Understanding model spread in sea ice volume by attribution of model differences in seasonal ice growth and melt

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Abstract. Arctic sea ice is declining rapidly, but predictions of its future loss are made difficult by the large spread both in present-day and in future sea ice area and volume; hence, there is a need to better understand the drivers of model spread in sea ice state. Here we present a framework for understanding differences between modelled sea ice simulations based on

10   attributing seasonal ice growth and melt differences. In the method presented, the net downward surface flux is treated as the principal driver of seasonal sea ice growth and melt. A system of simple models is used to estimate the pointwise effect of model differences in key Arctic climate variables on this surface flux, and hence on seasonal sea ice growth and melt. We compare three models with very different historical sea ice simulations: HadGEM2-ES, HadGEM3-GC3.1 and UKESM1.0. The largest driver of differences in ice growth / melt between these models is shown to be the ice area in summer (representing

15   the surface albedo feedback) and the ice thickness distribution in winter (the thickness-growth feedback). Differences in snow and melt-pond cover during the early summer exert a smaller effect on the seasonal growth and melt, hence representing the drivers of model differences in both this and in the sea ice volume. In particular, the direct impacts on sea ice growth / melt of differing model parameterisations of snow area and of melt-ponds are shown to be small but non-negligible.

1 Introduction

20   Arctic sea ice has undergone dramatic changes in recent decades, with a decline of 0.88 x 106 km2 per decade in September extent observed from 1979-2020 according to the HadISST.2.2 dataset (Titchner and Rayner, 2014) and associated thinning in summer and winter (Lindsay and Schweiger, 2015). Associated with the decline in sea ice has been winter warming (e.g. Graham et al., 2017), earlier onset of melt over the ice (Markus et al., 2009), and later onset of freezing (Stammerjohn et al., 2012).

25   Sea ice is an important component of the climate system, due to its high albedo, its ability to insulate the atmosphere from oceanic heat during the winter, and its effects on ocean circulation. Hence the accurate modelling, and future prediction of sea ice are of primary importance for climate science. These issues are an important focus of the Coupled Model Intercomparison Project (CMIP), in which results from coupled models worldwide are collated, compared and evaluated in a series of 'phases' every few years.

30   In the most recent three phases of CMIP (CMIP3, CMIP5 and CMIP6), sea ice was evaluated in the present-day by Stroeve et al. (2007), Stroeve et al. (2012), Shu et al. (2015) and Notz et al. (2020) amongst others, finding substantial spread in ice extent and volume. All studies have found a tendency to underestimate speed of sea ice extent loss; this may be due to internal variability (e.g. Notz, 2015), although Rosenblum and Eisenman (2017) and Notz et al. (2020) found that speed of decline was also underestimated as a function of rate of global temperature change.

35   There have been multiple attempts to understand the reasons behind the large spread in model sea ice simulation. Holland (2008) showed that model spread in Arctic sea ice volume during the historical period explained a large proportion of model spread in the rate of Arctic sea ice loss. Eisenman et al. (2007) and DeWeaver et al. (2008) linked differences in sea ice simulation in the CMIP3 ensemble to differences in atmospheric forcing using idealised models but disagreed on the exact relationship. Massonnet et al. (2012) evaluated a variety of metrics of sea ice state in CMIP5, finding a number of statistical
40   relationships between present and future sea ice state, but did not examine the underlying drivers in detail. Boeke and Taylor (2016) evaluated Arctic surface radiation in the CMIP5 ensemble, showing upwelling SW to be strongly dependent on sea ice area, but did not examine causation in the opposite direction. Keen et al. (2021) compared mass budget terms across the CMIP6 ensemble, identifying links between sea ice model parameters and the relative size of individual terms. In this study we aim to build on the strengths of these previous approaches, by combining evaluation of Arctic climate variables with simple physical
45   relationships between these variables.

The framework is based upon the induced surface flux (ISF) bias method of West et al. (2019), which is extended and enhanced to allow comparison of models to each other (as opposed to comparing models only to observations of the real world). The net downward surface flux is treated as the principal driver of the sea ice growth and melt. We use a system of simple models to understand the ways in which differences in individual model variables drive differences in the surface flux, and hence in the
50   sea ice growth and melt. In particular, we use the framework to separate the effects of model differences in sea ice area and thickness on sea ice growth and melt (representing the two most important feedbacks of the sea ice state, the surface albedo feedback and thickness-growth feedback) from the effects of model differences in other Arctic climate variables (representing, in a sense, external forcing of the Arctic sea ice state). In this way, we can analyse how model differences in forcing variables drive differences in ice state, and ice growth and melt, as a coupled system.

55   The framework is similar to that used by Holland and Landrum (2015) to quantify the contribution of changes in surface albedo and in downwelling SW to changes in net SW over 3 periods of the 21st century, but differs in two ways. Firstly, it quantifies the contribution of model processes to model biases, and inter-model differences, rather than to changes in time within model runs. Secondly, it is effectively a generalisation of this method, as it quantifies the contributions of model differences in a larger number of model variables.

60   The study is set out in the following way. In Section 2, the models and reference datasets used for evaluation are described. In Section 3, the Arctic climate simulations of the models are compared, and evaluated with respect to observations. In Section 4, the ISF framework is introduced and used to separate the effects of different surface albedo drivers on ice volume balance,

and the effects of the thickness-growth feedback during winter from other variables. In Section 5, we discuss how the results enable understanding of the sea ice state / sea ice growth and melt as a coupled system. In Section 6, conclusions are presented.

65   ## 2 Models and reference data

2.1 Models

In this paper we evaluate the UK CMIP6 models HadGEM3-GC3.1 (Williams et al., 2017) and UKESM1.0 (Sellar et al., 2019), comparing them to the previous generation CMIP5 model HadGEM2-ES (Collins et al., 2011). All are fully coupled models with interactive sea ice components, and HadGEM2-ES and UKESM1.0 employ additional components to simulate
70   terrestrial and oceanic ecosystems, and tropospheric chemistry (see Collins et al., 2011; Sellar et al., 2019).

Within CMIP6 HadGEM3-GC3.1 was run at multiple resolutions: in this study, we evaluate the low-resolution configuration, HadGEM3-GC3.1-LL (Kuhlbrodt et al., 2018), for consistency with UKESM1.0 -LL which was run at low resolution only. In the LL configuration , the atmosphere model is integrated on the N96 grid, with a resolution of 1.25 degrees latitude and 1.07 degrees longitude. The ocean and sea ice models are integrated on the ORCA1 grid, an irregular grid with a resolution of
75   approximately 50km in the Arctic. HadGEM2-ES was run at only one resolution, with the atmosphere model also on the N96 grid, and the ocean model on the HadGOM grid, a regular latitude-longitude grid with a resolution of one degree in polar regions.

We briefly describe differences in the sea ice components of the models here (differences in the atmospheric and ocean components are described in more detail in Williams et al., 2018). Some features of the sea ice components are shared between
80   all models. All employ a sub-grid-scale ice thickness distribution (Thorndike et al., 1975); elastic-viscous-plastic rheology (Hunke and Dukowicz, 1997) and incremental remapping (Lipscomb and Hunke, 2004). In addition, all models share a thermodynamic framework in which the surface energy balance over ice is calculated in the atmosphere model (West et al., 2016).

However, there are some fundamental differences between the sea ice component of HadGEM2-ES, and those of the CMIP6
85   models. Firstly, in HadGEM2-ES the sea ice has no heat capacity and responds instantly to surface thermodynamic forcing (zero-layer framework, appendix to Semtner (1979)), with vertical conduction assumed to be uniform through the ice. In the CMIP6 models the sea ice is divided into 4 equally spaced layers, each with a heat capacity, with temperatures calculated according to surface forcing using a forwards-implicit scheme (multi-layer framework, Bitz and Lipscomb, 1999).

Secondly, the radiative effect of melt-ponds is modelled explicitly in the two newer models, using the topographic scheme of
90   Flocco et al. (2014). In this scheme, while melt-pond albedo is a fixed parameter, melt-pond fraction of ice is able to vary according to the total volume of meltwater, and the ice topography. In HadGEM2-ES the radiative effect of melt-ponds is modelled implicitly, by reducing albedo linearly (from 0.84 to 0.67 for snow; from 0.64 to 0.565 for bare ice) as surface temperature increases from -1 to 0°C.

