EUMETSAT ECMWF

EUMETSAT/ECMWF Fellowship Programme
Research Report

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On the usefulness of additional cloud and tracking information for the assimilation of AMVs

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April 2024

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1 Executive Summary

Currently the vast majority of available AMVs are not assimilated into NWP models due to various quality control steps. The aim of this study is to examine whether additional information on the properties of the tracked clouds, or estimates from within the AMV derivation on the reliability of the tracking and height assignment steps, can be used to extend the use of AMVs in global NWP and improve the impact they have on NWP forecast accuracy.

Three sources of additional information available from the AMV derivation were considered with a view to enhance the assimilation of AMVs in global NWP. The additional information characterises the reliability of the pixel-level cloud-top pressure estimate used for height assignment in EUMETSAT AMVs, and the cloud type or phase of the scene, and variability of the tracked motion, in NOAA AMVs. Departure statistics are evaluated in order to see whether the additional information is able to discriminate between different departure regimes which would allow a refinement of either the quality control or observation-error modelling.

Firstly, a test dataset was supplied by EUMETSAT which applied filtering to pixels with a less reliable cloud-top pressure estimate from EUMETSAT's Optimal Cloud Analysis (OCA) product. This was found to be effective at reducing background departures of EUMETSAT's Meteosat-11 AMVs compared to the unfiltered dataset. Preliminary assimilation trials with the one-month dataset available showed some promising benefits for short-range forecasts in the tropics, though a longer trial would be required to corroborate this finding.

Secondly, an evaluation of NOAA AMVs showed that for some areas AMVs with a different cloud type or phase had different background departures to each other. However, generally it was found that the type of cloud is already implied by the AMV location and pressure and therefore mostly already accounted for in the current quality control choices or observation error modelling.

Thirdly, information on the consistency of tracking clusters in GOES AMVs was also looked at, it was found that in some areas the more consistent the cluster vectors the lower the background departures were, however in other areas the reverse was true. It is hence not straightforward to use this quantity to refine the assimilation of AMVs.

The study hence recommends that EUMETSAT generates a longer dataset that would allow a deeper investigation of the applied filtering and may ultimately lead to a useful refinement of the EUMETSAT AMV processing. A further recommendation is that additional cloud and tracking information should be included by EUMETSAT and other AMV producers within the AMV product to allow NWP centres to try using this information to further improve AMVs' contribution to forecast performance.

2 Introduction

Atmospheric Motion Vectors are a key observation type for NWP due to their excellent global coverage, and are the only direct wind observations available in many parts of the globe. In ECMWF's IFS model, currently around 35 million AMVs per day are monitored and around 500,000 AMVs per day are assimilated and recent data denial experiments have shown that they provide a strong improvement to forecast performance.

Presently, to decide which of the 35 million AMVs gets assimilated, the location and imager channel of the AMV is considered, along with a quality indicator (QI)[1] value based on consistency of the contributing subvectors to each other and of the final AMV to neighbouring AMVs. AMVs are also subject to geographical quality control, using relatively blunt exclusion criteria based on their location and pressure. Furthermore, a relatively tight check against the model first guess is used to exclude AMVs that deviate too much from the model first guess.

The properties of the tracked cloud features are not currently considered in AMV assimilation, nor is any information on how well the feature tracking solution was constrained. Both of these aspects are likely to affect the quality of the derived wind: for instance, for certain cloud types the height-assignment might be less prone to error; similarly, a poorly-constrained tracking solution is expected to be indicative of larger errors in the estimated wind. The motivation for studying AMVs' cloud and tracking information is to try and improve the impact of AMVs on forecast performance. Perhaps this information could help to identify high quality AMVs to be assimilated in areas currently subject to geographical and pressure based rejections. Alternatively, the additional information could be used in the observation-error modelling.

Previous research has shown the potential of using information on cloud properties such as optical depth, and cloud product pressure error estimates, to select AMVs with low background departures ([6], [9]). However, while that work was with test data, the operational AMV BUFR data format now has dedicated spaces for such information, and some fields are routinely provided within the operational GOES and VIIRS AMV products, opening up the possibility of operational use of the cloud and tracking information. Indeed, information on the tracking consistency of GOES AMVs is used in filtering AMVs for assimilation at NCEP. If such additional information proves generally beneficial to users, this would provide guidance for other AMV producers such as EUMETSAT to include similar information in their product.

Alternatively, additional tracking or height assignment information could be used to filter out poorer AMVs on the producer's side. In the present study, this approach is used to filter out AMVs for which the Optimal Cloud Analysis (OCA) used in the EUMETSAT processing suggests a less reliable height assignment. Here, a dedicated one-month test dataset has been produced by EUMETSAT, and our evaluation is expected to inform future algorithm developments in the EUMETSAT processing.

The structure of the report is as follows: We will first present evaluation of background departure statistics stratified by cloud type and phase information available with GOES and VIIRS winds, before assessing tracking information provided from the GOES clustering algorithm. Next we assess a EUMETSAT test-dataset for which AMVs with less reliable height assignment have been filtered out. Conclusions and further work are discussed in the last section.

[1] In our operational quality control, and in this report, the QI used is the forecast-independent QI.

3 Cloud Type and Phase

Currently, the type and phase of the clouds from which AMVs are derived is not directly considered in how AMVs are treated in NWP, only indirectly via AMV pressure and location. It is known that some cloud types cause more trouble with height assignment than others. For example thin cirrus is often semi-transparent in the infrared window channel, causing issues with height assignment as radiation from the cirrus is mixed with radiation from the Earth's surface. It is hoped that information on the cloud type may therefore be useful as a predictor for AMV quality and useful for data selection or setting AMV observation errors. Another related question is whether the cloud types could also be helpful in setting AMV observation errors. However, we must also consider to what extent cloud type is implied by the AMVs' location and therefore already accounted for in our AMV data selection and observation errors.

Cloud type and phase information is routinely provided with NOAA AMVs, from both the GOES-ABI AMVs from the geostationary GOES-16 and GOES-18 satellites, and from VIIRS AMVs from the polar orbiting Suomi NPP and NOAA-20 satellites. Both the cloud type and cloud phase are provided as descriptive types. The cloud classification scheme uses the difference in infrared absorption between ice and liquid water clouds from the 8.5, 11 and 12μm channels on GOES-ABI and VIIRS, plus the 7.4 μm channel for GOES-ABI, as well as a radiative transfer model accounting for surface and atmospheric properties, to assign each pixel a cloud type via a decision tree [7]. For each AMV the cloud classification is the most common situation observed in all pixels in the tracking scene, not necessarily the pixels of the cloud feature from which the tracked motion was observed or even a majority of the tracking scene pixels. This adds a degree of noise to the results as some AMVs have a cloud classification that doesn't represent the tracked feature.

The results for the GOES AMVs are based on test data from the Enterprise version, an updated version of the AMVs which went operational in February 2024, while the results for the VIIRS AMVs are based on the operational version of the AMVs available prior to 6 March 2024.

In this section the quality of AMVs is assessed by using background departure statistics as a guide to AMV quality. The GOES departure statistics were generated by running an IFS Cycle 48R1 assimilation experiment at TCo399 resolution (roughly 25km) for the period 4th July to 14th August 2023. The experiment assimilated the GOES AMVs being studied, which slightly reduces the size of the background departures, however what is of interest here is the departures of different cloudy types compared to each other, not the absolute size of the background departures. The VIIRS background departures were obtained similarly, but using version 47R3 and for January 2021.

3.1 Enterprise GOES version

Warm liquid water is the most common cloud phase in the GOES infrared AMVs as we see in Figure 1. Ice phase is the second most common, of which most have a cloud type of 'optically thin ice', some are optically thick and a handful are multilayered ice. Supercooled liquid water is the third most common phase comprising around 5% of the total number of AMVs. For the water vapour absorbing 6.2μm channel most AMVs were of the optically thin ice type with some optically thick AMVs also, while for the visible channel most were warm liquid water with some supercooled liquid water.

