Analyzing the Arctic Feedback Mechanism between Sea Ice and Low-Level Clouds Using 34 Years of Satellite Observations

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ABSTRACT

Satellite-based cloud, radiation flux, and sea ice records covering 34 years are used 1) to investigate autumn cloud cover trends over the Arctic, 2) to assess its relation with declining sea ice using Granger causality (GC) analysis, and 3) to discuss the contribution of the cloud–sea ice (CSI) feedback to Arctic amplification. This paper provides strong evidence for a positive CSI feedback with the capability to contribute to autumnal Arctic amplification. Positive low-level cloud fractional cover (CFC\textsubscript{low}) trends over the Arctic ice pack are found in October and November (ON) with magnitudes of up to about +9.6% per decade locally. Statistically significant anticorrelations between sea ice concentration (SIC) and CFC\textsubscript{low} are observed in ON over melting zones, suggesting an association. The GC analysis indicated a causal two-way interaction between SIC and CFC\textsubscript{low}. Interpreting the resulting $F$ statistic and its spatial distribution as a relation strength proxy, the influence of SIC on CFC\textsubscript{low} is likely stronger than the reverse. ERA-Interim reanalysis data suggest that ON CFC\textsubscript{low} is impacted by sea ice melt through surface–atmosphere coupling via turbulent heat and moisture fluxes. Due to weak solar insolation in ON, net cloud radiative forcing (CRF) exerts a warming effect on the Arctic surface. Increasing CFC\textsubscript{low} induces a large-scale surface warming trend reaching magnitudes of up to about +8.3 W m\textsuperscript{-2} per decade locally. sensitivities of total CRF to CFC\textsubscript{low} ranges between +0.22 and +0.66 W m\textsuperscript{-2} per percent CFC\textsubscript{low}. Increasing surface warming can cause a melt season lengthening and hinders formation of perennial ice.

1. Introduction

Present-day Arctic surface warming is about twice the global average, a phenomenon known as Arctic amplification. Several amplifying feedback mechanisms with melting sea ice as a centerpiece are assumed to cause the above-average heating and highlight the Arctic as very vulnerable to global climate change (Vaughan et al. 2013). A proposed interaction mechanism of sea ice with clouds describes enhanced cloud cover over newly ice-free ocean due to atmosphere–ocean coupling via strong turbulent surface fluxes (e.g., Palm et al. 2010; Kay and Gettelman 2009; Curry et al. 1996). A changed cloud cover will alter top-of-the-atmosphere and surface components of the energy budget through the cloud radiative forcing. Depending on the season, enhanced cloudiness can either trap more thermal radiation in the troposphere ("greenhouse effect of clouds"), thereby heating the surface, or induce a cooling by reflecting more solar radiation back to space. In lower latitudes, and on global average, the cloud-induced shortwave (SW) cooling dominates throughout the whole year but Arctic cloud radiative forcing (CRF) is characterized by a negative CRF (cooling) during summertime and a positive (warming) CRF in months with weak insolation. Shupe and Intrieri (2004) found surface SW CRF (SWCRF) to be a function of solar zenith angle, cloud transmittance, and surface albedo. Longwave (LW) CRF (LWCRF) was determined to be a function of cloud temperature, height, and emissivity (i.e., microphysics). Due to typically higher emission temperatures, low-level clouds exert stronger surface LW warming than clouds at higher levels, highlighting the climatological importance of low-level cloud CRF during the Arctic winter. Beside the dependence on cloud properties, CRF is sensitive to cloud fractional cover (CFC)
itself (Shupe and Intrieri 2004). Investigating trends of various microphysical cloud properties and their impact on the CRF would exceed the range of this study. Thus, here we focus on changes in CFC and their relation to Arctic sea ice. A positive CRF can lengthen the melting season and hinder sea ice recovery in autumn, and therefore slow down the formation of perennial ice. Despite the crucial role, Arctic cloud feedback, cloud processes, and surface coupling as a backbone of those amplifying processes are poorly understood and constitute the major source of uncertainties in simulated climate (Solomon et al. 2007).

To comprehend the mechanism and determine the strength of the cloud–sea ice (CSI) feedback, several studies using satellite data have been published but no clear answer has been found yet. Kay and Gettelman (2009) evaluated active NASA A-Train CloudSat/Cloud–Aerosol Lidar with Orthogonal Polarization (CALIOP) data records for the 2006–08 period and reported positive low-level cloud trends in autumn as a response to sea ice loss. They also stated that these mechanisms could contribute to the CSI feedback. Morrison et al. (2018), Taylor et al. (2015), and Palm et al. (2010) evaluated even longer active NASA A-Train data records to find a relationship between melting sea ice and increasing clouds during autumn. Passive Multitriangle Imaging Spectroradiometer (MISR) as well as active CALIOP data records were analyzed in Wu and Lee (2012) and revealed that a significant increase in especially low-level clouds in October is possibly responsible for enhanced warming during autumn, as reported in Serreze et al. (2009) as well. To the contrary, Schweiger et al. (2008) found that sea ice retreat is linked to a decrease in low-level and an increase in midlevel clouds simultaneously as a result of deepening Arctic boundary layer with the TIROS TOVS Polar Pathfinder (TPP) dataset and ERA-40 reanalysis results for the 1980–2004 period. They stated that the direct CRF is small and compensated by changes in atmospheric temperature and humidity profiles. A statistical quantification algorithm for feedback coefficients between changing sea ice and clouds has been applied to 2000–10 Moderate Resolution Imaging Spectroradiometer (MODIS) measurements by Liu et al. (2012) and showed an increase of total cloudiness as a response to declining sea ice. Simulation results presented in, for example, Morrison et al. (2019), Abe et al. (2016), and Vavrus et al. (2011, 2009) suggest that increased Arctic cloud cover as a result of retreating sea ice is enhancing Arctic amplification especially during autumn.

Barton et al. (2012), Taylor et al. (2015), and Morrison et al. (2018) addressed the separation of the influence of sea ice on clouds from other cloud-controlling factors such as large-scale atmospheric dynamics and thermodynamics. All three papers identified low-level Arctic clouds to be and sensitive to lower-tropospheric stability (LTS). Increased LTS is associated with less low-level cloud fraction. Barton et al. (2012) and Taylor et al. (2015) determined a significant relation between low-level clouds and the prevailing atmospheric thermodynamic regime as well as a—compared to other publications—rather weak but statistically significant covariance with sea ice in autumn. Morrison et al. (2018) explained that the rather weak signal might be due to the atmospheric regime classification by LTS because LTS can also change with sea ice cover. The isolated autumnal cloud response to sea ice variability presented in Morrison et al. (2018) is much more distinct than in Barton et al. (2012) and Taylor et al. (2015) and consistent with multiple previous studies mentioned above. According to Shupe et al. (2011) Arctic low-level clouds are not caused by low pressure frontal systems.

Difficulties in cloud detection over cold, highly reflective sea ice surfaces with passive satellite-based instruments combined with lacking knowledge of Arctic atmospheric profiles is responsible for controversial and sometimes contradictory results (e.g., Eastman and Warren 2010; Liu et al. 2007; Schweiger 2004; Wang and Key 2003; Comiso 2003). Cloud detection with active instruments like CloudSat/CALIOP and ICESat/CALIOP do not rely on thermal or visible contrasts but latitudes greater than about 82°N are not observed by CALIOP and both temporal and spatial coverage are inferior to most passive instrument datasets. On the other hand CALIOP can serve as an excellent reference for passive imagers, globally but also regionally in the Arctic. An error analysis in MODIS cloud detection over the Arctic with its dark ocean, bright sea ice, and weak insolation over a major part of the year and implications for observing feedback mechanisms is presented in Liu et al. (2010).

There have been several simulation- and observation-based studies that investigated Arctic cloud cover changes during recent decades. Nevertheless the vertical profile of those changes, the connection to sea ice, and the effect on CRF changes is still under debate. Most studies using space-based data inferred a relation between clouds and sea ice by focusing on short time periods or certain events (e.g., 2007 or 2012 sea ice minimum). Sensitivity simulations (e.g., Abe et al. 2016) are a good way find a connection between two variables but to infer a real causal relation from observations, by eye comparisons or instantaneous correlations are statistically insufficient. Causality testing in this field of research has (to our knowledge) only been done in Vavrus et al. (2011), Liu et al. (2012), and Abe et al. (2016) using cross-correlations but directionality is hard to infer from this method and results can be biased if one or more variables have a substantial memory (Runge...

