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Key Points:
- The observed rapid increase in summertime Greenland blocking during the first decade of the twenty-first century has not continued
- A period of increased summer Greenland blocking of similar magnitude to observed is rarely reproduced in a large ensemble of climate models
- Decadal variability in Greenland blocking in climate models is partly driven by SST/sea ice and/or anthropogenic aerosols

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Correspondence to:
J. W. Maddison,
j.maddison2@exeter.ac.uk

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Missing Increase in Summer Greenland Blocking in Climate Models

J. W. Maddison1, J. L. Catto1, E. Hanna2, L. N. Luu2, and J. A. Screen1

1Department of Mathematics and Statistics, University of Exeter, Exeter, UK, 2Department of Geography, University of Lincoln, Lincoln, UK

Abstract Summertime Greenland blocking (GB) can drive melting of the Greenland ice sheet, which has global implications. A strongly increasing trend in GB in the early twenty-first century was observed but is missing in climate model simulations. Here, we analyze the temporal evolution of GB in nearly 500 members from the CMIP6 archive. The recent period of increased GB is not present in the members considered. The maximum 10-year trend in GB in the reanalysis, associated with the recent increase, lies almost outside the distributions of trends for any 10-year period in the climate models. GB is shown to be partly driven by the sea surface temperatures and/or sea ice concentrations, as well as by anthropogenic aerosols. Further work is required to understand why climate models cannot represent a period of increased GB, and appear to underestimate its decadal variability, and what implications this may have.

Plain Language Summary An increasing trend in summertime atmospheric blocking over Greenland was observed during the early twenty-first century. However, this trend is not reproduced in climate models. This may have important implication for climate change projections, as summertime Greenland blocking drives the melting of its ice sheet which is a major contributing factor to global sea level rise. Here, recent trends in Greenland blocking are assessed in nearly 500 ensemble members from a large archive of state-of-the-art climate models. We find that a recent increasing trend like that observed is absent in all of the ensemble members, and a trend of such magnitude is very unlikely to be simulated in them, which suggests a deficiency in the climate model simulation of Greenland blocking. The model simulations do however suggest that Greenland blocking is partly forced by sea surface temperatures/sea ice concentrations and/or anthropogenic aerosols, but the response of the models to these forcings may be too weak. These results provide new understanding on drivers of Greenland blocking in climate models and offer avenues for model development designed to improve simulations of Greenland climate.

1. Introduction

Climate change over Greenland has global impacts. Its ice sheet is melting (e.g., Fox-Kemper et al., 2021; Stocker et al., 2014), and therefore contributing to global sea level rise (Andersen et al., 2015; Cazenave & Remy, 2011; Hanna et al., 2020; Hofer et al., 2020; Jacob et al., 2012). This fresh water released into the North Atlantic ocean may affect the Atlantic meridional overturning circulation (Bakker et al., 2016; Cheng et al., 2013), and hence the global transport of heat and energy (Ganachaud & Wunsch, 2000). From an atmospheric perspective, circulation changes over Greenland are closely related to the North Atlantic Oscillation (NAO), and consequently the location of the eddy-driven jet stream and downstream weather conditions over Europe (Barriopedro et al., 2023; Galfi & Messeri, 2023; Röthlisberger et al., 2016). Given this, and that recent changes to the atmospheric circulation and ice sheet on Greenland have been extreme (Hanna et al., 2016; Khan et al., 2015; Vaughan & Arthern, 2007), model simulations of Greenland climate variability need to be as accurate and as robust as possible. The summer temperatures need to be particularly well represented, as they are a key driver of ice sheet melt (Hanna et al., 2021; Nienow et al., 2017; Van den Broeke et al., 2016).

Extreme summertime temperatures in Greenland, and their effect on the ice sheet, are strongly related to the occurrence of atmospheric blocking (Fettweis et al., 2013; Hanna et al., 2014, 2021; McLeod & Mote, 2016). The reduced cloud cover within the blocking high pressure system, associated with widespread subsidence, as well as the advection of warm, moist air along the upstream flank of the block, are key drivers of ice melt (e.g., Preece et al., 2022; Tedesco & Fettweis, 2020). In reanalyses, summertime Greenland blocking (GB) has become more frequent since the 1990s, with a particularly strong increase at the start of the twenty-first century (Hanna...
et al., 2016, 2022; McLeod & Mote, 2015), potentially signaling a regional climate change signal. However, climate models suggest ongoing climate warming is associated with no clear trend, or a small decreasing trend, in GB in both summer and winter (Davini & d’Andrea, 2020; Delhase et al., 2021; Hanna et al., 2018; Michel et al., 2021; Woollings et al., 2018). This suggests the recent trends identified in the reanalyses may in fact be due to internal climate variability, and not representative of a forced climate change response. Alternatively, the climate model simulations may lack such a trend due to a deficiency in their representation of GB.