From Figure 2 we can see from the zonal distribution of GOES that there is a strict separation between the ice and liquid water types at 500 hPa. Within the liquid water types, the main area of overlap is in the southern hemisphere around 50° latitude; within this region the supercooled and warm water have similar root-mean-square vector difference (RMSVD) values versus our model background. The optically thin

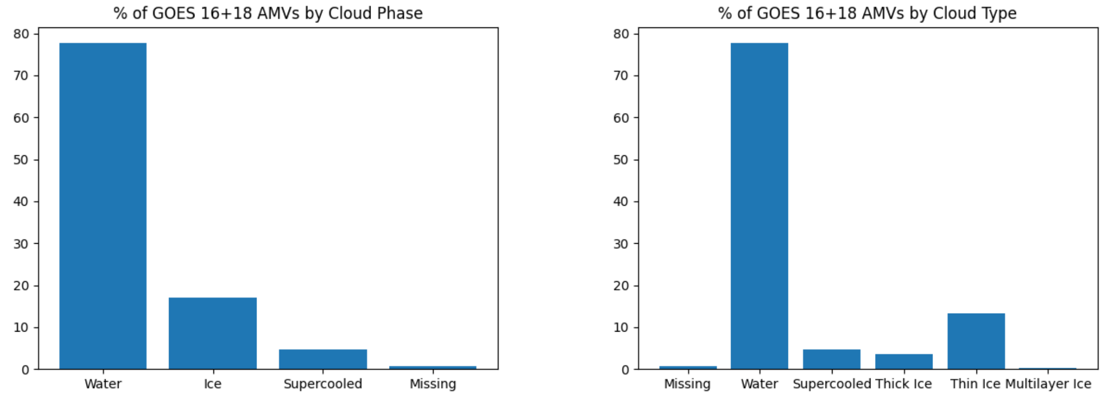

Figure 1: Frequency of each GOES IR cloud type and phase, all available AMVs, 'Enterprise' version, 4th July to 14th August 2023.

and thick ice types have some overlap in the tropics and southern hemisphere but also have similar RMSVD values despite the difficulties with cirrus height assignment that have been noted previously [8], although from the mean speed difference (Figure 3) we can see that the optically thin ice type has a higher positive speed difference than the optically thick ice. This is as expected for thin cirrus as infrared radiation from lower in the atmosphere is mixed with the emission from the cirrus, causing the motion of the high, fast cirrus to be assigned lower than the cloud height, where the AMV has a faster speed than the model background wind. Note that the zonal background departure plots in this section are filtered to QI>90 and the usual AMV first guess check was applied, as in operations, although we are looking at all regions of data and not applying our operational spatial rejections - so we can compare the quality in regions not currently used.

The distribution and background departures of the cloudy water vapour (6.15μm channel) AMVs are shown in Figure 4, which shows that the mean O-B speed difference is higher in the thin ice than the thick ice cloud type; this is qualitatively consistent with the finding for the infrared channel, but the difference is even larger. RMSVD values meanwhile are slightly higher for thick ice in the southern hemisphere, where there are significant numbers of AMVs of both types. For the visible channel (640nm) AMVs, background departures are generally small for the channel as a whole, but Figure 5 shows that the supercooled water AMVs have slightly higher RMSVD and speed bias values than the warm liquid water in the northern hemisphere, though the differences are very small in the southern (winter) hemisphere where the supercooled type is more common.

The background departures of each cloud type are largely similar in the areas where they overlap with each other. The result suggests that there is little scope for refining our blunt geographical AMV rejections on the basis of the provided cloud type and phase information. The finding may partly be because the types represent the most common type in the tracking scene and do not necessarily relate to the tracked feature. Also, as they are the most common type in the scene we cannot tell how dominant the most common type is - for example we would not expect a scene with 55% warm liquid water to 45% supercooled water to be radically different to a scene with those percentages reversed. The most consistent result was in the ice clouds, with the mean speed difference was higher for the optically thin type than the optically thick type in both the infrared and water vapour channels. The findings could be revisited if the cloud classification provided was linked more closely to the pixels of the tracked feature rather than the whole scene, as this may provide clearer discrimination between the relevant cloud types.

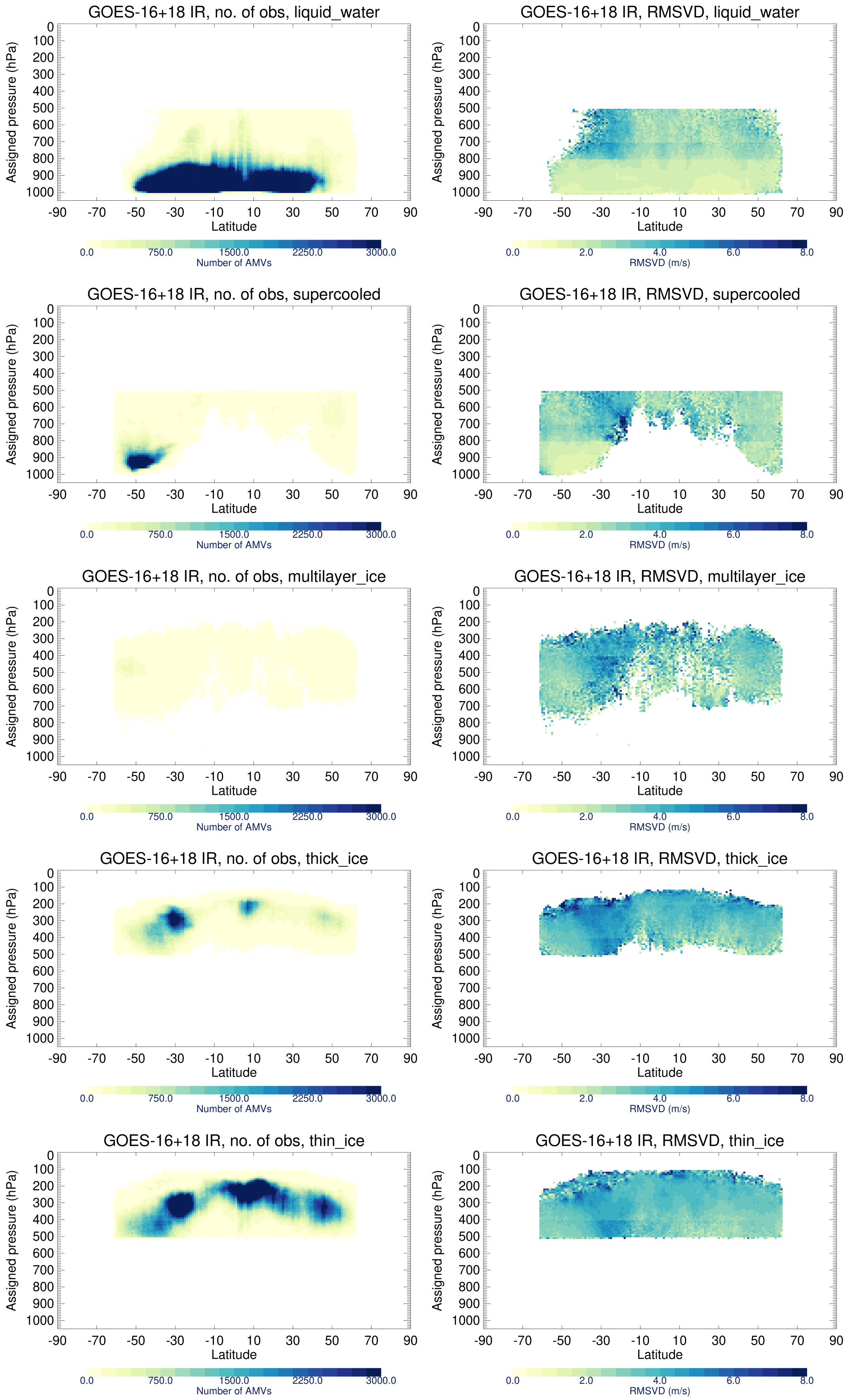

Figure 2: Zonal distribution (left) and RMSVD (right) of common GOES-16 and GOES-18 IR cloud types, data filtered to QI>90 and passing gross error check, 'Enterprise' version, 4th July to 14th August 2023. Figure titles indicate the cloud type considered.

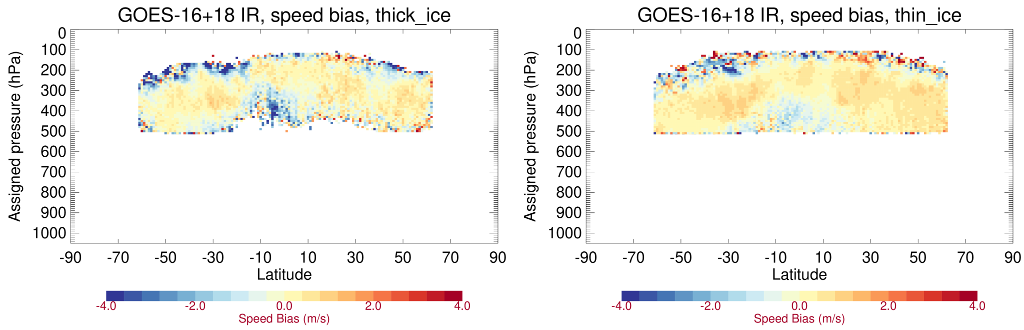

Figure 3: Mean O-B speed of GOES-16 and GOES-18 IR single layer ice cloud types, data filtered to QI>90 and passing gross error check, 'Enterprise' version, 4th July to 14th August 2023.

