

Response to RC1 on egusphere-2023-1953

The Chalmers Cloud Ice Climatology: Retrieval implementation and validation
Preprint <https://doi.org/10.5194/egusphere-2023-1953>

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Comments from the Anonymous Referee are presented in gray and our responses in black. Line numbers are given with respect to the revised manuscript.

We would like to thank the reviewer for their thorough review of our work and the constructive comments. We are convinced that the comments helped us to improve our manuscript. We hope that we could successful address the reviewer's concerns.

Changes to the manuscript

While the manuscript was in review we discovered a mistake in the radar retrievals from the Palaiseau cloud radar, which used a tropical instead of a mid-latitude PSD parametrization. For the revised manuscript, we have updated the results of the ground-based TIWP retrievals. This did not change the results considerably.

In addition to the issues highlighted by the reviewers, we have also corrected a number of smaller mistakes in the figures included in the manuscript.

1 Major comments

Comment 1

While the paper is well-written and includes multiple statistical examples demonstrating the efficacy of the machine learning technique, it lacks maps and certain plots illustrating the geographic representation of CCIC retrievals. To convincingly demonstrate the representativeness of these estimates, such examples are essential. The authors could add for example:

- Monthly global IWP maps showing the CCIC against the cloudsat estimates (no need to subsample the CCIC, just show that the global distribution is as expected)
- Percentage difference in these types of maps.

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- A latitude – altitude cross section of cloud ice fraction, again comparing versus the cloudsat one.
- global maps of IWC at different levels showcasing the variation with height
- Cross sections of IWC through different longitudes

Author response

We agree with the reviewer that the initial manuscript provided insufficient evidence of CCIC’s capability to capture the spatial distribution of TIWP and TIWC.

To address this, we will extend our analysis of the CCIC retrieval results on the test dataset, which comprises one full year of collocated geostationary observations and corresponding CloudSat measurements. Due to the sparse sampling of the CloudSat observations, we have decided against assessing the spatial distributions of the retrieval results and errors by month as the results would be extremely noisy. We will extend the manuscript with the figures shown in Fig. RC1.1 and Fig. RC1.2, which display the distribution of retrieved and reference TIWP and the zonal means and biases of the TIWC retrieval, respectively.

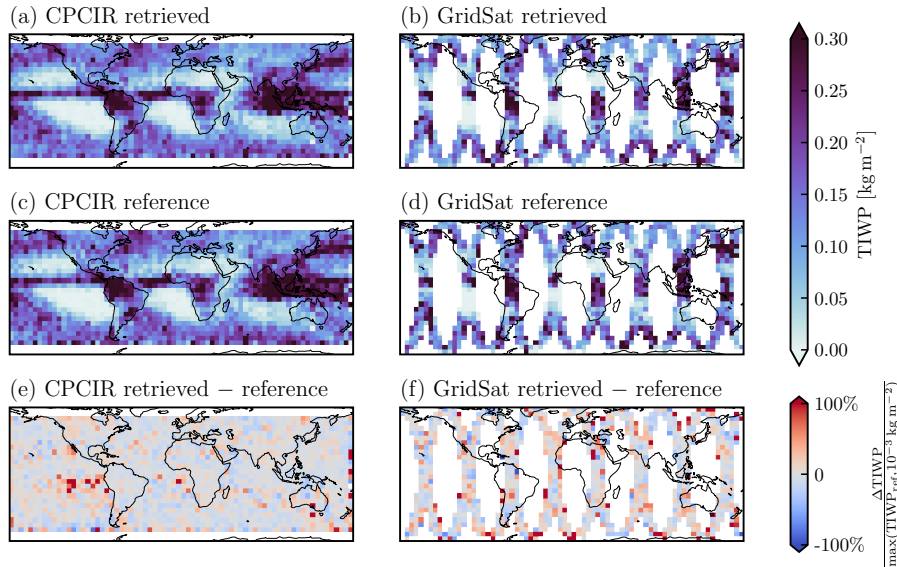


Figure RC1.1: Spatial distribution of retrieved TIWP and 2C-ICE-based reference TIWP for the CPCIR and GridSat test datasets over the domain covered by CCIC. Panels (a) and (b) show the retrieved TIWP aggregated to a resolution of 5° . Panels (c) and (d) show the corresponding distributions of the reference TIWP measurements. Panels (e) and (f) show the biases relative.

We also provide maps of retrieved and reference TIWC at discrete altitude levels and zonal averages of retrieved and reference TIWC for different longitude bands in Fig. RC1.3 to Fig. RC1.7. While these results provide further evidence

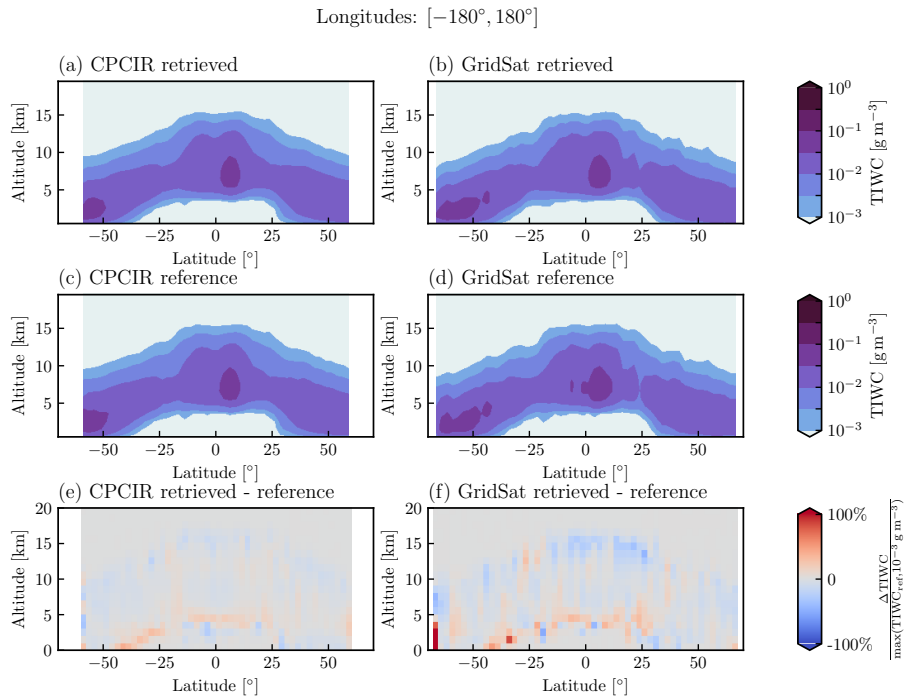


Figure RC1.2: Zonally averaged distributions of retrieved TIWC and 2C-ICE-based reference TIWC for the CPCIR and GridSat test datasets over the domain covered by CCIC. Panels (a) and (b) show the retrieved and reference TIWC for the CPCIR observations aggregated to a resolution of 2.5° . Panel (c) show the truncated relative bias of the retrievals. Panels (d), (e), and (f) show the corresponding distributions of the GridSat-based retrieval.

of the ability of CCIC to capture the three-dimensional distribution of TIWC in the atmosphere, we do not plan to include them in the manuscript as it already contains a large number of figures.