Climate models contain biases in blocking. They are biased to too few blocking events, with too little interannual block variability, for much of the Northern Hemisphere midlatitudes, and this has been the case for several generations of climate models (Davini & d’Andrea, 2020; Woollings et al., 2018). GB typically occurs following the cyclonic breaking of Rossby waves in the region (Michel & Rivière, 2011; Woollings et al., 2008), which often succeeds the development of upstream extratropical cyclones (Maddison et al., 2019; McLeod & Mote, 2015), and the associated advection of low potential vorticity air toward the high latitudes (Pelly & Hoskins, 2003; Tyrlis & Hoskins, 2008). However, this relationship between GB and cyclonic Rossby wave breaking is not always present in climate model simulations (Michel et al., 2021), and may be a contributing factor to the climate model biases in GB and lack of recent trend in climate model simulations.

An evaluation of summertime GB variability in a large ensemble of state-of-the-art climate models is presented here, with the main aim of determining if a sustained period of increased GB activity, such as that observed in the early twenty-first century, is simulated in these models.

2. Data

The climate simulations analyzed herein are from several contributions to the sixth phase of the climate model intercomparison project (CMIP6) (Eyring et al., 2016). Models from various experiments are analyzed, including the historical and amip experiments from the CMIP6 deck, as well as the hist-aer, hist-GHG and hist-nat experiments from the detection and attribution MIP (DAMIP) (Gillett et al., 2016), and coupled hist-1950 experiments (termed here HighResMIP) from the high resolution MIP (HighResMIP) (Haarsma et al., 2016). This gives a combined total of 488 model ensemble members across all of the experiments. Note that all available members from a given model are used, and equal weight is given to each member (rather than each model) when calculating the multimodel mean. The Supporting Information S1 of this article contains a complete list of model ensemble members used. The inclusion of a large ensemble is motivated by the desire for improved estimates of uncertainty and forced climate change responses. A brief description of the design of each experiment is provided below (with the number of ensemble members included for each and its parent MIP); for full details the reader is referred to the references listed above.

1. historical (191, CMIP): fully coupled simulations from 1850 to 2014 with all external forcings included.
2. amip (84, CMIP): atmosphere-only simulations from 1979 to 2014 with prescribed sea surface temperatures (SSTs) and sea ice concentrations (SICs) that are based on observations. All external forcings are included.
3. hist-aer (66, DAMIP): coupled simulations from 1850 to 2014 with forcing from anthropogenic-aerosols only.
4. hist-GHG (68, DAMIP): coupled simulations from 1850 to 2014 with only the well-mixed greenhouse-gas forcing included.
5. hist-nat (57, DAMIP): natural (solar irradiance and stratospheric aerosol) only forcing coupled simulations from 1850 to 2014.
6. HighResMIP (22, HighResMIP): coupled simulations from 1950 to 2014, including all forcings, from models with resolutions sufficiently high to resolve synoptic-scale weather systems (i.e., 25 km or higher).

Geopotential height at 500 hPa (Z500) is the variable used for the majority of analyses presented herein. Both daily and monthly Z500 are considered in the calculation of the blocking indices (Section 3.1). Monthly SSTs and SICs are also used from the amip and hist-aer experiments. The climate model data are generally used at their native spatial resolution unless stated otherwise. The European Center for Medium-range Weather Forecasts’ fifth generation reanalysis (ERA5, Hersbach et al., 2020) is used as a best estimation of reality and for verification purposes. ERA5 Z500, SSTs and SICs are retrieved during the period 1940–2022 at a 1° latitude, longitude resolution on daily timescales.
3. Methods

3.1. Greenland Blocking Indices

Methods to objectively identify blocking in a given data set have been the focus of much research (see Barriopredo et al., 2010; Woollings et al., 2018, for reviews). Several indices have been introduced, each with their own strengths and weaknesses. In light of this, four different blocking indices are used in this work. The four indices are all based on daily fields of the Z500. Three are based on those used in Woollings et al. (2018), but adapted to focus on Greenland. They are termed the absolute, anomaly, and mixed block indices (BI_ABS, BI_ANO, BI_MIX, respectively). The fourth index is that used in Hanna et al. (2018), known as GBI2. Each is described briefly below.