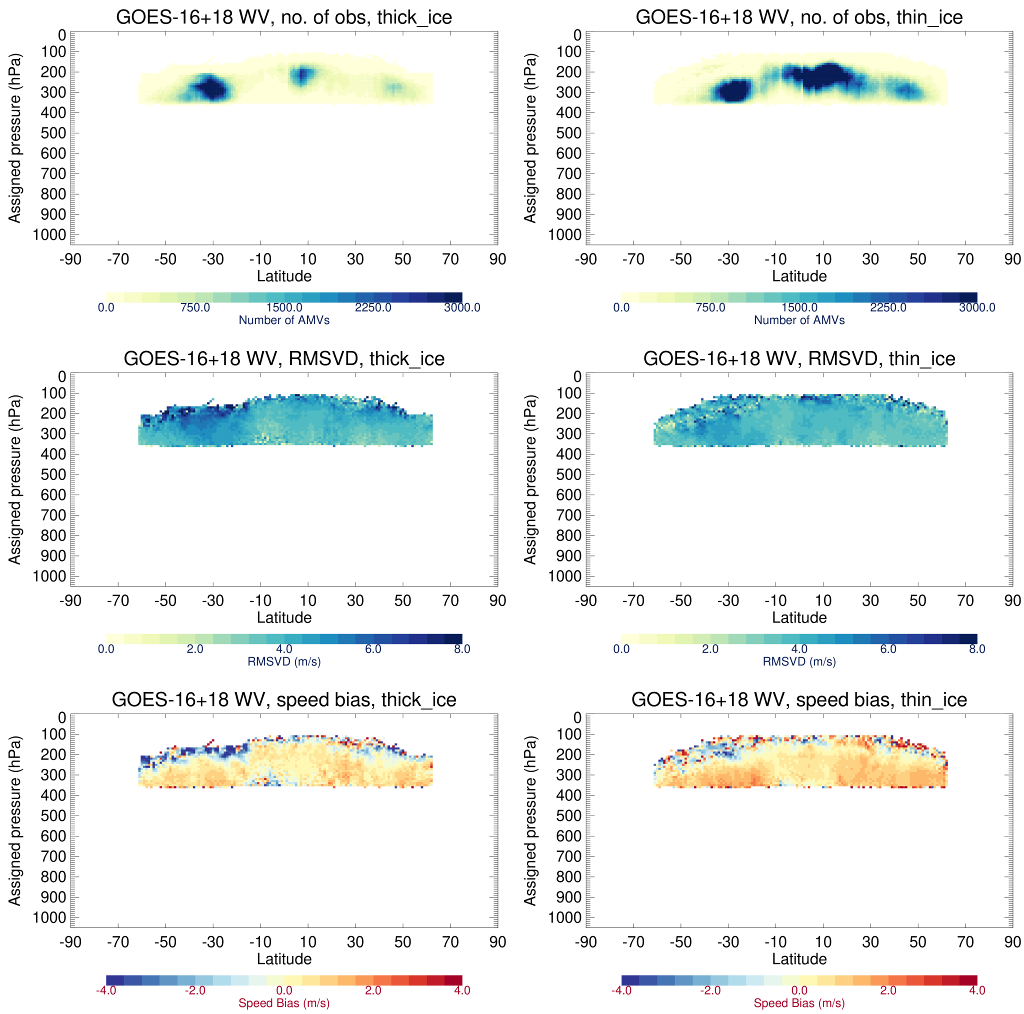

Figure 4: Distribution (top) , RMSVD (middle) and speed bias (bottom) of GOES-16 and GOES-18 cloudy water vapour (6.15 µm) AMVs, separated by thick (left) and thin (right) ice clouds. Data are filtered to QI>90 and passing gross error check, 'Enterprise' version, 4th July to 14th August 2023.

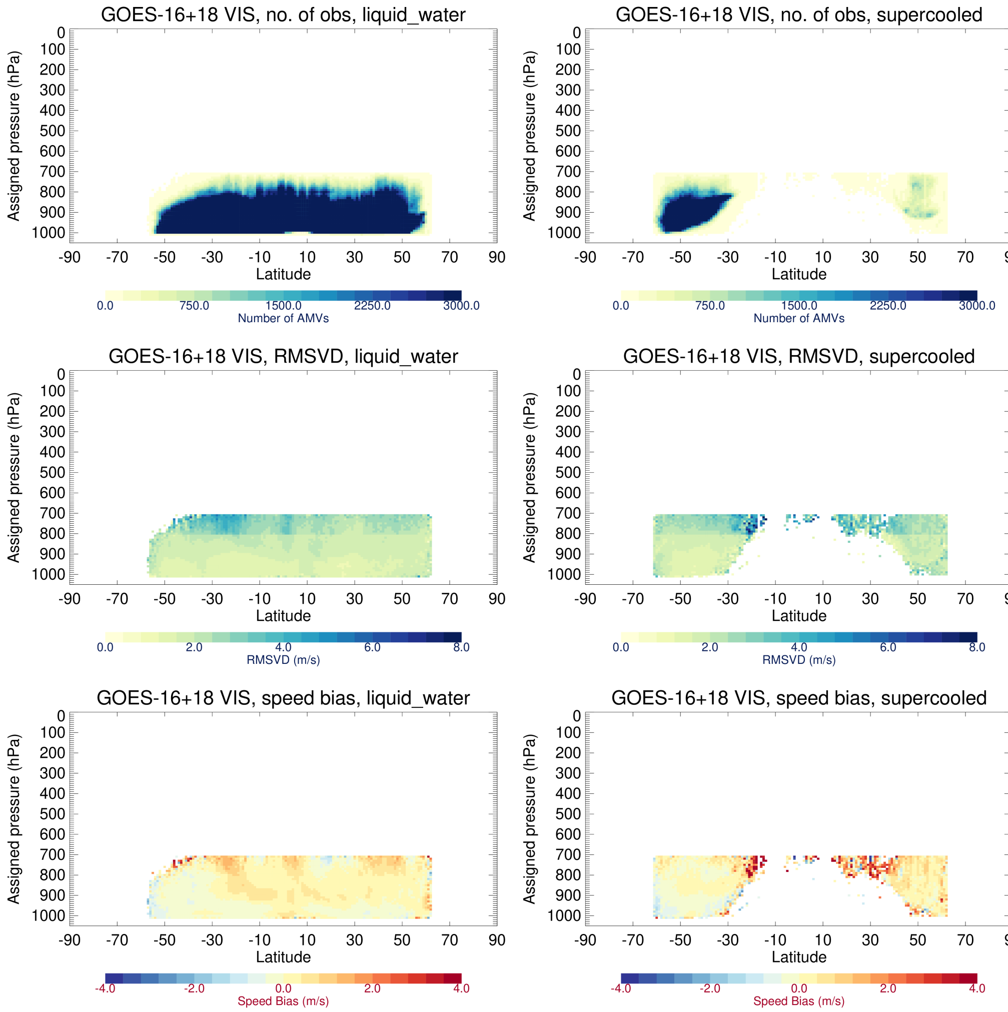

Figure 5: Distribution (top) , RMSVD (middle) and speed bias (bottom) of GOES-16 and GOES-18 visible channel (640nm) AMVs, separated by warm liquid water (left) and supercooled liquid water (right). Data filtered to QI>90 and passing gross error check, 'Enterprise' version, 4th July to 14th August 2023.

3.1.1 Use of AMV Cloud Types for Observation Error Estimates

Another possible use for the cloud information could be to assign observation errors differently for each cloud type. In the operational use of AMVs at ECMWF, the error scheme attempts to account for both the error in u and v wind from tracking, and the error in u and v wind from height assignment error. The observation-error model uses statistical estimates of the pressure error and the tracking error, derived from past statistics and tabulated in 200 hPa layers by satellite and wind type. These pressure and tracking errors are derived as follows (see also [4]): to calculate the pressure error we first obtain the best-fit pressure, that is, the pressure at which the AMV and model speeds are in best agreement. The pressure error is then worked out by standard deviation of the difference between the AMV pressure and best-fit pressure. The tracking error for each 200 hPa layer is worked out as the standard deviation of AMV-model wind speed differences for only those AMVs for which the error due to height assignment, previously mentioned, is small, so as to isolate the two sources of error.

