

Potential link between ice nucleation and climate model spread in Arctic amplification

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Key Points:

- INPs may trigger summertime cloud-phase feedback interactions with sea ice that strongly impact Arctic amplification.
- Arctic amplification is highly sensitive to temperature-dependent ice nucleation schemes.
- Summertime measurements of INPs are lacking but important for constraining Arctic cloud feedbacks.

Abstract

Arctic amplification is simulated by all global climate models, however the spread in the degree of projected warming is large and the underlying mechanisms driving it are poorly understood. The impact of the temperature dependence of immersion freezing on cloud feedbacks and Arctic amplification is studied using NASA’s GEOS-5 model. Parameterizations that exhibit low ice-nucleating particle concentrations in the high Arctic during summer are found to weaken the cloud-phase feedback. This allows sunlight to readily melt sea-ice in the summer, which decreases the stability of the lower troposphere, causing a decrease in wintertime cloud fraction over open ocean. Arctic amplification was found to span from ~ 1.4 to >2.6 , which spans 30% of the spread in Arctic amplification in the CMIP6 models, depending on the the temperature dependence of immersion freezing. These results suggest that summertime INP concentrations may provide an observational constraint on Arctic amplification.

Plain Language Summary

The Arctic is warming at more than twice the pace as the rest of the globe. Global climate models (GCMs) also exhibit the largest spread in surface warming in the Arctic region, where low-level stratiform clouds are poorly represented. These clouds frequently consist of mixtures of liquid droplets and ice crystals, the latter which form with the aid of ice-nucleating particles (INPs). Here, we show that the sensitivity of the activation of INPs in stratiform clouds to temperature results in a difference in Arctic amplification that spans over 30% of the spread in the latest generation of GCMs. The apparent warming mechanism is triggered by the extent of thermodynamic phase changes in Arctic mixed-phase clouds during the summer and their subsequent influence of sea-ice melt. Accurate measurements of collocated in-cloud INP concentrations and temperature are critical for improved constraints on Arctic amplification.

1 Introduction

Ice-nucleating particles (INPs) facilitate the formation of ice crystals in clouds by lowering the energy barrier for heterogeneous ice nucleation relative to homogeneous ice nucleation (Rogers & Yau, 1989). Ice crystals commonly coexist with supercooled liquid droplets in mixed-phase clouds at temperatures between 0 and $\sim -38^\circ\text{C}$ (Korolev et al., 2017). These clouds are radiatively important, particularly in the Arctic (poleward of 60°N), where they are ubiquitous in the boundary layer (Mioche et al., 2017). Despite their inherent thermodynamic instability, observations have revealed that Arctic mixed-phase clouds are persistent as a result of interactions between microphysical processes such as ice nucleation, as well as radiative and turbulent processes (Morrison et al., 2012). However, these processes are poorly represented in global climate models (GCMs) for a number of reasons. The coarse spatial resolution of GCMs necessitates parameterizations of many unresolved processes that are not consistently represented. There is also a lack of consistent and reliable observations available to constrain GCM processes. As a result, Arctic mixed-phase clouds tend to glaciate too rapidly in GCMs and lead to a reduction in downward longwave (LW) radiation compared to what would have otherwise been a cloudy state. This in turn leads to a positive bias in lower tropospheric stability (LTS) and colder Arctic surface temperatures (Pithan & Mauritsen, 2014; Barton et al., 2014; Taylor et al., 2019).

Previous studies have shown that INP concentrations [INP] impact cloud radiative forcing, particularly in the Arctic where they are substantially reduced relative to low-latitude regions (Prenni et al., 2007; Demott et al., 2010; Gettelman et al., 2010; Xie et al., 2013). However, the vertical distribution of INPs and therefore the temperature at which they are active also impacts cloud radiative forcing (Hawker et al., 2021). Here, we isolate the impact of this temperature dependence of [INP] in stratiform mixed-phase

clouds on Arctic amplification (AA) via cloud-sea ice interactions with a series of model simulations with four different parameterizations of ice nucleation that exhibit a wide range of [INP] and vertical distributions of INPs. All ice nucleation parameterizations represent immersion freezing — a mechanism whereby INPs trigger freezing while immersed in supercooled liquid droplets that has been shown to be the predominant mode of ice nucleation in various regions of the globe, including the Arctic (de Boer et al., 2010; Murray et al., 2012).

