An extended lidar-based cirrus cloud retrieval scheme: first application over an Arctic site

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Abstract: Accurate and precise characterization of cirrus cloud geometrical and optical properties is essential for better constraining their radiative footprint. A lidar-based retrieval scheme is proposed here, with its performance assessed on fine spatio-temporal observations over the Arctic site of Ny-Ålesund, Svalbard. Two contributions related to cirrus geometrical (dynamic Wavelet Covariance Transform (WCT)) and optical properties (constrained Klett) are reported. The dynamic WCT rendered cirrus detection more robust, especially for thin cirrus layers that frequently remained undetected by the classical WCT method. Regarding optical characterization, we developed an iterative scheme for determining the cirrus lidar ratio ($LR_{ci}$) that is a crucial parameter for aerosol-cloud discrimination. Building upon the Klett-Fernald method, the $LR_{ci}$ was constrained by an additional reference value. In established methods, such as the double-ended Klett, an aerosol-free reference value is applied. In the proposed constrained Klett, however, the reference value was approximated from cloud-free or low cloud optical depth (COD up to 0.2) profiles and proved to agree with independent Raman estimates. For optically thin cirrus, the constrained Klett inherent uncertainties reached 50% (60-74%) in terms of COD ($LR_{ci}$). However, for opaque cirrus COD ($LR_{ci}$) uncertainties were lower than 10% (15%). The detection method discrepancies (dynamic versus static WCT) had a higher impact on the optical properties of low COD layers (up to 90%) compared to optically thicker ones (less than 10%). The constrained Klett presented high agreement with two established retrievals. For an exemplary cirrus cloud, the constrained Klett estimated the COD($355$) at $0.28 \pm 0.17$ (29 ± 4 sr), the double-ended Klett at $0.27 \pm 0.15$ (32 ± 4 sr) and the Raman retrievals at $0.22 \pm 0.12$ (26 ± 11 sr). Our approach to determine the necessary reference value can also be applied in established methods and increase their accuracy. In contrast, the classical aerosol-free assumption led to 44 sr $LR_{ci}$ overestimation in optically thin layers and 2-8 sr in thicker ones. The multiple scattering effect was corrected using Eloranta (1998) and accounted for 50-60% extinction underestimation near the cloud base and 20-30% within the cirrus layers.

1. Introduction

Cirrus clouds play a key role in the Earth radiative budget. Cirrus are the only cloud genus inducing either cooling or heating at the top of the atmosphere during daytime, with the rest of the clouds producing a cooling effect [1,2]. The relative magnitude of short-wave cooling and infrared warming is highly dependent on the cloud geometrical, optical and microphysical properties [3–5]. Cirrus clouds occur on an average frequency of 40% over the mid-latitudes [6], which maximizes over the tropics (up to 70%) [7] and decreases towards the poles. Arctic ice clouds display highly variable occurrence frequencies, from 25% over Ny-Ålesund, Svalbard, (single layer clouds) [8] up to 50% over Eureka, Nunavut, Canada [9]. However, there is a lack
of studies focusing on the coverage, geometrical and optical properties of solely Arctic cirrus clouds. Accurate and precise cirrus cloud detection is of high necessity. Apart from affecting the Earth radiative budget [10], the geometrical cloud thickness is indispensable for parameterization schemes of cirrus cloud optical depth (COD) [11]. Cirrus optical properties have been globally assessed by collocated Cloud-Aerosol lidar with Orthogonal Polarization (CALIOP) and Cloud Profiling Radar measurements, yielding a quite stable cirrus lidar ratio ($LR_{ci}$, ratio of extinction ($\alpha$) to backscatter coefficient($\beta$) within the cirrus cloud range) of $33 \pm 5$ sr over the ocean [12]. However, satellite observations over the poles were limited, with dedicated aircraft campaigns bringing added value through alternated lidar and in-situ cirrus cloud measurements [13]. Cirrus geometrical and optical properties have also been derived from the synergy of active and passive remote sensing [14–17]. Nevertheless, exploiting infrared radiances to detect ice clouds [18,19] and retrieve their optical properties [20,21] is challenging over cold and bright surfaces such as snow and ice.

Lidar systems are capable of delivering vertically resolved geometrical and optical properties of optically thin clouds on fine spatio-temporal scales. Their operating wavelengths, i.e. at ultraviolet, visible and near infrared, are ideal for cirrus studies, as they are more sensitive to small crystal sizes compared to millimeter radar systems [22]. Lidar-relevant cirrus optical properties are the COD, the particulate linear depolarization ratio (LPDR, indicates the sphericity of ice crystals), the LR (indicates type of ice crystals) and the color ratio (CR, ratio of backscatter coefficients at two different wavelengths, indicates the size of ice crystals).

The accuracy of cloud optical properties is critical for high quality radiative effect estimates [23], cloud phase classification [24,25] and cloud – aerosol discrimination (CAD) [17,26–28]. Lofted dust and smoke layers transported into the Arctic, were miss-interpreted as ice clouds in previous CALIOP data releases and motivated their subsequent improvement [29–31]. Conversely, optically thin ice clouds are still frequently miss-classified as aerosols in the polar regions, although the latest CALIOP CAD algorithm has been significantly improved [31–33]. CALIOP cloud phase and CAD algorithms rely on LPDR and CR as a function of temperature, latitude and altitude [31,34]. Thus, ground-based lidar observations that provide similar optical parameters can provide a valuable validation for satellite lidar processing algorithms (e.g. currently CALIOP aboard CALIPSO [35] and imminently ATLID aboard EARTHCARE [36]).

Different lidar-based retrievals of cirrus cloud optical properties exist in literature, such as the transmittance [37–39], the double-ended Klett [40], the backward – total optical depth [41] and the Raman technique [40]. Each of these retrievals has its own strengths and limitations. For instance, the transmittance and backward – total optical depth methods cannot be applied to optically thin cirrus (COD < 0.05 and COD < 0.1, respectively). The Raman technique provides a vertically-dependent $LR_{ci}$ but is limited to night-time applications, contrary to the double-ended Klett method that, however, yields a layer-mean $LR_{ci}$.

In this study, we propose an extended cirrus cloud retrieval scheme, consisting of detection (dynamic WCT) and optical characterization (constrained Klett). The scheme is applied on representative cirrus clouds over Ny-Ålesund, Svalbard, and its limitations and strengths are investigated. Sensitivities related to cirrus detection are performed (section 3) and their effect on cirrus optical properties is also examined (section 4.3). The inherent uncertainties of the proposed constrained Klett are also quantified (section 4.2). Finally, the constrained Klett is compared with two established optical retrievals, namely the double-ended Klett and Raman (section 5), and their limitations and strengths are discussed (section 6). The optical properties are corrected for the multiple scattering effect (Appendix). Cirrus layers are divided in three regimes according to their COD, following the classification of Sassen and Cho (1992) [42] i.e. sub-visible (COD < 0.03), optically-thin (0.03 < COD < 0.3) and opaque cirrus layers (0.3 < COD < 3). Hereafter, the term cirrus cloud will refer to a set of consecutive cirrus layers.
2. Methods

2.1. Instrumentation and selection of cirrus clouds

In this work, we exploit a unique measurement dataset from the multi-wavelength Koldewey Aerosol Raman lidar (KARL) system, which is installed on the Alfred Wegener Institute – Institute Paul Emile Victor (AWIPEV) research base, Ny-Ålesund (78.9°N, 11.9°E), Svalbard Archipelago. KARL is a powerful so called $3\beta + 2\alpha + 2\delta + 2\omega$ system equipped with an Nd:YAG laser that emits pulses of 200 mJ at 1064, 532 and 355 nm with a 50 Hz repetition rate [43]. The receiver comprises a 70 cm diameter telescope with a 2.28 mrad field of view (FOV), while the laser beam divergence amounts to 0.8 mrad. The range of full overlap is 600 m. The combination of photon counting (PC) and analog (A) acquisition mode allows for large dynamical detection range. The specifications of KARL enable high quality signal acquisition at fine vertical and temporal scales (7.5 m, 1.5 min), which are ideal for the investigation of cirrus cloud properties. KARL has been deployed for the evaluation of aerosol optical, microphysical and radiative properties using classical approaches [44–46] or in combination with airborne lidar [47]. However, cloud optical retrievals with KARL were so far underexplored [48].