An initial assessment of the then-operational GOES AMVs showed some overlap in height of the different cloud phases and some differences in the error estimates for each phase. With the new Enterprise scheme, which became operational in February 2024, the ice and warm liquid water types are largely separated in height (Figure 6) either side of 500 hPa. The supercooled type does overlap with the warm liquid water but the error estimates come out very similar for tracking error, slightly smaller for height error. The situation is similar for the three ice types with the more common optically thin and thick ice types ending up with very similar error estimates. The multilayer ice situation is around 25 hPa higher in pressure error but as we saw previously this type is very rare. Error estimates were also derived for the warm and supercooled liquid water visible channel AMVs, and the optically thick and thin ice AMVs of the water vapour channel; the estimates were similar between cloud types for both channels. Overall, as the differences in error estimates are so similar between cloud types in the new Enterprise version of these AMVs, it would not be worth separately deriving errors for each cloud type operationally.

3.2 Current Operational VIIRS Version

As expected the distribution of cloud types for the VIIRS AMVs (Figure 7) is different to the GOES AMV distribution (Figure 2) as they are only available over the poles while the GOES AMVs cover the tropics and mid-latitudes. From Figure 8 we can see that the main VIIRS cloud types are quite neatly separated vertically, so to a large extent any differences between them would already be accounted for by our observation error profiles and pressure-based rejections. The one area where two types do overlap is around 800-1000 hPa in the northern hemisphere, where the RMSVD of the mixed phase AMVs is higher, up to around 9 m/s, than that of the supercooled liquid water AMV at around 5-7 m/s. Polar AMVs at those pressures are not assimilated presently, and the relative reduction in background departures for the supercooled type is not enough to compensate for their large absolute size to the extent that we could start assimilating them. Furthermore our polar QI threshold of 60 and gross error checking would likely reduce the difference between the mixed phase VIIRS and supercooled VIIRS AMVs in practice.

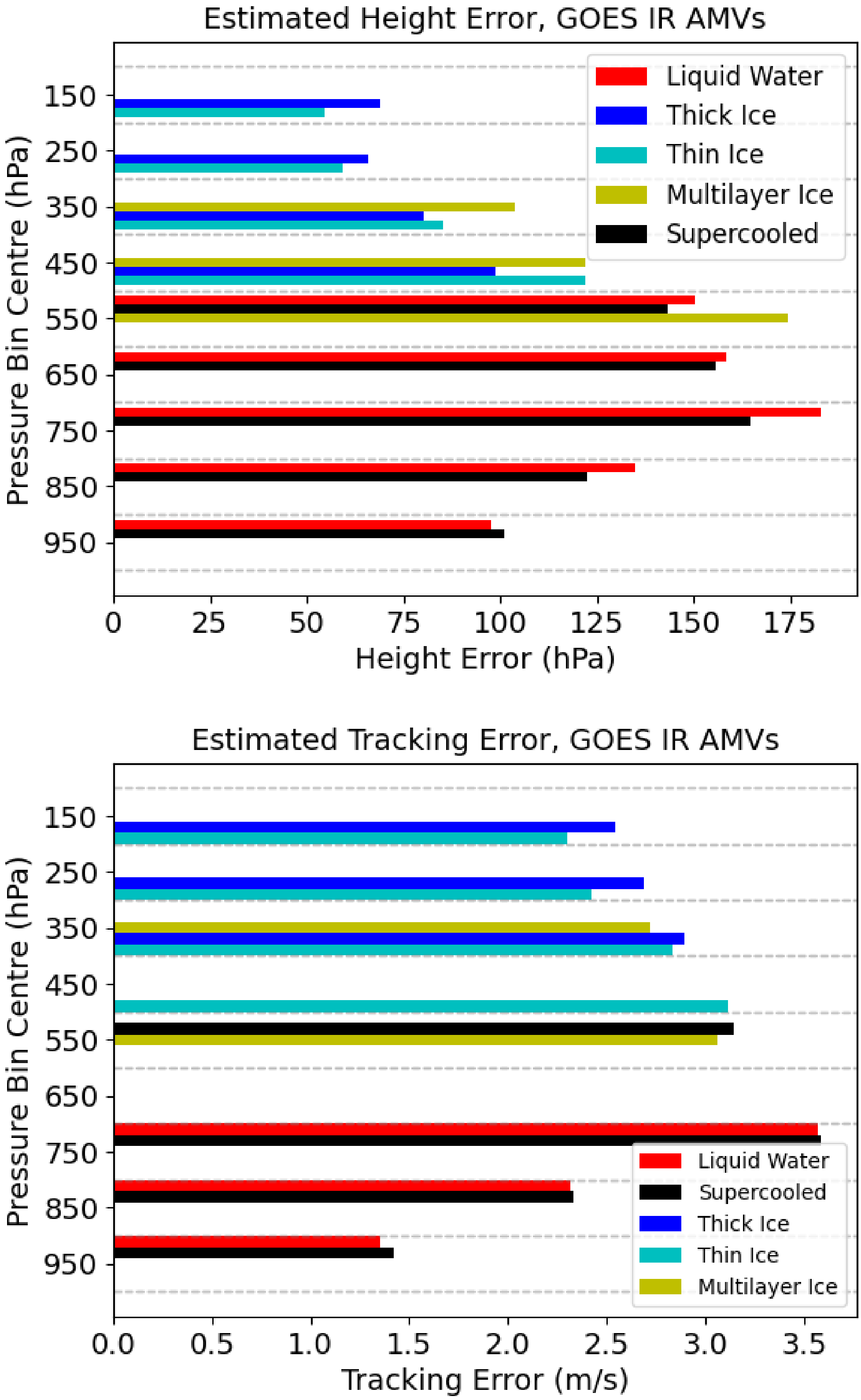

Figure 6: ECMWF-derived error estimates for each GOES IR cloud type, QI>50, AMVs for which a best-fit pressure solution exists. Top: estimate of the error in the assigned pressure; bottom: estimate of the tracking error. Tracking error plot: error due to height assignment less than 1.5 m/s in both u and v directions.

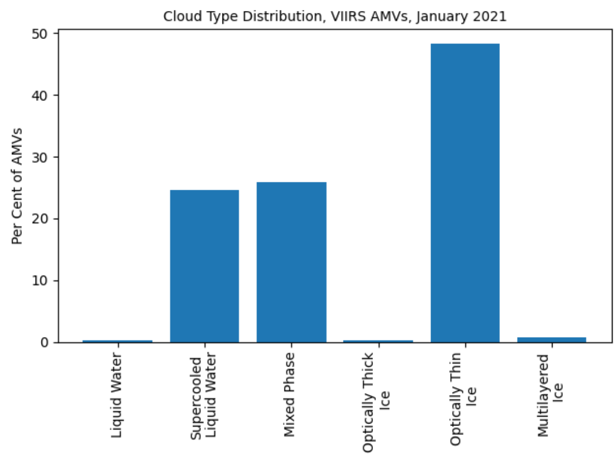

Figure 7: Frequency of each VIIRS cloud type, all available AMVs, Suomi-NPP and NOAA-20, January 2021.