Finally, the sea ice model of HadGEM2-ES runs on a regular latitude-longitude grid, with a polar island, while those of
95 HadGEM3-GC3.1 and UKESM1.0 run on the extended ORCA1 grid, an irregular tri-polar grid with poles in Antarctica, Russia
and Canada.

2.2 Reference data

The reference datasets used to evaluate HadGEM3-GC3.1 and UKESM1.0 in section 3 are identical to those used in West et
al. (2019) for HadGEM2-ES. A full description of these datasets is given in the earlier study, but they are summarised here,
100 together with some probable biases identified.

For ice concentration, we use the NSIDC 'Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS Passive
Microwave Data, Version 1' (Cavalieri et al., 1996), as well as versions 1.2 and .2.2 of the Hadley Centre Ice and Sea Surface
Temperature dataset (HadISST; Rayner et al., 2003 for HadISST1.2 and Titchner and Rayner, 2013 for HadISST.2.2). All
datasets use satellite passive microwave imagery as their primary data source (SSMI), but the algorithm used to calculate sea
105 ice area from microwave retrievals differs between the datasets. Uncertainty in ice area is known to be particularly high in the
summer, as satellites cannot distinguish between meltponds and open water.

For ice thickness, we use the Pan-Arctic Ocean-Ice Modeling and Assimilation System (PIOMAS; Schweiger et al., 2011), an
ice-ocean model forced by NCEP atmospheric data that assimilates ice concentration from HadISST and NSIDC. PIOMAS
has been evaluated with respect to satellite observations (Laxon et al., 2013; Wang et al., 2016) and found to compare quite
110 well, though Wang et al. (2016) and found PIOMAS to underestimate winter ice thickness relative to ICESat by 0.31m over
the Arctic Ocean from 2003-2008. We also use EnviSat radar altimetry observations from 1993-1999 (Laxon et al., 2003) and
a regression analysis of submarine sonar observations from 1980-1999 (Rothrock et al., 2008). Because the latter two datasets
are available only for restricted regions, they are used for model evaluation only and not for the ISF analysis.

For surface radiation, we use three datasets: CERES-EBAF (Loeb et al., 2009) and ISCCP-FD (Zhang et al., 2004) satellite
115 observations, obtained by the application of radiative transfer algorithms to reflected SW and upwelling LW retrievals, and
the ERAI reanalysis dataset (Dee et al., 2011). Comparison of downwelling LW observations from these datasets to in-situ
observations by Lindsay et al (1998) suggested a high bias in ISCCP-FD but no clear bias in CERES-EBAF or ERAI. By
contrast Lindsay et al. (2014) found ERAI to overestimate downwelling LW in winter by 15 Wm^{-2} and underestimate
downwelling SW in spring by 20 Wm^{-2}, but with no clear biases in other seasons, and Christenssen et al. (2016) found CERES-
120 EBAF to underestimate downwelling LW radiation in winter by 10-15 Wm^{-2} relative to in-situ observations at Point Barrow,
Alaska.

Finally, for surface melt onset we use the NSIDC 'Snow Melt Onset Over Arctic Sea Ice from SMMR and SSM/I-SSMIS
Brightness Temperatures' dataset (Anderson and Drobot, 2012).

3 Evaluating the UK CMIP6 models

125   In this section, we evaluate and compare the three models UKESM1.0-LL, HadGEM3-GC3.1-LL and HadGEM2-ES. We analyse first the sea ice state (ice area and volume), before proceeding to examine variables affecting the surface energy balance.

3.1 Sea ice state

Evaluation is performed for the 1980-1999 period, and for the Arctic Ocean region, defined in Figure 1b, unless otherwise

130   stated. The evaluation is performed for the four historically-forced members of HadGEM3-GC3.1-LL and HadGEM2-ES, and the first six historically-forced members of UKESM1.0-LL. For energy fluxes the sign convention used is that downwards is positive.

Total Northern Hemisphere sea ice extent is higher in both UKESM1.0-LL and HadGEM3-GC3.1-LL than in HadGEM2-ES, particularly during the summer (Figure 1a). HadGEM2-ES tended to underestimate Arctic sea ice extent from June-October

135   with respect to HadISST1.2, HadISST.2 and NSIDC, whereas ice extent in HadGEM3-GC3.1-LL and UKESM1.0-LL mainly lies within observational spread. However, HadGEM3-GC3.1-LL and UKESM1.0-LL simulate the minimum of the annual cycle in extent to occur in August, whereas in reality it occurs in September.

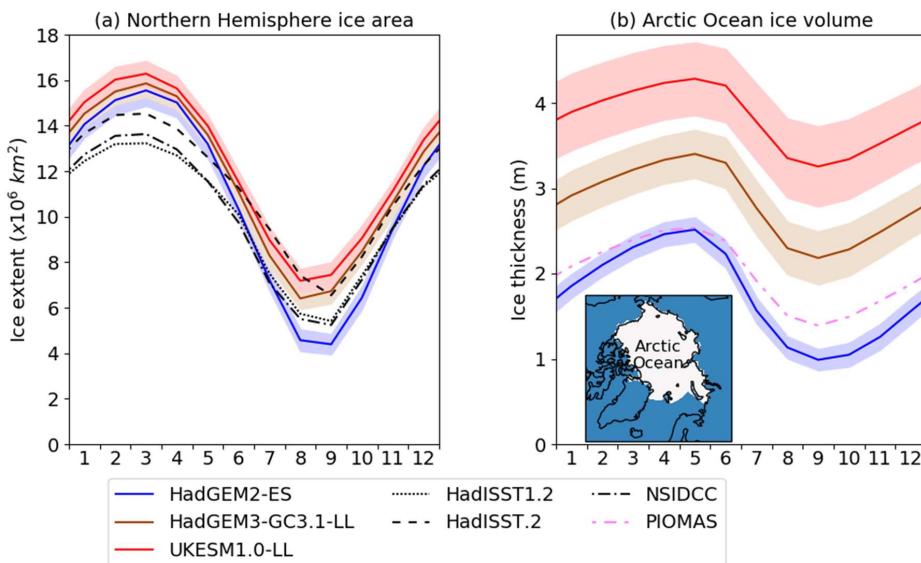



Figure 1. (a) 1980-1999 average sea ice extent for the whole Northern Hemisphere, for the evaluated models and reference datasets
140   **(HadISST1.2, HadISST.2 and NSIDC); (b) 1980-1999 average sea ice volume over the Arctic Ocean region shown in the subpanel, for the evaluated models and PIOMAS. For each model, ensemble mean (lines) and twice standard deviation (shading) is shown.**

Sea ice thickness is greatest in UKESM1.0-LL (Figure 1b, annual mean Arctic Ocean region thickness 3.9m) and least in HadGEM2-ES (1.7m) throughout the year with HadGEM3-GC3.1-LL tending to lie between the two (2.8m). UKESM1.0-LL and HadGEM3-GC3.1-LL are biased high relative to the ice-ocean model PIOMAS (Figure 1b, annual mean thickness 1.9m),

145 whereas HadGEM2-ES is biased low during the summer. We also evaluate the three models with respect to ERS satellite measurements from 1993-1999 and to the multiple regression of submarine data from 1980-1999 (not shown). In both cases UKESM1.0-LL and HadGEM3-GC3.1-LL are biased high and HadGEM2-ES is biased low year-round. However HadGEM3-GC3.1-LL lies somewhat closer to observations, and HadGEM2-ES somewhat further, than is the case when PIOMAS is reference dataset, consistent with PIOMAS being biased low during winter (Section 2.2). For all three models, internal

150 variability (shown as twice the ensemble standard deviation) is low compared to the inter-model differences and the model biases.

The large differences in ice thickness between the models are associated also with differences in the amplitude of the seasonal cycle of ice thickness, hereafter referred to as ice growth / melt. Ice growth / melt is greatest in HadGEM2-ES (1980-1999 Arctic Ocean mean 1.53m); it is lower in HadGEM3-GC3.1 (1.22m) and lower still in UKESM1.0-LL (1.03m). By

155 comparison, PIOMAS annual ice growth / melt is similar to HadGEM3-GC3.1 at 1.15m. The correspondence between the model annual mean ice thicknesses and volume balances are broadly consistent with what would be expected from the ice thickness-growth feedback (Bitz and Roe, 2004): thicker ice tends to grow less in winter, because it conducts heat from the ocean to the atmosphere less efficiently. It is also consistent with the surface albedo feedback (Bitz, 2008): thinner ice warms more quickly in early spring, creating melt-ponds sooner, and supports the creation of more extensive open water areas, leading

160 to greater absorption of shortwave (SW) radiation and greater ice melt.