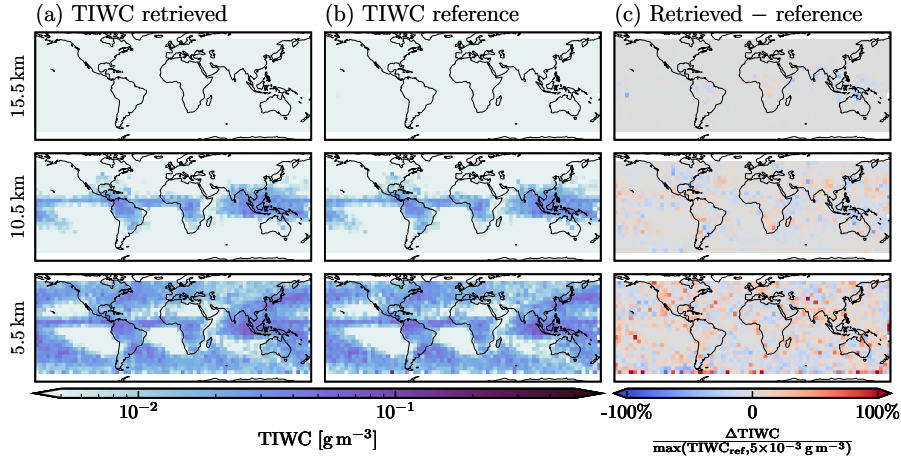


Figure RC1.3: Distribution of retrieved and 2C-ICE-based reference TIWC measurements for CCIC CPCIR retrievals at three atmospheric levels. Column 1 displays the mean retrieved TIWC. Column 2 displays the corresponding reference TIWC. Column 3 displays the truncated relative error. Rows contain the results for the atmospheric levels at altitudes of 5.5, 10.5 and 15.5 km, respectively.

Changes in manuscript

1. We will add the figure shown in Fig. RC1.1 together with the following paragraph discussing the results to the manuscript.

Changes starting in line 324:

The spatial distributions of mean retrieved and reference IWP concentrations from the test dataset are shown in Fig. 8. The distributions of the retrieved TIWP agree well with the distribution of the 2C-ICE measurements. Due to the low number of available 2C-ICE measurements in each 0.5 degree box, the relative bias field is noisy. The only region where the retrievals exhibit noticeable relative biases is the southeast Pacific dry zone. This is likely caused by the low amount of ice clouds in this region in combination with increased relative retrieval uncertainties for low- and mixed-phase clouds. Overall, for 90% of all assessed 5° boxes the biases remain within ±26.54% (±55.78%) for the CPCIR-based (GridSat-based) retrievals.

2. We will add the figure shown in Fig. RC1.2 together with the following paragraph discussing the results to the manuscript.

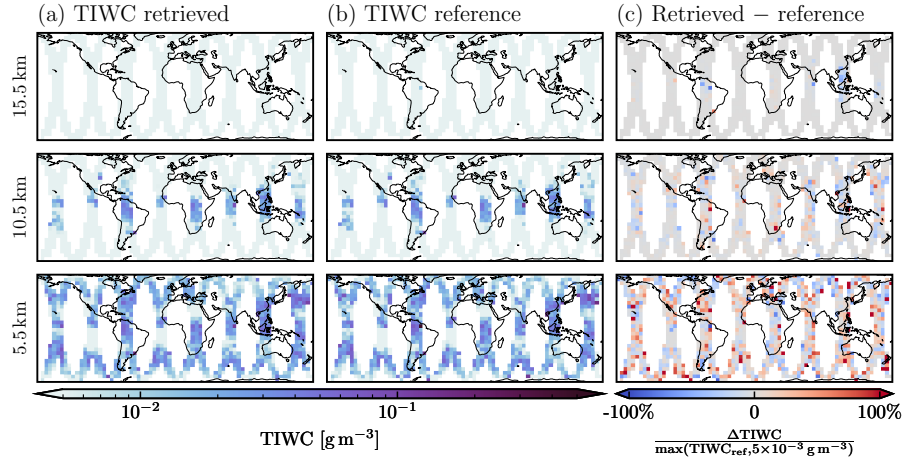


Figure RC1.4: As Fig. RC1.3 but for GridSat-based CCIC retrievals.

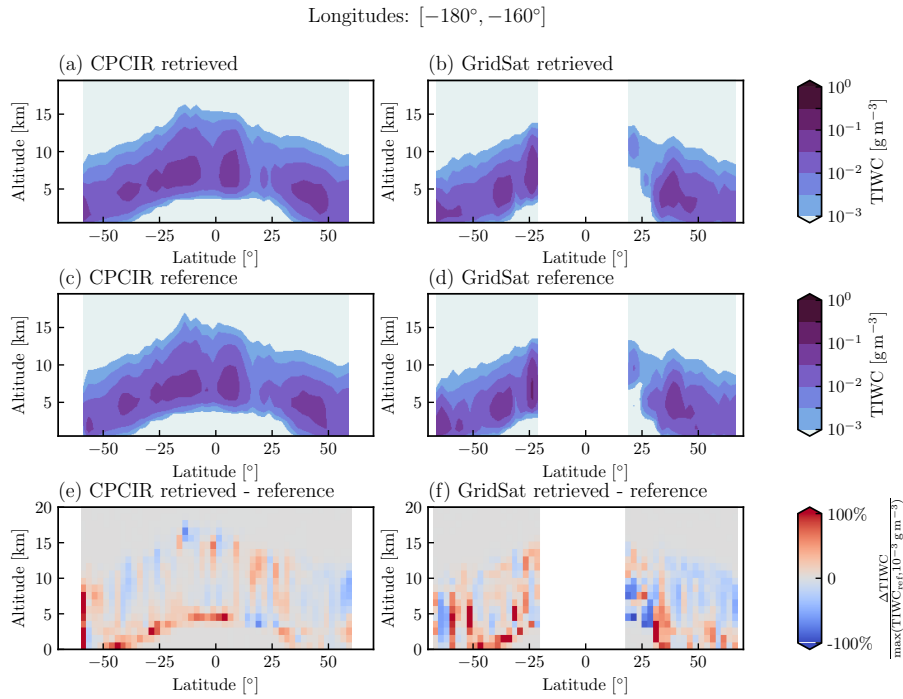


Figure RC1.5: As Fig. RC1.2 but for longitudes within -180° and -160° .

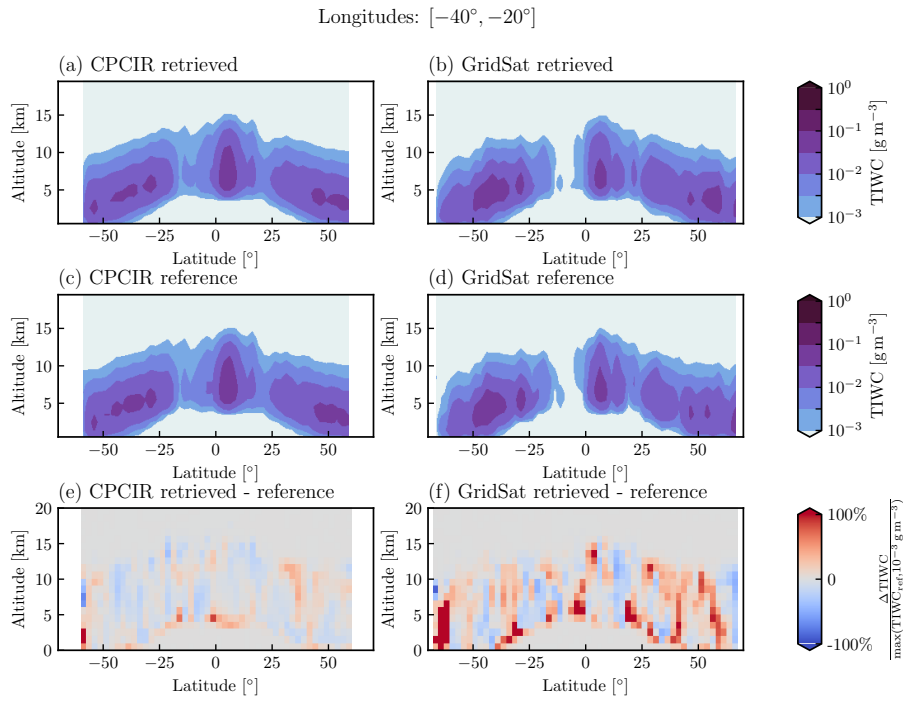


Figure RC1.6: As Fig. RC1.2 but for longitudes within -40° and -20° .