To perform a climatological analysis, this paper uses 34-yr-long state-of-the-art monthly mean satellite-based climate data records (CDRs). Cloud properties and radiation fluxes are consistently retrieved from AVHRR measurements and accumulated within one dataset. Using monthly mean data is well suited for detecting climatological trends but averaging might smooth out information about the relation between two fast interacting variables as sea ice and clouds. As mentioned above and presented in Morrison et al. (2018), Taylor et al. (2015), and Barton et al. (2012), active NASA A-Train measurements and simulations offer valuable insights in the underlying interaction processes between sea ice and clouds on a high temporal and spatial scale. But do those processes cause a real climatological signal and if yes is it possible to statistically identify the relations between sea ice and clouds using the same data? Certainly, conclusions drawn from the high-resolution but short-term and the monthly mean climatological data basis should be consistent.

This study aims to 1) document changes in especially low-level cloud cover and CRF in the Arctic, 2) assess their relation and causality with declining sea ice, and 3) discuss the contribution of the cloud–sea ice feedback to Arctic amplification. A highlight of this study is that causality between Arctic sea ice and clouds is—for the first time ever to our knowledge—assessed with Granger causality (GC) (Granger 1969), offering valuable advantages compared to often used cross-correlation. One of the major GC advantages is that the analysis directly offers the opportunity to judge causality for both influencing directions separately. Sensitivities of CRF to CFC are additionally calculated. This study explicitly focuses on autumnal months [September–November (SON)] due to excessive trends in sea ice in this season and most evidence for an amplifying CSI feedback (Serreze et al. 2009).

2. Data

a. ESA Cloud_cci cloud and radiation properties

CFC and surface [i.e., bottom of the atmosphere (BOA)] broadband radiation fluxes were obtained from latest version 3 AVHRR-PM CDR (Stengel et al. 2020) generated within the cloud component of the European Space Agency (ESA) Climate Change Initiative (ESA Cloud_cci) project. The dataset was chosen because 1) it offers a long temporal range of consistently retrieved cloud and radiation variables covering the whole globe and thus offers the opportunity to study Arctic cloud and radiation processes, 2) it is a state-of-the-art dataset that was officially published just recently, and 3) to our knowledge, it has never been applied to Arctic studies before. The CDR contains observations from the Advanced Very High Resolution Radiometer (AVHRR) onboard NOAA Polar Orbiting Environmental Satellites (NOAA-7, NOAA-9, NOAA-11, NOAA-14, NOAA-16, NOAA-18, NOAA-19) with an afternoon equator crossing time (ECT). NOAA-12 (morning ECT) observations are used from September 1994 to January 1995 to fill a gap between NOAA-11 and NOAA-14. Processing at Level-3C has been used and offers monthly averages on a global equal-angle latitude–longitude grid with 0.5° × 0.5° resolution for a 35-yr period (1982–2016). Cloud detection and cloud property retrieval is done using the Community Cloud Retrieval for Climate (CC4CL) algorithm (Sus et al. 2018; McGarragh et al. 2018). Broadband BOA radiation fluxes are retrieved using the BUGSrad algorithm (Christensen et al. 2016; Stephens et al. 2012). CC4CL cloud properties are ingested into BUGSrad allowing a consistent radiation flux retrieval. At BOA, the Cloud_cci CDR provides all-sky and clear-sky estimates of downwelling and upwelling shortwave and longwave radiation fluxes. In BUGSrad, clear-sky fluxes are determined from all-sky conditions by removing the clouds when existent. CFC is subdivided into three cloud levels (CFC_low, CFC_mid, CFC_high) judged by the cloud top pressure (CTP) following the ISCCP classification (Rossow and Schiffer 1999). The CC4CL optimal estimation retrieval directly outputs the CTP of pixels which are classified as cloudy by the binary cloud mask.

Due to insufficient spectral information provided by AVHRR, multilayer clouds were not handled in the dataset’s retrieval. Despite the in theory fixed ECT of sun-synchronous orbits, NOAA satellites show a drifting ECT, which results in a delay of observation and therefore inconsistent time sampling for variables with a diurnal cycle. In the Arctic the impact of this orbital drift on the climatological time series is rather weak because these satellites image the Arctic up to 14 times a day (i.e., at different stages of the diurnal cycle). To eliminate spurious trends in CFC due to different cloud detection efficiencies between sea ice and open water we applied a sea ice concentration (SIC)-dependent bias correction to CFC_low using CALIOP as a reference. Surface CRF trends are also corrected based on corrected CFC_low trends. A detailed description of the bias correction (BC) is given in the appendix.

It is worth mentioning that the bias between CALIOP and Cloud_cci CFC_low presented in the appendix (Fig. A1) is not only a statistical value derived for the BC. The bias is also a good characterization of the systematic Cloud_cci CFC_low error over a highly variable surface. It can be
interpreted as the under- or overestimation of Cloud_cci low-level clouds as a function of SIC.

b. Sea ice concentration

The EUMETSAT Satellite Application Facility on Ocean and Sea Ice (OSI-SAF) Global Sea Ice Concentration CDR (SIC CDR v2.0, 2017, Identifier: OSI-450; https://doi.org/10.15770/EUM_SAF_OSI_0008) provides daily SIC for the period from 1 January 1979 to 31 December 2015 gridded on a 25 × 25 km
2 EASE2 grid. Monthly means were created and subsequently resampled onto the regular Cloud_cci grid using nearest neighbor interpolation. OSI-450 is based on Scanning Multichannel Microwave Radiometer (SMMR), Special Sensor Microwave Imager (SSM/I) and the Special Sensor Microwave Imager Sounder (SSMIS) instruments, first onboard Nimbus-7 and a subsequent series of Defense Meteorological Satellite Program (DMSLP) satellites. The monthly mean sea ice edge is the calculated median 15% SIC contour line for each month and used as reference contour in some figures. A conventionally accepted 15% SIC threshold is applied to distinguish between ice-filled and ice-free pixels (Cavalieri et al. 1991).

c. Complementary data

CFC
low, and surface fluxes and various atmospheric variables are obtained from the ECMWF ERA-Interim reanalysis (Dee et al. 2011) on a 0.5° × 0.5° regular latitude–longitude grid. ERA-Interim is a widely used global reanalysis covering the study’s temporal range. Simulation of clouds especially in the Arctic is always a very challenging task, including for a reanalysis like ERA-Interim, and therefore accompanied by large uncertainties. However, Zygmuntowska et al. (2012) found that ERA-Interim agreed very well with surface-based cloud observation recorded during the Surface Heat Budget of the Arctic Ocean (SHEBA) campaign so that ERA-Interim is a reasonable choice for this study. ERA-Interim CFC
low was preprocessed so that it is comparable to satellite observations like our Cloud_cci dataset by applying the satellite simulator as documented in Stengel et al. (2018). The satellite simulator dataset is limited to the temporal range of 1982–2014. Boisvert et al. (2015) found that the ERA-Interim moisture flux is underestimated by up to 0.02 g m
−2 s
−1 (55 W m
−2 latent heat flux) over the Beaufort and East Siberian Seas compared to the Atmospheric Infrared Sounder (AIRS). Because the ERA-Interim moisture flux scheme remains unchanged over the whole time period, we assume that the bias is roughly constant. In this paper we are only interested in trends that are calculated from anomalies anyway so that the bias likely does not affect trends significantly.

Furthermore the EUMETSAT Satellite Application Facility on Climate Monitoring (CM-SAF) Cloud, Albedo, and Surface Radiation dataset (CM-SAF) version A2 (Karlsson et al. 2017) is used for CFC
low trend comparison. The CLARA-A2 dataset was chosen to get an additional cloud trend reference in the Arctic that is also based on AVHRR, covering the same temporal range and the same cloud variables as Cloud_cci. In contrast to Cloud_cci, CLARA uses a different retrieval framework and cloud detection algorithms are completely independent.