The ice growth / melt biases are associated with an energy balance bias. This could be associated with a bias in the surface energy balance, the oceanic heat convergence, or in ice divergence (or some combination of these). However, the ice divergence term is small, with indeterminate annual cycles, at 2.5, 4.0 and 5.1 Wm^{-2} in HadGEM2-ES, HadGEM3-GC3.1-LL and UKESM1.0-LL respectively. The oceanic heat convergence term is also small at 4.4 Wm^{-2}, 3.8 Wm^{-2} and 3.9 Wm^{-2}

165 respectively. Monthly differences in these terms between models are too small to explain the differences in ice melt / growth seen: with ice density of $917 kgm^{-3}$ and latent heat of fusion of 3.35×10^3 Jkg^{-1}, a difference of 1Wm^{-2} is equivalent to only an additional .84cm of ice melt per month. Hence we focus on comparing the surface energy balance between the models.

3.2 Surface radiation

We now evaluate surface radiative fluxes in the three models (Figure 2). Downwelling SW is very similar in all three models

170 year-round (Figure 2a). By contrast upwelling SW displays large differences from June-August (Figure 2b), with HadGEM2-ES lowest in magnitude and UKESM1.0-LL highest. This is consistent with the ice melt/growth differences: lower upwelling SW in HadGEM2-ES causes a higher net SW flux (Figure 2c), and more overall sea ice melting. It is also consistent with the ice extent differences: the lower summer ice extent of HadGEM2-ES causes a lower surface albedo and hence lower SW reflection. However, in June the ice area differences are small, and insufficient to explain the upwelling SW differences. Hence

175 another parameter influencing surface albedo is likely to be responsible for the model differences in this month. We examine possible drivers shortly.

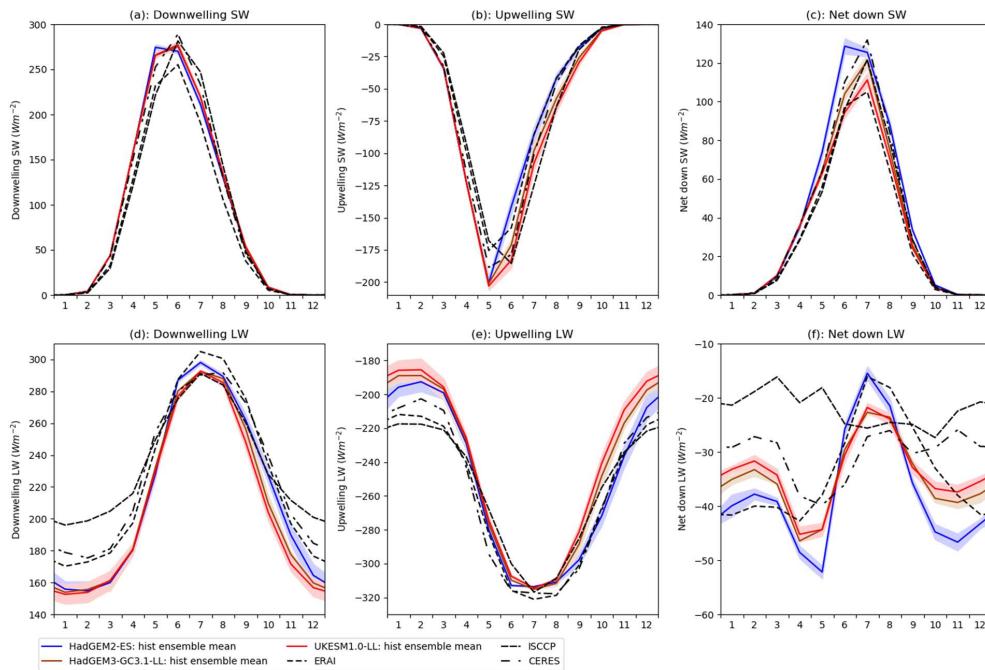



Figure 2. (a) Downwelling SW, (b) upwelling SW, (c) net downwards SW, (d) downwelling LW, (e) upwelling LW, (f)
180 **net downwards LW, from 1980-1999 in HadGEM2-ES, HadGEM3-GC3.1-LL and UKESM1.0-LL, together with observational estimates from ISCCP-FD, ERAI and CERES, averaged over the Arctic Ocean region. For each model, ensemble mean (lines) and twice standard deviation (shading) is shown.**

Downwelling LW fluxes are similar from January-May in the three models (Figure 2d), but from June-July, and October-
185 November downwelling LW is much higher in HadGEM2-ES than in UKESM1.0-LL and HadGEM3-GC3.1-LL, indicating a colder, or clearer, atmosphere in these months in the newer models. Upwelling LW fluxes are higher in magnitude in HadGEM2-ES than in UKESM1.0-LL and HadGEM3-GC3.1-LL from September – February (Figure 2e), indicating a colder surface in the newer models. Net LW is higher in HadGEM2-ES from June-August, and lower from September – May, than in the newer models (Figure 2f), indicating that the upwelling LW differences dominate during the winter. The net LW
190 differences are also consistent with the greater ice melting and ice freezing seen in HadGEM2-ES relative to the CMIP6

models. For both net LW during winter, and net SW during summer, model internal variability is small relative to the difference between HadGEM2-ES and the CMIP6 models.

To summarise, the weaker summer ice melt of the CMIP6 models relative to HadGEM2-ES is driven by a smaller upwelling SW flux from June – August. This is likely caused by ice area differences in July and August (the surface albedo feedback),
195 but in June other surface albedo drivers are responsible. The weaker winter ice growth of the CMIP6 models relative to HadGEM2-ES is driven by a smaller upwelling LW flux from October – April. This is likely caused by the ice thickness-growth feedback: thicker ice in HadGEM3-GC3.1-LL and UKESM1.0-LL causing a colder surface temperature, and less heat loss to space, than is the case in HadGEM2-ES.

3.3 Variables influencing surface albedo

200 We now evaluate other model variables that affect surface albedo: snow fraction, and the presence and extent of melt-ponds. We concentrate on the month of June as it is in this month that the models display differences in upwelling SW radiation that cannot be explained by ice area differences alone. Firstly, we compare snow cover in the three models. In June, snow thickness is highest in UKESM1.0-LL and lowest in HadGEM2-ES (Figure 3a-c), with Arctic Ocean average snow thicknesses of 6cm, 13cm and 18cm respectively. For each model, ensemble standard deviation snow thickness is mostly lower than 2cm, although
205 in UKESM1.0-LL standard deviation approaches 5cm between Fram Strait and the North Pole (not shown).