This study focuses on cirrus clouds and, thus, the presence of supercooled liquid–water layers should be excluded. Therefore, we only considered clouds with temperature lower than $-40^\circ C$, which is the homogeneous nucleation temperature, at the height of cloud base ($C_{\text{base}}$) and cloud top ($C_{\text{top}}$) [15,26]. Temperature profiles were obtained from radiosondes, which are daily launched at 11 UT from the AWIPEV research base [49–51]. The utilized temperature criterion is quite strong as Shupe (2011) [52] reported only 3-5% liquid water occurrence between $-40$ and $-30^\circ C$ within Arctic clouds. Thus, the possibility of liquid water presence is very low, even within the range of temperature uncertainty, i.e. sensor related uncertainties or errors due to radiosonde drift and temporal discrepancy with lidar observations.

In the following section we present in detail all the steps of cirrus detection, including the revised method and its newly introduced parameters. In parallel, the main steps are depicted in Fig. 1 and Fig. 2. Note that the code for the revised cirrus detection is publicly available [53].

2.2. Cirrus detection and underlying cloud screening

The Wavelet Covariance Transform (WCT) method [54] was extended with dynamic thresholds for detecting the cirrus $C_{\text{base}}$ and $C_{\text{top}}$. The classical WCT method is sensitive to lidar signal vertical gradients and has been employed for detecting either cirrus clouds [55,56] or the planetary boundary layer top height [57–59]. Firstly, the lidar signals were corrected for the dead-time, electronic noise and background illumination effects [43]. Then, the PC and A signal components were glued together as described in Hoffmann (2011) [43]. The gluing interval (several hundred meters zone) was selected as such that both signals were of high quality i.e. non-saturated PC and A with high SNR. Finally, the lidar range-corrected ($Pr^2$) signal was normalized (with respect to the median signal between the range of full overlap and 12 km). The latter step was essential for making the WCT profiles comparable to those from literature [60] and did not affect the $Pr^2$ signal and WCT gradients. In Fig. 1 the $Pr^2$ signal and WCT profiles corresponding to the lower part of a cirrus layer are presented. The WCT profile (Eq. 1) can be perceived as the low-pass filtered version of the $Pr^2$ signal [59] as it is based on the convolution of the $Pr^2$ signal with a Haar step function (Eq. (2)) of specific step width (dilation, $\alpha$) and step location ($b$).

$$W_{\alpha}(\omega, b) = \frac{1}{\alpha} \int_{C_{\text{base}}}^{C_{\text{top}}} P(r) \cdot r^2 \cdot h \left( \frac{r - b}{\alpha} \right) dr$$

$$h \left( \frac{r - b}{\alpha} \right) = \begin{cases} +1, & b - \frac{\alpha}{2} \leq r \leq b \\ -1, & b \leq r \leq b + \frac{\alpha}{2} \\ 0, & \text{elsewhere} \end{cases}$$
Fig. 1. Exemplary profiles of $Pr^2$ signal, Haar step function, WCT, WCT to signal standard deviation (std) ratio ($\frac{WCT}{std}$) and SNR ratio, which correspond to the lower part of a cirrus layer observed at 7-9 km by KARL over Ny-Ålesund. Horizontal lines denote the dynamic (cyan) and static (black) derived $C_{base}$. Grey (green) shaded areas denote the half dilation ($\alpha/2$) zone within (outside) the cirrus layer. The whole cirrus layer $Pr^2$ profile is given in the upper left inset figure. The signal std was calculated within the outer zone of each range bin.

The $Pr^2$ signal was integrated within half dilation ($\alpha/2$) below (outer zone, Fig. 1) and above (inner zone, Fig. 1) each range bin. An appropriate dilation is crucial for accurate cirrus detection. A relatively narrow dilation produces more noisy WCT profiles, while a too wide dilation may not resolve small-scale features such as thin clouds. In order to select an appropriate dilation, we assessed its effect on cirrus detection through a sensitivity analysis (section 3.1).

The knowledge of cloud presence below the targeted cirrus layers is important. For this reason, underlying cloud layers were screened with the WCT method. If both the $C_{base}$ and $C_{top}$ were identified below 5 km (6 km), the cloud was flagged as low-level (mid-level). It should be noted that the low-level Arctic ice clouds and ice fogs are not considered cirrus clouds [22]. Lidar profiles were retained for further evaluation on condition that signal quality was high. Otherwise, if the signal-to-noise ratio (SNR) was decreased (< 3 as in [41]) above the low- or mid-level clouds, the profiles were discarded. Likewise, the signal quality was checked above the cirrus $C_{top}$. The cirrus detection scheme is outlined in Fig. 2.

2.2.1. Revised detection method: dynamic wavelet covariance transform

A crucial parameter for cirrus detection is the WCT threshold, which determines whether a signal gradient denotes a cirrus layer boundary or not. Static WCT thresholds have been proposed so far [60,61]. However, in this study we introduce dynamic thresholds, which assess the strength of the detected gradients with respect to the given signal variability. The dynamic thresholds
Fig. 2. Flowchart of newly proposed cirrus detection scheme. For details see section 2.2. The cirrus detection algorithm is given in Code 1 [53].

depend on the ratio of WCT over the signal standard deviation \( \frac{WCT}{\text{std}} \) as well as on the SNR. This dynamic approach has a higher robustness potential, since it is adaptable to the given cloud strength and lidar specifications. After examining a significant number of characteristic profiles, we found that cirrus peaks were related to WCT values exceeding the signal standard deviation \( \frac{WCT}{\text{std}} > 1 \), e.g. Fig. 1. \( \frac{WCT}{\text{std}} \) thresholds of 1.5 and 2 were also investigated, but they frequently detected only stronger cirrus parts, leaving out the faint marginal parts. In the upward (downward) direction, a candidate \( C_{\text{base}} (C_{\text{top}}) \) was identified at one bin below (above) the range where \( \frac{WCT}{\text{std}} > 1 \).

In order to discriminate cirrus related peaks from noise, an SNR related criterion was also introduced. At each range bin, the median SNR was calculated at \( \alpha/2 \) bins below and \( \alpha/2 \) bins above, where \( \alpha \) is the dilation of the WCT profile (Fig. 1). More specifically, the median SNR was calculated within the inner and outer zones of bins, where \( \frac{WCT}{\text{std}} > 1 \). Then, the algorithm checked whether the inner to outer zone SNR ratio exceeded a given threshold in order to make sure that the detected peaks were not related to noise but to a real feature. The above mentioned procedure was performed in the upward (downward) direction for \( C_{\text{base}} (C_{\text{top}}) \) detection. Additionally, an increasing SNR ratio was demanded for three consecutive bins above the \( C_{\text{base}} \) (below the \( C_{\text{top}} \)). The SNR ratio values were found to slightly differ for each wavelength due to differences in the SNR of each channel and are summarized in the Appendix. A more detailed investigation on the WCT wavelength dependency is presented in section 3.2. An assessment of the dynamic thresholds in comparison to the static ones is presented in section 3.3.

In the following section we describe in detail all the steps of the proposed constrained Klett method (section 2.3.2), including the newly introduced parameters, i.e. the convergence range.
the estimated reference backscatter ratio ($BSR_{ref}$) as well as the recursive $LR_{ci}$ process and the factor used to adjust the $LR_{ci}$ after each iteration (Eq. (3)). Moreover, we depict the steps in Fig. 4 to outline the methodology. Note that we have made publicly available the code of the constrained Klett [53].

2.3. Cirrus optical characterization

2.3.1. Temporal averaging within stationary periods

High vertical (7.5 m) and temporal (1.5 min) resolution profiles allowed for reliable cirrus detection. However, the precision of optical properties was affected by statistical uncertainties (signal noise and reference value uncertainty) and, thus, temporal averaging was desirable. Nonetheless, care should be taken with long temporal averaging to avoid smearing out the cloud physical variability i.e. to avoid averaging cloud and cloud-free range bins and produce physically unrealistic profiles. More importantly, distorted particulate extinction ($\alpha_{part}$) profiles affect the accuracy of radiative effect estimates [23].