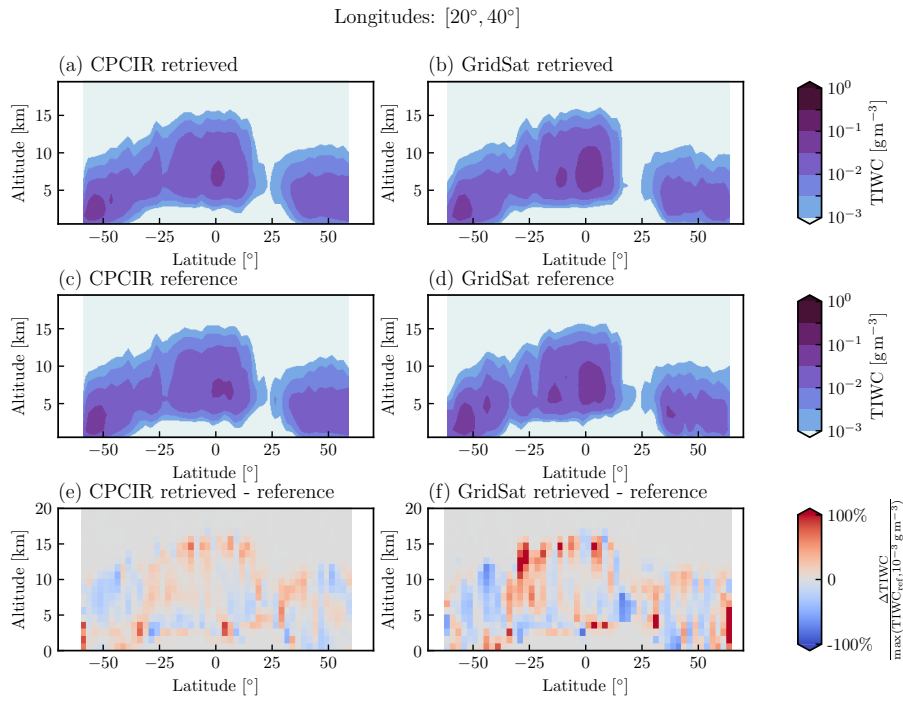


Figure RC1.7: As Fig. RC1.2 but for longitudes within 20° and 40° .

Changes starting in line 334:

~~The retrieval biases from TIWP and TIWC show small differences, in~~ Zonal means of all retrieved and reference TIWC estimates are displayed in Fig. 10. Although both retrievals exhibit a tendency to underestimate the TIWC at cloud top and overestimate it at cloud base, the spatial distribution of TIWC is represented well. In particular, the order of a few percent. However, those biases are likely negligible compared to other uncertainties affecting the retrievals. The retrieved TIWC can also be compared directly to retrievals correctly represent the double-peak structure caused by the seasonal variability of the ITCZ as well as the asymmetry of the TIWC distribution in the ITCZ and the storm tracks.

Specific comments

Comment 1

The title is not representative of the context of the manuscript. There is no mention of constructing a climatology or anything of that sort.

Author response

We thank the reviewer for pointing out that the introduction failed to properly present the CCIC project and the scope of the manuscript. We have reformulated the abstract to state that CCIC is a novel cloud-property dataset. Moreover, we have reformulated the two paragraphs starting in l. 65 of the revised manuscript to clearly state that the presented manuscript describes the first step towards the production of an ice water path climate record using the presented retrieval.

Changes in manuscript

1. We will make the following modifications to the abstract.

Changes starting in line 9:

The Chalmers Cloud Ice Climatology (CCIC) ~~addresses this challenge by applying novel~~ is a novel cloud-property dataset that aims to provide an improved climate record of ice hydrometeor concentrations by applying state-of-the-art machine-learning techniques to retrieve ice cloud properties from globally gridded, single-channel geostationary observations that are readily available from 1980. CCIC ~~aims to offer~~ offers a novel perspective on the record of geostationary IR observations by providing spatially and temporally continuous retrievals of the vertically-integrated and vertically-resolved concentrations of frozen hydrometeors, typically referred to as ice water path (IWP) and ice water content (IWC). In addition to that, CCIC provides 2D and 3D cloud masks and a 3D cloud classification.

2. We will modify the following paragraph in the introduction.

Changes starting in line 84:

~~This article presents the underlying retrieval algorithm of CCIC and validates~~ In this first article, we present the neural-network-based retrieval algorithm underpinning CCIC and validate it against independent measurements of ~~cloud concentrations~~ hydrometeor concentrations. This work constitutes the first step towards producing an updated climate record of TIWP estimates, which we plan to follow-up with the production and publication of TIWP estimates for the full record of available geostationary IR observations.

Comment 2

Line 41: “For the study of processes on annual and decadal scales it is therefore necessary to find ways to make better use of observations with a long record of availability”. The authors should mention that several IWP records exist with annual and even decadal scales, such as the ones from MODIS, Aura MLS, Odin SMR, CloudSat, etc. As currently written, the introduction implies that such records do not exist.

Author response

We thank the reviewer for pointing out this shortcoming of our manuscript. We will extend the introduction with a list of currently available records of comparable TIWP estimates and their respective shortcomings.

Changes in manuscript

1. We will modify the introduction as follows.

Changes starting in line 58:

Of the currently available cloud datasets providing global estimates of the ice water path, those derived from combined radar-lidar observations from the CloudSat and CALIOP satellite have to be considered the most accurate due to their ability to resolve the diurnal cycle of clouds
~~On the other hand, datasets derived from passive microwave sensors, only capture precipitating ice particles and were found to be at low end of the spectrum of global TIWP estimates. Although being derived from geostationary sensors, and thus capable of resolving the diurnal cloud cycle, TIWP estimates from the ISCCP dataset were found to be very low and not agree well with spatial distribution inferred from CloudSat measurements (Eliasson et al., 2011)~~vertical structure of clouds and the combination of active measurements at microwave, IR and visible wavelengths. However, due to the thin swath of these observations, their revisit time is of the order of a few weeks. Moreover, due to a technical failure, observations are limited to day-time measurements since April 2011, and day-and-night-time measurements are only available between 2006 and 2011. Although global estimates of water paths are also provided by the MODIS, ISCCP-H series (Young et al., 2018), and PATMOS-x (Foster et al., 2023) products, which can be used to estimate the ice water path using provided cloud-phase information, these estimates are all limited to day-time observations. Furthermore, we were not able to find validation results for the ice water path estimates provided by the MODIS, ISCCP, and PATMOS-x datasets thus making it difficult for users to gauge their accuracy.

Comment 3

Further since CCIC provides IWC, the authors could compare partial IWP versus those records matching their respective altitude coverage. The comparison versus the campaigns is limited to a few periods and it is limited geographically.

Author response

As per the reviewer’s suggestion, we will extended the analysis of the CCIC retrieval results to provide a more detailed assessment of the three-dimensional distribution or retrieved TIWC, as detailed in the response to major comment 1. The analysis is based on a full year of collocations with 2C-ICE estimates and thus covers the full geographical extent of the CCIC retrievals.

While the comment seems to suggest to also extend our comparison to estimates from limb-sounding instruments such as Aura MLS or Odin SMR, we choose not to do this as we do not think that this would offer any benefit over the comparison against the CloudSat/CALIPSO-based estimates.

Finally, we would like to point out that, while the individual field campaigns used in the validation are naturally limited in their spatial and temporal coverage, they cover both tropical and mid-latitude climate regimes and extend from instantaneous to seasonal time scales. With this, they exceed the scope of most validation efforts of TIWP/TIWC products that were able to find in published literature (Deng et al., 2010, 2013; Eriksson et al., 2008; Wu et al., 2008; Barker et al., 2008).