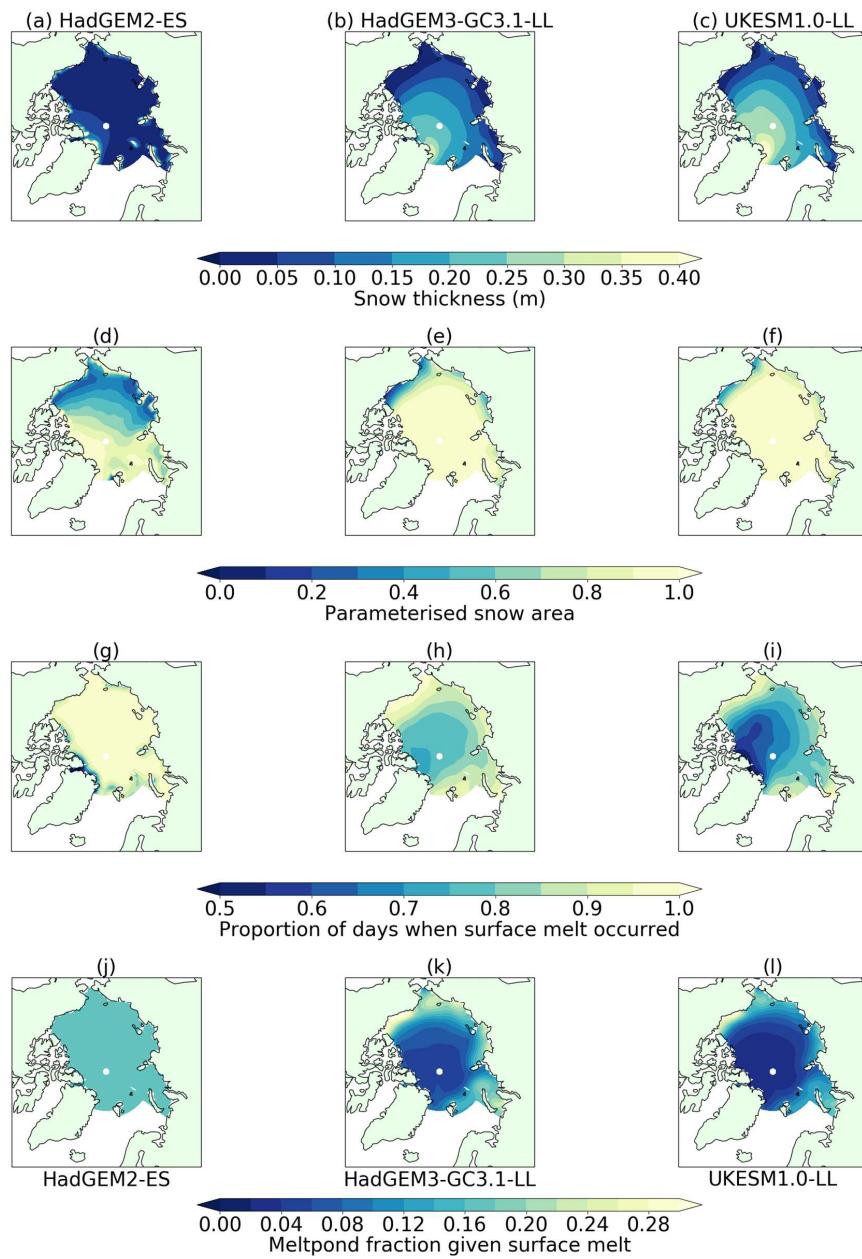



Figure 3. 1980-1999 June averages of variables affecting surface albedo in HadGEM2-ES (left column), HadGEM3-GC3.1-LL (middle column) and UKESM1.0-LL (right column). Showing (a-c) snow thickness, (d-f) parameterized snow area fraction, (g-i) fraction of month during which surface melting conditions were present, (j-l) melt-pond
210 **fraction during times in which surface melting conditions were present.**

The models differ in how snow area is parameterized from snow thickness. HadGEM2-ES uses the formula

$$a_{snow} = 1 - e^{-0.2h_{snow}\rho_{snow}}$$ (1)

While HadGEM3-GC3.1-LL and UKESM1.0-LL use the formula (from CICE)

215 $$a_{snow} = \frac{h_{snow}}{h_{snow} - 0.02}$$ (2)

The effect of this is that the newer models simulate a lower fraction of snow for the same snow thickness value, with the difference greatest at a thickness of 4cm when the newer models simulate 26% less snow area (Figure S1). We can see the effect of this when we compare maps of June snow thickness in the three models (Figure 3a-c) with maps of June snow area
220 estimated using the models' respective formulations (Figure 3d-f). Despite the substantially higher snow thicknesses in HadGEM3-GC3.1-LL and UKESM1.0-LL, the increase in ice area in the newer models is muted. The effect of the new parameterization is to reduce the surface albedo difference caused by the thicker snow in UKESM1.0-LL and HadGEM3-GC3.1-LL Despite this, the difference in snow area between HadGEM2-ES and the CMIP6 models (rising to 0.7 near the Bering Strait) is much larger than the ensemble standard deviations in snow area, which approach 0.15 near the Bering Strait
225 in HadGEM2-ES but are otherwise under 0.05 (not shown).

Next, we examine differences in melt-pond coverage between the models. As with the snow comparison, care is required as the explicit topographic melt-pond scheme of the CMIP6 models is more complex than the simple parameterization of HadGEM2-ES. We first compare the average date of melt onset between the three models: the first day, for each grid cell and year, for which the surface temperature exceeds a fixed threshold, chosen to be -1C. In this way we create a metric to compare
230 surface melting tendencies in each model, independent of the melt pond scheme.

Date of melt onset is earliest in HadGEM2-ES, at mid-to-late May in the Central Arctic, and latest in UKESM1.0-LL, in late June in the Central Arctic. By comparison, SSMI observations suggest melt onset occurred in mid-June, on average, in the Central Arctic for the period 1980-1999. Hence UKESM1.0-LL models melt onset to occur too late in the Central Arctic, but HadGEM2-ES is much too early (as identified by West et al., 2019). To demonstrate the effect of this on June surface albedo,
235 the proportion of June for which melting conditions are present (a_{melt}) is plotted (Figure 3g-i): for HadGEM2-ES, a_{melt} is 100% across most of the Arctic, but in HadGEM3-GC3.1-LL and UKESM1.0-LL a_{melt} approaches 70% and 50% respectively across the central Arctic. Ensemble standard deviation in a_{melt} is nowhere higher than 10% for any model (not shown).

To assess the effect of melt-ponds on surface albedo, the melt-pond fraction where melting is taking place must also be compared. In this way the proximate effect of the different melt-pond schemes is captured. HadGEM2-ES effectively simulates
240 a uniform, constant melt-pond fraction of 0.2 in the presence of surface melting, while UKESM1.0-LL and HadGEM3-GC3.1-LL simulate variable melt-pond fraction depending on total meltwater and ice topography. Hence June melt-pond fractions are

higher in the CMIP6 models than HadGEM2-ES at lower latitudes, but much lower in the Central Arctic (Figure 3j-l).
Ensemble standard deviation in the CMIP6 models is everywhere less than 4% (not shown). Hence the explicit melt-pond
scheme is contributing to a portion of the surface albedo differences in June, in addition to the different melt onset dates and
245 snow thickness.

4 Attributing differences in modelled ice melt/growth using an induced surface flux (ISF) difference framework

The model evaluation presented in Section 3 prompts two questions. Firstly, by how much do the model differences in snow
and meltpond variables affect the ice melt differences over the melting season? Secondly, does the thickness-growth feedback
250 fully account for the differences in ice growth, given the opposing effect of the downwelling LW differences during the early
winter? To address these questions we use a method similar to the 'induced surface flux' (ISF) framework described by West
et al. (2019). This framework attempts to separate and quantify the drivers of differences in seasonal ice growth/melt.

The ISF analysis works by approximating, at any point $(\boldsymbol{x}, t)$ of model space and time, the total net surface flux as a function
$g(v_i, \boldsymbol{x}, t)$ of variables v_i which are quasi-independent in the sense that while they affect surface flux instantaneously, they
255 affect each other on finite timescales. (For example, two such variables could be downwelling SW radiation and ice
concentration, as in Holland and Landrum, 2015). In this way the rate at which surface flux depends upon a model variable v_i
at point $(\boldsymbol{x}, t)$ can be estimated as $\partial g / \partial v_i$. Given two model estimates of v_i at point $(\boldsymbol{x}, t)$, $v_i^{MODEL1}(\boldsymbol{x}, t)$ and $v_i^{MODE}(\boldsymbol{x}, t)$,
we can characterise the induced surface flux difference between the models due to variable v_i at $(\boldsymbol{x}, t)$ as

$$\left(v_{i,x,t}^{MODE} - v_{i,x,t}^{MODE} \right) \left(\frac{\partial g^{MODEL}}{\partial v_i} + \frac{\partial g^{MODE}}{\partial v_i} \right) / 2 \quad (3)$$

260 The ISF differences obtained can be averaged over large regions of time and space to determine the large-scale effects of
specific model biases on surface flux, and hence ice volume balance. In particular, due to the quasi-independence of the
variables, the ISF differences for each variable represent separate effects, and the sum of the individual ISF differences should
approach the true surface flux difference, which is thereby divided into components, each representing the effect of a model
variable.

265 We briefly describe how the effects of different model variables on surface flux are quantified (West et al., 2019 gives a
complete description). Firstly, the division of the upwelling SW difference into components is demonstrated. Net downwelling
SW radiation can be expressed as

$$F_{SW-net} = F_{SW-down} - F_{SW-up}$$

$$= F_{SW-down}\left(1 - \alpha_{sfc}\right) \quad (4)$$

270 where α_{sfc} is surface albedo, F_{SW-do} is downwelling SW radiation and F_{SW-u} is upwelling SW radiation. α_{sfc} can be
further expressed as

$$\alpha_{sfc} = \sum_i a_i \alpha_i \qquad (5)$$

where i varies over all surface types present in a grid cell, a_i is the fractional area of surface type i and α_i is the surface albedo of surface type i.