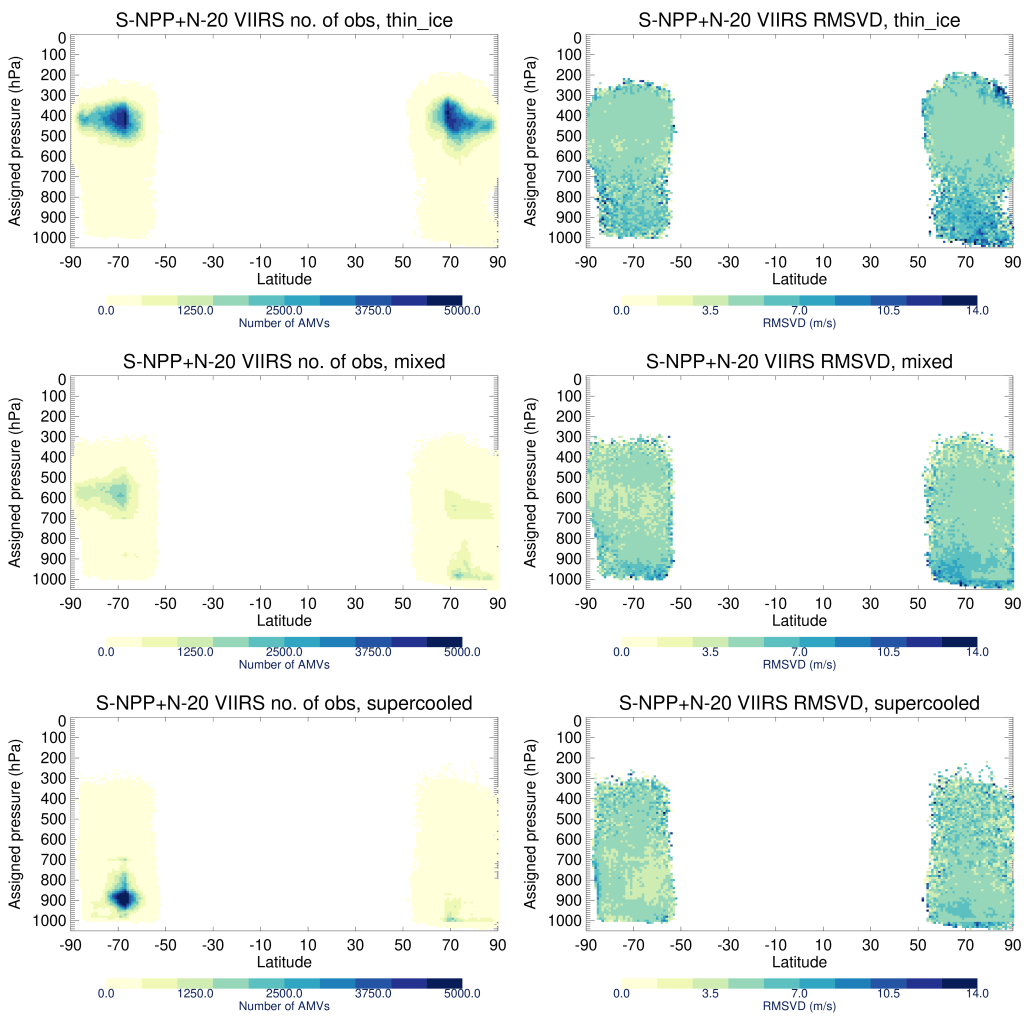

Figure 8: Spatial distribution (left) and RMSVD (right) of VIIRS cloud types for all available AMVs from Suomi-NPP and NOAA-20, January 2021.

4 Coefficient of Variation

4.1 Description of the CoV Parameter

The GOES AMVs are derived using a technique called nested tracking. This works by deriving a field of many vectors between two images, then using a clustering algorithm on this field of vectors to identify the dominant motion between the two images. This cluster is then averaged to find a vector between the two images, and two such vectors from three images are used to derive the final AMV [3]. This approach is designed to help isolate the dominant motion in scenes where there are multiple layers of cloud moving in different directions, preventing the final AMV from being an average of multiple motions.

In addition to information on the properties of tracked clouds, information that emerges from the AMV derivation process could also be useful for identifying high quality AMVs. There is space for such information within the new AMV BUFR sequence, with information on the GOES cluster properties an interesting source of information - one parameter of interest currently provided with NOAA's GOES AMVs is the 'coefficient of variation' (CoV). The CoV parameter is the standard deviation of the wind vectors within the largest cluster. Within the data it is provided as a figure normalised by the AMV speed. The parameter is available for both of the contributing subvectors of the AMV, between the three images from which the AMV is derived, however in this section we will use the average of the two values as CoV. Previous studies have found this is one of the more useful pieces of information provided with nested tracking AMVs and it is used for filtering AMVs at NCEP [6].

We could expect CoV to be a predictor of AMV quality as it gives some insight into how easy the tracking step was: if the vectors in the largest cluster agreed strongly with each other this suggests the cloud motion is clear, if they vary a lot, perhaps the feature tracking solution was ambiguous or even matched to the wrong feature. Currently such information is not used in our AMV assimilation, we only get a measure of the consistency with other AMVs and between the AMV subvectors via the QI value.

As in Section 3, here we examine the usefulness of CoV by using background departures as a proxy for AMV quality and seeing whether CoV can be used to filter out AMVs with large background departures. The background departures in this Section were derived by running an IFS cycle 48R1 assimilation experiment, at resolution TCo399, for January 2021. The experiment assimilated the GOES AMVs being studied, the interest here is in the characteristics of GOES AMVs with different CoV values compared to each other. We are also considering all of the GOES AMVs here, without QI filtering or a first guess check, as potentially the CoV parameter could provide an alternative to these quality control steps.

4.2 Using the CoV Parameter

An initial look at the CoV parameter as it is provided with the AMVs, normalised by speed, showed that CoV is highly correlated with AMV speed - the higher the speed, the lower the CoV value. Therefore it was decided to de-normalise CoV by multiplying by AMV speed. From this point onwards in this report CoV is simply the standard deviation of largest cluster vectors.

At first glance from Figure 9, the denormalised CoV is still not helpful as, from the overall distribution, we can see that CoV increases with AMV speed - simply filtering out the fastest AMVs would be a way to reduce background departures but would also exclude many meteorological situations. However, when the CoV distribution is split into height and latitude bands, we can see there are some height-latitude combinations where AMV speed does not vary so much with CoV, but background departures do - a much more useful situation for considering using CoV for AMV quality control.

Two examples are shown in Figure 10. The tropical low-level AMVs show the expected relation - that normalised RMS speed difference and mean speed difference increase with CoV. However, the southern hemisphere mid-level AMVs show the opposite relation - background departures decrease as the standard deviation of the cluster vectors increases. This is surprising as it the situations where the field of vectors was more variable result in better agreement with the model wind. The CoV distribution for the water vapour and visible GOES AMVs, and the VIIRS AMVs was studied but showed only a small change in background departures with CoV.

From this analysis the CoV parameter would seem to be unhelpful for AMV quality control. Filtering by CoV would be problematic in the areas where it is proportional to speed. For the two height-latitude areas highlighted, we would first need to understand why the relation goes in opposite directions, in particular why a more variable vector field at mid-level southern hemisphere produces an AMV that better agrees with the model wind.

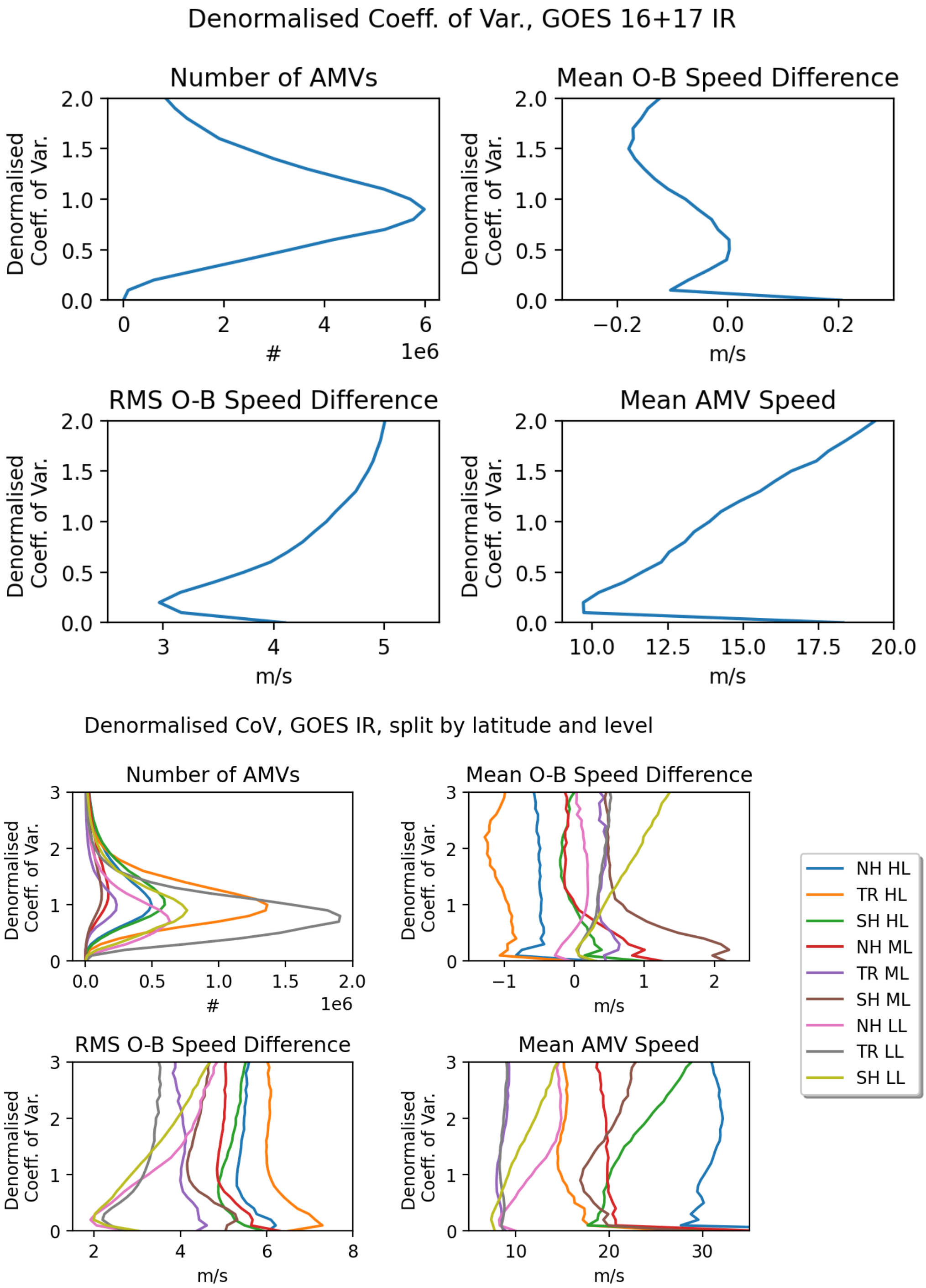

Figure 9: CoV distribution, January 2021, all GOES IR AMVs (top), split by height (HL: pressure < 400hPa , ML: 400-700hPa, LL: pressure > 700hPa) and latitude bands (Northern/Southern Hemisphere, Tropics), bottom.