2 Methods

We employ the fifth generation of NASA’s Goddard Earth Observing System (GEOS-5) model (Molod et al., 2015). The atmospheric component of GEOS-5 is coupled to the Goddard Chemistry Aerosol and Radiation and Transport (GOCART) aerosol module (Molod et al., 2020), which prognostically predicts aerosol transport and evolution. Dust and sea salt emissions are wind-dependent and prognostic. Biomass burning and anthropogenic surface emissions, including sulphate, black carbon and organic carbon are prescribed to the 2005 climatology obtained from MERRA-2 (Randles et al., 2017) to isolate the impact of immersion freezing on clouds. Neither INP sources from newly exposed terrestrial nor sea ice sources is explicitly represented in GEOS-5.

The immersion freezing parameterizations are all temperature-dependent and time-independent and include: a scheme that determines active [INP] based on their correlation with the number concentration of aerosol particles with diameters $>0.5\mu\text{m}$ collected on aircraft flying at or near clouds in numerous locations around the globe (Demott et al., 2010) (henceforth D10), a cloud chamber-based scheme based on the active site concept (Ullrich et al., 2017) (henceforth U17), a temperature-dependent and aerosol-independent scheme based on surface observations at a mid-latitude location (Meyers et al., 1992) (henceforth M92), and a semi-empirical scheme, based on classical nucleation theory (Barahona & Nenes, 2009) (henceforth BN09). BN09 is however not time-dependent, since a constant nucleation time scale is assumed (cf. Table 1, Barahona and Nenes (2009)). BN09 represents a limiting case, where INP are widely abundant. These parameterizations were chosen based on a number of factors including their ability to span a wide range in INP concentration and vertical distribution of INPs, how commonly they have been implemented in GCMs, their level of sophistication and the diversity in their method of derivation. M92 has frequently been employed as a deposition and/or condensation nucleation scheme, however in light of its well-known high bias in INP concentration a number of studies have adopted other schemes including D10 (Xie et al., 2013; English et al., 2014; Komurcu et al., 2014) to reduce these biases. Although BN09 is an outlier case used in this study, other CNT schemes (e.g. Hoose et al. (2010), Wang et al. (2014) as in Gettelman et al. (2019) and Zhang et al. (2019)) have been employed in CMIP6 models. In addition to these biases related to INP concentration, this study further demonstrates that the temperature dependence of immersion freezing in U17 and the subsequent sensitivity of AA to it suggests an additional important aspect of ice nucleation that has thus far not been considered. The rate of immersion freezing is parameterized as

$$\frac{dn_{\text{imm}}}{dt} = \min \left(-\gamma_c W f_c \frac{dn_{\text{INP}}}{dT}, \frac{N_{\text{drop}}}{\Delta t} \right), \quad (1)$$

where $\frac{dn_{\text{imm}}}{dt}$ is the immersion freezing rate calculated in units of m^{-3} , γ_c is the lapse rate, W is the vertical velocity, f_c is the liquid cloud fraction, n_{INP} is the parameterized INP concentration given by BN09, M92, U17 and D10, N_{drop} is the cloud droplet number concentration and Δt is the model’s 15-minute time-step. Equation 1 implies a time-dependence of immersion freezing, not in the traditional sense of a stochastic process, but rather through dynamical impacts via W . As such, the rate of immersion freezing does not increase over

time, but rather increases the more rapidly the droplet cools depending on updraft velocity. Except for M92, aerosol number concentrations are predicted from GOCART and only dust and soot aerosol particles are INPs in the parameterizations. Dust aerosols are represented using five lognormal bins whereas all other aerosol particles are represented using a single lognormal mode. Aerosol surface areas for dust and soot particles are predicted by GOCART for U17. The atmospheric component of GEOS-5 was run with a horizontal resolution of 1° and 48 vertical levels.

Two types of climate warming experiments were run. Type I experiments employed the standalone atmosphere model and was designed to isolate the influence of immersion freezing on the cloud feedback without influences from the coupled climate system. These eight experiments consisted of a pair of simulations with SSTs and sea ice prescribed to the 1979-2019 “present-day” or “control” climatology obtained from MERRA-2 and simulations with perturbed SSTs uniformly increased by 4K relative to the present-day. The perturbed and control Type I experiments were used to diagnose cloud feedbacks and are referred to BN09, M92, U17 and D10 for the four parameterizations. Analysis of all Type I experiments are based on the last 30 years of 40-year simulations. Type II experiments employed the fully-coupled model that include the influence of land, ocean and sea-ice. These experiments consisted of a pair of simulations with pre-industrial CO_2 levels (henceforth “piControl”) and quadrupled piControl CO_2 levels (henceforth “abrupt4x CO_2 ”) held constant for a duration of 150 model years. Due to constraints on computational resources Type II simulations were run for the M92 and U17 schemes only, and were selected based on their contrasting cloud phase and [INP]. Thus, there are a total of two pairs of Type II simulations, where each pair is referred to as “M92_CPL” and “U17_CPL”, respectively.