Changes in manuscript

See response to major comment 1.

Comment 4

Line 17: “considerable skill” is a qualitative description please provide a more quantitative description.

Author response

We will reformulate the sentence in question to provide quantitative accuracy estimate derived from independent test data.

Changes in manuscript

Changes starting in line 16:

A fully convolutional quantile regression neural network constitutes the core of the CCIC retrieval, providing probabilistic estimates of IWP and IWC. The network is trained against CloudSat retrievals using 3.5 years of global collocations. ~~Assessment of the retrieval accuracy~~ Assessed on a held-out test ~~set demonstrates~~ dataset, the CCIC-provided IWP and IWC estimates achieve correlations exceeding 0.7 and 0.6, respectively, and biases better than -5% and -2% demonstrating considerable skill in ~~reproducing the reference~~ estimating both IWP and IWC.

Comment 5

Line 20: “first order” is a qualitative description please provide a more quantitative description.

Author response

We will remove the formulation 'first order' and instead list the linear correlation coefficient and bias of the TIWC estimates in the previous paragraph.

Changes in manuscript

See changes in reponse to specific comment 4.

Comment 6

Line 45: please describe the rationale behind only using the 11micron channel. Presumably additional channels could provide more information.

Author response

We chose the 11 μm channel because it provides the best temporal and spatial coverage throughout the available record of geostationary satellite observations. While the GridSat B1 product also includes visible and water vapor imagery, which could likely help to improve the retrieval, they are not always available and therefore not considered in the current CCIC retrievals. We will revise the paragraph in question to include the motivation for this design choice.

Changes in manuscript

Changes starting in line 75:

CCIC ~~retrieves~~ provides estimates of TIWP and several other cloud properties from a single IR window channel ~~with a wavelength of centered~~ around 11 μm . Although these observations primarily provide information on the temperature of the atmosphere at the cloud top, ~~gridded datasets of observations at the 11 μm are readily available from 1980 onwards (Knapp et al., 2011); which significantly simplifies channel~~ provides the best availability among currently available gridded geostationary observation datasets (Knapp et al., 2011) and thus allows producing a long time series of spatially and temporally continuous TIWP measurements albeit limited to latitudes within $-60^\circ N$ to $60^\circ N$.

Comment 7

Line 55: "Estimates of TIWP differ widely between". Please give the ranges, this would allow you to later show how well (or bad) CCIC estimates are.

Author response

We will rewrite the relevant parts of the introduction and include the ranges of disagreement between satellite-based IWP estimates.

Changes in manuscript

Changes starting in line 52:

~~More specifically, Duncan and Eriksson (2018) showed that estimates of the vertically-integrated concentration of ice hydrometeors, the total ice water path (TIWP), can be obtained from geostationary IR channels and retrievals based on modern deep learning techniques.~~

~~TIWP shall be understood here as the vertically-integrated amount of all types of frozen hydrometeors. In currently available ice water path retrievals based on passive observations it is not always clearly defined which type of hydrometeors are considered. As a consequence, TIWP is not very well constrained by currently available observations and there remain large differences in ice hydrometeor concentrations between different models (Waliser et al., 2009; Eliasson et al., 2011; Duncan and Eriksson, 2018). Estimates of TIWP differ widely zonal mean ice water path, i.e. the column-integrated concentration of frozen ice hydrometeors, differ by up to a factor of five between currently available observational datasets (Duncan and Eriksson, 2018). While this is, at least partly, due to the inherent limitations of different observing techniques and the significant impact of uncertain microphysical assumptions on TIWP estimates, additional factors limit the potential of currently available datasets to inform studies of cloud processes. For example, datasets derived from sensors in sun-synchronous orbits such as the CloudSat CPR, MODIS or AVHRR are typically not able. The principal reasons for these discrepancies are differences in the sensitivity of the underlying sensors to ice particles of different sizes and uncertain assumptions on the microphysical properties of the observed clouds. Moreover, it is not always clearly defined whether the estimates provided by a product include all frozen hydrometeors or are limited to either only suspended or precipitating particles.~~

Comment 8

Line 87: why not use lat lon info as well? And day of the year?

Author response

We do not include spatial and/or seasonal context in the retrieval input data as we want the underlying neural network to learn relations between the satellite observations and the corresponding cloud properties and not their variability with respect to geographical location and season. Since the training data period is limited from mid-2006 through 2009, including geographical coordinates and seasonal information could limit the retrieval's ability to reproduce changes in the regional or seasonal variability of clouds outside of the training data period.

Comment 9

Line 108: The use of "2D" here is confusing since the authors are talking about profiles, I suggest deleting it.

Author response

We will replace ‘2D’ with ‘horizontal’.

Changes in manuscript

Changes starting in line 128:

TIWP, TIWC, a ~~2D~~horizontal cloud mask indicating the presence of a cloud anywhere in the vertical profile, and ~~vertically-resolved~~vertically-resolved cloud classification following the 2B-CLDLASS product.

Comment 10

Line 113 – Line 119: A schematic of this entire procedure will be appreciated. Also, what is the treatment for the uncertainties in 2C-ICE

Author response

We acknowledge the importance of making our training-data-generation process transparent and reproducible. To this end, we have published all relevant code in the repository accompanying this manuscript. However, since the manuscript already contains a large number of figures, we chose not to include a schematic of the data extraction process as we consider it of minor interest for the general audience.

We will add a sentence referring the interested reader to the relevant code to the revised manuscript.

Regarding the uncertainties of the 2C-ICE product: We treat the 2C-ICE estimates as ground-truth and do not make any effort to model the associated uncertainties. Synergistic radar-lidar retrievals of ice hydrometeor concentrations have to be regarded as the most accurate global measurements of TIWC and TIWP. Although even these combined radar-lidar estimates remain affected by significant systematic uncertainties, largely due to the underlying microphysical assumptions on particle shape and distribution, these uncertainties are not well characterized due to the limited amount of work that compares them with in-situ measurements (Deng et al. (2010, 2013) are the only studies that we are aware of). Since what ultimately matters to future users of CCIC is the uncertainty in the estimates provided by CCIC, we chose to extensively validate the resulting CCIC estimates instead of trying to handle uncertainties in the 2C-ICE product upfront.

Changes in manuscript

Changes starting in line 169:

Table 3 shows the ~~counts of the databases~~sizes of the training, validation and test datasets. All code required to generate the training datasets are made available through the code repository accompanying this article (Amell and Pfreundschuh, 2023).

Comment 12

Line 136: “Training scenes of 384×384 pixels”. Is the geographical size of this scene important? Is there an impact for using smaller or bigger scenes? Why this particular size.

Author response

We chose this size since it allows use to extract randomly rotated crops of size 256×256 pixels without generating invalid values. The scene size of 256×256 , which is ultimately used in the retrieval, was chosen because it corresponds to scenes covering more than 900 km in zonal and meridional extent. The resulting scenes should thus contain information on the mesoscale and, to limited extent, synoptic-scale context of the retrieval.

To make this point clear, we have reformulated the paragraph in question to provide a better description of the training-dataset generation and the underlying motivation.

Changes in manuscript

Changes starting in line 155:

~~Training scenes of~~ The collocated geostationary input observations and CloudSat-Calipso-based reference data are used to generate the training dataset, which consists of scenes of a horizontal extent of 384×384 pixels ~~were generated from the collocated input and reference data. The process involved input-observation pixels.~~ The scene size of 384 pixel was chosen as it allows for the extraction of randomly-rotated center crops of size 256×256 pixels, which is ultimately for training and inference. The extent of 256×256 pixels was chosen as it results in scenes exceeding 900 km in zonal and meridional extent and thus should contain information on the mesoscale and, to some extent, also the synoptic-scale context of the retrieval.