3. Methods

If not differently marked, the temporal range in this study is from 1982 to 2015 to exploit the maximum joint range of Cloud_cci AVHRR-PM and OSI-450. The Arctic is defined as latitudes north of 65°N. All results are based on bias-corrected CFC
low, and CRF, as described in the appendix.

a. Trends, correlation, and significance

Trends are calculated using a linear least squares regression model with the slope indicating a time series trend. Relationships between two variables are investigated using the Pearson correlation coefficient. Linear trends are removed before correlation. Significance of trends and correlations is tested using a Student’s t test outputting a double-tailed p value. The level of significance is set to 5% (p < 0.05).

b. Granger causality

Inferring causality from even significant instantaneous correlation is a well-known fallacy. A popular and often used tool in climate science to access causation is cross-correlation, which has been applied to the interaction between Arctic sea ice and clouds by Abe et al. (2016), Vavrus et al. (2011), and Liu et al. (2012). Runge et al. (2014) showed that correlations can be highly biased if one or more variables have a substantial memory and may therefore lead to an overinterpretation of a possible causal relationship. Granger (1969) presented a prediction method to access causality using linear autoregressive (AR) modeling, known as Granger causality (GC). GC is widely used and accepted in economics but is rather unknown in climate science with only a few applications (e.g., McGraw and Barnes 2018; Attanasio et al. 2013; Elsner 2007; Elsner et al. 2006; Mosedale et al. 2006; Kaufmann et al. 2003). Lagged autoregression is not susceptible to cases where one or more variables have a substantial memory and it offers a more stringent criterion for causation (McGraw and Barnes 2018). Additionally, the direction of influence
can be inferred directly from GC results. As for lagged correlations, the influence of a third variable linking or even driving the two investigated variables always needs to be considered.

The framework of GC analysis is based on two axioms formulated in, for example, Granger (1980):

1) The cause happens prior to its effect.
2) The cause has to have some unique information about the effect’s future.

Assume we have time series $X$ and time series $Y$. To analyze if $Y$ has a causal influence on $X$ the basic idea, based on the above axioms, is to determine if past values of $Y$ cause the future of $X$. This analysis is performed using two AR models to predict $X$. In the first “restricted” model [Eq. (1)], the future of $X$ is predicted based solely on $X$’s past values. The second bivariate “unrestricted” model [Eq. (2)] predicts the future of $X$ based on $X$’s and $Y$’s past. If adding $Y$ significantly improves the prediction of $X$ (reduces the model error), the analysis proposes that $Y$ has a causal influence on $X$. To distinguish between both influencing directions ($X$ causing $Y$ and $X$ causing $Y$) the same test can be performed with $Y$ being the variable to be predicted and $X$ the variable to be added to the unrestricted model [Eqs. (3) and (4)].

Following Ding et al. (2006), the autoregressive representation of $X$ in terms of a restricted [Eq. (1)] and an unrestricted [Eq. (2)] model of order $s$ [AR($s$) model] can be written as

$$X(t) = \sum_{k=1}^{s} a_{1k} X_{t-k} + \varepsilon_{1t}, \quad (1)$$

$$X(t) = \sum_{k=1}^{s} a_{2k} X_{t-k} + \sum_{k=1}^{s} b_{2k} Y_{t-k} + \varepsilon_{2t}, \quad (2)$$

In the same manner the restricted [Eq. (3)] and unrestricted [Eq. (4)] model for the prediction of $Y$ are formulated as

$$Y(t) = \sum_{k=1}^{s} d_{1k} Y_{t-k} + \eta_{1t}, \quad (3)$$

$$Y(t) = \sum_{k=1}^{s} c_{2k} X_{t-k} + \sum_{k=1}^{s} d_{2k} Y_{t-k} + \eta_{2t}, \quad (4)$$

with $t$ being the time, $k$ the time lag, $s$ the maximum number of lag (i.e., model order), and $a$, $b$, $c$, and $d$ the model coefficients. Also, $\varepsilon_{1t}$ and $\eta_{1t}$ are the restricted model residuals of $X(t)$ [Eq. (1)] and $Y(t)$ [Eq. (3)] where no causality is possible because the possibly causal variable is removed from the model; $\varepsilon_{2t}$ and $\eta_{2t}$ are the residuals (prediction errors) of the unrestricted models [Eqs. (2) and (4), respectively]. By comparing the residual variances of the restricted model to those of the unrestricted model $F$-test sample statistics for the influence of $X$ on $Y$ and vice versa are obtained (Ding et al. 2006):

$$F_{X \rightarrow Y, \text{sample}} = \frac{\text{var}(\varepsilon_{1t})}{\text{var}(\eta_{1t})}, \quad F_{Y \rightarrow X, \text{sample}} = \frac{\text{var}(\varepsilon_{2t})}{\text{var}(\eta_{2t})}. \quad (5)$$

If the test $F$ statistics are large (i.e., the numerator $>$ denominator), a causal relation is more likely because the added interaction terms improve the data variability description. The GC null hypothesis $H_0$ is that variable $X$ ($Y$) does not Granger-cause variable $Y$ ($X$). The null hypothesis $H_0$ can be rejected if the $p$ value of the $F$ sample statistic is smaller than the required level of significance (here 5%). The $p$ value is calculated as the probability $P$ that the value of a theoretical $F$ distribution $F(m, n)$ for this number of degrees of freedom ($m$: numerator and $n$: denominator) is larger than the sample $F$ statistic $F_{\text{sample}}$ under the condition that the null hypothesis $H_0$ is true:

$$p = P(F(m - 1, n - 1) \geq F_{\text{sample}} | H_0). \quad (6)$$

A generic expression written as $P(A|B)$ describes the conditional probability for the occurrence of $A$ given $B$. The optimal model order is determined as the order minimizing the Bayesian information criterion $\text{BIC} = k \ln(N) - 2 \ln(L)$ (Schwarz 1978) with $N$ being the number of observations, $\ln(L)$ the logarithmic likelihood function, and $k$ the number of parameters estimated by the linear model.

As GC requires stationary data, an augmented Dickey–Fuller (ADF) unit root test (Dickey and Fuller 1979) is applied. In case of ADF nonstationarity, the series is differentiated (e.g., $\Delta X_t = X_t - X_{t-1}$) until stationarity is achieved. Time series are typically stationary for first-order differences (linear trends). Subsequently the time series are standardized for zero mean and unit variance [e.g., $X_{\text{std}} = (X - \bar{X})/\sigma_X$].

c. Cloud radiative forcing

Ramanathan et al. (1989) proposed to quantify the CRF by comparing radiation fluxes in cloudy (all-sky) and noncloudy (clear-sky) conditions. The strong surface albedo dependency of the BOA CRF is removed by neglecting upwelling fluxes (Vavrus 2006), yielding

$$\text{CRF}_{\text{BOA}} = F^1 - F_{\text{clr}}^1. \quad (7)$$

Note that $F$ constitutes a broadband radiation flux and can be SW or LW. A down-pointing arrow indicates a downwelling flux. The subscript “clr” indicates a clear-sky
flux; no subscript indicates all-sky flux. The total CRF (TCRF) is the sum of SWCRF and LWCRF.

4. Results

An overview over the Arctic Ocean is given in Fig. 1, which introduces locations and names of Arctic regional seas according to National Snow and Ice Data Center (NSIDC) standards.

a. Arctic sea ice and cloud cover trends

Figure 2 shows 1982–2015 annual mean Arctic CFC$_{\text{low}}$ and SIC generated from Cloud_cci and OSI-SAF CDRs. Over the sea ice pack, CFC$_{\text{low}}$ ranges between 20% and 50%. Central Arctic SIC is above 90% surrounded by the marginal ice zones where the actual sea ice melt occurs (hereafter also referred to as “melting zones”). Lower mean CFC$_{\text{low}}$ over the sea ice pack compared to the ice-free ocean with a relatively sharp transition at the sea ice edge already demonstrates that surface properties likely influence low-level cloud cover.

Most studies and data reveal that Arctic sea ice is declining at impressive rates as a response to fast rising surface temperatures for the past three decades with strongest changes in summer (JJA) and autumn (SON) (e.g., Comiso et al. 2008; Deser and Teng 2008; Serreze et al. 2007; Stroeve et al. 2007). As shown by the red-colored annual cycle in Fig. 3, Arctic SIC has its minimum (maximum) in September (March) with statistically significant negative trends in every month. The strongest (weakest) negative SIC trends are also found in September (March), leading to an increasing amplitude of its annual evolution. In accordance with previous studies, the strongest melting rates are found in JJA and SON. Figure 3 also shows the monthly mean annual cycle of CFC$_{\text{low}}$ (blue dashed line) including its monthly trends (arrows). CFC$_{\text{low}}$ is averaged within each month’s corresponding 1982–90 median sea ice edge to focus on low-level clouds over sea ice. This averaging area represents the “maximum” sea ice extent before rapid sea ice loss occurred. Thus, always the same (number of)
pixels are averaged. By choosing the maximum sea ice extent as the averaging area, it is ensured that pixels close to the ice edge during the early years of the data record also contribute to the calculated statistics. Each month’s 1982–90 median sea ice edge is shown by the magenta contour line in the maps below the line plot.

