A seamless approach to understanding and predicting Arctic sea ice in Met Office modelling systems

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Recent CMIP5 models predict large losses of summer Arctic sea ice, with only mitigation scenarios showing sustainable summer ice. Sea ice is inherently part of the climate system, and heat fluxes affecting sea ice can be small residuals of much larger air–sea fluxes. We discuss analysis of energy budgets in the Met Office climate models which point to the importance of early summer processes (such as clouds and meltponds) in determining both the seasonal cycle and the trend in ice decline. We give examples from Met Office modelling systems to illustrate how the seamless use of models for forecasting on time scales from short range to decadal might help to unlock the drivers of high latitude biases in climate models.

1. Introduction

The Arctic climate system involves many components: atmosphere, ocean, sea ice, the Greenland ice sheet, vegetation, permafrost and methane in marine systems (figure 1). Understanding the complexities and interactions of this system represents a challenge to both observationalists and climate modellers.

The most dramatic indicator of Arctic climate in recent years has been the summer extent of Arctic sea ice, observed from space. The extent of Arctic sea ice has been declining since satellite records began 30 years ago [1]. Sea ice changes are more than just a sensitive indicator of climate change; changes in sea ice have potential
implications for the Arctic region and beyond. Low summer ice extents, during 2007 and subsequent years, have led to shipping routes opening up through the Arctic in summer [2] which has economic implications as well as possible political implications owing to the presence of mineral resources in the Arctic [3]. Beyond the Arctic, the reduction in ice extent has also been linked with changes in the jet stream and the severity of European winters [4–6]. However, while estimates of signal-to-noise suggest that the local near-surface temperature and precipitation responses to historical Arctic sea ice loss exceed internal variability and are thus detectable in observed records, the potential atmospheric circulation, upper-level and remote responses may be partially or wholly masked by variability [7].

Arctic sea ice is clearly iconic of change in the Arctic, but it is in many ways the ‘barometer’ for changes which are occurring in the atmosphere and the ocean. The observed decline in Arctic sea ice has been shown to be attributable to human influence via increasing greenhouse gases [8]. In climate model projections, Arctic sea ice extent is highly correlated with global mean surface temperature on annual mean time scales [9] illustrating the link with large-scale climate properties. Climate models project that the Arctic will become ice-free during summer at some point this century [1]. However, in September 2007 (and later 2012), sea ice extent reached a dramatic all-time record low. This has raised the question of whether the sea ice is likely to melt more quickly than has been projected by climate models [10]. The response of Arctic sea ice to greenhouse gases may be amplified by the ice albedo feedback [11]. More generally, the atmosphere and the ocean provide fluxes at the top and bottom interfaces of the sea ice and this has the potential to play a significant role in sea ice changes. For example, Serreze et al. [12] estimate that an additional annual heat flux of only 1 W m$^{-2}$ would be sufficient to melt 10 cm of ice at its melting point.

In this paper, we first briefly review projections of Arctic sea ice decline in current climate models (§2), look at how the use of energy budgets to evaluate climate models may be useful
2. Projections of Arctic sea ice decline from current climate models

Earth system models used for climate projections typically have a reasonable representation of sea ice processes; individual grid cells are partitioned to represent an ice thickness distribution, the stress–strain relationship within the sea ice is represented by a rheology such as elastic–viscous–plastic [13], and the vertical distribution of temperature (and sometimes salinity) within the ice is represented. Improving aspects of sea ice physics can play an important role in improving simulations of sea ice [14], but the atmosphere and ocean simulations can also play a role as seen in HadGEM1 [15] where the dynamical atmosphere forcing was well represented [14].

Projections of summer Arctic sea ice area from the HadGEM2-ES climate model [16] show large losses of Arctic sea ice occurring under all scenarios; only the low emissions scenario (RCP2.6) shows a sustainable (but small) amount of summer sea ice in the late twenty-first century (figure 2). This is typical of CMIP5 projections; the multi-model ensemble means of projections from CMIP5 climate models show large losses of summer Arctic sea ice of between 43% and 94% over the twenty-first century in September for the low (RCP2.6) and high (RCP8.5) emissions scenarios, respectively [1].

Within the CMIP5 results, there remains considerable spread across the ensemble in the results for individual emissions scenarios. As discussed by Hodson et al. [17], the spread could be due to both structural uncertainty and internal variability. Addressing first structural uncertainty, there is some evidence that estimates of Arctic sea ice loss can be improved by choosing a subset of the CMIP5 models; for example, by selecting models based on their skill in representing the mean and trend in September ice extent, magnitude of the seasonal cycle and sea ice volume. Massonnet et al. [18] show that the rate of ice area loss in the validated subset is faster than the ensemble mean.