1.1 Comment 13

Line 136: “The process involved randomly selecting a pixel with valid reference data as the starting point and then adding a random zonal offset.” I don’t really understand this please clarify

Author response

We have reformulated the paragraph in question to describe the training-data generation process more clearly.

Changes in manuscript

Changes starting in line 160:

Scenes are extracted by randomly selecting a pixel with valid reference data as the ~~starting point and then adding center point for the scene~~. Then, a random zonal ~~offset~~ shift of up to 50 pixels east or west is applied to the scene so that the relative position of the CloudSat swath within the scene is randomized. This process was repeated until all pixels with valid reference data were included in at least one training scene. Scenes with less than 20% of valid ~~input~~ reference data pixels were discarded.

Comment 14

Line 140: lower → coarser

Author response

We will adopt this suggestion in the revised version of the manuscript.

Changes in manuscript

Changes starting in line 165:

Figure 1 shows that there is a clear difference in the spatial distributions of the collocations between the two IR data products, which is a result of the fixed overpass times of CloudSat and the ~~lower~~ coarser temporal resolution of the GridSat data.

Comment 15

Figure 2 caption: Why is the brightness temperature normalized?

Author response

Normalizing the inputs to neural networks is common practice and generally leads to better results and faster training convergence.

Comment 16

Line 155: Good is the enemy of great. The authors should explore tuning of these parameters or rephrase this sentence to state that minimal tuning was required.

Author response

It is generally acknowledged that exhaustive tuning of all architecture-related hyperparameters of a neural network model is too resource consuming to be practically feasible and principled architecture search remains an active area of machine-learning research (Ren et al., 2021). We therefore consider the reviewer's request out of scope for our work.

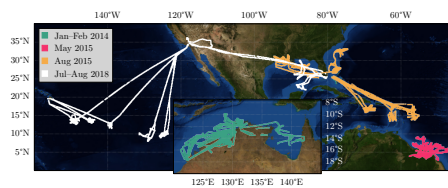


Figure RC1.8: Spatial coverage of in-situ measurements of TWC measured collected during the different HAIC-HIWC campaigns and collocated with CCIC retrievals. Flights during January and February 2014 were performed over Darwin, Australia and the surrounding oceans. Flights during May 2015 were performed out of Cayenne, French Guyana. Flights during August 2015 were performed out of Fort Lauderdale, USA. Flights in August 2018 were based out of Fort Lauderdale, Palmdale on the west coast of the USA and Kona on Hawaii. The map background is based on NASA Visible Earth imagery.

Comment 14

Figure 3, and 4 captions: specify the locations. for example, Aug 2015, and Jul-Aug 2018 flights were over the US and the US nearest oceans. Or, Flights took place over the Olympic Peninsula in the Pacific Northwest of the United States.

Author response

We will add the requested flight locations to the captions of Fig. 3 and 4.

Changes in manuscript

We have updated the figure captions of Fig. 3 and Fig.4. The figures and updated captions are shown in Fig. RC1.8 and Fig. RC1.9.

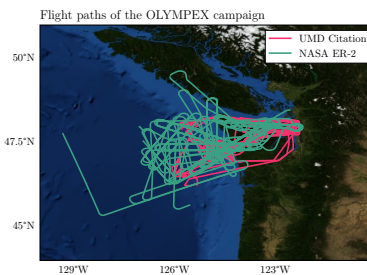


Figure RC1.9: Flight paths of the UND Citation and NASA ER-2 aircraft during the OLYMPEX campaign over the Olympic Peninsula in the Pacific North-West region of the USA. The map background is based on NASA Visible Earth imagery.

Comment 15

Line 229: Which of the four periods is the Darwin campaign?

Author response

We will extend the sentence in question to state that the Darwin campaign is the first set of flights of the HAIC-HIWC campaign.

Changes in manuscript

Changes starting in line 255:

In addition to the in-situ measurements collected during all flights of the HAIC-HIWC campaigns, the ~~Darwin campaign~~ first campaign in Darwin, Australia also included 95-GHz cloud radar measurements from the Radar Airborne System Tool for Atmosphere (RASTA) radar flown onboard the Falcon 20 of the Service des Avions Francais Instrumentations pour la Recherche en Environnement (SAFIRE) that are publicly available.

Comment 16

Line 237: Specify frequency

Author response

Following the reviewer's suggestion, we have replaced 'W-band' by '94-GHz'.

Changes in manuscript

Changes starting in line 263:

As part of the campaign, ~~W-band~~ 94-GHz cloud radar observations were performed by the NASA Cloud Radar System (CRS, Li et al., 2004) on board the NASA ER-2 aircraft.

Comment 17

Line 247: Which year?

1.1.1 Author response

The year was 2019. We will include this information in the revised manuscript.

1.1.2 Changes in manuscript

Changes starting in line 274:

For this study we use one year (2019) of radar measurements (Delanoë and Haeffelin, 2023) from the 95-GHz Bistatic Radar System for Atmospheric Studies (BASTA, Delanoë et al., 2016) from the site in Palaiseau, France.

Comment 18

Figure 5: panels g and h should say Cloud classification and cloud classification (retrieved) respectively.

Author response

We will update the panel titles in the revised manuscript to reflect this information.

Changes in manuscript

The updated figure is shown in Fig. RC1.10

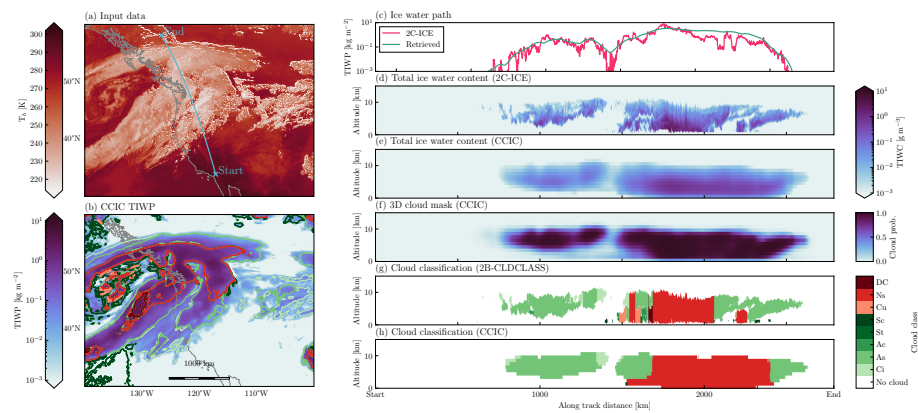


Figure RC1.10: Retrieved and reference cloud properties from a CloudSat overpass over a mid-latitude cyclone over the North-American West Coast on 3 January 2019. Panel (a) shows the CPCIR input observations. Panel (b) displays a map of the retrieved TIWP over the region as well as the dominant cloud type, which is defined as the most frequent non-clear cloud class (as defined in panels (g) and (h)) in the atmospheric column. Panel (c) shows the retrieved and reference TIWP along the CloudSat ground track marked by the blue line in Panel (a). Panel (d) shows the TIWC from 2C-ICE along the CloudSat ground track. Panel (e) shows the corresponding retrieved TIWC. Panel (f) shows the retrieved 3D cloud mask. Panel (g) shows the cloud classification from the 2B-CLDCLASS product. Panel (h) shows the corresponding retrieved cloud classes.

Comment 19

Figure 6 caption should mention cloudsat somewhere, as well as the period use for this comparison.

Author response

We will add the requested information to the figure caption.