Bearing the aforementioned aspects in mind, we adopted a temporal averaging that is constrained by periods of stationarity following Lanzante (1996) [62]. This procedure is based on the Mann–Wilcoxon–Whitney test, such that the data points of one stationary period share the same COD statistical distribution [62]. This method has already been applied to time-series of cirrus COD and geometrical thickness by Larroza et al. (2013) [39]. In this study, the procedure was applied on the integrated backscatter coefficient ($\beta_{int}$) time-series, which was obtained from an initial guess Klett-Fernald retrieval. The designation of stationary (yellow lines) and temporal (red lines) averaging periods is shown for the case of 23 January 2019 in Fig. 3. The $\beta_{int}$ was selected instead of the COD because the latter might be influenced by the assumed $LR_{ci}$. However, for the majority of the cirrus clouds analyzed over Ny-Ålesund (2011-2020) the $\beta_{int}$ and COD exhibited similar variability.

Fig. 3. Time-series of integrated backscatter ($\beta_{int}$, upper panel) and height-time plot of $Pr^2$ signal (lower panel) with overlaid stationary (yellow lines) and 9-min periods (red lines). Lidar observations were obtained on 23 January 2019 with KARL over Ny-Ålesund, Svalbard. Temporal averaging was only performed within each stationary period.

As expected the stationary periods have variable duration, since they reflect the physical variability of the investigated parameter. For instance, on 23 January 2019, each of the first two periods (9:11-10:19 and 10:20-11:54 UT) was over one-hour long, while the subsequent two periods (11:55-12:26 and 12:28-12:47 UT) did not exceed 30 min each. However, one should keep in mind that the $\beta_{int}$ is a columnar quantity and, thus, the cirrus vertical variability cannot
be accounted for by the stationary periods. Therefore, shorter averaging periods were obtained for ensuring non distorted profiles. In order to obtain homogeneous statistical uncertainties we constructed temporally averaged profiles of equal duration (9 min by averaging 6 consecutive raw profiles) within each stationary period. Gaps (no measurement or no cirrus detection) and periods shorter than 9 min were discarded. The cirrus $C_{\text{base}}$ and $C_{\text{top}}$ were newly determined by applying the dynamic WCT method on the averaged $Pr^2$ profiles.

2.3.2. Proposed optical retrieval: constrained Klett method

An extended method for cirrus optical retrievals is proposed, hereafter mentioned as constrained Klett. A backward Klett–Fernald retrieval [63,64] was employed, constrained by the backscatter ratio (BSR), which is the ratio of molecular and particulate backscatter over molecular backscatter, beneath the cirrus cloud. The $LR_{\text{ci}}$ was iteratively adjusted until the BSR matched with a reference BSR value ($BSR_{\text{ref}}$). The main steps of the constrained Klett method are outlined in Fig. 4. The constrained Klett algorithm is given in Code 1 [53]. The constrained Klett made use of the assumption that the aerosol content beneath the cirrus cloud was invariable. In order to enhance the validity of this assumption, the near-range reference value (also called calibration value) was set within the range of minimum $Pr^2$ signal variance (convergence range). The convergence range was bounded between the full overlap range (600 m) and 1 km beneath the minimum $C_{\text{base}}$. In this way, artificial signal gradients as well as cirrus adjacent areas, where turbulence and ice seeding are more likely, were avoided. The convergence range was a 500 m-zone, where the median $Pr^2$ signal presented minimum temporal variance. When the variance was equally low in more than one zones, the higher zone was selected, because the Klett errors increase with the integration from the far range. In order to further enhance the validity of aerosol content stability assumption, profiles not highly correlated with the temporal median profile ($r < 0.98$) were discarded.

![Flowchart of configuration procedure (section 2.3.1) and optical characterization (section 2.3.2) with constrained Klett method. The constrained Klett algorithm is given in Code 1 [53].](Fig_4.png)
An initial guess Klett–Fernald retrieval was first performed using two LR zones, one within the cirrus layer (assumed \( LR_{ci}^{355} = 20 \) sr and \( LR_{ci}^{532} = 28 \) sr) and one zone outside (assumed \( LR_{ci}^{355} = 35 \) sr and \( LR_{ci}^{532} = 36 \) sr). The \( LR_{ci} \) values were needed for initializing the Newton-Raphson method and they can be arbitrary provided that they are close enough to the unknown quantity [65]. Therefore, the \( LR_{ci} \) initial values were selected close to those most frequently reported by other studies (e.g. [56,66–68]). Regarding the LR values outside the cirrus layer we used background values for the site of Ny-Ålesund based on statistics provided by Ritter et al. (2016) [69]. These LR values should be adapted accordingly for different lidar sites.

Subsequently, the \( \beta_{int} \) within the cirrus range was estimated. Although the \( \beta_{int} \) was an initial guess, its minimum corresponded to low COD layers. The lower the \( \beta_{int} \) the lower the effect of a wrongly chosen \( LR_{ci} \) on the Klett solution. Therefore, the reference profile corresponded to the profile of minimum \( \beta_{int} \) or to a temporally close cloud-free profile (if available). The BSR, was estimated from the reference profile as the median BSR within the convergence range. In section 4.1 we investigate the upper COD limit for deriving an accurate BSR. The effect of BSR on statistical uncertainties on the optical properties is also investigated (section 4.2).

Once the convergence range, the reference profile and the BSR were defined, the recursive Klett procedure was initiated. Two initial guess Klett retrievals were performed, one with \( LR_{ci}^{1} \) and another with \( LR_{ci}^{2} = LR_{ci}^{1} + 1 \) sr (see lower part of Fig. 4). Upon each iteration, the median BSR within the convergence range was estimated (BSR and BSR2 as derived from the retrieval with \( LR_{ci}^{1} \) and \( LR_{ci}^{2} \), respectively). When the ratio of BSR1 over BSRref exceeded the desirable convergence percentage (set to 0.3% after sensitivity analysis, see section 4.2), the \( LR_{ci} \) was adjusted by a factor \( \Delta LR_{ci} \) (Eq. (3)). Following the Newton–Raphson method (described in Ryaben’kii and Tsynkov (2006) [65]), the \( \Delta LR_{ci} \) factor was formulated as the difference of BSRref and BSR1 over the difference of BSR1 and BSR2, the latter being equivalent to \( \frac{\Delta BSR}{dLR} \) with \( dLR = 1 \) sr.

\[
\Delta LR_{ci} = \frac{BSR_{ref} - BSR_1}{BSR_1 - BSR_2}
\]  

The iterative process was bounded by physically meaningful \( LR_{ci} \) values, i.e. between 5 sr and 90 sr. A wide range of bounding \( LR_{ci} \) values was employed as we did not want to a priori exclude physically possible \( LR_{ci} \) values. The selection was based on previous experimental (at different locations) [40,70] and modeling studies [71–73]. For instance, Ansmann et al. (1992) [40] reported values between 5-15 sr over a marine mid-latitude site, using the Raman technique. Chen et al. (2002) [70] reported over Taiwan \( LR_{ci} \) values lower than 10 sr in some cases. Okamoto et al. (2019) and (2020) [72,73] performed modeling simulations and reported \( LR_{ci} \) values at 355 and 532 nm starting from approximately 5 sr and exceeding 100 sr for 2-D plates depending on the effective angle between the particle symmetrical axis and the laser beam (Fig. 5 from Okamoto et al. (2019) [72], Fig. 8 and Fig. 9 from Okamoto et al. (2020) [73]).

The retrieval was considered successful once the BSR1 solution matched with the BSRref. The resulting \( \beta_{part} \) and vertically-constant \( LR_{ci} \) were used for estimating the COD according to Eq. (4):

\[
COD = \int_{C_{base}}^{C_{top}} LR_{ci} \cdot \beta_{part}(r) dr
\]  

2.3.3. Existing optical retrievals: double-ended Klett and Raman

In order to gain confidence in the proposed constrained Klett method, two established retrievals were also applied, namely the double-ended Klett and Raman [40]. Concerning the constrained Klett, different sets of backward and forward Klett–Fernald retrievals [63,64] were performed with changing \( LR_{ci} \) value. The \( LR_{ci} \) resulting in the lowest root mean square error between the backward and forward \( \beta_{part} \) profiles was selected. The \( LR_{ci} \) was modified within physically expected values of 5 and 90 sr as in the constrained Klett [40,70–73]. In this work the
Klett–Fernald calibration window was set in the stratosphere for the backward retrieval and in the convergence range for the forward retrieval. In this way, the retrieval was comparable to the constrained Klett. However, it should be noted that the classical double-ended Klett method assumes zero \( \beta_{\text{part}} \) below and above the cirrus cloud [40]. The impact of this aerosol-free assumption is investigated in section 5.