It remains difficult to fully assess the impact of internal variability on Arctic sea ice; however, results from ensemble climate projections suggest that internal variability could be responsible for half of the observed sea ice loss from 1979 to 2005 [19]. Additionally, the spread in 1979–2013 trends from a large ensemble (30 members from a single model [20]) and the CMIP5 ensemble are comparable [21] suggesting that internal variability is an important factor in all climate projections of Arctic sea ice.

A further aspect to climate projections not explored within CMIP5 is the impact of model resolution. Changing the resolution of the ocean and atmosphere models can have a significant impact on the simulation of the seasonal cycle of sea ice extent; in the HadGEM3 climate model...
Rae et al. [23] show that increasing ocean resolution can lead to changes in sea ice which are larger than or comparable to changing parameters in the sea ice model physics, whereas Williams et al. [24] show that the simulation of ice extent and volume is more accurate at higher atmosphere resolution. There is also indication of the sensitivity to resolution in future projections of Arctic sea ice in the HadGEM3 [25]; when atmosphere model resolution is increased, the rate of ice decline appears to be increased. There is clearly uncertainty over internal variability, as discussed earlier, yet current computing resources preclude the possibility of large ensembles of climate projections at high resolution. Nevertheless, these results point to the fact discussed earlier that the sea ice simulation and its decline is highly sensitive to the climatic forcing of the system.

3. Using energy budgets to evaluate climate models

As discussed in §2, estimates of Arctic sea ice decline can be improved by subselecting models based on their skill at representing certain aspects of the present-day sea ice state. However, comparing models based on their ability to simulate sea ice extent and volume accurately may lead to choosing models which have compensating errors (i.e. they may give a good simulation for the wrong reasons). Evaluating models at the process level of their energy budgets would not only allow model fidelity to be better assessed, but would also allow errors to be identified and quantified.

As discussed in the Introduction, the fluxes forcing sea ice can be small residuals of much larger fluxes. For example, in HadGEM1, by far the largest fluxes in the energy budget are the atmospheric heat convergence and the top-of-atmosphere flux, being 1066 and 1139 TW, respectively. The sum of the ice-to-atmosphere and ocean-to-atmosphere fluxes is a mere 73 TW, a value close to the ERA-40 ice-and-ocean-to-atmosphere flux of 110 TW reported by Serreze et al. [12], especially given that the reanalysis estimate includes part of the Nordic Seas in the budget domain (a region of very high sensible heat loss from the ocean), but a long way from the 189 TW reported by Tsubouchi et al. [26]. The modelled ocean heat convergence is 41 TW, and modelled ice heat convergence is 32 TW (also quite close to the 30 TW estimated by Serreze et al. [12]).

A combination of IceSat and submarine data was also used to estimate a decrease of mean ice thickness in the central Arctic from 3.64 to 1.89 m over the period 1980–2008 [27] which gives an approximate rate of thinning of 60 cm per decade. As discussed in the Introduction, an annual mean heat flux into the ice of an additional 1 W m\(^{-2}\) [12] is all that is required in order to produce the observed basin-wide thinning. A ‘missing’ flux as small as this would represent an adjusted heat exchange of only 2% of the magnitude of the seasonal cycle of surface heat flux into the ocean and sea ice. In spite of the relatively small model biases that we may be looking to identify, we suggest that closed energy budgets are the only way to really get to the bottom of understanding which processes are causing problems with the simulation of sea ice in climate models.

Analysis of the atmospheric energy budget in HadGEM2-ES shows that relative to ERA-40 the model reproduces the main features of the seasonal cycle of the heat budget in the Arctic (figure 3) [28] noting that the uncertainty in radiation fluxes is large compared with the signal [29]. The main model issues are that the surface and top of atmosphere fluxes are slightly too strongly downward in May/June, whereas the surface flux is too strongly upward in late autumn. Comparing HadGEM2 fluxes with ISCCP suggests that in May the downwelling surface shortwave is too high. This leads to a positive feedback with the initial excess ice melt causing the upwelling shortwave to be too low (as the mean surface albedo is now too low) and therefore further anomalous melting and anomalously low sea ice area later in the melt season. The most likely cause of the initial problem with the shortwave flux in the late spring is due to insufficient cloud cover being simulated. Future work will be focused to understand and improve the simulation of spring and summer clouds over the Arctic.