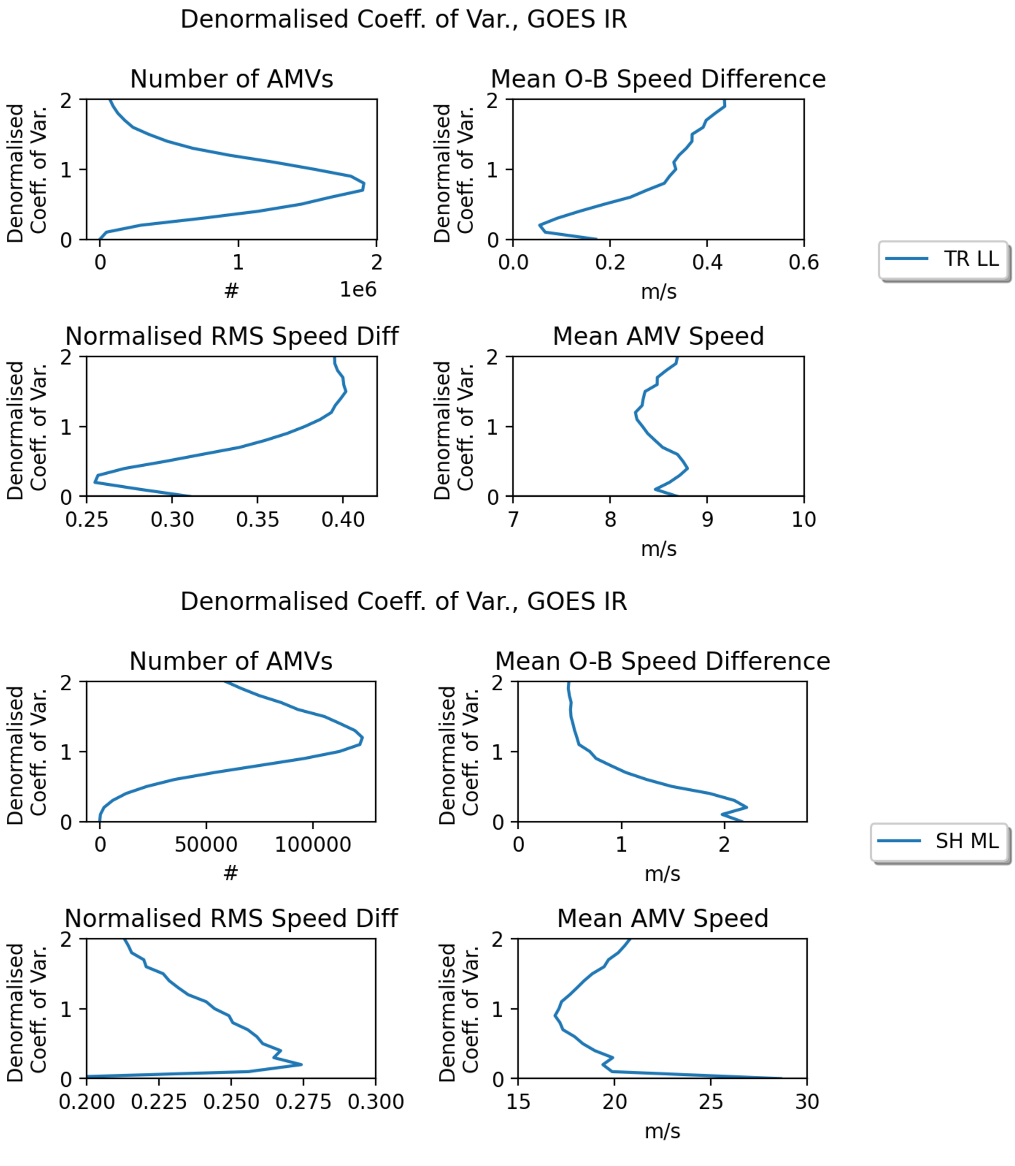

Figure 10: CoV distribution, January 2021, all GOES IR AMVs, for tropics P>700 hPa (top) and southern hemisphere 400-700 hPa (bottom).

5 OCA Filtering

5.1 Assessment of the test data

Optimal Cloud Analysis (OCA) is a cloud properties product available from EUMETSAT, using an optimal estimation approach. It retrieves a variety of cloud properties by minimising a cost function, making use of most of the SEVIRI channels. The solution cost value is retained and can give an indication of confidence in the cloud height retrieval, with high cost values common at cloud edges and over deserts. Where a multilayer cloud situation is suspected, the retrieval is repeated to fit the cost function to a two-layer cloud model, while cloud retrievals that do not do this can end up giving a pressure that is the average of the two layers. OCA also contains a cloud-top-pressure error estimate, high values of this parameter are associated with high, optically thin clouds, and with a low ECMWF forecast temperature lapse rate for optically thick clouds [1]. When OCA is used for AMV height assignment, the contributing pixels from the tracked feature are determined using the CCC method [2].

In the following, we use an AMV test dataset in which pixels that show either a high OCA cloud-top-pressure error or a high OCA solution cost function value have been excluded from the AMV height assignment. The dataset has been prepared by EUMETSAT for July 2019, and the thresholds applied are given in Table 1. As height assignment is known to be the largest source of AMV error, filtering by these parameters ought to produce a better quality AMV, especially, as mentioned above, there are physical explanations for why high cost and pressure error values could be linked to unreliable height assignment. The thresholds were chosen to try and limit the pixel rejection rate to no more than 20% for each cloud situation.

The AMVs in the test dataset are a little different to the near-real time Meteosat product as they use the Climate Data Record derivation which has a different cloud mask and uses ERA-Interim for model information rather than IFS, and because they are using OCA as the height assignment method rather than the situation-dependent Cloud Analysis scheme. Another key difference is that the dataset only includes AMVs from the infrared window channel (10.8μm); it does not contain AMVs from the water vapour absorbing 6.2 and 7.3 μm channels or from visible imagery as the near-real time product does. However, the test data contains a reference dataset without the OCA-based filtering applied and an OCA-filtered dataset, and it is the difference between the reference and filtered datasets that is of interest here.

Parameter	Single-Layer Water	Single-Layer Ice	Two-Layer Cloud
OCA Cloud-Top Pressure Error	40 hPa	30 hPa	70 hPa
OCA Height Assignment Optimal Estimation Cost	200	110	150

Table 1: Pixel exclusion criteria for the OCA height assignment step in the AMV test data, by cloud situation.

Figure 11 shows the difference in observation count between the reference dataset in which the filtering is not applied, and the filtered data where the pixel exclusion criteria have been applied. The filtering removes around 5-20% of pixels from the height assignment, depending on the criteria in Table 1 which results in a reduction in AMV count in many areas as can be seen in the zonal plot in Figure 12. In a few places the AMV count increases due to the filtering - this is the result of the binning applied in the figure; a given AMV may end up in a different pressure bin than before when some pixels are excluded from the height assignment.

Background departures for the reference and filtered datasets were produced by running IFS assimilation

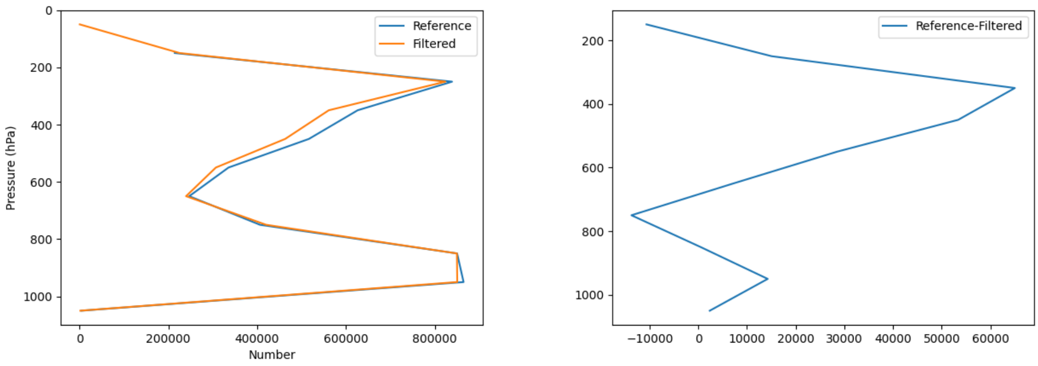

Figure 11: OCA filtering data, all available AMVs, profiles of total AMV count (left), difference in AMV count (right).