The cirrus optical characterization and the \( BSR_{\text{ref}} \) estimation was also performed via the Raman technique. This technique provides the backscatter and extinction coefficients independently [40] and, thereby, a vertically-dependent \( LR_c \) can be derived. In this study, we report the vertically averaged Raman derived \( LR_c \) to facilitate the comparison with constrained Klett (section 2.3). The \( \alpha_{\text{part}} \) at 355 and 532 nm is based on the rotational-vibrational Raman signals of 387 and 607 nm, respectively. Since the Raman cross-sections are orders of magnitude smaller than the elastic scattering cross-sections, the Raman technique is usually limited to night-time applications. In order to reduce the noise of the weak Raman signals, profiles were smoothed with a Savitzky–Golay filter [74]. The smoothing window was equal to one-third of the minimum cirrus cloud thickness. The molecular number density, which is needed for estimating the \( \alpha_{\text{part}} \), was derived by collocated radiosonde ascents from the AWIPEV research base. The Ångström

Fig. 5. Height-time plot of lidar \( Pr^2 \) signal (a). Different symbols present the \( C_{\text{base}} \) and \( C_{\text{top}} \) resulting from dilation values between 30 and 120 m. Red vertical lines (panel a) denote the selected profiles of \( Pr^2 \) and WCT (presented in panels b and c). Higher inter-dilation spread was observed for smooth-shaped boundaries (b).
exponent of ice crystals for the wavelength pairs of 355-387 nm and 532-607 nm was assumed equal to unity. This is a reasonable assumption since the size of the ice crystals is usually sufficiently large compared to the ultraviolet and visible wavelengths [40]. Raman extinction uncertainties stem from statistical signal noise and uncertainties in molecular number density, which were, however, low within the cirrus layers. The comparison between the constrained Klett, the double-ended Klett and Raman retrievals is presented in section 5 and their limitations and strengths are discussed in section 6.

2.4. Multiple scattering correction

The effect of multiple scattering cannot be neglected when the size of the scatters is large compared to the emitted wavelength. The effect is more pronounced if the lidar system has a wide telescope FOV and a non-negligible laser beam divergence. The multiple scattering effect does not only depend on the COD but also on ice crystal effective radius ($r_{\text{eff}}$) and laser beam cloud penetration depth. For this reason, an analytical model is needed in order to correct for high order scattering events. In this study, we used the multiple scattering correction (MSC) model of Eloranta (1998) [75], which is openly available (http://lidar.ssec.wisc.edu/multiple_scatter/ms.htm). The Eloranta model assumes the presence of hexagonal ice crystals for phase function calculations. Moreover, a mono-disperse ice crystal vertical distribution was assumed. The ice crystal $r_{\text{eff}}$ was estimated as a quadratic function of temperature, following the parameterization of Wang and Sassen (2002) [76] given by Eq. (5):

$$r_{\text{eff}} = 90.14 + 0.659 \cdot T - 0.004 \cdot T^2$$  

(5)

The model simulates the ratio of up to seven-order ($P_{\text{tot}}$) to single scattering photon power ($P_1$) as a function of range ($r$) and wavelength ($\lambda$). Sensitivity tests revealed that higher than three-order scattering events contributed negligibly to the total photon power. Therefore, the first four scattering orders were finally taken into account as a compromise between accuracy and computational speed. Initially, the apparent $\alpha_{\text{part}}$, denoted as $\alpha_{\text{app}}$ ($\alpha_{\text{part}}$ multiplied by the $LR_{ci}$) was incorporated into the MSC model. Subsequently, a first estimation of the multiple scattering factor $F(\lambda,r)$ (Eq. (6)) and the quasi-corrected extinction ($\alpha(\lambda,r)$) (Eq. (7)) were obtained:

$$F(\lambda,r) = \frac{d}{dr} \left( \frac{\ln P_{\text{tot}}(r)}{P_1(r)} \right) + \frac{d}{dr} \ln \left( \frac{P_{\text{tot}}(r)}{P_1(r)} \right)$$  

(6)

$$\alpha(\lambda,r) = \frac{\alpha_{\text{app}}(\lambda,r)}{1 - F(\lambda,r)}$$  

(7)

As a next step, the quasi-corrected $\alpha(\lambda,r)$ was incorporated again into the MSC model. This recursive procedure was repeated until the MSC model converged to a stable $F(\lambda,r)$. Usually, only two iterations already provided sufficient convergence. A similar procedure was followed in previous studies [56,66,68]. A simplified MSC approach, which is only dependent on the COD was introduced by Platt (1973) [14] and is frequently used in literature ([42,70]). Eq. 8 describes the simple MSC factor $n$, with the MSC COD being the ratio of the apparent COD over the factor $n$. The analytical and simplified MSC approaches are compared in the Appendix.

$$n = \frac{\text{COD}}{e^{\text{COD}} - 1}$$  

(8)

3. Sensitivities on cirrus geometrical properties

3.1. Wavelet covariance transform - dilation sensitivity

Since the WCT dilation is an important parameter for accurate and precise cirrus detection (section 2.2), a relevant sensitivity analysis is performed here. Thanks to the high vertical
resolution (7.5 m) of KARL signals, we explored small dilation values between 30 m (4 range bins) and 120 m (16 range bins), presented with different symbols in Fig. 5. After analyzing a significant number of cirrus layers, it was observed that dilation values smaller than 90 m were less sensitive to smooth-shaped cirrus layers, as shown in Fig. 5(b) (smooth signal gradients close to $C_{\text{top}}$). On the contrary, the 90 m dilation was more effective for faint layers and efficiently captured layers thinner than 200 m layers, as for 7:30-9:00 UT on 23 January 2019 (Fig. 5(a)). Detecting faint layers near the $C_{\text{base}}$ is important, since the multiple scattering effect is higher there ([77] and Appendix of this study). Overall, the discrepancies arising from the dilation selection were low, with the majority of inter-dilation spread being lower than 50 m.

3.2. Wavelet covariance transform - wavelength dependency

The dependency of cirrus detection on wavelength was assessed both by the dynamic and static WCT methods. Since the SNR depends on background illumination conditions, both daytime (25 April 2015, Fig. 6(a)) and night-time (23 January 2019, Fig. 6(b)) cirrus clouds were investigated. In Fig. 6(a) and 6(b) the dynamic (open symbols) and static (dot symbols) WCT derived boundaries are demonstrated for different wavelengths. Thin and faint cirrus layers were not so discernible in the 355 nm channel with parallel polarization (355_p - cyan symbols) as in the other wavelengths due to the strong UV Rayleigh scattering (Fig. 6(b), for example at 8:30–10:00 UT). This behavior was more profound for the static WCT method. Concerning the 355 nm channel with perpendicular polarization (355_s - black symbols), this was strongly affected by noise during daytime (Fig. 6(a)), with noise peaks frequently detected even with increased SNR ratio thresholds. In the 532_p channel (green symbols) both the static and dynamic methods mostly detected the stronger cirrus parts (Fig. 6(a), for example at 14:00–16:00 UT).

The cirrus layer presented in Fig. 6(c) was characterized by smooth-shaped $C_{\text{base}}$ and strong-shaped $C_{\text{top}}$. Therefore, the discrepancies across different wavelengths were larger for the $C_{\text{base}}$. The static (dotted lines) and dynamic (dashed lines) WCT derived boundaries are given for the different channels. The 355_p and 532_p channels detected mostly central cirrus parts. In contrast, the 355_s, 532_s (light green) and 1064 nm (red symbols) channels were more sensitive to faint marginal parts and showed better inter-agreement, especially for the dynamic method. Moreover, the SNR of the perpendicular polarization channels was higher compared to those with parallel polarization and the SNR_{355} was higher than SNR_{355}. In general, longer wavelengths perform better in discriminating clouds from aerosol. However, the KARL system records 1064 nm signals in analog mode, which is more prone to noise.

For the aforementioned reasons, the 532_s channel was finally selected for cirrus detection as the longest wavelength and highest quality available channel. It should be mentioned, however, that under specific conditions the 532_s derived boundaries also presented variability. For instance, fluctuating geometrical boundaries can be seen at 8:00–10:00 UT (Fig. 6(b)) due to weak gradients, especially close to the $C_{\text{top}}$. Variability was also revealed during 13:00–14:00 UT (Fig. 6(b)), with weak signal gradients overhead of strong ones. This variability was lower for temporally averaged signals thanks to higher SNR. The optimal SNR ratio thresholds for each channel of KARL are given in the Appendix.