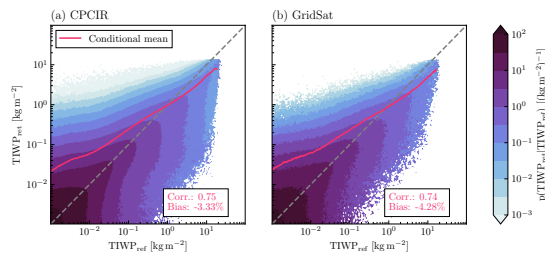


Figure RC1.11: Conditional distributions of retrieved TIWP conditioned on the [2C-ICE-based](#) reference TIWP. ~~Left panel for the test samples from the year 2010.~~ Panel (a) shows the distribution for the CPCIR input observations; ~~right~~ panel (b) shows the corresponding distributions for the GridSat dataset. The displayed bias and correlation coefficients are computed using all test samples including those outside the range of the scatter plot.

Changes in manuscript

The figure with the updated caption is shown in Fig. RC1.11

Comment 20

Section 3.2.1. It is not clear which period this comparison cover.

Author response

To make it clear to the reader that all results in this sub-section are derived using the independent test dataset, we will add an introductory sentence to Section 3.2. Furthermore, we will include this information in the all figure captions from this section.

Changes in manuscript

1. We will add the following introductory sentence to the beginning of Sect. 3.2.

Changes starting in line 310:

[The following sections quantitatively assess the accuracy of the CCIC retrieval on the independent test dataset, which consists of all CloudSat collocations from the year 2010.](#)

2. We have updated the captions of all figures in this section to clearly state that the results were derived from the test dataset.

Comment 21

Line 297: This should be shown as a separate subsection to emphasize its importance: Zero order comparison of IWP and IWC (for example)

Author response

Following the reviewers suggestion, we have added a new section titled ‘Consistency of retrieved TIWP and TIWC profiles’ and moved the discussion of the consistency of the retrieved TIWP and TIWC there.

Changes in manuscript

Changes starting in line 339:

~~Since TIWC is retrieved on evenly-spaced altitude levels, the differences in the relative retrieval biases between TIWP (Fig. 6) and TIWC (Fig. 9) indicate small, systematic differences between the retrieved TIWP by integrating vertically the TIWC. Using a trapezoidal integration and for either input data, the correlation results 1, and the column-integrated retrieved TIWC. When the retrieved TIWP and the column-integrated retrieved TIWC are compared directly, their linear correlation is 1.0 and the overall bias is at most 2.52%, and the conditional mean virtually follows the identity line. Surprisingly, the integrated TIWC agrees better with . Compared to the reference TIWP when comparing the overall, the integrated retrieved TIWC yields slightly smaller biases (−0.72% and −1.90% for CPCIR and GridSat) and yields the same, respectively) but similar correlation values. Nonetheless, the integrated TIWC shows a larger retrieval spread, thereby suggesting a weaker performance as a proxy for retrieving TIWP than the direct retrieval of TIWP. However, since these differences are of the order of a few percent, they can be considered negligible compared uncertainties in the reference data.~~

Comment 22

I think the whole classification is barely working and the authors should just not show any of those results.

Author response

We respectfully disagree with the reviewer’s comment but acknowledge that results presented in the first version of the manuscript may give an overly negative view of the retrieval’s capabilities. We would like to point out, however, that the classification results from the case study presented in Fig. 5 demonstrate the ability of the retrieval to distinguish the types of the principal cloud systems in the scene. To provide a more comprehensive picture of the retrieval’s classification skill, we will add curtain plots (conceptually similar to the ones the reviewer requested to demonstrate the skill of TIWC retrieval) showing the spatial distributions of the retrieved and reference cloud classes with respect to latitude and altitude. The results, shown in Fig. RC1.12 below, show good agreement between the distributions of the retrieved and reference cloud classes for all cloud classes except the stratus (St) class, whose frequency in the training dataset is only 0.03%. We consider this compelling evidence that the CCIC retrieval, in fact, has skill in classifying different cloud types.

In addition to adding the curtain plots to the manuscript, we will add text that discusses the results and points out that the confusion matrix shown in Fig. 10 assesses the classification of cloud layers at a vertical resolution of 1 km, which leads to high uncertainties in the classification of individual layers.

Changes in manuscript

1. We will add the figure shown in Fig. RC1.12 to the manuscript.
2. We will add the following paragraph extending the discussion of the classification results.

Changes starting in line 372:

While the confusion matrix shown in Fig. 12 suggests high uncertainties for the classification of the 1-km vertical levels used by CCIC, the results from the case study shown in Fig. RC1.10 indicate that the retrieval can nonetheless successfully identify the dominant cloud systems in the scene and their vertical extent. To assess the ability of the retrieval to distinguish different cloud systems on larger scales, Fig. RC1.12 shows the frequency of occurrence of the different retrieved and reference cloud types by altitude and latitude band. As these results show, the spatial distribution of the cloud types agrees well with the reference distributions for all cloud types except St, which is never detected. These results confirm that the retrieval has certain skill in distinguishing different cloud systems and their vertical extent despite uncertainties in the classification of individual layers.

Comment 23

Figure 13 is missing the conditional mean line

Author response

We have made the conscious decision to not show conditional mean lines for the validation results as some of the campaigns have very few samples causing the conditional mean lines to become very noisy. While the HAIC-HIWC in-situ data used in Fig. 13 contains sufficient samples to show the conditional mean lines (see Fig. RC1.13 below) we feel that we would have to add conditional mean lines to all following scatter plots to be consistent. Since we do not think that the conditional mean lines add significant information to the scatter plots, we have decided against showing conditional mean lines for the validation results.

Comment 24

Line 417: CCIC is not representing the diurnal variability well, it is really flat.

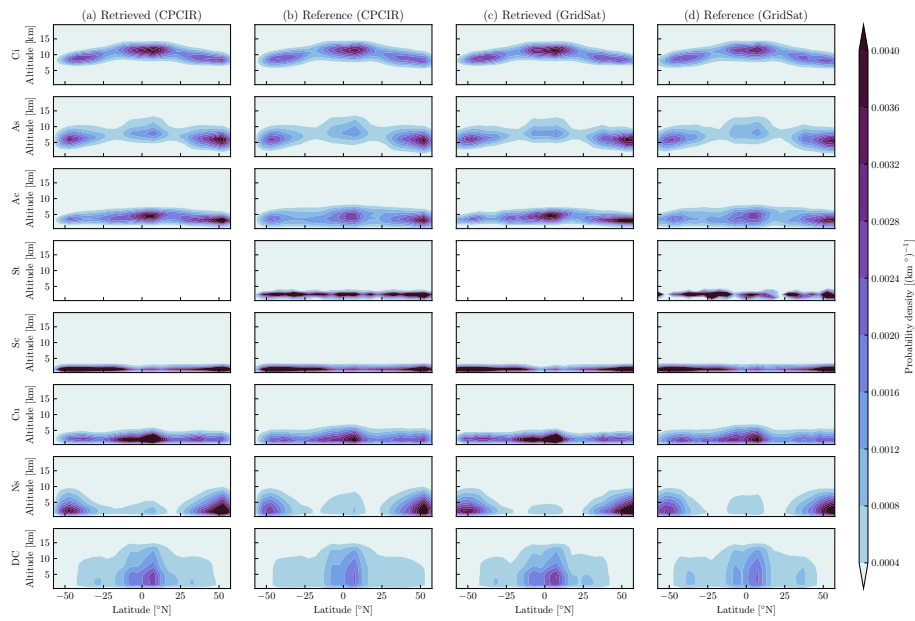


Figure RC1.12: Spatial distribution of retrieved cloud classes and 2B-CLDCLASS-based reference cloud classes for the test samples from the year 2010. Each row of panels shows the distribution of one of the 8 cloud classes distinguished by the 2B-CLDCLASS product. The first column shows the results retrieved from CPCIR observations while the second column shows the corresponding reference distribution. Column three and four show the corresponding results for retrievals based on GridSat observations.