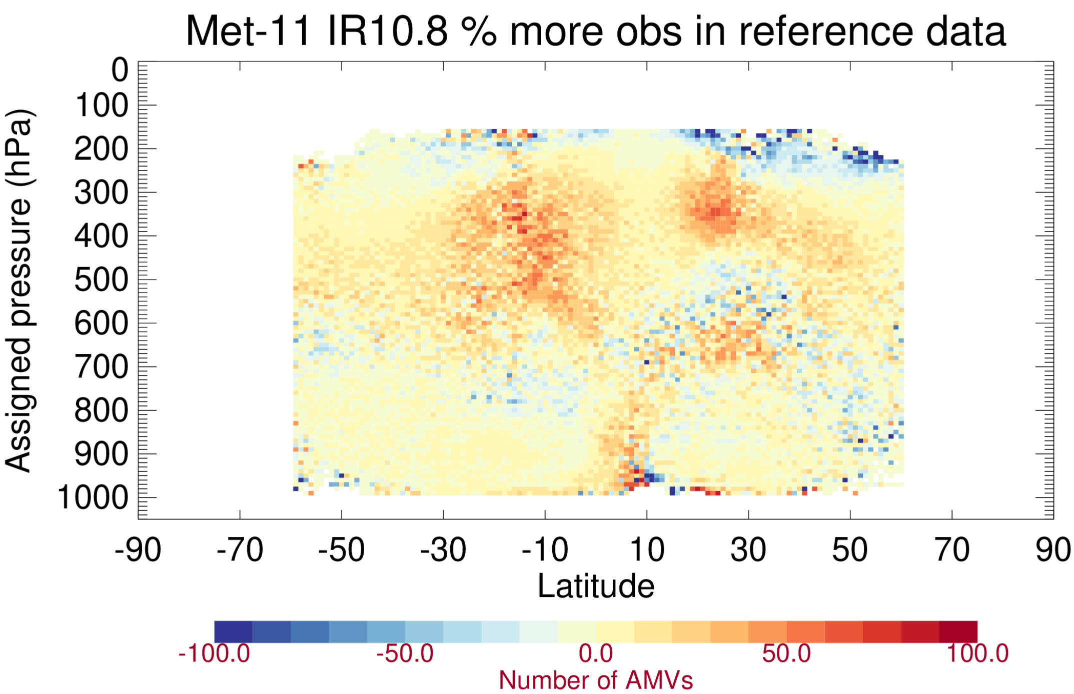

Figure 12: AMV count: reference data AMV count as a % of filtered data AMV count, for AMVs with QI>85 in the reference and filtered datasets.

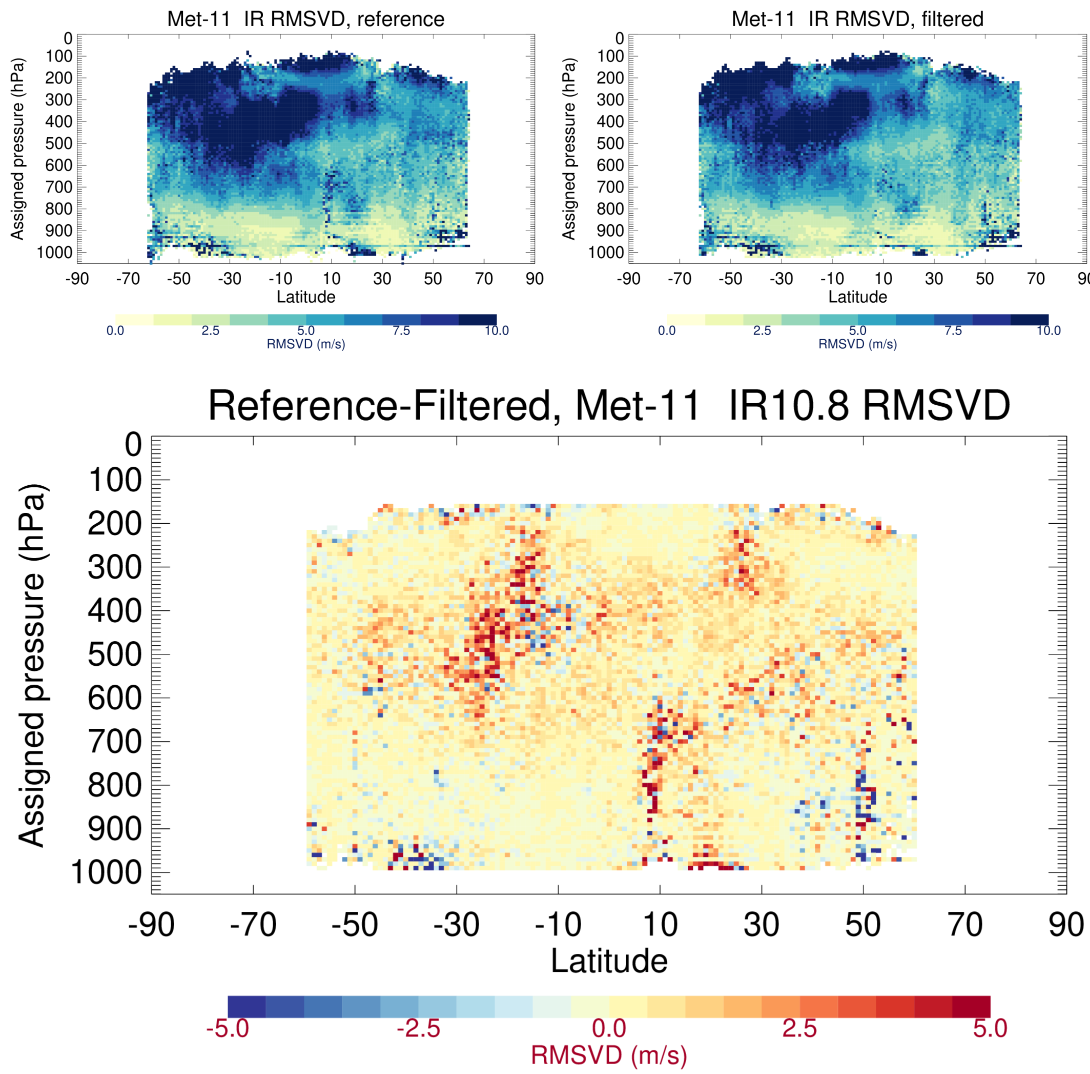

Figure 13: Top: reference and filtered data RMSVD values, bottom: Reference data RMSVD values minus filtered data RMSVD, all for AMVs with QI>85.

experiments at TCo399 resolution, cycle 48R1 over the month of July 2019 covered by the test data. The forecast length was reduced from the operational 240 hours to 12 hours in order to quickly generate the background departure statistics. In each experiment either the filtered or reference test data Meteosat-11 AMVs are assimilated, and the near-real-time Meteosat-11 AMVs are excluded.

The difference in RMSVD from applying the filtering can be seen in Figure 13, there are some reductions in RMSVD values from applying the filtering, and the areas of RMSVD reduction correspond nicely with the areas of data count reduction in Figure 12. Mean speed biases, both positive and negative, were also slightly reduced in some areas. The data shown is already filtered to QI values above 85, as it would be in operational use at ECMWF, so the pixel-level filtering is further enhancing the quality control.