1. BI_ABS: Meridional gradients in Z500 are calculated for every grid point in the region 35°–75°N. Gradients are taken 15° to the north and south of each grid point and blocking is identified when the gradient from the south is positive and the gradient to the north is less than minus 10 m per degree. This method is designed to identify the flow reversal signature of blocking, together with a strong flow to the north. It is a 2D extension of the index introduced in Tibaldi and Molteni (1990). Sensitivity tests were also performed with the modification to this index suggested to improve high-latitude blocking in Tyrlis et al. (2021) (where the criterion on the northern gradient is reduced to 0 m per degree for latitudes north of 60°). We note where this modification was impactful.

2. BI_ANO: Daily anomalies in the Z500 field are computed with respect to the climatological seasonal mean for every grid point. Grid points with anomalies in Z500 above the 90th percentile of the climatological distribution of anomalies in the hemispheric band enclosed by 50°N and 80°N are considered blocked. This method is similar to that introduced in Schwierz et al. (2004), but here using Z500 rather than potential vorticity.

3. BI_MIX: This index combines both the BI_ABS and BI_ANO indices. At least one of the grid points identified in BI_ANO is also required to satisfy the gradient criteria of BI_ABS, that is, there must be a region with a strong positive anomaly in Z500 as well as a reversal of the flow.

4. GBI2: This GB index is calculated as the area-weighted average Z500 in a region covering Greenland (60°–80°N, 20°–60°W) with the hemispheric mean in the zonal band between 60° and 80°N subtracted. The subtraction of the zonal band is designed to remove the influence of the strong background warming associated with Arctic climate change on the geopotential heights over Greenland (Hanna et al., 2018).

The daily blocking indices are converted to monthly GB indices by summing the total number of blocked grid points on each day within the Greenland region (60°–80°N, 20°–60°W) for blocking indices 1–3 (without setting a threshold for number of grid points blocked to define blocking), and then taking the monthly mean. The monthly mean of the GBI2 index is also taken. Extreme monthly GB values can therefore result from relatively few days of large block areas or many days with smaller regions of Greenland blocked. The monthly indices are each normalized to the 1951–2000 period (by subtracting the mean of this period and dividing by its standard deviation) and are hence presented as anomalies with respect to this period. In the case of amip, for which the simulations start in 1979, the time series are normalized to the period 1979–2000. Finally, a smoothing is applied to the normalized time series to highlight longer-term variability: a weighted running mean is performed for the GBI2 index introduced in Tibaldi and Molteni (1990). Sensitivity tests were also performed with the modification to this index suggested to improve high-latitude blocking in Tyrlis et al. (2021) (where the criterion on the northern gradient is reduced to 0 m per degree for latitudes north of 60°). We note where this modification was impactful.

3.2. Greenland Blocking Trend and Variability Analysis

The recent period (2000–2010) of increased observed GB activity (e.g., Delhasse et al., 2021) is characterized in two ways here to allow for an assessment of the climate models. First, the rate of increase in GB is quantified by calculating 10-year trend distributions in the monthly time series of summer GB for ERA5 and each of the ensemble members from the experiments including their full time periods. Ten-year trends are calculated using a linear least-square regression for each 10-year period of the time series.

Second, the magnitude of the period of increased GB around 2000–2010 is separated into a length and average component. Specifically, the length component is defined as the number of years the (smoothed) GBI 2 time series remains positive, that is, how many consecutive years one of the lines in Figure 1 remains above zero. The average component is calculated as the mean GBI 2 anomaly during these years. Sustained positive GB anomalies are
identified in the ensemble members during the common period of their integrations (1979–2014) and the fraction of members that represent a period like the recent strong positive anomaly in ERA5 is calculated. (For reference, the recent period of strongly positive GB anomaly in ERA5 (shown in Figure 1) had a length of 14 years and an average anomaly in GBI 2 of 0.57.)