FIG. 3. Red and blue lines indicate Arctic SIC and CFClow monthly mean annual cycle, respectively. Arrows on each data point represent monthly decadal trends. The value of the trend is given by the number next to the arrow. The unit of the trend is percent per decade. Yellowish shaded numbers are statistically significant. CFClow is averaged over pixels within each month’s 1982–90 median sea ice edge. Each month’s 1982–90 median sea ice edge is shown in the lower contour plots of Fig. 3. CFClow shows two local maxima in late spring and early autumn. Especially October and November indicate statistically significant increases in CFClow, which could shift the second maximum to late autumn, when sea ice starts recovering. Whether these trends are related to SIC will be investigated within this study. In the following we exclusively focus on SON because surface–atmosphere coupling is assumed to be strongest in months with fast dropping atmospheric temperatures (Kay and Gettelman 2009) and previous studies found most evidence for an amplifying feedback mechanism (Serreze et al. 2009).

Figure 4 shows spatially resolved decadal SIC trends for SON. The strongest negative SIC changes are found in the Beaufort, Chukchi, East Siberian, Laptev, and Kara Seas along the Canadian, Alaskan, and Russian coasts with magnitudes of up to about −30% SIC per decade in September. During summer and early autumn
the strongest sea ice melting is found in these areas, whereas from November to May the strongest trends are seen in the Kara and Barents Seas.

Decadal Cloud_cci CFC_{low} SON trends are shown in Fig. 5a. Statistically insignificant trends are marked by dotted areas. The magenta line indicates the 1979–2015 monthly median sea ice edge. For September weak positive trends are found mainly collocated with strongest SIC trends in this month (Fig. 4). October and November (ON) have extensive increases over the whole Arctic sea ice area with up to +9.6% decade^{-1}. Following Fig. 3, mean CFC_{low} trends are +0.30%, +3.88%, and +3.50% decade^{-1} for September, October, and November, respectively. The latter two are statistically significant. Outside the sea ice edge over permanently ice-free ocean, CFC_{low} is decreasing in every month.

Cloud_cci CFC_{low} trends in Fig. 5a are further compared to CLARA-A2 (Fig. 5b), ERA-Interim (Fig. 5c), Abe et al. (2016), and Vavrus et al. (2011, 2009). The three external simulation-based studies offer a direct comparison of 2D CFC_{low} trends. CLARA-A2 was not corrected for sea ice–ocean differences in detection.

Fig. 5. Decadal SON (a) ESA Cloud_cci, (b) CMSAF CLARA-A2, and (c) ERA-Interim CFC_{low} trends. The magenta contour line indicates the 1979–2015 monthly median sea ice edge. Dotted areas mark statistically insignificant trends.
efficiency. In September, ERA-Interim overestimates cloud trends over the ice pack (not collocated with melting zones) compared to Cloud_cci and CLARA. Both Cloud_cci and CLARA have only weak trends over the ice pack in September. Consistent with Cloud_cci, CLARA detects positive October trends over melting zones that are possibly related to sea ice. Contrary to Cloud_cci, magnitudes of positive CFC_{low} trends fade toward the pole but remain mostly positive over the central Arctic. ERA-Interim did only simulate a few statistically significant positive October trends over the Arctic but cloud increases over melting zones are visible, although they are weaker than those of Cloud_cci and CLARA. However, November patterns and strengths over sea ice are in good agreement throughout all three datasets shown in this study. Abe et al. (2016) used the ocean–atmosphere coupled Model for Interdisciplinary Research on Climate in version 5 (MIROC5) (Watanabe et al. 2010) to simulate autumnal Arctic total cloud cover trends. The October trends are in good agreement with Cloud_cci October trends, whereas almost no significant November trends were simulated. Twenty-first-century Community Climate System Model (CCSM3) (Collins et al. 2006) ensemble projections presented in Vavrus et al. (2011) show that autumnal cloud cover is increasing over the whole Arctic ice pack, likely as a response to melting sea ice. Also consistent with our results, cloud cover trends are found to be primarily due to low-level clouds. Patterns and strengths of low-level cloud trends in Vavrus et al. (2011, Fig. 3 therein) are in good agreement with our October and November results in Fig. 5a. Vavrus et al. (2009) used simulations of late-twentieth- and twenty-first-century Arctic clouds from multiple models in phase 3 of the Coupled Model Intercomparison Project (CMIP3) (Meehl et al. 2007) to show that the Arctic cloud cover increases especially during autumn and over sea ice. Total cloud cover during autumn (Fig. 6 in Vavrus et al. 2009) was simulated to increase [similarly to Vavrus et al. (2011)] over the whole Arctic ice pack, thus being also in good agreement with our observations. Overall, Cloud_cci is in agreement with Abe et al. (2016) in October but November observations are comparable to CLARA and ERA-Interim. Autumnal positive cloud change patterns as shown in Vavrus et al. (2011, 2009) are in good agreement with October and November Cloud_cci low-level cloud trends, also over the central Arctic. Cloud_cci, CLARA, Abe et al. (2016), Vavrus et al. (2011, 2009), and ERA-Interim agree that low-level cloud cover increased by about 8% decade^{-1} in November over the Beaufort, Chukchi, and East Siberian Seas, where sea ice is melting drastically. Concerning the ERA-Interim September cloud trend overestimation over the Canadian Archipelago and the Lincoln Sea as well as the November positive cloud trends over the permanently ice-free North Atlantic, no satisfying mechanism could be identified. Both observational datasets show only weak September trends over the ice pack and near-zero or rather negative trends over the North Atlantic. ERA-Interim relative humidity at 850 and 925 hPa is increasing over these areas so that the discrepancy between the reanalysis and the observational datasets is likely related to moisture and/or temperature transport/flux issues in the lower model layers. Analyzing further variables and investigating if other reanalyses like MERRA-2 (Gelaro et al. 2017) reproduce that trend patterns could help to resolve that issue in future studies.

Midlevel cloud trends have almost no significant trends in SON (not shown). High-level cloud cover is slightly decreasing over sea ice areas in ON with magnitudes at about a third of those of CFC_{low} increases (not shown). However, CFC_{high} constitutes overall only a minor part of the Arctic total cloud cover. Collocation of areas with positive low-level CFC trends and areas of declining sea ice is also observed for winter and early spring (not shown), consistent with simulated results in Morrison et al. (2019). Generally speaking, positive CFC_{low} trends seem to be located over intense melting zones in the Beaufort, Chukchi, East Siberian, and Kara Seas but strong positive trends are also observed over the central Arctic sea ice pack where SIC is basically constant. The observed central Arctic CFC_{low} trends will be addressed later. However, a coupling of low-level [planetary boundary layer (PBL)] clouds to the surface is more likely than for high-level clouds, justifying the focus on low-level clouds in this study. Additionally Shupe and Intrieri (2004) found that low-level clouds exert the strongest radiative effect on the Arctic surface. Increasing low-level cloud cover is in agreement with, for example, Wu and Lee (2012), Palm et al. (2010), and Kay and Gettelman (2009) using active as well as passive instruments. Increasing overall cloud cover was also reported in Liu et al. (2012). A decrease in CFC_{low} with an simultaneous increase in CFC_{mid} due to a deepening PBL as reported in Schweiger et al. (2008) is not represented in Cloud_cci data.

b. Relation between CFC and SIC

Instantaneous monthly correlations between bias-corrected CFC_{low} and SIC were calculated pixel-by-pixel over the whole Arctic and are shown in Fig. 6. Statistically significant anticorrelations between SIC and CFC_{low} are observed in ON over melting zones. The same holds for all other polar night months up to April (not shown), implying an association between decreasing sea ice (more open water) and increasing low-level CFC that could cause climatological trends of the two variables. May–September
correlations between SIC and CFC\textsubscript{low} (not shown) are statistically insignificant over most areas of the Arctic Ocean, consistent with model-based results in Morrison et al. (2019). Mid- and high-level clouds are almost not correlated with SIC in autumn (not shown), indicating that the association between those cloud levels and SIC is distinctly weaker and that they are rather controlled by large-scale circulation variability.

Going beyond correlations, in the following, considerations are made to reveal if more precise indications of a causal relation, including the direction of information flow, exist. Decorrelation time as a measure for the persistence or memory is calculated using \( T = \frac{1 + \alpha}{1 - \alpha} \), where \( \alpha \) is the 1-month lagged autocorrelation (von Storch and Zwiers 2002, 373–374). Figure 7 shows \( T \) of SIC for the 1982–2015 time series. SIC memory ranges between 2 and 9 months with longest memories in the marginal ice zone where sea ice variability is high due to intense melting and freezing. This implies that negative SIC anomalies in September can cause negative SIC anomalies in the following months. Hence, sea ice as a variable with a long memory and thus slowly decaying autocorrelation could distort causality interpretations using the cross-correlation method (McGraw and Barnes 2018; Runge et al. 2014), justifying the application of GC.