Cloud feedbacks at the top of the atmosphere (TOA) were decomposed into contributions from changes in optical thickness, i.e. the cloud optical depth feedback (λ_τ), amount and height using cloud radiative kernels (CRKs) (Zelinka et al., 2013) for both Type I and Type II experiments. Cloud feedbacks were also computed by adjusting the change in the TOA cloud radiative effect by the masking of tropospheric non-cloud feedbacks using the Huang et al. (2017) radiative kernels. Poleward atmospheric (oceanic) energy transport was calculated by integrating the zonal mean net TOA (surface) radiation anomaly with respect to the global mean across all latitudes. Since poleward energy transport was calculated from nonequilibrium simulations, heat storage, particularly in the ocean may be non-negligible and differ from the equilibrium response. However, values have been shown to resemble equilibrium responses in piControl and abrupt4x CO_2 simulations (Huang et al., 2017). The contributions of atmospheric and oceanic poleward heat transports to warming in the tropics and high Arctic were calculated by averaging over the respective regions and normalizing the radiation anomalies by the global mean Planck feedback parameter. More details of the climate feedback methodology are included in the Supporting Information.

The supercooled liquid fractions (SLFs) in GEOS-5 were calculated as the ratio of liquid water path (LWP) to the sum of LWP and ice water path (IWP), i.e. the total water path obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) simulator. Observed SLFs were computed using the level 2 Collection 6 MODIS data (Platnick et al., 2016) from 2004-2010 onboard the Aqua satellite. Observations from Polarization and Directionality of the Earth’s Reflectances (POLDER) were used to filter pixels with inconsistent CTP retrievals according to Coopman et al. (2020). Note that observed LWP may be biased high in the case of large solar zenith angles, the Arctic SLF calculation only includes data from 60°N to 70°N (Grosvenor & Wood, 2014). Furthermore, MODIS CTP retrievals are also known to be biased high in the Arctic. Thus, it is likely that the observational values of Arctic SLF may overestimate the actual value during summer but that our objective is not to realistically constrain SLFs.

Airborne in situ measurements of [INP] were obtained from the Polar Airborne Measurements and Arctic Regional Climate Model Simulation Project (PAMARCMiP) campaign that took place during March 23 to April 4, 2018 in the vicinity of Villum Research Station in Northeast Greenland (Hartmann, Jentzsch, et al., 2019). Twelve polar 5 research aircraft flights (Wesche et al., 2016) sampled aerosols onto polycarbonate pore filters. The INP analysis was performed using the Leipzig Ice Nucleation Array (LINA) and Ice Nucleation Droplet Array (INDA) instruments that measure total immersion-mode [INP] assuming that immersion freezing is temperature dependent and time independent (Hill et al., 2016; Chen et al., 2018; Hartmann, Blunier, et al., 2019). The observed and simulated [INP] at different temperature ranges were compared in the high Arctic at latitudes northward of 80°N, and from longitudes between 17°S to 16°E during the months of March and April.

Ground-based in situ measurements of immersion-mode [INP] were obtained from quartz-fibre filter samples collected in Canada, Alaska, Svalbard and Greenland (Wex et al., 2019). Samples were collected on a regular (up to weekly) basis and remained frozen until analyzed with INDA. Over 60 different INP-temperature relationships compiled from all over the globe are also included for reference (Petters & Wright, 2015).