275   We can use this equation to approximate net SW flux in each model (due to nonlinearities in taking temporal means, the exact model net SW flux will not be reproduced). Over ocean, there are four surface types: open water, melt-pond, snow and bare ice, the albedos of all of which are model parameters. The open water fraction is in all models equal to $1 - a_{ice}$, while the fraction of ice covered by snow is parameterised as in (1) (HadGEM2-ES) or (2) (HadGEM3-GC3.1-LL and UKESM1.0-LL). For UKESM1.0-LL and HadGEM3-GC3.1-LL melt-pond area fraction is a model diagnostic, but for HadGEM2-ES they are
280   implicit in the parameterization, which assigns an aggregate 'melting surface albedo' to any grid cell judged to be undergoing surface melting. Relative to the HadGEM3-GC3.1-LL melt-pond albedo parameter, this means that melting grid cells in HadGEM2-ES have a uniform, constant melt-pond fraction of 0.23 (when snow is present) or 0.18 (when snow is not present).

For any model, month and grid cell, in addition to approximating the net SW flux, we can then characterise the dependence of the net SW flux on any model variable or parameter by taking the derivative of equation (4) with respect to that parameter. For
285   example, net SW varies with ice concentration by $F_{SW-down}(\alpha_{ocean} - \alpha_{ice})$. We illustrate what this means by considering the month of August 1980 for a grid cell in the Canadian Basin. $F_{SW-down}$ is 133 Wm⁻² and 145 Wm⁻² for UKESM1.0-LL and HadGEM2-ES respectively, giving a model mean of 139 Wm⁻²; $\alpha_{oce} - \alpha_{ice}$ is -0.56 at the same point, meaning that net SW varies with ice concentration by -78 Wm⁻². As ice concentration for this point in the two models are 0.95 and 0.83 respectively, the net SW difference induced by ice concentration is -9.0 Wm⁻².

290   The variable a_{melt} defined in Section 3, the tendency of a grid point to be undergoing surface melting, also usefully emerges as an independent variable in this framework, with

$$\frac{\partial F_{SW-ne}}{\partial a_{melt}} = F_{SW-down} a_{meltpond} (\alpha_{meltpond} - \alpha_{ice-snow}) \qquad (6)$$

Hence we can assign a component of the surface flux difference to that induced by difference in the tendency of the model atmosphere to induce surface melting, as well as a component due to difference in melt-pond fraction when melting occurs. In
295   a proximate sense, the effect of the structural model differences can be separated from the effect of the model climate differences.

In general therefore, given a model difference in a variable at any point in model space and time, we multiply that difference by the model mean dependence of net SW on that variable, to obtain an estimate of the surface flux difference induced by the difference in that variable. In this way, the model differences in upwelling SW can be decomposed into contributions from
300   different model parameters, and the contributions can be averaged in time and space to determine the large-scale effects of differences in each variable.

We demonstrate this by showing how components of induced surface flux difference evolve through the summer when comparing the models in turn. As daily data is available for only the first ensemble member of HadGEM2-ES, the evolution is demonstrated using only first historical ensemble members for each model. As the ensemble spread in the driving model variables is small relative to the model differences (demonstrated in Section 3.3), this is likely to give a similar result to using the ensemble means.

When comparing UKESM1.0-LL with HadGEM2-ES (Figure 4a), the total ISF difference is negative throughout the summer, consistent with the weaker ice melt and reduced net SW radiation in UKESM1.0-LL. In April, the total ISF difference is weakly negative, but it falls steeply through May to reach values of over -30 Wm^{-2} in mid-June, rising very slowly thereafter. Consistent with the evaluation in Section 3, ice area difference does not become the dominant contribution to the total ISF difference until early July, with significant contributions occurring both from surface melt onset occurrence (peaking at the beginning of June, at -15 Wm^{-2}) and from snow area (peaking in mid-to-late June, at -18 Wm^{-2}). The melt-pond scheme contributes only a small negative ISF difference, because large negative differences in the Central Arctic are mostly outweighed by large positive differences near the coasts. The difference in snow parameterization, as expected, contributes a positive ISF difference, rising to a maximum of 8 Wm^{-2} in early June. The downwelling SW term contributes a negative difference in May, becoming a positive difference in June, but this is counteracted by the downwelling LW term which is shown for comparison. These terms likely represent the response of modelled cloud cover to the weaker ice melt of UKESM1.0-LL, and collectively contribute little surface flux difference.

Examining the ISF terms over the melt season as a whole (Figure 4b) we see that the ice area term contributes about two-thirds of the total ISF difference (18.6 Wm-2 of 27.2 Wm-2), with the snow area and melt onset terms contributing -3.2 Wm-2 and -2.4 Wm-2 respectively. The value of using daily data is demonstrated: the snow area and melt onset terms appear very small over the season as a whole, but the daily data shows that they play a vital role in the early part of the season, and help generate the ice area differences that contribute the major part of the surface flux differences. The downwelling radiative differences collectively contribute -4.9 Wm-2, but the effect is much more uniform over the melting season than that of the snow area and melt onset terms.

When HadGEM3-GC3.1-LL is compared to HadGEM2-ES (not shown) the picture is qualitatively similar but the ISF terms are smaller in magnitude, consistent with the rate of ice melt being more similar in these two models. The total ISF difference is smaller still when UKESM1.0-LL is compared to HadGEM3-GC3.1-LL (Figure 4c), but in this case it is the snow thickness difference that appears to drive most of the ISF difference over the melt season as a whole (Figure 4d), with the ice area difference contributing very little to the surface flux differences. The other notable difference with this comparison is that the effect of the downwelling radiative differences is also more concentrated in the early part of the melt season.

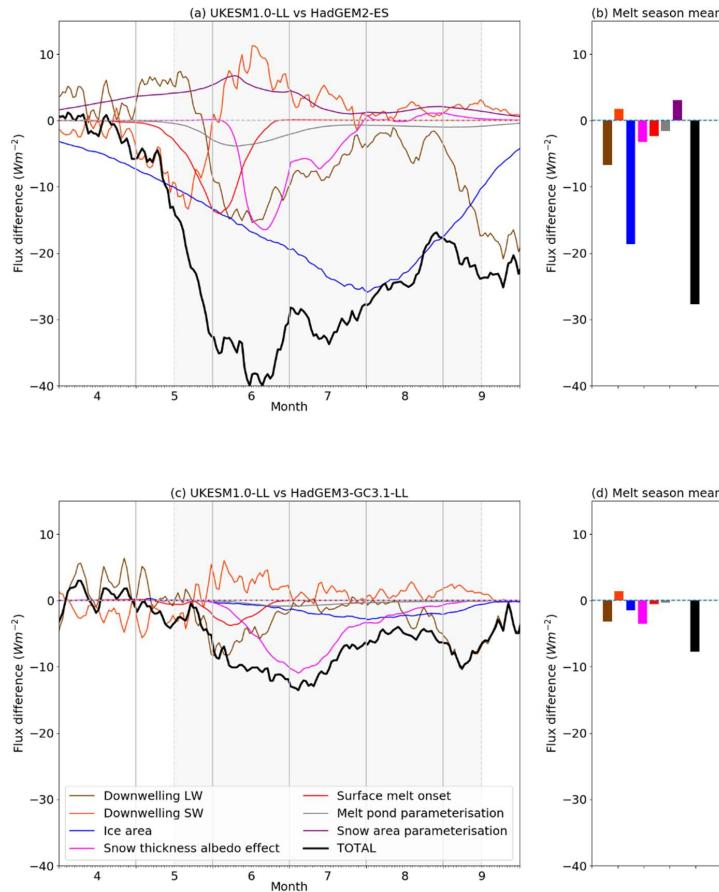



Figure 4. Illustration of drivers of summer melting differences, using the ISF framework. Shown are ISF differences between (a,b) UKESM1.0-LL and HadGEM2-ES; (c,d) UKESM1.0-LL and HadGEM3-GC3.1-LL, apportioned by
335 **downwelling SW, ice area, snow thickness, surface melt onset, direct impact of snow fraction parameterization, and direct impact of the UKESM1.0 melt-pond scheme. Showing April – September daily evolution (left column) and melt season mean (right column, 16ᵗʰ May – 15ᵗʰ September). For each comparison, only the first ensemble member is shown, as daily data is not available for other members of HadGEM2-ES.**

