-to-noise criterion (S/N > 1). Bracketed values refer to the standard deviation of emergence times.*
earlier emergence. The mean emergence year is 2021 over the 83% of the GrIS area that emerges, with 51% of the emergence area coming from the interior (mean emergence year 2014) and 49% from the periphery (mean emergence year 2028). Use of a 99% significance level does not change these values notably. An $S/N > 2$ criterion gives later emergence, with a mean emergence year of 2060 for the 52% of the GrIS area that emerges. Of this area, 44% comes from the interior (mean emergence year 2059) and 56% from the periphery (mean emergence year 2061). Thus, our primary results using an $S/N > 1$ criterion are bracketed by results from the more sensitive $t$ test and more conservative $S/N > 2$ criteria. The range of criterion-dependent emergence statistics leads us to concur with other studies, in that the quantitative timing of emergence is criterion-dependent [Mahlstein et al., 2011; Hawkins and Sutton, 2012]. Qualitatively, however, we highlight that all three criteria (including the conservative $S/N > 2$ criterion) yield strong spatial patterns of anthropogenic signal emergence, with substantial positive (interior) and negative (peripheral) emergence regions and early emergence occurring both around the GrIS periphery and in the GrIS interior.

4. Discussion and Conclusions

Analysis of anthropogenic signal emergence in GrIS SMB allows for several conclusions. Most importantly, we predict that unambiguous anthropogenic signal emergence in GrIS SMB is (and will be) a robust response to 21st century anthropogenic climate forcing, and one which is potentially reproducible by other climate models. The emergence signal will be bimodal, with interior emergence arising from modest snowfall increases in the presence of low SMB variability, and peripheral emergence arising from substantial surface melt increases in the presence of high SMB variability. The spatial pattern of emergence timing is characterized by early emergence both in the deep GrIS interior and around the ice sheet margins, with simulated emergence in both locations ongoing at the present day. Simulated present-day emergence is consistent with the sign of statistically significant observed SMB trends in both the lower ablation and interior dry snow accumulation areas [van de Wal et al., 2012; Hawley et al., 2014], supporting (though not formally confirming) suggestions that an anthropogenically forced trend is underlying and amplifying recent SMB trends related to internal climate variability [e.g., Fettweis et al., 2013b].

We also highlight that simulated local anthropogenic signals emerge well before emergence of the integrated SMB (and associated sea level rise) signal. This suggests that in situ SMB monitoring in well-chosen locations could provide a robust early warning of anthropogenic signal emergence in the global sea level rise component related to GrIS SMB [Bamber and Aspinall, 2013; Wouters et al., 2013]. To this end, the GrIS summit region may be an optimal long-term SMB observing location, and perhaps also one of the best global locations for assessing evolving anthropogenic climate change. This is because here, a clear SMB control state record can be obtained from snow, firm, and ice cores, surmounting a key problem in anthropogenic signal detection [Stone et al., 2013]. In contrast, continuous ablation area SMB records are limited to direct observations, which at best span 21 years at the K-transect [van de Wal et al., 2012]. Furthermore, present-day interior SMB trends are measurable at existing facilities (e.g., Summit Camp [Dibb and Fahnestock, 2004], located ∼250 km southward of the center of earliest simulated interior emergence), and low interior SMB variability allows small anthropogenically forced trends to be detected quickly, in agreement with the impact of variability found in other studies [Mahlstein et al., 2011; Hawkins and Sutton, 2012]. Finally, simulated summit region emergence occurs early in the 21st century, and summit region SMB trends are reasonably correlated with trends around the GrIS margin (Figure S1). This suggests that the summit emergence signal could be used as a rough proxy for the margin emergence signal, in the absence of long-term margin-based monitoring efforts.

GrIS SMB change will be an important component of the broader climate system response to future anthropogenic forcing. Our analysis suggests that an increasingly clear bimodal signal of human forcing will emerge in GrIS SMB in the coming decades, modulated by the magnitude and spatial pattern of anthropogenically forced SMB change and natural SMB variability. Further work related to internal climate variability, model structural design, and emission scenarios [Hawkins and Sutton, 2012; Deser et al., 2012] will help to constrain uncertainty in this emergent GrIS SMB signal and thus enable better understanding of the role of anthropogenic forcing in determining long-term GrIS stability and sea level rise.
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