3 Results and discussion

The slope of the linear regression of the logarithm of total active INP concentration as a function of temperature ($d\log N_{\text{INP}}/dT$) during spring in the high Arctic (poleward of 80° N) are compared against airborne in situ measurements in the same season (Fig. 1a). The total Arctic INP concentration at almost all temperatures is orders of magnitude larger than the in situ aircraft observations in each simulation, however this does not invalidate GEOS-5 as a tool for this sensitivity study for the following reasons. First, the simulations were not nudged to reanalysis data but based on data spanning the high Arctic as opposed to sampled along the track of the aircraft so the observations are not directly comparable. Second, overestimates of [INP] are typical of many GCMs. In particular, the overestimate in Arctic INP concentration in M92 is expected (Prenni et al., 2007; Xie et al., 2013; English et al., 2014) since they were based on measurements from Wyoming, USA and the BN09 parameterization was formulated to be an extreme case where large amounts of dust and soot aerosols nucleate ice crystals due to the fact that it does not account for active sites on INPs. Third, the Type I experiments are able to simulate present-day Arctic cloud properties and radiation in reasonable agreement with satellite observations (Table S1). Furthermore, the Arctic sea ice concentration in the piControl experiments for M92 and U17 although not comparable with present-day observations being piControl experiments, are not vastly different from each other (Fig. S1). Nonetheless, sea ice concentration is larger in M92 suggesting that differences in the climate feedbacks in these experiments are indeed partially affected by state dependence. The lack of dependence of the climate feedbacks on the initial climate state in the fully-coupled simulations is later further demonstrated by examining their consistency with the feedbacks in the Type I experiments which hold SST and sea ice fixed.

The [INP] that actually nucleated ice via the immersion freezing mode in GEOS-5, $n_{\text{imm,int}}$, i.e. the time integral of Equation 1 over the 15-minute model time step that is modulated by the presence of liquid droplets generally compares more favourably with the observations for each parameterization (Fig. 1b). $n_{\text{imm,int}}$ represents the INP concentration that actually nucleated ice via immersion freezing rather than the total active INP concentration and is thus more suited for comparison with the airborne observations from the PAMARCMiP campaign that measure immersion-mode INPs. Note that $n_{\text{imm,int}}$ for each parameterization plateaus at temperatures lower than approximately 246K, where relatively fewer cloud droplets exist for immersion freezing to create new ice crystals. Therefore, the $n_{\text{imm,int}}$ values displayed in Figure 1b were calculated only for $T > 245$ K. Of the four parameterizations, the magnitude and sign of the $\frac{d\log n_{\text{imm,int}}}{dT}$

slope for U17 best resembles the observed slope during springtime. U17 is also in best agreement with the surface immersion-mode [INP] at four different locations within the Arctic (Fig. 1c). Only U17 produces N_{INP} values that are within the observed range of Wex et al. (2019) at all temperatures except between the 253–251 K. D10 overestimates the surface-level N_{INP} values compared to Wex et al. (2019) but is closest in magnitude to the PAMARCMiP observations. Compared to the global observations of Petters and Wright (2015), the N_{INP} produced by U17 falls well within the observed range and those produced by D10 are also within a comparable range for $T < 268$ K.

By influencing thermodynamic phase shifts in mixed-phase clouds, [INP] influence the cloud-phase feedback (Murray et al., 2021) for which there is evidence in GCMs (Tan et al., 2016). Satellite observations also support the potential influence of INPs on thermodynamic phase shifts over different surface types in the mid-latitudes (Tan et al., 2019). The cloud-phase feedback mechanism depends on the SLF. In all simulations, higher [INP] lead to lower SLFs year-round. Compared to the observed SLF value of 26% obtained using a combination of MODIS and POLDER observations at -30°C , all parameterizations are within $\pm 6\%$ of the observed value.

Clouds with lower control-state SLFs exhibit larger increases in LWP and simultaneous decreases in IWP as a result of a deeper troposphere in the perturbed warmer state that shifts isotherms upwards relative to the control climate state. This causes the clouds to become optically thicker and therefore reflect more sunlight back out to space, as indicated by the more negative summertime Arctic λ_{τ} that is highly correlated with the change in LWP in the four pairs of simulations ($R^2 = 0.93$). Note that λ_{τ} represents changes in τ in response to global warming due to all processes and not solely the cloud-phase feedback, however, it is strongly correlated with the cloud-phase feedback since thermodynamic phase shifts influence τ . Other net changes in cloud properties are small in comparison to increases in τ (Fig. S2). Here, the feedback is strongest in Arctic summertime (June, July, August), however, U17 is a notable exception given its increase in IWP in response to warming. The reduced [INP] at relatively warm mixed-phase cloud temperatures indicated by the large $d\log N_{INP}/dT$ value in U17 (displayed as a green triangle in Fig. 2) implies that [INP] are further reduced with global warming and therefore SLFs are enhanced as surface temperature warming is exacerbated until the cloud-phase feedback is weakened to the point that other processes driving the increases in IWP dominate. When comparing the magnitudes of $d\log N_{INP}/dT$, it is apparent that experiments with larger magnitudes exhibit more negative λ_{τ} as expected since a higher [INP] in the control state decrease SLF and therefore result in a stronger cloud-phase feedback (Murray et al., 2021). However, this breaks down for the extreme case of U17 which has a large $d\log N_{INP}/dT$ magnitude and exceptionally limited INPs at warm temperatures particularly during summer.