Secondly, we describe how the thickness-growth feedback can be separated from the atmospheric radiative components. This
340 is done using a single-column model after Thorndike (1992), discussed more extensively in West et al. (2019). As in the

models, each grid cell is divided into five sea ice categories, plus a 'zero' category for open water. For each category, we assume a uniform conductive flux through the ice (no sensible heat storage) and flux continuity at the surface. Hence

$$F_{cond}(\pmb{x}, t, cat) = \frac{T_{surface}(\pmb{x}, t, cat) - T_{base}}{R_{ice}(\pmb{x}, t, cat)} \qquad (7)$$

where cat represents the category number (ranging from 0 to 5), F_{cond} is conductive flux through the ice, T_{base} is ice base temperature, $T_{surface}$ ice surface temperature. R_{ice} denotes the thermal insulance of the ice-snow column, defined as

$$R_{ice} = \frac{h_{ice}(\pmb{x}, t, cat)}{k_{ice}} + \frac{h_{snow}(\pmb{x}, t, cat)}{k_{snow}} \qquad (8)$$

where h_{ice} and h_{snow} are category ice and snow thickness respectively, and k_{ice} and k_{snow} are fresh ice and snow conductivity. The latter are parameterized as 2.03 and 0.30 Wm^{-1}K^{-1} respectively, similar to the values used in HadGEM2-ES, HadGEM3-GC3.1-LL and UKESM1.0-LL.

By flux continuity, $F_{cond} = F_{sfc}$, where F_{sfc} is the downwards surface energy flux, linearised as $F_{surface}(\pmb{x}, t, cat) = F_{atmos-ice}(\pmb{x}, t) + B_{up}T_{surface}(\pmb{x}, t, cat)$. Eliminating $T_{surface}$ and rearranging gives

$$F_{surface} = \frac{F_{atmos-ice} + B_{up}T_{base}}{1 + B_{up}R_{ice}} \qquad (9)$$

Summing over categories gives

$$F_{surface} = (1 - \sum_{cat=1}^{5} a_{ice})F_{atmos-ocea} + F_{atmos-ice}\sum_{cat=1}^{5}\frac{a_{ice}}{1 + B_{up}R_{ice}} \qquad (10)$$

In this equation $F_{atmos-ice}$ represents the part of the atmosphere-ice energy flux that is independent of the surface temperature, or the components that do not vary instantly when surface temperature is varied. After West et al. (2019) we identify $F_{atmos-ice}$ with the sum of the net SW flux, the downwelling LW flux, and the turbulent fluxes.

Using equation (10) we can separate the ice thickness-growth feedback from the different atmospheric forcing parameters at any point in model space and time. For a given model, at a point ($\pmb{x}$,t), the dependence of net surface flux on any component of $F_{atmos-ice}$ under freezing conditions is $\sum_{cat=1}^{5}\frac{a_{ice}}{1 + B_{up}R_{ice}}$, the 'ice thickness scale factor', which tends to $\sum_{cat=1}^{5} a_{ice}$ in the limit of thin ice and 0 in the limit of thick ice. In this way, given a model difference in downwelling LW of -50 Wm^{-2} (for example), we multiply this by the model mean ice thickness scale factor to estimate the difference in net surface flux induced. Under thicker ice conditions, a given difference in atmospheric forcing will tend to induce a smaller difference in net surface flux, and hence a smaller difference in ice growth.

Given full information about the modelled ice thickness distribution, we can also use equation (10) to diagnose the effect of the thickness-growth feedback itself. At each model point ($\pmb{x}$,t) this effect is represented by the sum over all categories of the

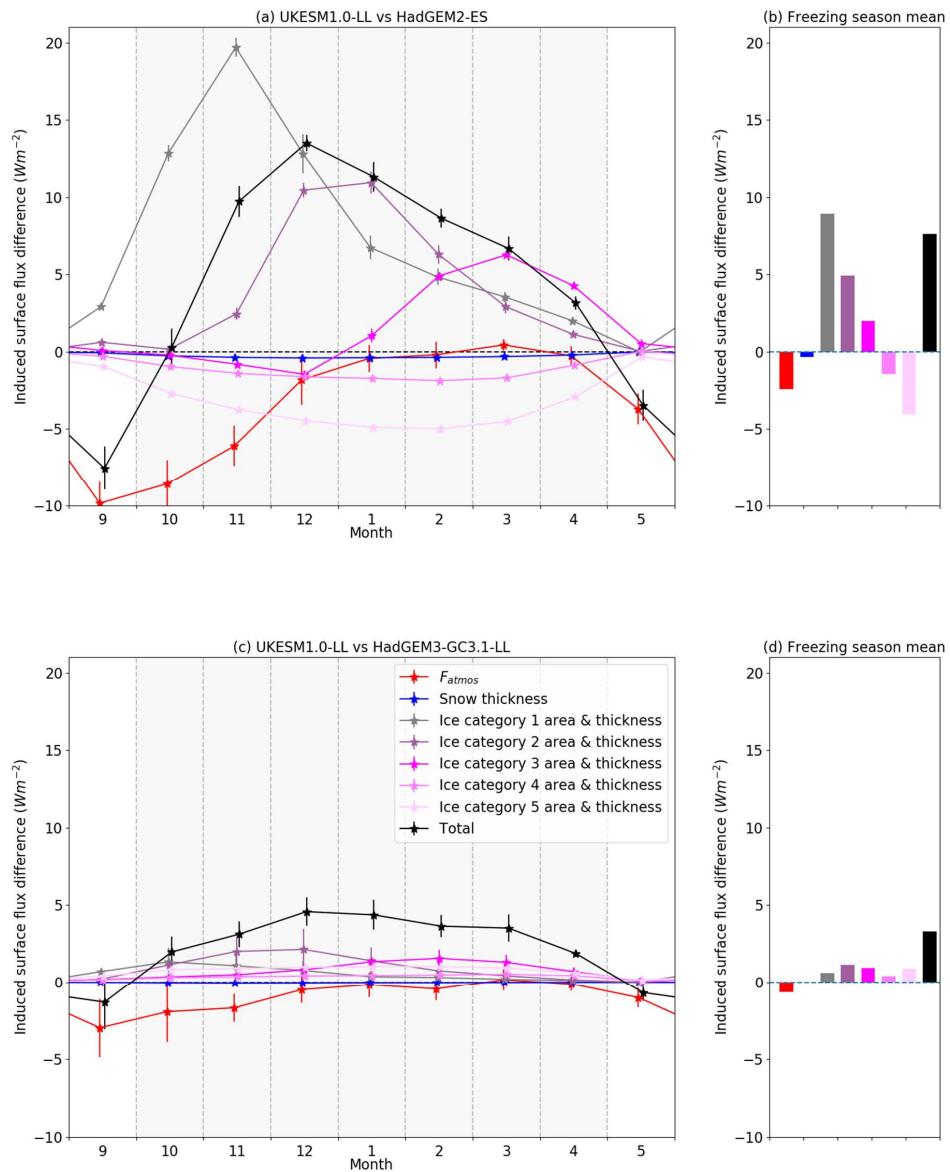
effects of differences in category ice area and thickness. For each category, the rate of dependence of surface flux on category

ice area is $1/(1 + B_{up}R_{ice})$, while the rate of dependence on category ice thickness is $-B_{up}a_{i-cat}/(k_i(1 + B_{up}R_{ice}))^2$.

370   Hence we can calculate surface flux difference induced by differences in atmospheric forcing (F_{atmos}), snow thickness, and in the ice thickness distribution, at each point in model space and time, and average these over the Arctic Ocean region and the period 1980-1999 to understand the effect of the evolving differences over the ice freezing season (Figure 5). For all three pairs of models, the effect of the ice thickness distribution (represented by the sum of the individual category terms) greatly outweighs the effects of differential atmospheric forcing, and of differences in snow cover. For example, when comparing UKESM1.0-LL to HadGEM2-ES (Figure 5a) the total ice thickness-induced surface flux difference achieves a maximum of

375   15 Wm^{-2} in November, representing a weaker upwards surface flux, and hence reduced ice growth, in UKESM1.0-LL. F_{atmos} contributes significant differences only at the beginning of the freezing season, being -9.4 Wm^{-2} in September but near-zero from December onwards, while snow differences contribute a maximum of -0.3 Wm^{-2} surface flux difference, in January.