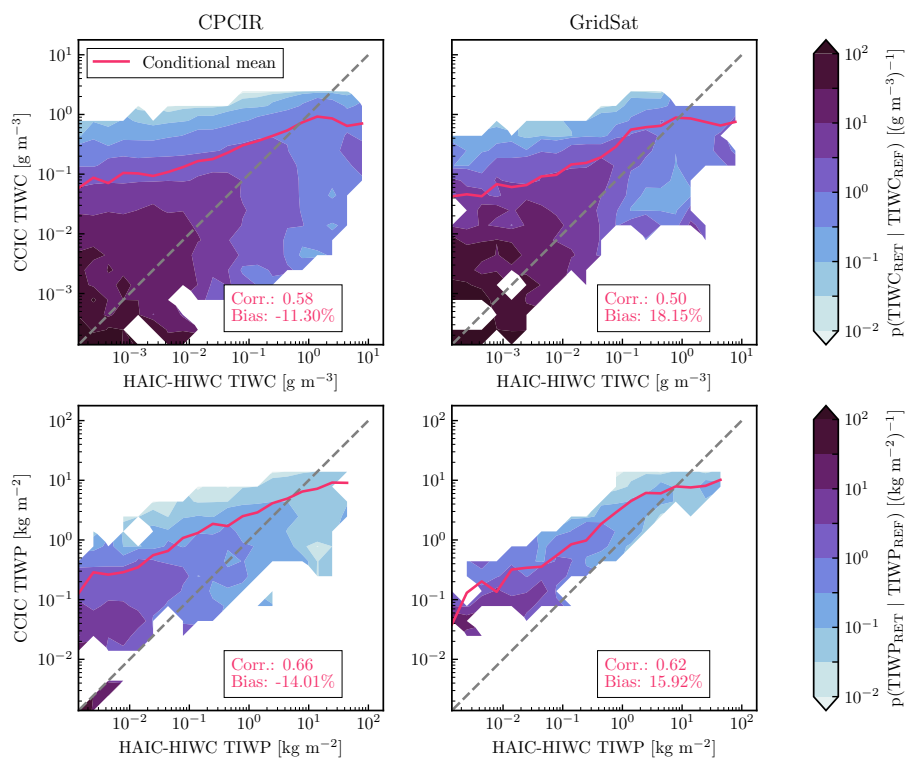


Figure RC1.13: As in Fig. 13 from the preprint, but with conditional mean lines.

Author response

While the CCIC results certainly do not represent the diurnal variability perfectly, the retrieved and reference diurnal cycles show a high degree of correlation. To make this point clear we will add a table containing the relative biases and linear correlation coefficients of the retrieved mean TIWP to the manuscript. These results show that the correlation of the diurnal cycles calculated over the full year is 0.86 (0.97) for CPCIR-based (GridSat-based) retrievals and does not fall below 0.74 for any of the assessed three-month periods.

Changes in manuscript

1. We will add the table shown in table RC1.13 to the manuscript.
2. We will reformulate the discussion of the diurnal cycles.

Changes starting in line 459:

Figure 21 shows diurnal cycles of TIWP retrieved from the ground-based radar and the CCIC retrievals. Calculated over the full year 2019, the CCIC retrievals ~~correctly reproduce the early-morning peak observed in the radar measurements although they underestimate its strength~~ reproduce the TIWP peak in the morning but underestimate the reduction in TIWP occurring around 15 h. The CCIC retrievals ~~still capture most changes in the diurnal variations on seasonal time scales~~ capture most of the seasonal variation of the diurnal cycle. The exception ~~here~~ are the summer months, during which the CCIC results ~~only show a very weak early-morning peak, whereas it is fairly pronounced in the radar data. This seems to indicate that the retrieval uncertainty in individual events is too large to capture diurnal variations reliably over the course of a single season~~ capture the general shape of the diurnal cycle but underestimate the magnitude of the variation. Nonetheless, as shown in table 5, the correlation of the retrieved diurnal cycles and those derived from radar simulations using the Large-Plate Aggregate particle exceed 0.7 during all seasons. Due to their lower temporal resolution, the GridSat-based results generally exhibit weaker variations than the CPCIR retrievals but yield higher correlations compared to the reference diurnal cycles calculated at 3h resolution.

Overall, it is notable that the CCIC retrievals manage to reproduce the diurnal and seasonal variation relatively well, as presented in Table RC1.13: the linear correlation between retrievals from CCIC and the Cloudnet radar used is at least 0.74 for any of the assessed three-month periods. It is important to note that CloudSat measurements are essentially limited to two discrete local overpass times due to the sun-synchronous orbit of the satellite. Therefore, they cannot resolve the diurnal cycle of cloud properties. The good agreement with the ground-based measurements shows that, despite being based on CloudSat measurements, the CCIC retrieval can reproduce diurnal variations in TIWP. The CCIC retrievals thus have the po-

tential to provide an important novel perspective on ice clouds in the atmosphere.

Table RC1.13: Relative bias and linear correlation coefficient of the diurnal cycles retrieved using CCIC compared to those derived from ground-based cloud-radar observations.

Time period	CPCIR		GridSat	
	Bias [%]	Correlation coeff.	Bias [%]	Correlation coeff.
All year	27.43	0.86	34.59	0.97
DJF	37.97	0.92	23.58	0.97
MAM	53.04	0.81	73.47	0.92
JJA	45.76	0.74	30.92	0.96
SON	-0.66	0.84	25.79	0.92

Comment 25

Line 438: provide an estimate of the uncertainties associated with the estimates of the ice hydrometeors.

Author response

We have extended the sentence in question to reference the validation study of A-train-based IWC retrievals by Deng et al. (2013) and mention the biases of up to 59% compared to in-situ measurements.

Changes in manuscript

Changes starting in line 487:

The biases with respect to in-situ measurements were within or close to 50% for both flight campaign series, which is an encouraging result considering ~~the overall uncertainty associated with estimates of ice hydrometeors that~~ biases in combined radar-lidar retrievals, which are taken as reference estimates here, can be up to 59% for comparisons against in-situ measurements (Deng et al., 2013).

Comment 26

Line 456: “Despite these encouraging results, CCIC should still be considered a proof of concept. CCIC’s principal objective remains to explore the potential of modern deep-learning techniques to expand the observational climate record of ice clouds”. This should be mentioned upfront in the abstract and the introduction.

Author response

Since we have in the mean time processed the full observational record of available geostationary observations, it is not adequate anymore to consider CCIC

Table RC1.13: Cloud class frequencies, in percent, from all levels in the training set and total fraction of cloudy profiles, defined as a profile with at least one cloudy level.

Cloud class	GridSat	CPCIR
No cloud	91.7	92.2
Cirrus	1.4	1.5
Altostratus	2.2	2.0
Altostratus	0.6	0.6
Stratus	0.03	0.03
Stratocumulus	0.9	0.9
Cumulus	0.3	0.3
Nimbostratus	2.0	1.5
Deep convection	0.9	0.9
Cloudy pixel* <u>profile*</u>	46.7	44.3

merely a proof of concept. We will therefore the sentence from the revised manuscript.

Changes in manuscript

Changes starting in line 507:

~~Despite these encouraging results, CCIC should still be considered a proof of concept.—CCIC’s principal objective remains to explore the potential of modern deep-learning techniques to expand objective is to improve the observational climate record of ice clouds~~ sice-hydrometeor concentrations using modern deep-learning techniques.

1.2 Comment 27

Table A1: “Cloudy pixel” Cloudsat or retrieved? how come the cloudy pixel is 40ish while the no cloud is 97 %, please clarify

Author response

“Cloudy pixel” refers to cloudy profiles containing a cloud anywhere at the 20 vertical levels used by CCIC. The 97 %, on the other, hand refer to the fraction of non-cloudy levels. To make this point clearer we will replace ‘cloudy pixel’ with ‘cloudy profile’ in Table 1 and update the caption.