Experiment	Description
No_Met11	No assimilation of Meteosat-11 AMVs
Reference	Assimilate the reference Meteosat-11 AMV data
Filtered	Assimilate the filtered Meteosat-11 AMV data
Reference_Tropics	Assimilate the reference Meteosat-11 AMV data, no 250 hPa restriction in tropics
Filtered_Tropics	Assimilate the filtered Meteosat-11 AMV data, no 250 hPa restriction in tropics

Table 2: Experiments run using the OCA test data

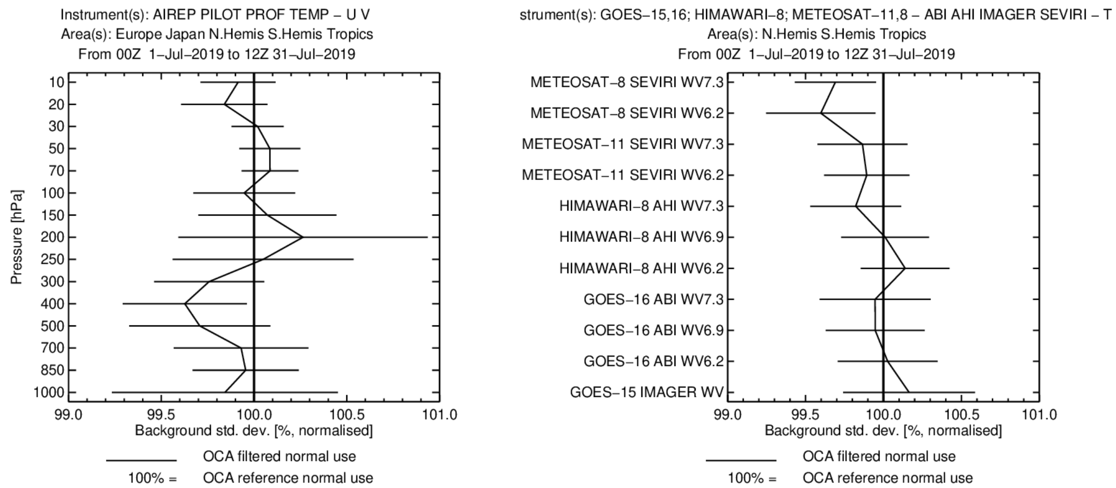

*Figure 14: Global standard deviations of background departures for conventional wind observations (left) and geostationary radiances (right) for the **Filtered** experiment, normalised by values from the **Reference** experiment. Horizontal bars indicate 95% statistical significance intervals.*

5.2 Assimilation Experiments

Given the reduction in background departures from the filtering scheme, and the physical rationale for excluding questionable pixels from the height assignment, it was decided to run assimilation experiments to assess the impact of the filtered and reference test data on forecast performance. Since much of the reduction in AMV count was between the surface and 250 hPa in the tropics (Figure 11) where we currently reject Meteosat infrared AMVs, another pair of experiments were run to see whether the filtered data delivers an improvement to forecast performance at those heights relative to the reference data. Five assimilation experiments were run, they are summarised in Table 2.

The configuration of the experiments was the same as those previously mentioned in this section, but with the full 240 hour forecast length. The same data selection steps as would normally be applied to Meteosat-11 IR AMVs were used [2], including strict limits on the use of AMVs over land in the northern hemisphere, and for **Reference** and **Filtered**, a rejection of infrared AMVs between the surface and 250 hPa in the tropics (25° N/S).

From Figure 14 we can see that there is a slight improvement in the forecast fit to conventional winds at 400 hPa from applying the filtering, as well as an improvement in fit to Meteosat-8 radiances, though the change in fit overall is small. Nevertheless, these reductions suggest a slight improvement in the

[2]Current ECMWF AMV quality control is summarised here: https://nwp-saf.eumetsat.int/site/monitoring-winds-quality-evaluation-amv-amv-use-in-nwp-ecmwf/

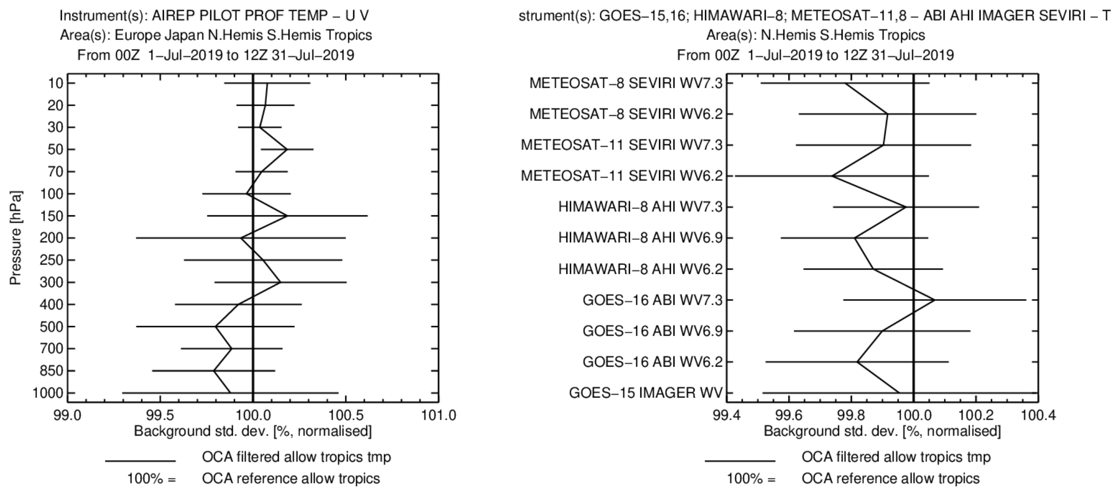

*Figure 15: Global standard deviations of background departures for conventional wind observations (left) and geostationary radiances (right) for the **Filtered_Tropics** experiment, normalised by values from the **Reference_Tropics** experiment. Horizontal bars indicate 95% statistical significance intervals.*

short-range forecast over the region most affected by the filtering, and they are hence a promising finding. For the case of extending the use of data in the tropics (Figure 15), there is no significant change in the forecast fit to conventional winds from applying the filtering. As for the impact of removing the rejection of infrared AMVs in the tropics below 250 hPa, various verification metrics showed that **Filtered_Tropics** and **Reference_Tropics** had degraded forecast quality compared to **Filtered** and **Reference**, respectively. It is important to note that we would not normally expect to see much impact from a one month dataset, these are merely preliminary results. However there are hints that the filtering could be beneficial, both from the background departures and from the **Filtered** results compared to **Reference**. A longer test dataset would allow us to see if the impact could become significant.

6 Discussion, Conclusions and Future Plans

In this report we considered additional cloud and tracking information available from the AMV derivation step to enhance the assimilation of AMVs in NWP. Our evaluation was primarily based on considering background departure statistics, and the additional parameters describe the cloud type and phase as well as the variation of tracking solutions. We also consider a test dataset from EUMETSAT, in which the pixel selection in the height assignment was based only on those pixels for which the OCA-based height assignment is considered more reliable. Our findings provide guidance for the future evolution of AMV products at EUMETSAT and elsewhere.

Sorting AMVs by cloud type revealed some small differences in background departures between cloud types - supercooled liquid water AMVs had larger background departures than warm liquid water, the same was generally true of optically thin ice compared to optically thick ice, especially in the water vapour AMVs. It was hoped that this information could be used to relax the spatial rejection of AMVs only for specific cloud types. To a large extent though, AMV cloud types are already implied by their assigned pressure, and therefore already accounted for in our quality control via pressure-based rejections and error profiles. Observation error estimates derived for each cloud type were also fairly similar for the same pressure levels. If the cloud types were linked to the tracked pixels rather than being the most common type within the tracking scene, there could be more dramatic differences between the background departures of different AMV cloud types, and this information would be worth revisiting.

The CoV parameter, an estimate of the robustness of the tracking solution, showed some correlation with AMV background departures in certain areas, in other areas a higher CoV was actually linked to lower background departures.The fact that the correlation between CoV and background departures goes in opposite directions in different areas would make it difficult to use operationally, and the fact that CoV is proportional to AMV speed in many areas would also make it inappropriate to filter by. Perhaps another way of involving the tracking reliability would be to use information from the cross-correlation surfaces to tell us how well constrained the feature matching solution was [5].

Filtering out pixels from the AMV height assignment using their pressure error estimates and their height assignment solution cost from the OCA product showed some skill at reducing background departures, even in addition to the strict QI filtering normally applied at ECMWF. Assimilation experiments could not reveal a significant positive or negative impact from the filtering using own-analysis based verification, though there were hints of an improvement in forecast-fit-to-observations from applying the filtering. A longer version of the test data with an improved version of OCA is being prepared at EUMETSAT that may be able to answer this question more conclusively. Future experiments could also look at extending the use of AMVs over land, and testing the filtering in the presence of water vapour and visible Meteosat AMVs to more closely resemble applying the filtering in an operational context.

The most promising of the three areas studied was the pixel-level filtering using the OCA pressure error and optimal estimation cost. An alternative approach to using the error and cost information would be to include it in the AMV product, perhaps just as the average value for the pixels used for each AMV's height assignment. If such information were to be included by the producers, this would allow AMV users to tune their own filtering to deliver the best forecast improvement. As the OCA cost and error values are themselves linked to the OCA optical thickness estimates, optical thickness would also be of interest for AMV quality control, and this could be considered as future additional information provided in the AMV product.

Acknowledgements

Francis Warrick is funded by the EUMETSAT Fellowship Programme. Thanks to Alessio Bozzo, Alessio Lattanzio, Phil Watts and Marie Doutriaux-Boucher of EUMETSAT for preparing the OCA test data. Thanks to Jaime Daniels and Wayne Bresky of NOAA for answering my questions about the GOES cloud and derivation information.

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