The presence of the cloud-phase feedback in M92_CPL shields Arctic sea ice from strong solar radiation in the summertime and mitigates sea-ice melt (Figs. 3a and b). In contrast, the weak summertime cloud-phase feedback in U17_CPL and large overall reduction in total water path allows solar radiation to freely pass through the atmosphere unobstructed by opaque clouds and efficiently melts sea ice in the high Arctic (Figs. 3c and d). The loss of sea ice in the high Arctic in U17_CPL to the point that open ocean is exposed causes the release of latent and sensible heat fluxes (Fig. 3e) that is more pronounced in winter than summer (Dai et al., 2019). This release of surface turbulent heat fluxes thermodynamically destabilizes the lower troposphere (Fig. 3f) — a phenomenon that has been consistently observed by satellite instruments (Kay & Gettelman, 2009). The exposed open ocean in the high Arctic and decreased thermodynamic stability of the lower troposphere reduce low-cloud fraction (Klein & Hartmann, 1993; Taylor et al., 2015) through entrainment mixing of dry air into the Arctic boundary layer (Fig. 3g). Conversely, when summertime Arctic sea ice is insufficiently reduced due to the presence

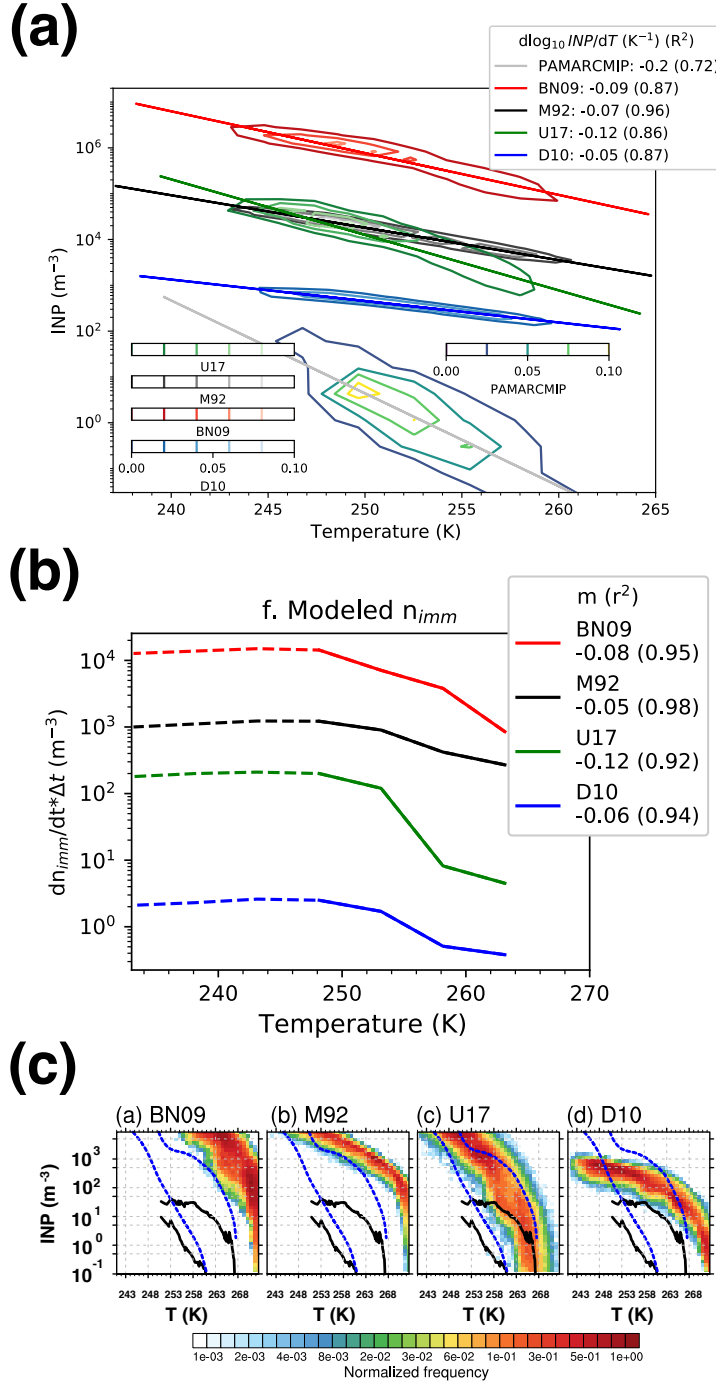