Ice thickness distribution-induced differences dominate also when HadGEM3-GC3.1-LL is compared to HadGEM2-ES (not shown) and also when UKESM1.0-LL is compared to HadGEM3-GC3.1-LL (Figure 5c), but in this last case differences in

380   the thicker categories contribute much more towards the total. Unlike for the summer analysis, the required data exists for all model ensemble members, and ensemble standard deviation is seen to be small compared to the ensemble mean ISF differences. Hence the model differences in ice thickness distribution contribute to a systematic difference in seasonal ice growth and melt between models.

385 **Figure 5. Illustration of drivers of winter freezing differences, using the ISF framework. Shown are ISF freezing season differences due to atmospheric forcing, snow thickness and ice thickness for (a,b) UKESM1.0-LL relative to HadGEM2-ES; (c,d) UKESM1.0-LL relative to HadGEM3-GC3.1-LL. Showing September – May monthly evolution (left column) and freezing season mean (right column, October – April). For a) and c), the bars denote ensemble mean and standard deviation.**

390 These two approaches can be combined to provide a complete breakdown of the drivers of surface flux differences between pairs of models (Figure 6). We illustrate this with the UKESM1.0-LL – HadGEM2-ES comparison, performed using monthly means year-round as daily data is not available for the ice thickness distribution. The total ISF difference is negative May – September and positive from October – April. This indicates that model differences tend to drive a lower net down surface flux in the summer in UKESM1.0-LL (less ice melt) and a higher net down surface flux in the winter (less ice growth).

395 In summer, the ice area differences account for most of the negative ISF difference except in June. In this month, the ice area difference contributes only -13.2 Wm^{-2} of the total -29.2 Wm^{-2}. The remaining negative ISF difference is accounted for by snow area albedo effect (-7.8 Wm^{-2}), surface melt onset (-4.5Wm^{-2}), and meltpond parameterization (-2.6Wm^{-2}), with an opposing effect from the snow area parameterization (4.4 Wm^{-2}). In addition, there are opposing contributions from the downwelling SW (6.8 Wm^{-2}) and downwelling LW (-9.8 Wm^{-2}) terms which largely cancel out.

400 In winter, the ice thickness distribution contributes almost the entire positive ISF difference, except in October and November, when there is a substantial negative term from the downwelling LW (-5.0 Wm^{-2}, comparing to 12.4 Wm^{-2} from the ice thickness distribution over these two months).

Viewing the year as a whole, the ice growth/melt differences are almost all driven by differences in the ice state (area and volume) itself, with other drivers being important mainly during the early summer. The implications of this are discussed in

405 Section 5 below. The other model comparisons are qualitatively similar (not shown): only when comparing UKESM1.0-LL to HadGEM3-GC3.1-LL in the melting season does a variable other than ice area or volume dominate the total ISF (snow thickness albedo effect). The ice area ISF difference in the melting season can be identified with the surface albedo feedback; the ice thickness ISF difference in the freezing season the thickness-growth feedback.

Finally we note that the total ISF difference is qualitatively consistent with the difference in net radiation between the models,

410 and also with the difference in ice growth/melt, shown in Figure 6 for comparison. This gives confidence that the ISF framework is producing meaningful results. For example, from October – April the surface flux differences imply 58cm less ice growth in UKESM1.0-LL than in HadGEM2-ES; from May – September, they imply 75cm less ice melt. This compares to a total growth/melt difference of 50cm. The difference in summer melt is likely overestimated in the ISF framework because some of the ISF differences occur over regions of already-melted ice, where they would affect the heating of the surface ocean

415 layer, rather than the ice volume balance. This is consistent with the biggest difference between the total ISF and the ice growth/melt being in August, and the net radiation difference being closer to the total ISF than to the ice growth/melt in July and August.

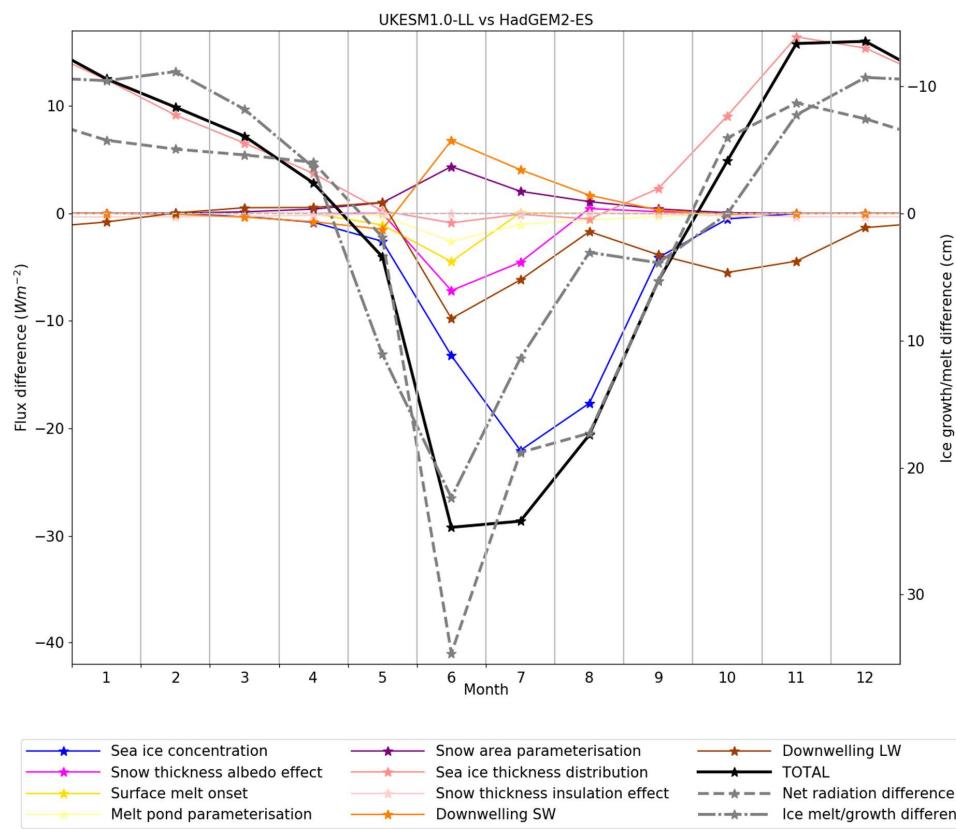



Figure 6. ISF differences compared between pairs of models over the year as a whole, for UKESM1.0-LL relative to
420 **HadGEM2-ES. Averages are taken over the 1980-1999 period, and the Arctic Ocean region. The grey lines show, for comparison, the total net radiation difference and the ice growth/melt difference. All values are plotted in Wm⁻² (left axis) while the right axis shows the equivalent monthly ice growth/melt difference in cm, assuming ice density of 917 kgm⁻³ and latent heat of fusion 3.35 × 10⁵ Jkg⁻¹.**

425 **5 Discussion**

In this section, we discuss the extent to which the ISF framework is able to explain the differences between the sea ice states of UKESM1.0-LL, HadGEM3-GC3.1-LL and HadGEM2-ES.

The ISF framework shows that for the assessed models, the differences in seasonal ice growth/melt between models are driven almost entirely by differences in ice area and thickness. In a proximate sense however, the ice area and thickness – collectively

430 representing the ice volume – are driven by the seasonal ice growth/melt in turn. Because of this it is helpful to consider the

ice volume, and the seasonal ice growth/melt, as a simple coupled system, with points of equilibrium where seasonal ice growth and melt are equal. Given an initial equilibrium, changes to an external variable such as downwelling radiation, or snow cover, lead to an initial change in annual growth and/or melt. This in turn induces a change in the ice volume (i.e. in the ice area or thickness), inducing a further change in the growth or melt via the effect of the surface albedo feedback, and/or thickness-

435   growth feedback, on the surface flux. The chain of causality continues until ice growth and melt are once again in balance, and a new equilibrium is reached.

Therefore the ISF differences not due to ice area and thickness show the proximate causes of the differences in the whole ice volume – seasonal ice growth/melt coupled system. For example, comparing UKESM1.0-LL and HadGEM2-ES, when the ice thickness and area contributions are excluded the largest remaining ISF differences are from the variables affecting surface

440   albedo in early summer: surface melt onset, melt pond parameterisation, snow thickness and snow parameterisation (contributions from downwelling SW and LW radiation largely cancel each other out). Collectively, they account for far less ISF difference than the ice area term. Yet they likely account for a major part of the difference between the ice volume – seasonal ice growth/melt systems of UKESM1.0-LL and HadGEM2-ES, because the ice area and ice volume differences can be traced to the initial reduced ice melting they trigger.