3.3. Dynamic - static wavelet covariance transform comparison

In the following, the dynamic WCT method is compared to the static one. Both methods were applied on 532_s signals using a 90 m dilation. Two daytime cirrus layers (Fig. 7(b) and 7(c)), which were highly affected by background illumination, are analyzed in detail. The dynamic method was more sensitive to weak signal gradients that, however, exceeded the signal standard deviation. For instance, on 25 April 2015, 7:59 UT (Fig. 7(b)), the cirrus layer presented -0.07
Fig. 6. Height-time plot of lidar $P_r^2$ signal for daytime (a) and night-time (b) cirrus clouds. Overlaid with different colors are the cirrus geometrical boundaries as derived by the dynamic (open markers) and static (dot markers) WCT method. Selected profiles of $P_r^2$, WCT, $\text{WCT/\text{std}}$, SNR and $\text{SNR ratio}$ are presented together with the dynamic (dashed lines) and static (dotted lines) WCT derived boundaries (c). The 532s channel was finally selected for cirrus detection.
WCT and $|WCT/\text{std}|$ equal to 3 at the $C_{\text{base}}$. Therefore, the $C_{\text{base}}$ of this cirrus layer was not detectable with the static method (0.3 WCT threshold, see [61]).

![Graph showing height-time plot of lidar $Pr^2$ signal with overlaid dynamic (cyan) and static (black) WCT derived cirrus boundaries. Signal normalization accounts for background color changes (see section 2.2). Selected profiles are denoted with red vertical lines (a) and presented in panels (b) and (c), where horizontal lines indicate the dynamic and static cirrus boundaries. Solid (dashed) blue lines correspond to upward (downward) profiles used for $C_{\text{base}}$ ($C_{\text{top}}$) detection. The dynamic WCT was more sensitive to faint and marginal parts of cirrus layers.](image)

Another strength of the dynamic method lies on its increased sensitivity to marginal cirrus layers. On 25 April 2015, 15:01 UT (Fig. 7(b)), the static method was only sensitive to stronger cirrus parts, while the dynamic method detected the $C_{\text{base}}$ ($C_{\text{top}}$) 277.5 m (285 m) out of the static-derived boundaries. Hence, the cirrus geometrical thickness was underestimated by more than 500 m by the static method. Increased sensitivity to cirrus marginal layers is also an important advancement of the latest CALIOP CAD algorithm. More details will be discussed in section 6. It should be mentioned that sometimes both the dynamic and static WCT methods
failed to detect the cirrus boundaries, especially for faint cirrus layers, as for 8:00–9:00 UT on 25 April 2015 (Fig. 7(a)). Overall, the dynamic method detected faint cirrus layers that otherwise could not have been detected by the static method.

4. Accuracy and uncertainty assessment

4.1. Reference value accuracy and limitations

The cirrus cloud of 23 January 2019 was selected for assessing the accuracy and inherent uncertainties of constrained Klett, since it comprised different regimes from sub-visible to lower opaque layers [42]. Concerning the reference value (see section 2.3.2), this was calculated from a cloud-free profile \( \text{BSR}_{\text{cloud-free}}^{\text{ref}} \) observed at 7:47-7:56 UT prior to the cirrus cloud passing over Ny-Ålesund. The convergence range (see section 2.3.2) was selected at 5.5–6 km, where the signal temporal variance was minimum. The \( \text{BSR}_{\text{ref}} \) accuracy was evaluated by estimating the same quantity via the Raman technique \( \text{BSR}_{\text{Raman}}^{\text{ref}} \). This analysis is illustrated in Fig. 8.

The blue line and shaded area (median ± standard deviation) denote the \( \text{BSR}_{\text{cloud-free}}^{\text{ref}} \), while the \( \text{BSR}_{\text{Raman}}^{\text{ref}} \) (black symbols) and \( \text{BSR}_{\text{guess}}^{\text{ref}} \) (blue symbols) are also presented.

At 355 nm (532 nm, not shown) the initial guess Klett provided a median ± standard deviation \( \text{BSR}_{\text{cloud-free}}^{\text{ref}} \) of 1.03 ± 0.03 (1.07 ± 0.02), while the Raman yielded \( \text{BSR}_{\text{Raman}}^{\text{ref}} \) equal to 1.06 ± 0.01 (1.06 ± 0.02). \( \text{BSR}_{\text{cloud-free}}^{\text{ref}} \) and \( \text{BSR}_{\text{Raman}}^{\text{ref}} \) were in agreement within the range of uncertainties, this being satisfactory, taking into account the high Raman statistical uncertainties especially for fine temporal scales (here 9 min). Thus, the \( \text{BSR}_{\text{ref}} \) parameter was estimated with sufficient accuracy.
If cloud-free profiles were not available, the minimum $\beta_{int}$ (or COD) profile would have been selected as reference profile (see section 2.3.2). However, in such cases the $BSR_{ref}$ accuracy would have been subject to an upper COD limitation. More specifically, the lower the cirrus COD the more accurate is the $BSR_{guess}^{ref}$ expected to be, with the impact of a wrongly assumed $LR_{ci}$ on the initial guess Klett being lower. In order to quantitatively assess the effect of COD on the $BSR_{guess}^{ref}$ accuracy, we compared the $BSR_{guess}^{ref}$ with $BSR_{Raman}^{ref}$ for every single profile of the 23 January 2019 cirrus. Then, we assessed up to which COD the $BSR_{guess}^{ref}$ accuracy is acceptable. As it can be seen, a sufficiently accurate $BSR_{guess}^{ref}$ can be obtained for COD up to 0.2 (Fig. 8, right axis). This is illustrated more clearly on the upper left inset figure, with the $BSR_{guess}^{ref}$ lying within the $BSR_{cloud-free}^{ref}$ uncertainty (dashed line) for 0.2 maximum COD. Hence, even if the minimum COD profile (here time bin 1) was selected instead of a cloud-free profile, the resulting $BSR_{guess}^{ref}$ would have agreed with the $BSR_{cloud-free}^{ref}$ and $BSR_{Raman}^{ref}$.

Another significant remark concerns the aerosol content stability beneath the cirrus cloud, which is assumed both by the constrained and double-ended Klett retrievals. As displayed in Fig. 8, the $BSR_{Raman}^{ref}$ variability lied within the uncertainty of the $BSR_{cloud-free}^{ref}$ reference value, indicating that the stability assumption was valid. Finally, it should be underlined that the upper COD limitation discussed above only concerns the reference profile selection. As long as a sufficiently accurate $BSR_{ref}$ is obtained, the constrained Klett can be applied on any cirrus cloud regime.

### 4.2. Inherent uncertainties of constrained Klett

In order to assess the inherent uncertainties, we investigated the response of cirrus optical properties to the parameters of the constrained Klett method, namely the convergence percentage and reference value $BSR_{ref}$ (see section 2.3.2). In the first sensitivity analysis (Fig. 9(a)) the convergence percentage was modified between 0.1% and 0.5%, with 0.3% being the default. The $LR_{ci}$ of optically thinner layers was more sensitive (maximum spread 10% or 3 sr) compared to thicker layers (maximum spread 5%). Overall, the COD was modified by less than 0.004 (1-10% spread depending on the COD). Less strict convergence percentage (higher than 1%, not shown) were incapable of constraining the $LR_{ci}$ with acceptable accuracy.

The impact of $BSR_{ref}$ statistical uncertainties on the optical properties was also evaluated (Fig. 9(b)). In the control case, the median value ($BSR_{ref} = 1.03$) was used, while in the perturbed cases the $BSR_{ref}$ was increased by 0.01 (blue symbols), 0.02 (grey symbols) and 0.03 (cyan symbols). These uncertainties were typically encountered during the analysis of different cirrus clouds (2011-2020) over Ny-Ålesund, Svalbard. Low COD layers (corresponding to time bins 1–5) were more sensitive to the $BSR_{ref}$ parameter. More specifically, if the $BSR_{ref}$ was perturbed too far from the control case, reasonable results were not always possible to obtain. Therefore, an accurate $BSR_{guess}^{ref}$ is crucial. The $LR_{ci}$ displayed higher sensitivity for optically thinner layers (14–19 sr or 74 and 60% with respect to control values of 19 sr and 32 sr). Lower sensitivity (less than 3 sr or 13% with respect to control value of 24 sr) was found for opaque layers. The COD sensitivity was higher for lower optically-thin and opaque regimes, varying between 0.02 and 0.03 (7-50% with respect to control values of 0.3 and 0.06) for the most perturbed case.