Linear regression models, as used in the GC tests, require normally distributed predictands. Histograms and time series in Figs. 8a–d show CFC\textsubscript{low} and SIC data that are averaged over the Chukchi Sea (CS) subregion (sketched in Fig. 7) and prepared for GC tests. The time series in Figs. 8a and 8b look homogeneous without severe drifts or discontinuities. Histogram shapes (Figs. 8c,d) are unimodal and almost not skewed (i.e., close to a normal distribution) so that based on this exemplary analysis it is assumed that linear regression models are applicable to the here used variables. All plots shown in Figs. 8–10 are based on all months (not just SON) in the 34-yr time period (408 months) to provide the largest possible data basis for most reliable results.

GC methods are applied to the CS subregion time series (Figs. 8a,b). Figure 9 shows the \( p \) value (red) and \( F \) statistic (blue) returned by the GC test as a function of the model order. For model orders between 2 and 9 results indicate both an impact of CFC\textsubscript{low} on SIC and of SIC on CFC\textsubscript{low}, with the latter being slightly more pronounced by higher \( F \) statistics and high \( p \) value stability throughout the model orders. In other words, the results...
imply a close two-way feedback where the influence of SIC on CFC$_{low}$ is stronger than the reverse. This conclusion is solely based on visual comparison. Below in this paragraph as well as in the next one we will try to support our conclusion from above that, despite a strong two-way interaction signal, the influence of SIC on CFC$_{low}$ is likely a bit stronger. The BIC selected the AR(10) model to be the optimal order (black arrow pointing to the abscissa in Fig. 9). This is consistent with the $p$ value jump at model order 10 for the impact of CFC$_{low}$ on SIC (11 for SIC on CFC$_{low}$). The fast $p$ value increase after model order 10 is attributable to over-fitting. However, the AR(10) model outputted an $F$ statistic of 1.65 with a $p$ value of 0.088 for the influence of CFC$_{low}$ on SIC. The reverse direction (SIC → CFC$_{low}$) has an $F$ statistic of 3.05 with a $p$ value of 0.001 and is therefore stronger in the CS subregion. The statistical significance of the latter direction evaluated at the optimum model order (10) supports our above conclusion that the influence of SIC → CFC$_{low}$ is dominating. Mid- and high-level clouds do not show statistically significant Granger-causal relations with sea ice, in keeping with rather inconspicuous trends and insignificant correlations.

Spatially resolved AR(1), AR(5), and AR(10) $F$ statistics for both influencing directions are presented in Fig. 10. Statistically significant patterns remain similar throughout the three model orders with varying $F$ statistic strengths so that conclusions do not depend on the model order selection. For both directions we find statistically significant causal relations. Nevertheless, for the SIC → CFC$_{low}$ direction the values of statistically significant $F$ statistics are overall higher. Beside higher $F$ statistics, there are also distinctly more significant pixels compared to the CFC$_{low}$ → SIC direction. Based on this
visual judgment we conclude that, even though we have a two-way feedback, the influence of SIC on CFC\textsubscript{low} is likely stronger than the converse. This finding is consistent with the conclusion drawn above based on the 1D analysis. In general, significant causal regions are collocated with areas of intense sea ice melt and high anticorrelations. Judged by locations of melting zones (Fig. 4) and anticorrelations (Fig. 6), F statistic signals in the Beaufort, Chukchi, East Siberian, and Laptev Seas can be primarily assigned to early autumn months, whereas high F statistics in the Kara and Barents Sea originate very likely from the long period from November to early spring. The sea ice retreat during summer does not show statistically significant correlations and might rather damp F statistics. As F statistics are statistically significant at autumnal as well as winter and early spring melting zones (collocated with negative correlations), this relationship might be present from autumn until early spring when sunlight is rare.

A physical mechanism for the influence of cloud cover on sea ice is given with a cloud-induced surface warming/cooling, impacting subsequent sea ice evolution. The cloud response to sea ice loss was diagnosed to be the result of a destabilizing atmosphere–surface coupling via turbulent fluxes of sensible heat $H$ and moisture (evaporation $E$) in earlier publications (e.g., Kay and Gettelman 2009; Curry et al. 1996; Palm et al. 2010). ERA-Interim reanalysis results were used in this study to investigate this mechanism again for our temporal period. September shows weak but statistically significant positive $E$ and $H$ trends at the corresponding melting zones, consistent with only faint CFC\textsubscript{low} changes. In ON these $H$ and $E$ trends reach magnitudes of up to about $+15$ W m\textsuperscript{2} decade\textsuperscript{-1} and $+0.005$ g m\textsuperscript{-2} s\textsuperscript{-1} decade\textsuperscript{-1} ($+18.0$ g m\textsuperscript{-2} h\textsuperscript{-1} decade\textsuperscript{-1}), respectively. These trends are completely absent during summertime because the colder ocean gains heat from the relatively warm atmosphere (i.e., surface fluxes are pointing downward) whereas during winter the surface

![Fig. 10. Arctic year-round F statistics of GC tests for CFC\textsubscript{low} and SIC. (top) Influence of CFC\textsubscript{low} on SIC for an (a) AR(1), (b) AR(5), and (c) AR(10) model. (bottom) As in the top panels, but the influence of SIC on CFC\textsubscript{low} is shown. Dotted areas mark statistically insignificant F statistics below a 95% level of confidence. Black shaded areas indicate where SIC was constant over the whole analysis period and thus no F statistic was calculated. Please note the different color bar ranges.](http://journals.ametsoc.org/jcli/article-pdf/33/17/7479/4984922/jclid190895.pdf)
flux direction is reversed. Ice-free ocean in late autumn and winter provides heat or moisture to the atmosphere. Atmospheric temperatures start dropping in September so that \( H \) and \( E \) start pointing from the newly exposed ocean to the atmosphere, even though those gradients are still small. Two mechanisms could potentially raise \( H \) and \( E \) in ON: 1) Due to long sea ice memories, low SIC from summer (including September) can proceed to ON. Autumnal atmospheric temperatures drop faster than those of the ocean (different heat capacities) so that surface fluxes from the ice-free ocean, which had already been exposed in, say, September, can contribute to ON \( H \) and \( E \) extremes. 2) Sea ice insulates the ocean beneath from the cooling atmosphere so that less sea ice in ON exposes relatively warm ocean to the cold atmosphere. A combination of these two effects is very likely responsible for strong observed atmosphere–ocean coupling in autumn. Based on this it is clear that a negative trend in sea ice coverage is likely to lead to an increase in surface fluxes, and this mechanism is consistent with the observed response of low-level clouds, which are typically governed by turbulent surface fluxes.

c. Central Arctic low-level cloud trends

Beside the \( \text{CFC}_{\text{low}} \) trends over melting zones that are causally related to SIC, October and November low-level clouds are also increasing in the central Arctic near the North Pole where SIC is roughly constant. At this point it is not completely clear if the central Arctic low-level cloud trends in October reflect the truth and what the underlying mechanisms are. However, infrared channel measured radiances also indicate significant trends over the Arctic Ocean so that cloud cover trends are likely not just an artifact of trends in the auxiliary data used as input to the cloud retrieval. Unfortunately, the central Arctic is not observed by CALIOP so active instrument measurements are not available. To shed more light on this issue, conceivable indices and variables causing central Arctic low-level cloud trends were analyzed and will be discussed in the following. Even though ERA-Interim does not show central Arctic cloud trends like the Cloud_cci data, it is likely that the critical point is the subgrid-scale cloud parameterization and not the simulation of grid-scale variables such as wind and temperature. So it might be worth taking a look at those grid-scale fields to identify possible mechanisms.

The northern annular mode (NAM; also known as Arctic Oscillation) is the leading large-scale mode of climate variability and describes air pressure contrasts between the Arctic and the midlatitudes (Devasthale et al. 2012). It is measured by the dimensionless Arctic Oscillation index, which can either be in a positive or negative phase (cf. Fig. 11a). A negative (positive) phase is associated with more (less) air mass exchange with lower latitudes. Li et al. (2014) and Devasthale et al. (2012) found that the NAM phase is controlling high-level clouds eastward and westward of Greenland. Monthly mean NAM indices were retrieved from the NOAA Center for Weather and Climate Prediction (2019). As shown in Fig. 11a, October NAM features a statistically significant negative trend for the 1982–2015 period (\(-0.32 \text{ decade}^{-1}\)), which could enhance the transport of midlatitude air into polar regions. However, correlations between \( \text{CFC}_{\text{low}} \) and NAM (Fig. 11b) are mostly insignificant over the ice pack so that the NAM is unlikely to have sufficient influence on \( \text{CFC}_{\text{low}} \) over the central Arctic ice pack.