445   More generally, the 'external' variables – such as downwelling radiation, snow cover and surface melt – set the parameters of the ice volume - seasonal ice melt/growth coupled system. In effect, they determine the climate in which the sea ice will find an equilibrium volume, with ice melt and growth equal. This can be visualised by calculating ice melt and ice growth curves, as a function of annual mean ice thickness, with the simple model used in Section 4 (Figure 7), forced with the Arctic Ocean average surface radiative fluxes from each model. For each model, and for the real world, the external variables determine the

450   relationship between ice thickness, and ice growth and melt: an equilibrium ice thickness lies where the two curves meet.

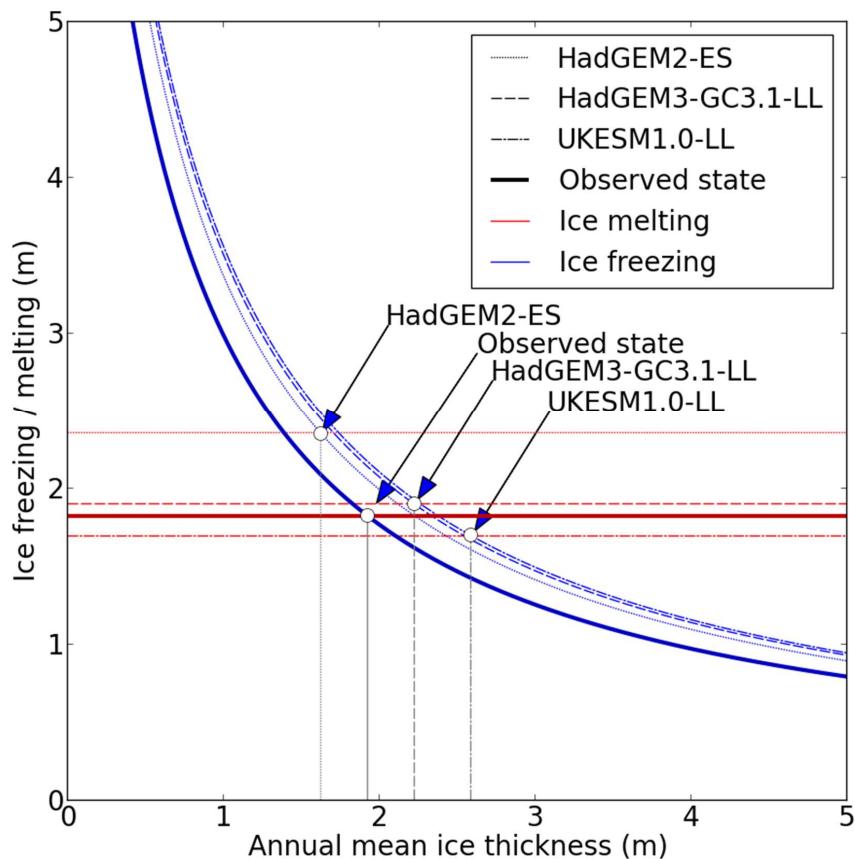



Figure 7. An illustration of idealised ice thickness-ice growth (blue line) and ice thickness-ice melt (red line) relationships in the evaluated models and in observations, as produced by the ISF parameterisation. The graph demonstrates how the ice growth and ice melt curves determine equilibrium ice thickness in each model climate.

455   This conceptual picture accurately reproduces the qualitative differences between each model, and the model biases. All three

models share similar ice growth curves, biased high relative to the real world: this reflects the similar low downwelling LW

biases. The differences between models are caused by the ice melt curves. For example, the equilibrium ice thickness of

HadGEM2-ES is much lower than that of UKESM1.0-LL because this is the only way to achieve the greater ice growth required to balance the ice melt differences.

460   The impact of external drivers on the sea ice varies greatly by time of year, because of this interplay between ice thickness and ice growth/melt. On the one hand, the effect of surface flux biases during the freezing season is diminished by the thickness-growth feedback, particularly early in the season. Differences created are reduced as the freezing season proceeds, because thin ice grows more quickly than thick ice. On the other hand, the effect of surface flux biases during the melting season is enhanced by the surface albedo feedback, particularly early in the season. Differences created increase as the season progresses,

465   as thinner, warmer, less extensive ice has a lower albedo than thicker, colder, more extensive ice. Hence small differences in forcing can have a large effect in the late spring and early summer, whereas small differences during the freezing season will tend to only have a small impact. This is consistent with the prediction of DeWeaver et al. (2008) that that sea ice state is more sensitive to surface forcing during the ice melt season than during the ice freezing season.

A particularly useful aspect of the ISF analysis is that the direct effect of model parameterisation changes can be quantified,
470   namely the change to an explicit melt-pond scheme and the change of snow area parameterisation. In each case, the impact on the surface flux, although small compared to the melt onset and snow thickness terms (let alone the ice area term), is not negligible, and because the impact is felt in the early summer likely has a significant impact on the sea ice state. This offers a useful perspective on the importance of sea ice model improvements versus model forcing. The effect of such model improvements may be small, but could still have significant effects, particularly if the effects are concentrated in the crucial
475   late-spring to early-summer time of the year.

6 Conclusions

The models HadGEM2-ES, HadGEM3-GC3.1-LL and UKESM1.0-LL have been compared using a systematic framework (the ISF, or induced surface flux framework) to quantify the impact of differences in individual model variables on differences in modelled sea ice and growth. Of the three models, UKESM1.0-LL displays the highest annual mean ice thickness and
480   September ice area, and the least annual ice growth/melt, while HadGEM2-ES displays the lowest annual mean ice thickness, and the most annual ice growth/melt. These are consistent with differences in surface fluxes, with UKESM1.0-LL (HadGEM2-ES) displaying the lowest (highest) net SW flux during the summer and the highest or least negative (lowest or most negative) net LW flux during the winter. The ISF framework shows that the major part of the difference in surface flux between each pair of models is caused by differences in the ice state itself, via the surface albedo feedback in the summer and the thickness-
485   growth feedback in the winter. In this way, it demonstrates how closely coupled the seasonal ice growth/melt is to the ice volume.

The remainder of the surface flux differences can mostly be attributed to variables influencing surface albedo in June. The snow thickness and melt onset terms, in particular, drive a higher surface albedo, and hence a lower surface flux, in both CMIP6 models relative to HadGEM2-ES, and in UKESM1.0-LL relative to HadGEM3-GC3.1-LL. These represent the

490 proximate causes of model differences in the ice volume – seasonal ice melt/growth coupled system. Small differences in surface flux at this time of year are magnified by the surface albedo feedback into much larger differences in ice melt later in the season, as represented by the ice area ISF term.

The ISF framework focuses attention on model processes most likely to be implicated in driving inter-model spread, helping inform future model development. For the models examined in this study for example, small differences in the surface energy
495 budget in the early summer appear to lead to very large differences in the sea ice state. Differences in snow area and melt onset in particular are implicated. This underlines that these are likely to be particularly important variables to model correctly in order to reduce sea ice state errors.

The framework also allows the proximate effect of some specific model improvements on seasonal ice growth/melt to be measured directly. The effect of the explicit melt-pond scheme and new snow parameterization of the CMIP6 models on the
500 sea ice volume balance, relative to other model drivers, is shown to be small but non-negligible, precisely because their greatest effect on the surface flux occurs in the early summer, when small differences in ice melt can lead to much greater differences later in the season.

Code availability

Code used to calculate the ISF contributions, and to plot all figures in the paper, is archived at
505 https://zenodo.org/record/5675109.

Data availability

Sea ice and surface flux data for HadGEM3-GC3.1-LL and UKESM1.0-LL can be downloaded from the CMIP6 archive at https://esgf-index1.ceda.ac.uk/search/cmip6-ceda/ under the model labels HadGEM3-GC31-LL and UKESM1-0-LL. Data for HadGEM2-ES can be downloaded from the CMIP5 archive at https://esgf-index1.ceda.ac.uk/search/cmip5-ceda/.

510 **Author contribution**

The ISF framework was designed and carried out for the case study models, along with the model evaluation and comparison in Section 3, by Alex West. The paper was written in its final form by Alex West with assistance and advice from Ed Blockley and Mat Collins.

Competing interests

515 The authors declare that they have no conflict of interest.

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