Moving into the seasonal cycle of the energy budget of ice itself, Keen et al. [30] show that summer melting in HadGEM1 is dominated both by surface melting and the ocean to ice heat
flux, whereas winter ice recovery is controlled by growth at the base of the sea ice. This can be taken further to examine the terms in the budget which lead to the decline of Arctic sea ice in a warming climate; the sea ice decline in HadGEM1 can be seen to be caused by surface melting in the early part of the melt season and the ocean to ice heat flux (via the ice-albedo feedback) later in the melt season. Melting from the surface in the early summer is currently parametrized by a temperature dependence of albedo which crudely represents meltponds. Representing meltponds more accurately is expected to have an impact on the climate simulation via the positive feedback on albedo [31] and in the future a more physical representation of meltponds will be included [32]. While work to date suggests that summer processes are dominant in the ice decline, winter recovery may also require further examination in the future; snow on ice is an important factor in winter recovery, and there are plans to improve snow processes in the Met Office models [33]. However, as pointed out by Blazey et al. [34], the relationship between snow cover and ice thickness/area is a complex one.

One of the limitations with understanding the ice energy budget is the lack of direct observations but a way forward with this could be to compare with output from a system such as PIOMAS [35] which assimilates observations of sea surface temperature and ice concentration in the Arctic into an ocean–ice model. However, given that PIOMAS computes the energy budget from specified atmospheric conditions which do not respond to the ice state, there may be issues with the heat budget terms derived from systems such as PIOMAS as well as uncertainty in the terms owing to internal variability. Other reanalyses (G Smith et al. 2014, unpublished data) or observational products [36] could also be employed to assess model budgets.

Figure 3. Comparison of Arctic atmospheric energy budget in HadGEM2 and ERA-40. Orange denotes top of atmosphere flux, blue denotes surface heat flux, grey denotes atmospheric heat convergence and pink denotes atmospheric heat uptake. We show here the budget for the region north of 70° N.
Holland et al. [37] examined the changes in the energy budget of a range of CMIP3 models although with less detail in the terms than the budget analysis of Keen et al. [30]. The ensemble mean showed that ice loss was attributable to increased melting and reduced growth offset by reduced transport out of the Arctic. However, individual models showed a wide variety in responses with differences in both sign as well as magnitude in growth and melting of sea ice. This suggests that a comparison of detailed budgets from CMIP5 models would yield useful insights into model structural uncertainty.

4. Using seamless prediction to unlock drivers of high latitude biases

The Met Office Unified Model (UM) is used for prediction and projection on all time scales from global NWP to climate projections in IPCC. The UM is used for weather forecasting as well as seasonal forecasting (with GloSea systems [38,39]) and climate modelling (HadGEM1, HadGEM2-ES and HadGEM3 as discussed in §3). The various modelling systems are listed in appendix A. One of the potential benefits of employing the same model across a range of time scales is the potential to be able to unlock errors in the simulation of the sea ice state and the Arctic energy budget. Here, we discuss two examples of the seamless approach.

First, we look at how short-range forecasts might provide insights into problems seen in climate models. In the budget analysis of §3, we discussed the early summer problems with clouds. The Met Office global NWP version of the UM can provide some insights into this issue. The model was evaluated during Arctic summer against field experiment data from the Arctic Ocean Experiment (AOE 2001) [40] and Arctic Summer Cloud Ocean Study (ASCOS 2007) [41]. This analysis shows that the UM has reasonable skill in predicting the passage of large frontal systems on a 1- to 3-day time scale, with deep frontal cloud being well captured. However, the model struggles to simulate summertime Arctic stratus and stratocumulus, observed in the lowest few hundred metres of the boundary layer [40]. Decreasing the cloud condensation nuclei to the pristine values observed during the ASCOS field experiment leads to some improvements in boundary layer structure and cloud prediction. Work such as this, using short-range hindcasts combined with observations from field campaigns or satellites, provides a means to identify the meteorological characteristics which result in model errors [42,43].