Enhanced advection of clouds or moist warm air (e.g., from melting zones) onto the ice sheet, where the air mass cools and starts condensation, could account for enhanced low-level cloudiness even in regions with no sea ice loss (Curry 1983). To find evidence for this mechanism, ERA-Interim 925- and 850-hPa October mean wind speed and wind direction have been calculated to determine whether the mean wind could advect air mass from melting zones toward the central Arctic (Figs. 11c,d). The two chosen model levels represent levels at which low-level clouds are especially enhanced. The graphic reveals that in October mean winds are blowing from the Chukchi, East Siberian, and Laptev Sea melting zones toward the central Arctic at both heights with about 1.5 m s\(^{-1}\). Wind speed as well as wind direction indicate that the advection mechanism could possibly cause at least some of the observed central Arctic cloud trends. At this point we cannot explicitly show with our data that this mechanism is responsible, but future work could use high-resolution ocean–atmosphere coupled simulations to further analyze this mechanism.

ERA-Interim moisture flux convergence (MFC; not shown) and near-surface static stability \( \Delta \theta \) (Figs. 11e,f) were further used to comprehend central Arctic cloud trends. Vertically integrated MFC trends are not significant over the central Arctic and therefore too weak to cause observed cloud trends, consistent with conclusions in Abe et al. (2016). Near-surface static stability trends are calculated as the decadal trend of the potential temperature difference between the 925- and 1000-hPa model levels (\( \Delta \theta = \theta_{925} - \theta_{1000} \)). Note that \( \Delta \theta \) has significantly decreased over October (Fig. 11e) melting zones as a result of enhanced sensible heat fluxes from the surface but no significant near-pole changes are visible. However, November (Fig. 11f) \( \Delta \theta \) is decreasing over the whole ice pack and could contribute to enhanced cloud formation over the ice pack, as also seen in ERA-Interim and CLARA-A2 data. Decreases in November \( \Delta \theta \) point to the fact that changing atmospheric circulations as well as humidity and temperature profiles under recent climate change may contribute to central Arctic low-level cloud formation beside sea ice over melting zones.
Further ideas that are not undergirded by data in this paper are presented in section 5.

d. Changes in Arctic CRF and sensitivity of CRF to CFC

Whereas in lower latitudes and on global average BOA TCRF is mainly negative (SW cooling prevailing), Arctic CRF shows a strong seasonal cycle. Figure 12 displays the annual cycle of BOA CRF components averaged over the Arctic. LW cloud forcing is positive over the whole year with only little seasonal variation compared to the SW component. SWCRF peaks in midsummer and approaches zero in months with weak or complete absence of solar radiation. Between April
and August, TCRF is dominated by the SW component and therefore negative. During the rest of the year (September–March) LW heating offsets SW cooling, yielding a positive TCRF (i.e., warming at the surface).

Sensitivities of BOA CRF components to changes in \( CF_{\text{Cl}} \) have been determined using the regression slope of all monthly Arctic-mean value pairs of these two properties. Linear trends are removed before running the regression model. Results are presented in Table 1. Units are watts per square meter per percent low-level cloud cover.

As shown in Table 1, SON LWCRF responds with an increased surface warming to an increase in \( CF_{\text{Cl}} \). TCRF sensitivities are roughly those of the LW component, except the relatively small SWCRF contribution due to some remaining incident solar radiation in September.

The sensitivity of BOA LWCRF to total cloud cover (\( CF_{\text{Cl}} \)) using ground-based measurements from the SHEBA program (Shupe and Intrieri 2004) is \(+0.65 \text{ W m}^{-2} \text{ %}^{-1}\) and therefore in good agreement with our results. Even though this sensitivity is determined from year-round measurements, the LWCRF seasonal cycle shows a relatively small amplitude and remains positive throughout the year (see Fig. 12) so that both sensitivities are still comparable. The agreement emphasizes the conclusion that more low-level clouds in the polar night enhance CRF surface warming.

Decadal BOA LWCRF trends are presented in Fig. 13. Due to the bias-correction method it is not possible to provide \( p \) values for significance testing of the BOA CRF trends but as reference, values more extreme than about \( \pm 2.5 \text{ W m}^{-2} \text{ decade}^{-1} \) were statistically significant for the uncorrected trends (not shown). Based on the rationale and results above, it can be assumed that LWCRF trend patterns are primarily governed by changes in \( CF_{\text{Cl}} \). This could be confirmed by calculating LWCRF solely as the product of \( CF_{\text{Cl}} \) changes and the corresponding sensitivity slope leading to nearly the same trend strengths and patterns as in Fig. 13a. As expected from the annual cycle and sensitivities, increasing low-level cloud cover forces a statistically significant LW surface warming trend over the whole Arctic ice pack in ON. September has only few regions with weak but significant positive LWCRF trends over the ice pack, consistent with only faint cloud changes. LWCRF trends can reach up to \(+8.3 \text{ W m}^{-2} \text{ decade}^{-1}\) locally in November.

Due to weak solar insolation, SWCRF (Fig. 13b) is almost negligible in ON and trends are weak. September has negative SWCRF trends with up to \(-4.7 \text{ W m}^{-2} \text{ decade}^{-1}\) over the Beaufort and Chukchi Seas, collocated with relatively weak positive low-level cloud trends. As the low-level and total cloud cover trends seemed to be too weak for observed SWCRF trends, it is likely that changes in cloud properties, such as cloud optical thickness (COT), might play a role.

To summarize, the SW and LW effects to obtain the TCRF (Fig. 13c) yields an increased September cooling over melting zones in the Beaufort, Chukchi, and East Siberian Seas. For ON, severely increased CRF-induced warming is observed over the whole ice pack as a result of increasing low-level clouds (up to \(+8.3 \text{ W m}^{-2} \text{ decade}^{-1}\) locally).

### Table 1. BOA CRF sensitivities to changes in \( CF_{\text{Cl}} \) for SON.

<table>
<thead>
<tr>
<th></th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
</tr>
</thead>
<tbody>
<tr>
<td>LWCRF</td>
<td>+0.37</td>
<td>+0.58</td>
<td>+0.66</td>
</tr>
<tr>
<td>SWCRF</td>
<td>-0.15</td>
<td>-0.02</td>
<td>-0.00</td>
</tr>
<tr>
<td>TCRF</td>
<td>+0.22</td>
<td>+0.56</td>
<td>+0.66</td>
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5. Discussion and conclusions

In this study, changes in all components of the CSI feedback have been estimated and their relation has been investigated using statistically sound methods. Correcting the data for passive instrument cloud detection issues over melting sea ice using CALIOP strengthens the reliability of the here presented trends. Results suggest the existence of an overall amplifying (positive) feedback mechanism exerting a severe cloud-induced warming effect on the Arctic surface in autumn.
The relevance of this warming (up to $+8.3 \text{ W m}^{-2} \text{ decade}^{-1}$ locally) can be illustrated by a comparison with the radiative forcing estimates presented in the Fifth IPCC Assessment Report (AR5). The global mean radiative forcing of well-mixed greenhouse gases (WMGHG) was estimated to be $+2.83 \text{ W m}^{-2}$ (Myhre et al. 2013) so that the locally extreme surface warming within 10 years is roughly three times the global mean WMGHG forcing. This underlines the statement that the CSI feedback mechanism is not negligible at all and likely contributes to Arctic amplification. A balancing of warming CRF trends by changing atmospheric temperature and humidity profiles, as reported in Schweiger et al. (2008), is not observed in our data.

Using Granger causality a possible causal two-way interaction between SIC and low-level clouds where the influence of SIC on low-level clouds is stronger than the reverse was identified. Liu et al. (2012) found a two-way interaction and stated that the influence of SIC on clouds is more dominant based on lagged correlation statistics. A relation between sea ice variability and dark season clouds was determined by Morrison et al. (2018), who...
concluded that the direction of causality is from the surface to the atmosphere using logical argumentation but no statistical sound test.