Changes in manuscript

We will update the table and caption which are shown in table RC1.13.

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Response to RC2 on egusphere-2023-1953

The Chalmers Cloud Ice Climatology: Retrieval implementation and validation
Preprint <https://doi.org/10.5194/egusphere-2023-1953>

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April 24, 2024

Comments from the Anonymous Referee are presented in gray and our responses in black. Line numbers are given with respect to the revised manuscript.

We thank the reviewer for investing their time into reading our manuscript and providing valuable feedback. We are convinced that the comments helped us to improve our manuscript. As the reviewer noticed, the stability of the retrieval will be assessed with a follow-up work. We address the specific comments below.

Changes to the manuscript

While the manuscript was in review we discovered a mistake in the radar retrievals from the Palaiseau cloud radar, which used a tropical instead of a mid-latitude PSD parametrization. For the revised manuscript, we have updated the results of the ground-based TIWP retrievals. This did not change the results considerably. We have also corrected a number of smaller mistakes in the figures included in the manuscript.

1 Specific comments

Comment 1

Since the input data is only tested on geostationary data with no input from polar-orbiting satellites, it is worth mentioning that high latitudes are not represented in the study/or something about the likely difficulties in retrieving IWP over snow-covered surfaces. This fact is pertinent since, as far as I understand, GridSat (or at least the new ISCCP-NG, another similar global geostationary dataset) may include polar-orbiting satellites to fill in the missing data at the poles in the future.

Author response

As suggested by the reviewer, we will add a remark regarding the limited latitudinal coverage of the CCIC retrievals to the paragraph starting in line 68 of the revised manuscript.

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Moreover we will add a paragraph to the discussion section in which we discuss the prospects of applying the CCIC retrieval to high-latitude and polar regions.

Changes in manuscript

1. We will add the following remark to the introduction.

Changes starting in line 76:

Although these observations primarily provide information on the temperature of the atmosphere at the cloud top, ~~gridded datasets of observations at the 11 μm are readily available from 1980 onwards [Knapp et al., 2011], which significantly simplifies channel~~ provides the best availability among currently available gridded geostationary observation datasets [Knapp et al., 2011] and thus allows producing a long time series of spatially and temporally continuous TIWP measurements albeit limited to latitudes within -60°N to 60°N .

2. We will add the following paragraph to the discussion section.

Changes starting in line 538:

Since CCIC was designed to be applied to geostationary observations, its retrievals are currently limited to the range -60°N (-70°N) to 60°N (70°N) for the CPCIR-based (GridSat-based) retrievals. We are confident that the approach could also be applied to high-latitude and polar regions using observations from polar-orbiting satellite such as those used by the PATMOS-x dataset. While cloud retrievals of low clouds over snow-covered surfaces present specific technical difficulties, the machine-learning-based approach could benefit from improved spectral information provided by AVHRR-type sensors and the increased coverage of CloudSat/CALIPSO observations at high latitudes.

Comment 2

The datasets apply inter-satellite normalization. ” This is not obvious. One method of ”normalizing” the geostationary satellites is to use spectra band adjustments to make all the satellite’s 11-micron channels look like a particular sensor, for instance, the SEVIRI 11-micron channel. Is this how it was done? Either way, more information is needed here

Author response

While we do not apply any normalization ourselves, we used the GridSat and CPCIR data as is, which have been already normalized. We updated the text in question to provide a high-level summary of the normalization applied by these datasets.

Changes in manuscript

Changes starting in line 112:

Both datasets provide merged and gridded IR brightness temperatures from the channels closest to 11 μm from the global constellation of historical and current geostationary meteorological satellites. ~~The datasets apply intersatellite normalization and Knapp et al. [2011] references therein detail that both datasets are provided after an intersatellite normalization, i.e. viewing angle and parallax corrections, and GridSat, in addition, GridSat applies a temporal normalization employs a temporal calibration against High-Resolution Infrared Radiation Sounder (HIRS) near-11 μm channel data, targeting long historical analyses [Knapp et al., 2011].~~

Comment 3

The existence of the 2C-ICE equivalent dataset, DARDAR, should be mentioned somewhere, at least in reference, and possibly half a sentence on why 2C-ICE was chosen as the reference dataset here.

Author comment

We will add this information to the revised manuscript.

Changes in manuscript

Changes starting in line 120:

The reference data for the CCIC retrieval targets is derived from two CloudSat products: the level 2 cloud scenario classification version R05 [2B-CLDCLASS, Sassen and Wang, 2008] and the level 2 CloudSat and CALIPSO ice cloud property version R05 [2C-ICE, Deng et al., 2010, 2013b, 2015]. The 2B-CLDCLASS product assigns each CloudSat radar bin one of nine different cloud classes (Table 1). This choice of reference data over similar products, e.g. DARDAR-cloud [Delanoë and Hogan, 2010], which can be regarded as the alternative to 2C-ICE, was motivated by the 2C-ICE product yielding smaller biases against in-situ measurements [Deng et al., 2013a]. We acknowledge that this study was performed using now-outdated versions of the retrievals, however, we were not able to find more recent validation studies involving the two products.

Comment 4

The authors rightfully point out that the largest source of uncertainties in IWP retrievals is the assumed ice particle microphysical model. However, nothing is mentioned about which microphysical model the 2C-ICE IWP retrievals assume. This needs to be mentioned, especially as it is rightfully considered when retrieving IWP from ground-based Radar.

Author response

We will add the information regarding the particle habit and PSD used by 2C-ICE to the discussion section.

Changes in manuscript

Changes starting in line 515:

Since CCIC uses the 2C-ICE and 2B-CLDCLASS products as reference data, it will directly inherit their characteristics. In particular this means that CCIC is based on the same microphysical assumptions as these two products and will therefore reproduce their errors. ~~However~~The 2C-ICE product uses a modified gamma particle size distribution (PSD) with a habit mixture of randomly oriented particles to retrieve TIWC from combined CloudSat and CALIPSO measurements [Deng et al., 2010], however, since it does not provide detailed information regarding the properties of the particles it is not possible for us to assess the impact of those assumption . Nonetheless, our validation showed that the resulting CCIC estimates agree reasonably well with in-situ measurements, thus instilling confidence in the reliability of both the reference data and the CCIC retrievals.

Comment 5

Cloudnet offers several years of W-band data and more sites than just the one, Palaiseau, in France. Why (only) this site? For instance, I don't know if it is too far North, but Norunda in Sweden would add sub-arctic conditions to the validation. A comment would suffice here

Author response

The Norunda radar at 60.0860° , unfortunately, is right outside the latitude covered by the CCIC CPCIR retrievals. We only looked into latitudes covered by both datasets. From these, the radar in Palaiseau can be considered to be the Cloudnet site with the most complete and high quality W-band radar data record, in particular for 2019, the year used (2023 is complete as well, but it is when the manuscript was written). Furthermore, we did not want to overload the paper with figures and restricted the validation to one radar. An additional reason for this is that running the radar-only retrievals for a full year computationally expensive. Hence the choice of Palaiseau.

We will add a sentence summarizing this motivation to Sect. 2.2.3.

Changes in manuscript

Changes starting in line 275:

For this study we use one year (2019) of radar measurements [Delanoë and Haeffelin, 2023] from the 95-GHz Bistatic Radar System for Atmospheric Studies (BASTA, Delanoë et al., 2016) from the site in Palaiseau, France. This Cloudnet site was chosen as it presented one of the most complete

W-band cloud radar data records, in particular for 2019, for the latitudes covered by the CCIC retrievals.

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