### 4.3. Effect of geometrical boundaries on the optical properties

In the following we assess the effect of cirrus detection method on the apparent optical properties. To this end, the cirrus geometrical properties were determined via the dynamic (Fig. 10(a), cyan symbols) and static WCT methods (black symbols). Based on the dynamic and static derived boundaries, we retrieved the optical properties via the constrained Klett and investigated the resulting discrepancies (Fig. 10(b)). The optical discrepancies are illustrated as a function of
Fig. 9. Sensitivity of optical properties with respect to the convergence percentage (a) and the reference value ($BSR_{ref}$, b) parameters of the constrained Klett. Absolute differences with respect to the control case are presented with open symbols on the right axis. Dashed horizontal lines denote the optically-thin and sub-visible COD regimes according to [42]. Optically thinner layers displayed higher sensitivity, especially with respect to the $BSR_{ref}$ parameter.
geometrical discrepancies (symbol size). As geometrical discrepancies we defined the cumulative difference of $C_{\text{base}}$ and $C_{\text{top}}$ between the static and dynamic method.

Fig. 10. Height-time plot of temporally averaged $Pr^2$ signal with overlaid dynamic (cyan) and static (black) WCT cirrus boundaries (a). Corresponding optical properties as derived by the constrained Klett method (b) and differences (blue dots) as a function of the geometrical discrepancy (dot size). The geometrical discrepancies varied from 30 to 1613 m. Optically thinner layers were affected more intensely.

Higher geometrical discrepancies mostly occurred for faint cirrus layers (Fig. 10(a)). The dynamic method provided higher COD values, since thanks to its higher sensitivity, it usually yielded wider boundaries. Higher optical discrepancies arose for upper sub-visible and optically thin layers. The highest $LR_{ci}$ and COD differences (45% or 17 sr and 93% or 0.037, respectively) were related to the maximum geometrical discrepancy (1613 m). The geometrical discrepancy, however, was a necessary but not sufficient condition for optical discrepancies to occur. More specifically, in opaque layers despite the non-negligible geometrical discrepancy (up to 490 m), the $LR_{ci}$ and COD solution discrepancies were low (less than 1 sr and 0.025, respectively). This indicates that the solution converges faster within the main part of optically thicker layers.
thanks to sufficient light attenuation and, thus, marginal parts play a less critical role. Overall, for optically thin and opaque layers the $LR_{ci}$ difference was lower than 10% (3 sr) and the COD difference did not exceed 8% (0.025). Finally, one should bear in mind that the MSC optical discrepancies are expected to be higher than the apparent ones, which were presented here. The same sensitivity is performed on the double-ended Klett and Raman derived optical properties in the Appendix.

5. **Inter-comparison of cirrus optical properties**

The comparison of constrained Klett derived optical properties with those from the double-ended Klett and Raman retrievals is shown for the cirrus cloud of 23 January 2019. The dynamic WCT method provided the $C_{base}$ at 7 ± 0.2 km and $C_{top}$ at 8.8 ± 0.2 km, with the ambient temperature at -48 and -63°C, respectively. The MSC $LR_{ci}^{355}$ and $COD_{ci}^{355}$ as derived from the different retrievals are presented in Fig. 11. More details on the multiple scattering effect are given in the Appendix.

![Fig. 11. Inter-comparison of constrained Klett, double-ended Klett and Raman retrievals in terms of MSC optical properties at 355 nm (mean ± standard deviation given in the legend). For Klett retrievals, errorbars represent uncertainties due to 0.01 BSR reference value error. For the Raman method, $LR_{ci}$ errorbars represent the standard error of the mean (extremely high for vertically inhomogeneous layers), while COD errorbars represent the integral-propagated $\alpha_{part}$ uncertainty.](image)

The double-ended and constrained Klett exhibited high agreement, especially in the COD. The Raman technique provided lower vertically-averaged $LR_{ci}$ and COD solutions, probably because of the vertical smoothing process. Higher $LR_{ci}$ discrepancies occurred for layers with COD lower than 0.1. This could be attributed to less efficient convergence of the constrained Klett as well as to higher Raman statistical uncertainties. The mean (± standard deviation) discrepancy between constrained and double-ended Klett amounted to 3 ± 4 sr for $LR_{ci}^{355}$ (1 ± 2 sr for $LR_{ci}^{532}$) and 0.01 ± 0.007 for $COD_{ci}^{355}$ (0.02 ± 0.02 for $COD_{ci}^{532}$). The corresponding discrepancies between constrained Klett and Raman were equal to 10 ± 6 sr for $LR_{ci}^{355}$ (14 ± 12 sr for $LR_{ci}^{532}$) and 0.07 ± 0.04 for $COD_{ci}^{355}$ (0.06 ± 0.06 for $COD_{ci}^{532}$). Overall, the three retrievals exhibited agreement within the range of uncertainties on the mean cloud optical properties. The $COD_{ci}^{355}$ ($LR_{ci}^{355}$) was estimated 0.28 ± 0.17 (29 ± 4 sr) by the constrained Klett, 0.27 ± 0.15 (32 ± 4 sr) by the
double-ended Klett and 0.22 ± 0.12 (26 ± 11 sr) by the Raman retrievals. Similar agreement was found for the optical properties at 532 nm (not shown). The optical properties are comparable to those derived, via double-ended Klett and Raman retrievals, over the sub-Arctic site of Kuopio (62.7°N) with COD\textsubscript{355} of 0.25 ± 0.2 and LR\textsubscript{ci}\textsubscript{355} of 33 ± 7 sr \cite{56}.

The high agreement between the double-ended and constrained Klett retrievals can be attributed to the fact that both rely on elastic signals. There is an additional reason, however, behind this agreement. In this study, we used identical far- and near-range reference values for both methods in order to make them as comparable as possible. Nevertheless, we should underline that the classical double-ended Klett is based on aerosol-free assumptions above and below the cirrus cloud \cite{40}. Therefore, we performed a sensitivity analysis to assess the impact of the latter assumption. In Fig. 12, the LR\textsubscript{ci} and COD are presented as in Fig. 11 but the double-ended Klett with aerosol-free assumptions (BSR = 1) is additionally given. As revealed, optically thinner layers (time bins 1 to 5) were the most affected ones by the aerosol-free assumption, displaying LR\textsubscript{ci} of 75 ± 7 sr (mean ± standard deviation). Previously, the LR\textsubscript{ci} was assessed as 31 ± 2 sr by the double-ended Klett, 24 ± 5 sr by the constrained Klett and 38 ± 5 sr by the Raman retrieval. For optically thicker layers the aerosol-free assumption led to positive discrepancies (2–8 sr) as well, while the overall COD discrepancies lay between 0.01 and 0.03. Hence, the LR\textsubscript{ci} was overestimated since the amount of extinction that was overlooked due to the aerosol-free assumption was instead attributed to the cirrus layers. Consequently, a non-realistic BSR\textsubscript{ref} assumption can make a fundamental difference in the solution accuracy.