3.3. Ratio of Predictable Components

Individual ensemble members of weather or climate models often contain some predictable signal but this may be too weak (Eade et al., 2014; Smith et al., 2020). In Eade et al. (2014), a correction was introduced for the ensemble mean that ensures its temporal variance is equal to the variance of the predictable component of the observations. The monthly ensemble mean is corrected, for only those experiments with a ratio of predictable components (RPC, Equation 2) greater than one, using the following equation.

\[
\frac{\overline{GB}_t^G - \overline{GB}_t^B}{\sigma_{\text{obs}} r} \quad \text{GB}
\]

where \(\overline{GB}_t^G\) is the corrected ensemble mean, \(\overline{GB}_t^B\) is the raw ensemble mean (with \(t\) representing the timestep of 1 month), \(GB\) is the temporal mean across all \(\overline{GB}_t^B\), \(r\) is the temporal correlation between the ensemble mean and ERA5, and \(\sigma_{\text{obs}}\) and \(\sigma_{\text{mod}}\) are the temporal standard deviations of ERA5 and the ensemble mean, respectively. All terms are calculated for the period 1979–2014. The RPC itself is defined as

\[
\text{RPC} = \frac{r}{\sigma_{\text{mod}}^2 / \sigma_{\text{obs}}^2}
\]

where \(\sigma_{\text{mod}}^2\) and \(\sigma_{\text{obs}}^2\) are the variances of the ensemble mean and the average variance of the individual ensemble members, respectively.

4. Results

4.1. Temporal Evolution of Greenland Blocking

Time series of summertime GB are shown in Figure 1, for the period 1950–2020 and for each of the blocking indices considered in the coupled historical simulations and for ERA5. The recent period of increased GB is identified here in ERA5 in the four GB indices, with a rapid increase in block frequency after 2000 (peaking at an anomaly around 1 with respect to the unfiltered GB time series). The increasing trend peaks around 2010 and then GB anomalies return to more typical values. Prior to this, the ERA5 temporal evolution in GB is characterized by small fluctuations, with anomalies in the block indices between 0.5. The evolution of GB is in good agreement among the blocking indices considered. The absolute blocking index (BI_ABS, Figure 1b) is different, with a later onset of the period of increased GB and a smaller maximum anomaly. The modified BI_ABS (following Tyrilis et al. (2021)) has an increase with an onset similar to the other indices but with an even smaller maximum anomaly. Nevertheless, the broad agreement among the indices suggests the recent increase observed is a robust feature of the atmospheric circulation over Greenland. The historical simulations from CMIP6 are shown in blue. The observed ERA5 blocking evolution in the early twenty-first century is not reproduced in any model, in agreement with Delhasse et al. (2021), but here using more ensemble members, with none of the ensemble members having an increase in GB at the same time and of the same magnitude to that found in ERA5. The ensemble mean in each index shows little variation. If the recent trend was a forced climate change response, the climate models should reproduce it (at least in the multimodel mean) during the same time period. That is, as long as the climate models adequately capture the key processes relevant to the dynamics of GB, which may not be the case as considerable biases remain (e.g., Davini & d’Andrea, 2020; Narinesingh et al., 2022; Woollings et al., 2018). If, on the other hand, the increase, and subsequent decrease, were driven by internal atmospheric variability, we would not necessarily expect the signal to be reproduced in the models at the same time.
Figure 1. Time series of summertime Greenland blocking in four different blocking indices in the historical simulations from CMIP6. Colored lines represent the CMIP6 ensemble, the orange line the ensemble mean, and the black line the ERA5 time series. The time series are normalized to the period 1951–2000 and a 10-year rolling-mean applied, shortening the data length by 10 years resulting in end years of 2009 and 2010 for models in which the simulations end in 2014 and 2015, respectively.

Possible forcings of GB can be identified by considering the different CMIP6 experiments, which are now analyzed. As the time series of GB are consistent across the blocking indices, we now only show results for the GBI2 index. This index is based on the mean of the geopotential height over Greenland and hence can be computed from monthly data, allowing for more ensemble members to be included.