Even though clouds have been identified to be causally related to sea ice by turbulent surface fluxes, central Arctic low-level cloud trends where sea ice is constant are not completely understood. Comparisons with CLARA-A2, ERA-Interim, Abe et al. (2016), and Vavrus et al. (2011, 2009) revealed conflicting results in terms of CFClow trend patterns and strengths. November central Arctic CFClow trends are in good agreement with CLARA-A2 and ERA-Interim whereas October central Arctic trends were only simulated by Abe et al. (2016). Model results shown in Vavrus et al. (2011, 2009) show significant increases in cloud cover over the central Arctic during autumn. Vavrus et al. (2011) additionally stated that low-level clouds mainly drive total cloud cover patterns.

Most variables and indices evaluated in section 4c cannot explain the central Arctic observations. ERA-Interim atmospheric stability trend pattern in October seem to be related to melting sea ice. The strongest November near-surface static stability changes do not seem to be related to melting zones. These findings support 1) the hypothesis of Morrison et al. (2018) that atmospheric regime classification by atmospheric stability as applied in Barton et al. (2012) and Taylor et al. (2015) may weaken the relation signal between sea ice and low-level clouds as atmospheric stability is also influenced by surface type changes via turbulent surface fluxes and 2) the conclusion drawn in all three studies that atmospheric stratification is not negligible when analyzing changes in Arctic low-level clouds. It is again important to mention that reanalyses like ERA-Interim are poorly constrained in the Arctic and thus results may not represent the truth. For sure low-level clouds are influenced by atmospheric large-scale changes year-round, but consistent with Morrison et al. (2018), who investigated the isolated relation between sea ice and low-level clouds, a statistical significant causal relation was found using a novel causality test. Advection of moist and warm air masses from melting zones to the central Arctic was identified to be a possible mechanism. However, further work is needed to shed more light on whether central Arctic cloud trends are the result of changes in atmospheric dynamics and thermodynamics or if they are really related to melting sea ice at the edges. In the following some more technical considerations as well as ideas based on literature are presented:

1) During the polar night, cloud detection over sea ice strongly relies on an exact knowledge of ice skin temperature as it is used as the temperature reference for the infrared cloud detection. With increasing warming, wet spots of relatively warm water on the ice surface could increase thermal contrasts between the surface and clouds, leading to a positive trend in low-level cloud cover. Low-level clouds are likely more susceptible than higher clouds in that respect. Misclassified cloud levels are likely only a minor source of uncertainty compared to those induced by the cloud detection over snow or ice surfaces during the polar night. Once a cloud has been correctly detected, the CTP retrieval and therefore the cloud level assignment do not directly depend on the thermal and visible contrast between the surface and the cloud.

2) A basic space-based remote sensing technique problem is that high- and midlevel clouds with high COTs can prevent the satellite from detecting low-level clouds below. A negative trend in, for example, CFChigh may induce a positive trend in CFClow solely because more low-level clouds could be observed. In our data, midlevel clouds do not show any significant changes but a significant CFChigh decrease over the sea ice is observed in ON (not shown). However, the magnitudes are only about a third (~2% decade⁻¹) of those of spatially corresponding positive CFClow trends. To get an estimate for the worst case impact, the year-round Arctic Ocean instantaneous correlation between CFClow and CFChigh was determined to be $r = -0.26$, implying that less high-level cloud cover is associated with more low-level cloud cover. Approximatively scaling the CFChigh trend with the correlation coefficient yields a maximum erroneous low-level cloud trend induced by high-level shading of about 0.52% decade⁻¹. Multiplying this estimate with the autumn mean TCRF sensitivity (~0.5 W m⁻² %⁻¹; cf. Table 1) yields a maximum impact of 0.26 W m⁻² decade⁻¹ on the surface TCRF trends. Consequently, high-level cloud shading could potentially only explain a smaller portion of the signal found for CFClow and CRF in the Arctic. More reliable estimates for this effect and a potential correction using active instruments would be valuable. Nevertheless, the complexity to develop this, also accounting for effects like lidar attenuation (e.g., Guzman et al. 2017), would exceed the scope of this study and should be addressed in a separate study.

3) Leads (quasi-rectilinear cracks in the sea ice resulting from dynamic motions covering 1%–2% of the sea ice area; Alam and Curry 1997) that are likely not an input to ERA-Interim were diagnosed to provide heat and moisture to the above-lying atmosphere and drive convective events, as summarized in Curry et al. (1996). Schnell et al. (1989) demonstrated that plumes emerging from leads can be transported up to
250 km downwind of the lead. With continuously thinning sea ice (Kwok and Rothrock 2009), it is possible that the lead area is increasing with time and the cumulative effect of leads contributes to central Arctic low-level cloud enhancement. To the contrary, Li et al. (2020) recently found that newly opened and subsequently frozen leads are dissipating Arctic low-level clouds in midwinter. The freezing suppresses the latent heat flux but has less influence on the sensible heat flux so that the relative humidity over leads decreases, leading to a dissipation of low-level clouds. This finding weakens the possibility that leads are responsible for positive low-level cloud trends. Nevertheless, temperatures in SON are higher than in midwinter, slowing down the freezing process that could weaken the impact of this mechanism in autumn.

In the introduction it was mentioned that instantaneous active footprint-level data are probably better suited for detecting relations between two relatively fast interacting variables but when approaching this problem from a climatological point of view, results have to be consistent at least. In fact, results for cloud trends and the relation with sea ice are consistent with, among others, Kay and Gettelman (2009), Palm et al. (2010), Barton et al. (2012), Wu and Lee (2012), Taylor et al. (2015), and Morrison et al. (2018). The consistency between low-resolution climatological passive and high-resolution active measurements covering shorter periods strengthens the theory of an amplifying Arctic feedback mechanisms driven by sea ice and low-level clouds.

6. Summary

This study investigated the CSI feedback mechanism by estimating autumnal Arctic cloud cover changes as well as their relation with melting sea ice and trends in surface CRF using 34 years (1982–2015) of satellite-based CDRs. Figure 14 summarizes the identified autumnal CSI feedback loop. Negative influences from a generic variable $A$ to $B$ describe that variable $B$ decreases (increases) if $A$ increases (decreases), similar to a negative correlation. Positive influences from $A$ to $B$ represent a positive correlation so that an increase (decrease) of $A$ results in an increase (decrease) of $B$. In the following we will summarize our results while parsing through the proposed CSI feedback mechanism in Fig. 14:

- Increasing surface temperatures due to climate change trigger a reduction in Arctic sea ice.
- Less sea ice exposes more ice-free ocean to the Arctic atmosphere.
- Results show a strong increase of CFC$_{low}$ in October and November over the Arctic ice pack with strongest trends over extreme melting zones. Instantaneous correlations suggest that increasing cloud cover is related to a reduction in sea ice. Applying GC to the relation between CFC$_{low}$ and SIC indicates a two-way interaction where the influence of SIC on CFC$_{low}$ is stronger than the reverse based on $F$ statistic score strength and spatial distribution. The proposed different relation strengths are indicated by the arrow width in Fig. 14 (see discussion in section 4b). Together with ERA-Interim surface fluxes it is found that in nonsummer months melting sea ice enhances low-level cloud cover through surface–atmosphere coupling via turbulent surface fluxes of heat and moisture which destabilize the lower troposphere and facilitate low-level cloud formation. The coupling of low-level clouds to surface forcings is negligible during summertime so that no negative CSI exists. Unfortunately no satisfying
explanation for central Arctic cloud trends could be identified but several ideas for future studies addressing this open question were issued.

- The annual cycle of BOA TCRF shows that on average in the Arctic it exerts a warming effect on the surface energy balance between September and April. Sensitivities of TCRF to CFC$_{low}$ were calculated and are positive for SON ranging between +0.22 and +0.66 W m$^{-2}$ per percent CFC$_{low}$. Positive sensitivities imply that with increasing low-level cloud cover surface warming will increase as well. This increasing surface warming can hinder the formation of perennial ice and/or lengthen the melt season. Calculated CRF trends confirm the proposed feedback mechanisms and show extensive positive warming trends over the whole ice pack with patterns mainly governed by those of CFC$_{low}$ trends. With the warming autumnal CRF trend, the last component of the CSI feedback was identified giving the whole mechanism a positive (amplifying) sign.

All in all, this study investigated all components of the CSI feedback and provides evidence that the ice–cloud interaction plays a crucial role in Arctic amplification. Central Arctic low-level cloud trends need to be investigated in further studies.