The constrained Klett method was applied to a large number of cirrus layers with variable vertical structure, geometrical and optical thickness observed at different altitudes both during day-time and night-time. The LR\textsubscript{ci} and COD distributions as obtained from the three different retrievals, i.e. constrained Klett, double-ended Klett and Raman (when applicable) presented high similarities both at 355 and 532 nm. Moreover, it was found that LR\textsubscript{ci} close to the bounding values (5 and 90 sr) were associated with cirrus layers of low geometrical depth and COD. For these regimes cirrus detection and optical characterization is more challenging (section 3.3, 4.2, 4.3 and Appendix) and therefore care will be taken when providing long-term cirrus properties statistics (e.g. exclude cirrus layers with COD lower than 0.02).
6. Discussion

6.1. Limitations of existing cirrus cloud retrievals

The limitations of cirrus optical retrievals already existing in literature are briefly discussed here. Starting with the transmittance method, it relies on the ratio of backscattering signals at $C_{\text{base}}$ and $C_{\text{top}}$, which is quadratically proportional to the cirrus layer transmission [37–39]. However, the transmittance method cannot converge adequately for optically thinner cirrus (COD below 0.05) [70]. Concerning the backward - total optical depth method [41], this derives an initial guess COD via the slope method. Then, an $\alpha_{\text{part}}$ profile is obtained by a backward or forward Klett and, finally, it is modified to match with the initial guess COD. Nevertheless, the slope method requires negligible molecular extinction and backscatter contribution within the cloud, clear air at $C_{\text{base}}$ and $C_{\text{top}}$ and negligible multiple scattering effect. Therefore, no reasonable accuracy can be achieved either for optically thinner cirrus (COD below 0.1) or in the presence of overhead aerosol layers. Finally, the Raman technique [40] is typically limited to night-time applications because it relies on the weak Raman signals (section 2.3.3). Therefore, Raman signals are usually smoothed vertically at the expense of effective resolution [78] and clustered over long temporal periods. However, distorted $\alpha_{\text{part}}$ profiles might be produced, with ice crystal related peaks being suppressed, having a critical impact on the accuracy of radiative effect estimates [23]. Exemplarily, vertical smoothing of 780 m can lead to biases of 64% (7.7 Wm$^{-2}$) at surface and 39% (11.8 Wm$^{-2}$) at top of the atmosphere for opaque cirrus layers [23]. Likewise long temporal averaging that smears out the cirrus physical variability, is expected to induce radiative effect biases. Therefore, an application of high-resolution daytime profiling, an approach developed for Raman lidar (as in [79]) is in our upcoming research interests.

6.2. Strengths and limitations of extended cirrus cloud retrieval

Cirrus detection and optical characterization is, in general, more challenging for geometrically and optically thinner cirrus layers. However, the proposed dynamic WCT method proved to be more sensitive to faint cirrus layers that were partly or completely overlooked by the static method (section 3.3). A similar advancement has been achieved in the 4th version of CALIOP CAD algorithm [31], which shows increased sensitivity to optically thinner layers adjacent to cirrus clouds (cirrus fringes). At the same time, however, miss-classification into aerosol increased slightly, as a side effect of higher calibration accuracy and increased sensitivity to high altitude depolarizing aerosol. Consequently, there is still place for improvement in the CALIOP CAD algorithm. The optical biases, which result from cirrus boundary miss-determination and can be relatively high for optically thinner layers (section 4.3 and Appendix), render CAD optimization crucial. To this end, the satellite-derived cirrus geometrical properties can be evaluated by ground-based lidar observations and, thereby, the CAD thresholds might be improved. Added value can be brought by ground-based lidar observations in the Arctic, where miss-classification issues are frequently reported [31–33].

The dynamic WCT method enables the investigation of optically thinner layers (section 3.3) that are, however, characterized by higher inherent uncertainties (section 4.2) and more challenging $LR_{ci}$ value adjustment process (section 2.3.2). From a numerical viewpoint, the constrained Klett cannot always provide a robust $LR_{ci}$ value for low COD layers. The light attenuation within such layers is not sufficiently strong to scale the solution and appoint the best match. Likewise the double-ended Klett solutions exhibit lower absolute differences and, hence, the best matching solution is more challenging to find. Based on our analysis, the constrained Klett adjusts effectively the $LR_{ci}$ for apparent COD as low as 0.02 for both 355 and 532 nm. Comparable minimum COD values were reported over the sub-Arctic site of Kuopio ($COD_{355} = 0.24 \pm 0.21$ and $COD_{532} = 0.22 \pm 0.2$ [56]). In this respect, the constrained Klett is expected to be more
robust for mid-latitude and tropical cirrus (accompanied by cloud-free profiles to ensure an accurate $BSR_{ref}$), the majority of which fall into the optically thin regime [55,66–68].

In this study, we demonstrated that highly accurate optical properties can be derived solely by a stable backward Klett retrieval, as long as an additional reference value is appointed beneath the cirrus cloud. More importantly, the near-range reference value is not simply assumed but approximated by an initial guess BSR value ($BSR_{guess}$). This is a step towards more accurate retrievals, as this initial guess proved to agree with independent Raman estimates (section 4.1), as long as low COD (below 0.2) reference profiles are selected. This upper COD limitation was only encountered in a minority of the analyzed cases over Ny-Ålesund (2011-2020). Even for mid-latitude and tropical cirrus, this limitation is nearly raised as the majority of these clouds mostly belong to the optically thin regime [55,66–68]. It should also be pointed out that our system KARL is not in 24/7 operation and, thus, cirrus clouds were neither monitored from their formation nor clear-sky observations prior to the cirrus passing were always available. However, for continuously operating lidar systems as those of the Micro-Pulse Lidar Network (MPLNET) [80] the maximum COD limitation can be lifted more easily.

One can benefit from the highly accurate near-range reference value proposed here, even if the double-ended Klett is applied. As demonstrated in section 5, the double-ended Klett aerosol-free assumption can lead to $LR_{ci}$ positive biases (Fig. 12), especially in optically thinner layers. Further limitations of the constrained Klett relate to the assumed as vertically-independent $LR_{ci}$. However, this is a common limitation in existing methods such as the transmittance, double-ended Klett and backward - total optical depth. Finally, the aerosol content stability assumption beneath the cirrus cloud proved valid (Fig. 8) according to independent Raman estimates.

7. Summary and outlook

In this study, we explored the limitations and strengths of an extended cirrus cloud retrieval scheme. The scheme is based on lidar observations and comprises newly proposed cirrus detection (dynamic WCT) and optical characterization (constrained Klett). Cirrus clouds observed over the Arctic research site of Ny-Ålesund, Svalbard, were used for evaluating its performance. The WCT method (section 2.2) [54], which is sensitive to signal gradients, was revised for $C_{base}$ and $C_{top}$ detection. For the first time, two dynamic WCT criteria were introduced (section 2.2.1).

The first one was related to the ratio of WCT over the signal standard deviation (\[ WCT/\text{std} \]). The second criterion compared the SNR in marginal cirrus areas to the SNR of adjacent areas (SNR ratio). Cirrus optical properties were derived by a newly introduced iterative Klett–Fernald method [63,64], called constrained Klett (section 2.3.2). The novelty of constrained Klett is the recursively determined $LR_{ci}$ that was constrained by an additional reference value ($BSR_{ref}$) beneath the cirrus cloud. The $BSR_{ref}$ was estimated either from cloud-free profiles or profiles with minimum cirrus influence (COD up to 0.2). The main findings of this study can be summarized as follows:

- Increased sensitivity to thin cirrus layers (less than 200 m) was achieved thanks to the dynamic WCT method and the high vertical resolution (7.5 m) of KARL signals. The dynamic WCT method was more sensitive to faint layers, which were, in some cases, partly or completely missed by the static method (section 3). Fine-scale temporal averaging (9 min) was only performed within periods of physical stationarity to obtain non-distorted profiles (section 2.3.1).

- The constrained Klett was applicable to all cirrus regimes for COD values down to 0.02. The reference value ($BSR_{ref}$) was highly accurate, since it agreed with independent Raman estimates. Even without cloud-free reference profiles, accurate $BSR_{ref}$ estimates were obtained from layers with COD up to 0.2 (section 4.1).
• The main constrained Klett inherent uncertainty was related to the reference value ($BSR_{ref}$) parameter. Optically thinner layers displayed higher sensitivity (up to 50% in the COD and 60-74% in the LR) induced by typical $BSR_{ref}$ uncertainties (section 4.2). However, the inherent uncertainties were lower (10% in the COD and 15% in the LR) for opaque layers.

• The detection method (dynamic versus static WCT) affected the optical retrievals more critically in optically thinner layers, with COD underestimation by the static method reaching 90% (section 4.3 and Appendix). This underestimation might lead to miss-classification from the optically-thin into the sub-visible regime. Upper optically thin and lower opaque layer errors were lower than 10% in the double-ended and constrained Klett retrievals, whereas the Raman errors reached 30% in the LR and 12% in the COD.

• The constrained Klett derived optical properties (section 5) agreed within the range of uncertainties with those from the double-ended Klett and Raman retrievals. For an exemplary cirrus cloud, the \(CD^{555} (LR_{ci}^{555})\) was estimated at \(0.28 \pm 0.17 (29 \pm 4\ sr)\) by the constrained Klett, \(0.27 \pm 0.15 (32 \pm 4\ sr)\) by the double-ended Klett and \(0.22 \pm 0.12 (26 \pm 11\ sr)\) by the Raman retrievals. Contrary, when the classical aerosol-free assumption was applied in the double-ended Klett, the agreement was significantly lower.