In Figure 2, the full time series of the GBI2 index is shown in the historical experiment, as well as during the period 1980–2010 in the amip, hist-aer, hist-GHG, hist-nat and HighResMIP experiments. The recent ERA5 extreme GB anomaly is not replicated in any member in the longer historical period (Figure 2a), nor in any of the different experiments (Figures 2b–2f), with the recent ERA5 increase in GB lying outside the ensemble spread in each. The multimodel mean of the ensembles from each experiment (orange solid lines) show little or no trend. The discrepancy between ERA5 and the models may result from an underestimation of GB variability in climate models. Comparing the temporal variability of the GB time series in ERA5 and each experiment reveals models do tend to have weaker variability than ERA5, though as the latter typically lies within the ensemble spread we cannot conclude the models are deficient (not shown).

The correlations between the ensemble mean GB time series and the ERA5 GB time series are shown in each panel of Figure 2, for the smoothed GB time series shown, as well as the range in correlations for varying rolling window lengths. In the amip and hist-aer experiments, the ensemble mean correlates strongly with the reanalysis time series (correlations 0.92 and 0.67, respectively). In calculating the ensemble mean, the noise in each experiment is removed, leaving behind the forced component in that experiment. This suggests there is a forced
Figure 2. Time series of the summertime GBI in six different CMIP6 experiments smoothed with a 10-year rolling mean. The experiments included are (a) the historical coupled simulations, (b) the amip atmosphere-only experiments, (c) the hist-aer, (d) hist-GHG, and (e) hist-nat single-forcing experiments as well as (f) the HighResMIP experiments. ERA5 is shown by the black line, the experiment ensemble members are shown in blue, and the ensemble mean of each experiment is shown in the orange line. The RPC-corrected (see text) ensemble mean is shown by the dashed orange line for experiments with an RPC greater than one. The vertical line in the top panel identifies the start of the time period shown in the bottom panels. Correlations between the ensemble mean of each experiment and ERA5 are shown by the values in each panel, as well as the maximum and minimum correlations for rolling window lengths between 4 and 14 years.

The uncorrected ensemble means of the historical, and the hist-GHG experiments (as well as the HighResMIP for certain rolling window lengths) are all negatively correlated with ERA5. This suggests the forced response due to climate change, as well as that solely due to increased GHGs, acts in an opposite sense to what has been observed. Indeed, several previous studies have reported a decrease in blocking frequency over Greenland due to climate change (Woollings et al., 2018; Davini & d’Andrea, 2020; Delhasse et al., 2021). Therefore, the recent ERA5 trend in GB appears to originate from anomalous dynamical circulation patterns, potentially forced by the SST/SIC and/or aerosol variability, but not a forced response due to increased GHGs. The amip experiments do however include part of the internally and externally forced components (as the SSTs/SICs follow the real world) so it is not possible to fully exclude the role of GHGs.
Figure 3. (a) Distributions of all 10-year Greenland Blocking trends in ERA5 (gray bars) and all members of the historical, AMIP, DAMIP (hist-aer, hist-GHG, and hist-nut) and HighResMIP experiments during their full integrations (colored lines). Trends are calculated for the time series with a 10-year rolling mean. The numbers in parentheses in the legend show the fraction of ensemble members with a trend exceeding the maximum trend in ERA5. (b) The fraction of models that exhibit a period of anomalous positive Greenland blocking with the mean GBI 2 anomaly during that period equal to that in ERA5 (in ERA5 the mean GBI 2 during the positive GB period equals 0.57), shown as a function of rolling window length. (c) The fraction of models that exhibit a period of anomalous positive Greenland blocking as long as that in ERA5 (in ERA5 the positive GB period lasted 14 years), again shown as a function of rolling window length.

4.2. Strong and Persistent Greenland Blocking

The recent period of increased GB between 2000 and 2010 identified in ERA5 appears, by examining Figure 2, to be outside of the range of scenarios deemed possible by all of the climate model simulations analyzed herein (around 500 individual ensemble members). The likelihood that a trend of that magnitude occurring in the CMIP ensemble is now quantified systematically. Ten-year trends in GB are calculated in ERA5 and all ensemble members from each experiment and presented in Figure 3a. Ten-year trends in GB in ERA5 are commonly between 0.02. There is an additional peak near 0.05, which reflects the strong GB increase between 2000 and 2010 previously discussed. Ten-year trends in GB in CMIP6 experiments are approximately normally distributed, with a mean near zero. The additional peak in the distribution around 0.05 in ERA5 is absent in each of the experiments and only a small fraction of the members in each experiment have a trend exceeding that in ERA5 (values shown in the legend in Figure 3a).