Our second example looks at the synergy between seasonal forecasts and climate models. Climate models show that the magnitude of the seasonal cycle of sea ice extent in the Arctic has a significant correlation with the date of ice-free conditions in the Arctic [18]. This suggests that if we can improve the model simulation of sea ice on seasonal time scales, we have the potential to improve long-term projections of sea ice. Climate models also show that summer ice loss depends strongly on winter ice thickness [30,44] which suggests that if seasonal forecasts can be initialized with accurate sea ice conditions, there is a good opportunity to predict summer sea ice extent several months ahead. Peterson et al. [45] have shown that the GloSea4 system [38], which is also based on the UM, has predictive skill for the September sea ice extent with a six month lead time. Figure 4 shows the predictions of September sea ice from GloSea5 (initialized in April), which shows the skill in the hindcast as well as the skill in the 2013 ensemble forecast. It is noteworthy that the seasonal forecast can show more skill than the trend or persistence forecast; skill throughout the season (not shown) starts relatively high in spring (with correlations exceeding 0.8 for forecasts initialized in April), drops off slightly during late spring/early summer before increasing again from July onwards. This variation in skill throughout the season has also been seen by Merryfield et al. [46]. Schroeder et al. [31] use the early season meltpond fraction as a statistical predictor of the September sea ice minimum demonstrating that the start of the melt season is key to skilful prediction. As discussed in §3, an improved physical representation of meltponds is soon to be included in the UM which may enhance skill in seasonal forecasts if it improves the evolution of the melt season.
Climate model projections of Arctic sea ice are clearly improving; the CMIP5 model ensemble is much closer to simulating the trend in Arctic sea ice extent than CMIP3 models [47]. The structural uncertainty in the models remains large though with the spread in projections varying dramatically between models. Sea ice models used in climate models have broadly similar physics and, as shown by Rae et al. [23], there is limited scope for improving the model simulation with the existing physics. The inclusion of more sophisticated sea ice physics such as the meltpond representation of Flocco et al. [32] may prove to be more fruitful; it corresponds to physical processes shown to be important in the ice energy budget by Keen et al. [30] and has proven skill in seasonal forecasting [31] which taken together might be expected to lead to an improvement in both the simulation of the sea ice seasonal cycle and long-term ice projections.

It is important, however, to see sea ice as part of the larger climate picture (cf. figure 1) where sea ice is strongly driven by atmospheric and oceanic forcing. This view is consistent with the experiments of Tietsche et al. [48] where sea ice reformed in a climate model within a few years of complete removal. Budget analysis of the atmospheric energy budget in the Arctic suggests that at least one part of the problem with the Arctic simulation in the Hadley Centre climate models may be the simulation of summer cloud. This was also seen in the short-range forecast simulations of Birch et al. [41] and was improved via changes to the cloud scheme. At the Met Office, we are fortunate to use the same model across a range of time scales (so-called seamless prediction). This provides us with a range of tools to identify and reduce errors in the model on all time scales. The potential to unlock drivers of high latitude climate model errors in relatively short runs [49] is a real opportunity offered by seamless prediction.
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Appendix A. Met Office modelling systems

(a) HadGEM1

Met Office climate model based on UM atmosphere, ocean and sea ice model as described in Johns et al. [15]. The sea ice model is effectively a zero-layer version of CICE, including EVP rheology and ice thickness categories. The atmosphere model resolution is N96 (approx. 130 km) and the ocean is nominally 1° increasing to 1/3° on the Equator. Climate projections produced with this model were submitted to CMIP3.

(b) HadGEM2-ES

Met Office climate model configured as HadGEM1 but with improvements to the physical model [16] and inclusion of Earth systems [50]. Climate projections produced with this model were submitted to CMIP5.

(c) HadGEM3

Met Office climate model coupling UM atmosphere, NEMO ocean and CICE sea ice via the OASIS coupler as described by Hewitt et al. [22]. In the initial configuration [22], the sea ice model using CICE is configured to be very similar to that used in HadGEM1, the atmosphere resolution is N96 and the ocean resolution is based on the ORCA1 grid-a tripole grid with nominal 1° resolution increasing on the Equator as in HadGEM1.

GC2 [24] is based on the infrastructure described in Hewitt et al. [22] with both improved physics and resolution increased to N216 (approx. 60 km) in the atmosphere and ORCA025 (nominally 0.25°) in the ocean although with the capability to run at N96 resolution in the atmosphere.

(d) GloSea

GloSea4 [38] is the operational seasonal forecasting system based on HadGEM3 which is at N96-ORCA1 resolution. GloSea5 [39] is an upgrade to GloSea4 including an increase to N216-ORCA025 resolution, with initial sea ice and ocean conditions now being provided by the NEMOVAR assimilation scheme [51] as configured for the FOAM ocean forecasting system [52].

References


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