• As a step towards more accurate optical retrievals, the constrained Klett near-range reference value was not simply assumed, as in classical approaches (e.g. double-ended Klett), but approximated by an initial guess BSR value ($BSR_{ref}$). Established approaches can benefit from the more realistic reference value. Based on sensitivity analysis with aerosol-free conditions assumed, the double-ended Klett overestimated the $LR_{ci}$ by 44 sr in optically thin layers and by 2-8 sr in thicker ones (section 5).

• The multiple scattering effect, which was corrected using the Eloranta analytical model [75], was significant in all cirrus regimes ( Appendix). But for MSC, the extinction would have been underestimated by 50-60% near the $C_{base}$ and 20-30% within the cirrus. A simplified MSC approach [14], depending only on the COD, underestimated the MSC for low COD (less than 0.1) layers, especially in terms of the $LR_{ci}$ (by 30%). Conversely, for an opaque layer the simplified MSC approach overestimated the COD (by 50%) and $LR_{ci}$ (by 85%).

The dynamic WCT method proposed here can also be applied for detecting the planetary boundary layer top height, with optimized specific modifications. The constrained Klett can be employed towards more accurate aerosol retrievals in scenes with broken clouds aloft. This can be achieved through a more realistic estimate for the LR of broken clouds. As a next step, we are going to investigate the long-term variability of cirrus properties over Ny-Ålesund, Svalbard, based on the dynamic WCT and constrained Klett schemes, with the dataset to be made publicly available. In the future, it is worth comparing and reviewing different cirrus detection schemes (e.g. static and dynamic WCT as well as simple multi-scale algorithms [54,81]) based on synthetic lidar signals, while the potential effect of multiple scattering on cirrus detection needs investigation.

Appendix

Selected dynamic wavelet covariance transform thresholds

The proposed thresholds of $\frac{WCT/\text{std}}{\text{SNR ratio}}$ are presented here and summarized in Table 1. The SNR ratio was investigated separately at $C_{base}$ and $C_{top}$ due to changes in the signal noise, with higher ratios prescribed at $C_{top}$. Due to increased noise, stricter SNR ratio values were selected for the 1064 nm and the daytime 355 nm profiles (see Fig. 6(c)). Less strict
thresholds were assigned to the 532 channel, which was finally selected for cirrus detection (section 3.2). The proposed thresholds worked well for cirrus clouds appearing in different altitudes. A sensitivity test is recommended before applying the \( \text{SNR ratio} \) thresholds to systems with different specifications than KARL, since the SNR is dependent on the operating wavelength, averaging time and background illumination conditions. A sensitivity on the \( \frac{\text{WCT}}{\text{std}} \) threshold is not necessary as this parameter displayed high stability for different wavelengths and averaging periods.

| channel (nm) | dynamic WCT/\text{std} | > 1 | static WCT/\text{std} | > 1 | dynamic SNR ratio | \( \text{SNR} \) | static SNR ratio | \( \text{SNR} \) |
|--------------|------------------------|-----|------------------------|-----|------------------|--------|-----------------|--------|
| 355\( _{p} \)  | \( \text{WCT/\text{std}} \) > 1 | 0.1 | 1.1 | 1.2 | > 2 |
| 355\( _{s} \)  | \( \text{WCT/\text{std}} \) > 1 | 0.1 | 1.2 (d) / 1.1 (n) | 1.5 (d) / 1.2 (n) | > 2 |
| 532\( _{p} \)  | \( \text{WCT/\text{std}} \) > 1 | 0.3 | 1.1 | 1.3 | > 2 |
| 532\( _{s} \)  | \( \text{WCT/\text{std}} \) > 1 | 0.3 | 1.1 | 1.2 | > 2 |
| 1064         | \( \text{WCT/\text{std}} \) > 1 | 0.3 | 1.2 | 1.5 | > 2 |

**Effect of geometrical boundaries on the optical properties: double-ended Klett and Raman retrievals**

Here we evaluate the impact of detection method (dynamic versus static WCT) on the optical properties derived by the double-ended Klett and Raman retrievals (Fig. 13), following the same rational as in section 4.3, where the effect on the constrained Klett was examined. Regarding the double-ended Klett (Fig. 13(a)), the discrepancies were higher for optically thinner cirrus. Maximum \( \text{LR}_{ci} \) and COD differences amounted to 20% (8 sr) and 90% (0.04) for a low COD layer. For opaque layers the \( \text{LR}_{ci} \) and COD discrepancies did not exceed 10% (2 sr and 0.025). Concerning the Raman technique (Fig. 13(b)), maximum discrepancies occurred within a low COD layer and amounted to 65% (25 sr) for the \( \text{LR}_{ci} \) and to 95% (0.034) for the COD, probably due to higher impact of noise on the retrievals. Within optically thicker layers the discrepancies did not exceed 30% (6 sr) in the \( \text{LR}_{ci} \) and 12% (0.03) in the COD.

**Multiple scattering correction for different cirrus cloud regimes**

Here we investigate the effect of multiple scattering on the optical properties of sub-visible (Fig. 14(a)), optically-thin (Fig. 14(b)) and opaque layers (Fig. 14(c)) observed over Ny-Ålesund by KARL. Primarily, the Eloranta MSC model [75] was employed with corrections based on Eq. (6) and Eq. (7) and then a comparison to the simplified MSC (Eq. (8)) was made. The investigation was performed separately for the \( \alpha_{\text{part}} \) derived by the Klett and Raman retrievals. In Fig. 14 the apparent and corrected \( \alpha_{\text{part}}^{355} \) profiles are presented together with the multiple scattering factor (F). The MSC simulations revealed 50-60% \( \alpha_{\text{part}} \) underestimation near the \( C_{\text{base}} \), as presented by Wandinger (1998) [77], which dropped to 20-30% within the layer and typically got negligible near the \( C_{\text{top}} \). In ranges with high \( \alpha_{\text{part}} \) variability, F was oscillating (Fig. 14). It should be noted that the multiple scattering effect was significant in all cirrus regimes. Overall, for the cirrus cloud of 23 January 2019, the vertically-mean F (equal to mean \( \alpha_{\text{part}} \))
Fig. 13. Same as Fig. 10, except for the double-ended Klett (a) and Raman derived optical properties (b). Higher dynamic - static induced discrepancies were found for optically thinner cirrus layers.
biases) amounted to 0.11–0.23 for Klett and 0.1–0.43 for Raman. For the upper opaque layer of 24 January 2013 (Fig. 14(c)) F was on average higher.

Our analysis showed that the simplified MSC factor underestimated the MSC within sub-visible and optically-thin layers, especially in terms of the $LR_{ci}$. The simplified $LR_{ci}$ bias reached 30% (9 sr) for Klett and 38% (15 sr) for Raman retrievals. Conversely, for opaque layers the simplified factor overestimated significantly the Klett COD (by 50% or 1.4) and $LR_{ci}$ (85% or 27 sr) as well as the Raman $LR_{ci}$ (by 40% or 22 sr). Multiple scattering events are more common in the UV compared to visible and infrared wavelengths due to stronger forward scattering [68]. The present investigation, however, that was also applied to $a_{532}^{\text{part}}$ (not shown) did not clearly show such a behavior. The MSC at 532 nm was mostly comparable to that of 355 nm.

**Funding.** Deutsche Forschungsgemeinschaft (268020496–TRR 172).

**Acknowledgments.** Konstantina Nakoudi wholeheartedly thanks the members of the Remote Sensing Laboratory at the Faculty of Physics, University of Warsaw, for their academic hosting and support. We are thankful to Dr. Edwin Eloranta for developing and making publicly available the multiple scattering correction model. We appreciate the scientific discussions with Dr. Roland Neuber, Dr. Marion Maturilli and Dr. Elina Giannakaki. The long-term support and technical development of KARL at the AWIPEV research base by Wilfried Ruhe and Ingo Beninga, Impres GmbH, are more than appreciated. We are thankful to Dr. Jan Chylik for proof-reading our manuscript. We gratefully acknowledge the funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) - Project Number 268020496 - TRR 172, within the Transregional Collaborative Research Center - Arctic Amplification: Climate Relevant Atmospheric and Surficial Processes, and Feedback Mechanisms (AC$^3$). Finally, we would like to thank the three anonymous reviewers that improved this work through their comments.

**Disclosures.** The authors declare no conflicts of interest.

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