Figure 1. (a) Normalized density plots of total [INP] as a function of air temperature in the high Arctic during springtime (poleward of 80°N) predicted by the four Type I experiments along with [INP] measured by during PAMARCMiP near Northern Greenland (Hartmann, Jentzsch, et al., 2019). (b) n_{imm} as a function of air temperature. The slopes were calculated for $T > 245$ K as shown by the solid lines. Least square linear regression slopes and Pearson correlation coefficients are displayed in the top right-hand corner of each panel. (c) Normalized density plots of the surface-level n_{imm} as a function of surface temperature. The black (blue) lines indicate the range of [INP] based on Wex et al. (2019) (Petters and Wright (2015)).

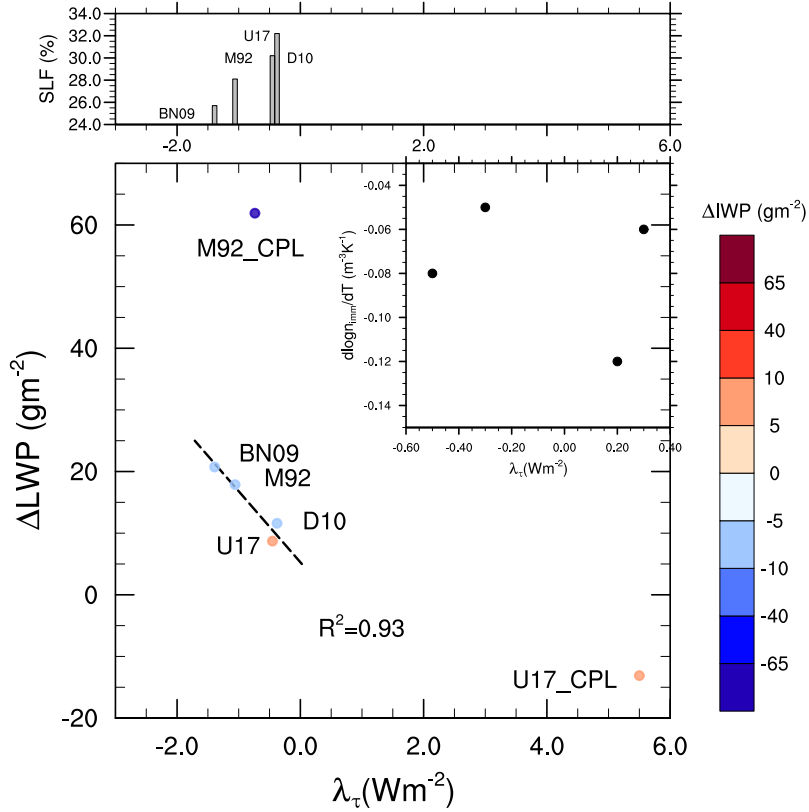


Figure 2. Scatterplot of the change in average LWP, ΔLWP defined as the difference between the perturbed and control LWP (corresponding to the left abscissa) as a function of the SW λ_τ in the Arctic during summer. The colour contour indicates the change in IWP, defined as the difference in IWP between the perturbed and control experiment ΔIWP . The Pearson correlation coefficient for the linear regression of ΔLWP against λ_τ for the Type I simulations is also provided. The fully-coupled simulations, U17_CPL and M92_CPL are also displayed. A bar plot of the satellite-simulated SLF at a cloud-top temperature of -30°C during boreal summer for the four standalone simulations are shown above the scatterplot. The inset at displays ($d\log n_{\text{imm}}/dT$) as a function of λ_τ for the D10, U17, M92 and BN09 simulations.