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**APPENDIX**

**CALIOP-Based CFC$_{low}$ Bias Correction**

Over the Arctic Ocean with its highly variable SIC, passive radiometers like AVHRR hold the property to overestimate cloud trends over melting zones. The reason is that the visible and infrared contrast over the warm and dark ocean is higher than over cold and white sea ice. With diminishing sea ice, a positive cloud trend might be partially attributable to changing cloud detection capabilities over melting zones where the area of ocean increases and that of sea ice simultaneously decreases. Active measurements from the CALIOP instrument mounted on board the CALIPSO satellite are not susceptible to those surface property changes and are therefore used as an accurate reference. With CALIOP the susceptibility of Cloud_cci records to sea ice/ocean surface transitions is determined and corrected if necessary. The COT threshold represents above which CALIOP COT the CALIOP pixel is classified cloudy.

A problem that comes along with CALIOP lidar observations is that for cloud optical thicknesses of about 3–5 the lidar becomes attenuated and may miss clouds below an opaque cloud layer as shown in Guzman et al. (2017). However, Morrison et al. (2018) calculated that the mean altitude of full lidar attenuation over the Arctic Ocean is at 750 m and that it almost never exceeds 1 km. The ISCCP upper low-level cloud regime CTP limit (680 hPa) corresponds to an altitude of roughly about 2.7 km so that the lidar attenuation height is within the low-level cloud regime for most cases and the upper opaque cloud is identified as a low-level cloud anyway. The altitude at 680 hPa was estimated using the barometric formula using a mean atmospheric temperature of 240 K and a reference pressure of 1000 hPa.

The correction is developed only for low-level clouds and applied before calculating anomalies. From the CFC$_{low}$ trend errors and the sensitivity of CRF to CFC$_{low}$, CRF trends can be corrected as well to obtain more reliable estimates.

**a. CALIOP data and collocation**

Active CALIOP measurements between July 2006 and December 2014 are collocated in space and time with Cloud_cci Level-3U daily composites and daily OSI-SAF SIC data using nearest neighbor search. In contrast to the primarily used monthly 0.5° gridded Cloud_cci Level-3C data, daily Level-3U records are sampled on a 0.05° grid. For nearest neighbor search, daily SIC is kept on the native 25-km EASE2 grid. Latitudes are limited from 65°N (minimum Arctic latitude) to about 82°N (maximum CALIOP latitude). The CALIOP CAL_LID_L2_05kmCLay-Prov-V3–01 product has been used (Winker 2010).

**b. Cloud detection over ocean and sea ice surfaces**

The bias between Cloud_cci CFC$_{low}$ and CALIOP is used as a measure whether Cloud_cci detects more clouds over the ocean than over sea ice. The bias is calculated with

$$\text{bias} = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i), \quad (A1)$$

where $\hat{y}_i$ are Cloud_cci and $y_i$ CALIOP (reference) observations. Table A1 shows that for all COT thresholds Cloud_cci detects more clouds over ocean than over ice, indicated by positive differences between ocean and ice biases. To obtain a more reliable CFC$_{low}$ trend, a bias correction (BC) as a function of SIC will be applied to
Cloud_cci data. The below described correction aims to damp the effect of cloud detection efficiency dependencies on the surface properties.

c. Bias correction

As shown in Figs. A1a–d, the bias between Cloud_cci CFC$_{\text{low}}$ and CALIOP at the COT threshold of 1.0 has been calculated as a function of SIC for 3-month averages. Depending on the averaged period, one (Figs. A1b,c) or two (Figs. A1a,d) linear regression lines have been chosen to fit calculated bias values.

In the cases where two regression lines are required, SIC is split into two sections, S1 ($0\% \leq SIC < 75\%$) and S2 ($75\% \leq SIC \leq 100\%$). The first (second) regression line is then estimated from S1 (S2) data points. Slope $m$ and intercept $b$ of the linear fit are given in the corresponding orange or red box in Fig. A1. The CFC$_{\text{low}}$ pixel at $i, j$ is then corrected with

$$CFC_{\text{BC}}^{i,j} = CFC_{i,j} - (mSIC_{i,j} + b).$$  \hspace{1cm} (A2)

where $m$ and $b$ depend on the month and the SIC at $i, j$. The index “low” is omitted in Eqs. (A1)–(A4) for readability. It is noticeable that in Figs. A1a and A1d (Figs. A1b,c) bias shapes are quite similar with the characteristics that the former ones are more dependent on SIC (two regression lines necessary). Differences in summertime and wintertime BC are mainly due to the usage of different AVHRR channels for cloud detection. October to March cloud detection solely relies on infrared channels whereas between April and September visible channels are available, providing additional information for the cloud mask. Subtracting CFC$_{ij}$ from both sides of Eq. (A2) and subsequent differentiation with respect to time yields the “anomalous cloud amount decadal trends caused by SIC changes” as used in Liu et al. (2010) only for low-level clouds:

$$\frac{d}{dt}CFC_{i,j}^{\text{ano}} = \frac{d}{dt}CFC_{i,j} - \frac{d}{dt}CFC_{i,j}^{BC} = \frac{d}{dt}mSIC_{i,j}. \hspace{1cm} (A3)$$

From the above derivation it is obvious that the difference between bias-corrected and uncorrected trend equals the anomalous CFC$_{\text{low}}$ trends. Approximated CRF trend errors (“anomalous CRF decadal trends”) are calculated as the product of CRF sensitivity to

<table>
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<th>COT threshold</th>
<th>Ocean bias</th>
<th>Ice bias</th>
<th>Ocean – ice</th>
</tr>
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<tr>
<td>0.00</td>
<td>+17.57</td>
<td>+6.23</td>
<td>+11.34</td>
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<tr>
<td>0.15</td>
<td>+11.30</td>
<td>+0.75</td>
<td>+10.55</td>
</tr>
<tr>
<td>1.00</td>
<td>+5.65</td>
<td>−1.47</td>
<td>+7.12</td>
</tr>
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</table>

| TABLE A1. Bias between between Cloud_cci and CALIOP CFC (Cloud_cci − CALIOP) at different COT thresholds and for pixels over ocean and over ice. Bias is given in percent CFC$_{\text{low}}$. A pixel is identified as an “ice pixel” if SIC > 15% (Cavalieri et al. 1991). |

Fig. A1. Three-month averaged CFC$_{\text{low}}$ bias as a function of SIC between Cloud_cci and CALIOP at COT threshold of 1.0: (a) January–March (JFM), (b) April–June (AMJ), (c) July–September (JAS), and (d) October–December (OND). Dark (light) shaded areas in (a) and (d) correspond to correction section S1 (S2). For (b) and (c) only one correction section is defined. Orange (red) dashed line indicates linear regression line of the corresponding section. Regression parameters given in the orange (red) boxes.
CFC_{low} changes (λ) and the anomalous cloud amount trends:

\[
\frac{d\text{CRF}_{ij}}{dt}_{\text{ano}} = \left(\frac{d\text{CFC}_{ij}}{dt}_{\text{ano}}\right) \times \lambda. \quad (A4)
\]

Sensitivities are presented in the section 4d. The CFC_{low} bias-corrected CRF trend is then derived by subtracting the anomalous CRF trend from the uncorrected:

\[
\frac{d\text{CRF}^{\text{BC}}_{ij}}{dt} = \frac{d\text{CRF}_{ij}}{dt} - \left(\frac{d\text{CRF}_{ij}}{dt}_{\text{ano}}\right). \quad (A5)
\]

d. Impact on low-level CFC and CRF trends

The bias correction reveals that uncorrected September CFC_{low} trends are underestimated with up to about 2% decade\(^{-1}\) in the Beaufort and Chukchi Seas. To contrary, up to about 5% decade\(^{-1}\) of the positive October trends in the Beaufort, Chukchi, and East Siberian Seas are caused by cloud detection. November anomalous CFC_{low} trends are less distinct and stay below 5% decade\(^{-1}\). Underestimated CFC_{low} trends in September over melting zones can lead to an underestimation of warming LWCRF trends of up to about 1 W m\(^{-2}\) decade\(^{-1}\). Correcting anomalous October and November CFC_{low} trends would reduce the heating effect trend by up to about 8 W m\(^{-2}\) decade\(^{-1}\) locally. Due to weak solar insolation no significant anomalous SWCRF trends were calculated. TCRF anomalous trends feature the same characteristics as LWCRF. All in all, correcting cloud detection-induced CFC_{low} and SIC trends leads to an overall reduction in autumnal cloud surface warming trends over the marginal ice zone. The central Arctic is sparse in data from severe correction and remains roughly unchanged. However, TCRF trends remain strongly positive over the whole ice pack and most of the melting zones. The correction demonstrates that observed ON warming trends are not vanishing—that is, that these trends are not the result of limited cloud detection capabilities of passive imagers when observing melting sea ice surfaces. Comparable results are presented in Liu et al. (2010) for the correction applied to MODIS.

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