The fraction of the ensemble members in each experiment that have a period of increased GB like the recent ERA5 period are shown in Figure 3, in terms of the average GB anomaly during years when the index was positive (Figure 3b) and the length of such a positive GB anomaly (Figure 3c). They are shown as a function of rolling window length. For the 10-year smoothing shown in Figures 1 and 2, a 14-year period of positive GB, with an average anomaly of 0.57, was found in ERA5, whereas around one fifth of ensemble members produced a period of positive GB of that length (Figure 3c) and none with such a strong GB anomaly (Figure 3b). Considering different smoothing lengths, it is clear that a period of increased blocking activity as strong as in ERA5 is rare in the CMIP6 models, particularly for the average GB anomaly during positive GB periods (Figure 3b). For many of the experiments and for different rolling average lengths, less than one in 50 of the members have such a period of anomalous GB at any point during their integrations. An anomaly in GB of the same length as that in ERA5 is less rare in the CMIP6 models (Figure 3c). It appears therefore that the intensity of the recent blocked period, rather than its length, is what the CMIP6 ensemble struggles to simulate. The results presented in Figure 3 emphasize how extraordinary the recent period of increased GB was, and how unlikely such a period is to occur in the climate models, which suggests a possible model deficiency in the representation of the variability of GB. Indeed, the variability in GB in ERA5 lies at the very upper end of the spread in the historical ensemble, with temporal
standard deviations of the time series shown in Figure 2 of 0.309 in ERA5 and a maximum of 0.313 among the ensemble. As ERA5 lies within the ensemble spread we cannot say for certain the models are deficient, likewise it is unclear if the models have weaker variability in GB due to too weak internal variability or a too weak response to forcing.

4.3. Forced Response of Greenland Blocking

The ensemble mean time series of GB suggest there is a component of GB variability forced by the SSTs/SICs and/or from anthropogenic aerosols. Here, we briefly investigate if these two forcings are acting through a common pathway. If they are, we would expect the evolution of the SST/SICs to be similar in the amip and hist-aer experiments. The correlation between the monthly time series of SSTs and SICs in the ensemble mean of the hist-aer experiments and ERA5 are shown in Figure 4. As the amip SSTs and SICs are based on observations, they correlate very strongly with ERA5 (not shown).

The SSTs do not have similar temporal evolutions in hist-aer and ERA5 (Figure 4a), with a global mean correlation of approximately 0.2 and no coherent regions of high positive correlation. Certain regions of correlation are statistically significant (stippling in Figure 4a), though they include both positively and negatively correlated regions. This is also the case for the sea ice concentrations (Figure 4b). The spatial patterns of SST anomalies during the recent period of increased GB (2005–2014) have also been compared in ERA5 and the ensemble means of the amip and hist-aer. As expected, the ERA5 and amip SST anomalies show consistent features (they are both based on the true SST evolution, not shown). Positive anomalies are identified in the North Atlantic, particularly around Newfoundland and south of Greenland (Figure 4c). SST anomalies during the increased GB period in the hist-aer ensemble mean do not show similar features (Figure 4d), with small anomalies in the ensemble mean implying greater differences among members. We therefore conclude that the forced response of GB due to anthropogenic aerosols is not acting through a pathway via the SSTs/sea ice distributions. Reduced anthropogenic aerosol emissions in Europe, together with increased aerosol emissions in developing countries, can change the meridional midlatitude temperature gradients near the surface and in the lower–mid troposphere, and therefore impact the strength of the westerly jets (Dong et al., 2022), which may in turn impact block occurrence. This mechanism may take place without influencing the SST/SIC distributions. Further investigation into the drivers of GB and the role of SSTs/SICs and anthropogenic aerosols is the focus of ongoing work but is outside the scope of this article.
5. Conclusions

An extensive analysis of the temporal evolution of summertime GB was presented here, with the output from approximately 500 members of the CMIP6 program analyzed, motivated by the recent identification of a strongly positive trend in GB (e.g., Hanna et al., 2022; McLeod & Mote, 2015), that was apparently absent in climate model simulations (Delhasse et al., 2021). A deficiency in simulations of summertime GB is of major concern. GB impacts surface temperatures, and therefore ice sheet melt (Fettweis et al., 2013; Hanna et al., 2014) and global sea level rise (Hofer et al., 2020), with the Greenland ice sheet contributing more than half a millimeter per year to global sea levels (Andersen et al., 2015; Khan et al., 2014; Otosaka et al., 2022).