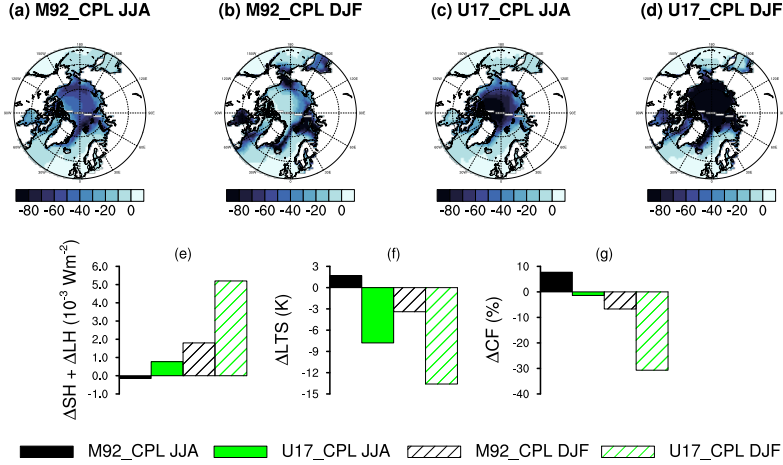


Figure 3. Arctic projections of the percentage loss in sea ice concentration over the last 50 years in (a) M92_CPL during summer, (b) M92_CPL during winter, (c) U17_CPL during summer and (d) U17_CPL during winter. The change in (e) the sum of high Arctic sensible and latent heat fluxes, (f) LTS (defined as the difference in potential temperature between 800 hPa and 2m above the surface) and (g) low-cloud fraction in the summer and winter.

of the cloud-phase feedback in M92_CPL, low-cloud fraction is enhanced — a feature that is typical of GCMs with an active cloud-phase feedback (Tan & Storelvmo, 2019).

The effective climate sensitivity values of M92_CPL and U17_CPL derived from regression analysis (Gregory et al., 2004) are $2.33^{\circ}C$ and $2.37^{\circ}C$, respectively (Fig. S3). To quantify the degree of amplified warming in the Arctic relative to the rest of the globe, we define the AA factor as the ratio of the increase in Arctic mean 2-metre air temperature (T_{2m}) to the increase in global mean T_{2m} based on the last 50 years of the control and perturbed climate states. Despite the small difference in effective climate sensitivity between M92_CPL and U17_CPL, the AA factor of M92_CPL and U17_CPL ranges from approximately 2.1 to 2.5, which spans over 30% of the range in AA predicted by the GCMs participating in the sixth phase of the Coupled Model Intercomparison Project (CMIP6) (Fig. S4). Furthermore, the fully-coupled simulations consistently show that the cloud-phase feedback is the dominant contributor to the total cloud feedback and is present in M92_CPL yet overwhelmed by other processes in U17_CPL in the high Arctic, where the latter simulation shows a simultaneous increase and decrease in IWP and LWP, respectively.

The albedo feedback dominates the contribution to AA in M92_CPL (Fig. 4a) and U17_CPL (Fig. 4b) and is particularly pronounced in U17_CPL, contributing over $10^{\circ}C$ of surface warming in the Arctic. In the annual mean, the cloud feedback is dominated by the summertime contribution of the SW radiative component due to changes in cloud opacity as revealed by the cloud radiative kernel method (Zelinka et al., 2013). Although the SW λ_{τ} dominates the net total cloud feedback during sunlit months, a noteworthy contribution from the LW lapse rate feedback during wintertime also warms the Arctic substantially (Figure 4). The LW surface feedbacks were in fact shown to dominate AA in a previous generation of GCMs (Pithan & Mauritsen, 2014). This large lapse rate feedback, however, appears to be linked to cloud amount changes as opposed to changes in τ during wintertime that influence the local Arctic surface temperature. This supports

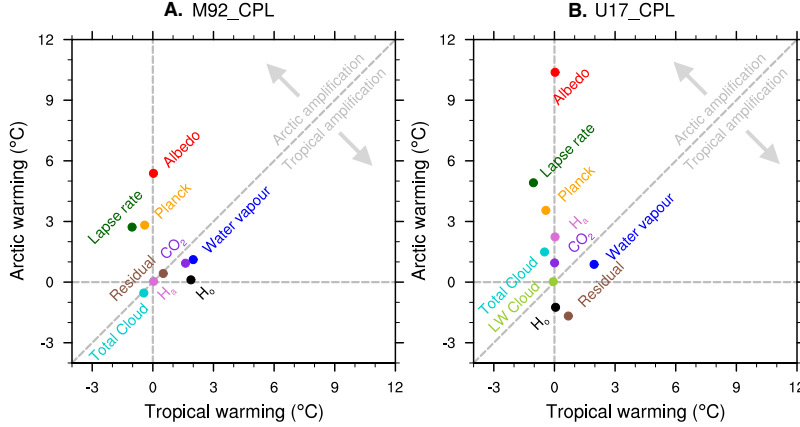


Figure 4. The contribution of climate feedbacks to high Arctic surface temperature warming as a function of tropical warming for (a) M92_CPL and (b) U17_CPL. The distance of each individual feedback process from the 1-1 line indicates the degree to which it contributes to Arctic and tropical amplification.

that the lapse rate feedback is dictated by multiple processes that affect surface temperature changes as opposed to degree of stable stratification (Boeke et al., 2020).

4 Conclusions

The temperature dependence of immersion freezing in Arctic stratiform mixed-phase clouds critically determines the extent to which sea-ice melt is influenced by the cloud-phase feedback in the summer. The cloud-phase feedback may also imply ramifications for precipitation efficiency (McCoy et al., 2015; Ceppi et al., 2016; Tan & Storelvmo, 2019; Mulmenstadt et al., 2021) and also cloud particle size (J. Zhu & Poulsen, 2019) that may represent substantial cloud feedbacks. We note that large perturbations to Arctic sea ice leading to their nonlinear interactions with clouds are conducive to a lack of radiative closure in the Arctic radiation budget (T. Zhu et al., 2019) as indicated by the non-negligible residual term. However, the simulations presented herein clearly demonstrate and uniquely isolate the large impact of temperature-dependent immersion freezing on cloud-sea ice interactions. These findings importantly highlight the high sensitivity of AA to ice nucleation via immersion freezing in the summertime, which is poorly represented if represented at all and poorly diagnosed in CMIP6 GCMs.

Although U17 most closely resembles the temperature dependence of INPs compared to springtime airborne in situ observations in the high Arctic and is within the observed range of observed ground-level [INP], the current unavailability of summertime in situ airborne measurements of INPs at cloud-level in the high Arctic that is critical for determining cloud-sea ice interactions precludes an assessment of the extent to which immersion freezing impacts AA. Recent airborne in situ measurements of biological INPs at cloud-level near Greenland suggest that [INP] are higher in summer with values of 18 m^{-3} at $T \geq -10^\circ\text{C}$ than spring when collected snow samples measured $<4 \text{ m}^{-3}$ at $T \geq -10^\circ\text{C}$ (Šantl-Temkiv et al., 2019). However, these observations are not directly comparable with the simulations herein since biological INPs are not represented in the GEOS-5 model. Similarly, ground-based observations at various locations in the Arctic show enhanced [INP] in summer (Wex et al., 2019), however these observations may not be representative of [INP] at cloud-level. A few existing cloud-level INP observations, how-

ever, have shown that high Arctic INPs can be particularly efficient at nucleating ice crystals within clouds. This was shown, for example by Tobo et al. (2019) who analyzed ground-based observations at Zeppelin Observatory that are occasionally covered with low-level clouds and Sanchez-Morroquin et al. (2020) who analyzed airborne in situ observations in Iceland. In conclusion, these observations along with the importance of summertime INPs demonstrated in our study motivates the need for both improved representations of highly variable [INP] and INP types in GCMs and accurate aircraft in situ observations of summertime INPs in the high Arctic in order to place tighter process-level constraints on AA.

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Open Research

All data produced by the model simulations generated in this work is available through the Federated Research Data Repository of Canada at <https://doi.org/10.20383/102.0493>. Data from PAMARCMIP are available for download at <https://doi.pangaea.de/10.1594/PANGAEA.898788>. MODIS data are available for download at <https://cmr.earthdata.nasa.gov/search/concepts/C1655784008-LAADS.html>. CERES observations are available for download at <https://ceres.larc.nasa.gov/data/>. MAC-LWP observations were downloaded from https://disc.gsfc.nasa.gov/datasets/MACLWP_mean_1/summary?keywords=mac-lwp. CMIP6 data are available for download at <https://esgf-node.llnl.gov/search/cmip6/> by searching for the variable ‘tas’ for the “piControl” and “abrupt4xCO₂ experiments”.

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