Here, the recent period of increased GB was shown to not be a sustained trend, but more likely a strong manifestation of decadal variability. The ensemble means of the atmosphere-only (amip) and anthropogenic aerosol (hist-aer) experiments were found to have strong positive correlations with the observed variability in GB (regardless of the smoothing performed). The ensemble mean of the climate model simulations is used to estimate the forced response in that particular experiment. The results therefore suggest that the temporal evolution of GB may be partly driven by SST/SIC variability and/or aerosol forcing, but the model response to these forcings might be too weak. The response of climate models to boundary conditions or external forcings is known to be too weak, the so called signal-to-noise paradox, especially in the Atlantic region (Scaife & Smith, 2018; Smith et al., 2020). Indeed, correcting for the weak forced signal in these experiments produced ensemble mean time series that more closely matched the reanalysis. The SSTs/SICs and anthropogenic aerosols did not however appear to influence GB through the same pathway. The representation of blocking in climate model simulations is known to depend on both SSTs (O’Reilly et al., 2016; Scaife et al., 2011) and anthropogenic aerosols (Dong & Sutton, 2021), as further evidenced here. Furthermore, surface boundary conditions are known to influence circulation patterns over Greenland: tropical Pacific SSTs induce a wave train with a center of action over Greenland (Ding et al., 2014), reduced Arctic SICs promote ridging over Greenland and a southward shift of the jet stream (Screen, 2013; Wu et al., 2013), and reduced snow cover over North America can initiate a stationary Rossby wave pattern that leads to a ridge over Greenland (Preece et al., 2023). The recent trends of these drivers all point toward more frequent Greenland blocking in recent years. On the contrary, greenhouse gas forcing is shown here to be expected to reduce GB in summer, in line with previous studies (Davini & d’Andrea, 2020; Woollings et al., 2018), emphasizing the need for more research into Greenland blocking and its drivers and their representation in models.

A sustained period of anomalously high GB activity, similar to that observed in ERA5, was shown to be largely irreproducible in the CMIP6 experiments: the 10-year trend in GB during this period in ERA5 lay at the tail of the distributions of 10-year trends in the models and almost none of the ensemble members reproduced a positive GB anomaly as large as in ERA5. The recent period of increased GB activity was also notably absent in the climate models considered in Delhasse et al. (2021), lying well outside the ensemble spread. This remained the case in the much larger ensemble of models considered here. Climate models contain biases in their representation of blocking, simulating less blocking than observed and with less variability (e.g., Davini & d’Andrea, 2020; Woollings et al., 2018). The representation of blocking can be improved in models via improvements to: the model resolution (Anstey et al., 2013; Berckmans et al., 2013; Schemann et al., 2017), parameterized physical processes (Jung et al., 2010; Pithan et al., 2016), the model dynamical core (Martinez-Alvarado et al., 2018) and the SSTs (Scaife et al., 2011), offering several avenues for further research into improving GB simulation. As long as model biases persist, extreme GB events may be poorly simulated and improperly understood.

The early twenty-first century period of increased blocking activity over Greenland was impactful in terms of summertime temperatures (Hanna et al., 2016; Jiang et al., 2020), ice sheet melt (Ballinger et al., 2018; Hanna et al., 2014; McLeod & Mote, 2015), and in driving extreme weather conditions further afield (Simonson et al., 2022; Wang et al., 2019). If climate models are incapable of representing such a period of increased summertime GB, as suggested by the results presented herein, these impacts and their larger scale effects will be missing in the simulations. Future work should be focused on understanding why the climate models struggle to represent these extreme, persistent summertime Greenland blocking events.
Data Availability Statement

The climate model data are all available from the World Climate Research Programme website (WCRP, 2023) (https://esgf-index1.ceda.ac.uk/projects/cmip6-ceda/) and ERA5 from the Copernicus climate data store (Climate Data Store, 2023) (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-complete).

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