



Automated VNIR-only Cloud Detection for the WorldView Series and Similar Spacecraft

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Abstract

The WorldView-110 imager on board the WorldView-3 spacecraft has spatial resolution that is an order of magnitude higher than Landsat or Sentinel platforms. This imager instrument has been in extensive use by the land applications community. It presents a unique opportunity to atmospheric scientists as well. However, cloud masking remains a challenge. Currently available cloud products from Vantor Holdings Inc. are limited in detail and quality, and cloud coverage is represented as a percentage for the entire satellite image scene. Additionally, Vantor does not make its cloud masking product public and does not disclose the methodology behind it. The limited spectral channel complement of WorldView-3 also presents a challenge in detecting clouds.

We have developed a unique method for detecting clouds in WorldView-3 scenes using only visible and near-infrared (VNIR) spectral channels. VNIR-only acquisitions dominate the available WorldView-3 data record. Unlike traditional algorithms, this pixel-level algorithm, Cloud Mask for Ultra-high Resolution Spaceborne Imagers (CM-URSI), does not rely on any sources of a priori surface classification. The algorithm detects clouds and clear sky correctly, including in challenging scenes, such as reflectively varied snow/ice present underneath thin cloud cover. Validation proved challenging due to the scarcity of reference datasets that match the high image resolution. In the limited situations where in-situ or lidar data existed for validation, CM-URSI results agreed with in-situ data 100% of the time. Though this result is extremely encouraging, additional validation is necessary prior to any large-scale application.

In this paper, we show CM-URSI cloud masking results for a variety of scenes and initial validation. We describe WorldView data preparation and give some background on previous attempts at solving the WorldView cloud masking problem. We also discuss future directions such as extensions to commercial spacecraft with fewer channels than WorldView-3 and use in conjunction with computer vision machine learning methodologies.

Popular summary

Commercial satellite platforms such as Vantor's WorldView-3 present a unique source of data for a wide variety of applications due to their extremely high resolution (sub-meter). To make the data usable for land feature detections, researchers need to screen clouds from scenes in an automated fashion. Although Vantor does have a proprietary cloud mask product, it is presented as a single percent cloudy number, which is sometimes inaccurate. Also, the methodology is not made public. In this paper, we present a new general-purpose cloud masking algorithm for WorldView-3 that is free for the community to use and develop further. We show cloud masking results for a variety of scenes and initial validation. We discuss future directions such as extensions to commercial spacecraft with fewer channels than WorldView-3 and possible use in conjunction with computer vision machine learning methodologies.

1. Introduction



Traditional atmospheric research has always been performed using moderate-resolution imagers such as MODIS (Barnes et al., 1998) or VIIRS (Cao et al., 2017) with resolution on the order of hundreds of meters per pixel. Research-level cloud property retrieval algorithms have been successfully adapted for higher-resolution sensors traditionally used for land applications such as Landsat OLI (Operational Land Imager) (Knight et al., 2014) and Sentinel-2A and -2B MSI (Multi-Spectral Imager) (Spoto et al., 2012) through the Cross-platform High-resolution Multi-instrument Atmospheric Retrieval Algorithms (CHIMAERA) system (Wind et al., 2019).

OLI and MSI have resolutions of their narrowband channels on the order of tens of meters. There is a whole other class of sensors that has resolution on the order of 1-3m. The imager on board the WorldView-3 spacecraft managed by Vantor Holdings Inc., formerly Maxar Technologies (WorldView-3 datasheet), is one such sensor. We will refer to the entire class as Ultra-high Resolution Spaceborne Imagers (URSI). Due to their extremely high resolution and limitations on optics and data transmission rates, these sensors have a very limited spectral range.

WorldView-3 arguably has one of the widest spectral ranges among URSI. It carries 8 Visible and Near Infrared (VNIR) bands and a set of Shortwave Infrared (SWIR) channels. This configuration makes the main imager, the WorldView-110 camera, suitable not just for land applications, but also as a source of cloud microphysics data. WorldView-3 also carries the Cloud, Aerosol, water Vapor, Ice Snow (CAVIS) instrument (WorldView-3 datasheet), which has 30m spatial resolution. CAVIS spectral range is in some ways more convenient for cloud retrievals, but it has a very low number of acquisitions compared to the amount of data from the main imager, especially VNIR-only WorldView-3 acquisitions.

WorldView-2 (WorldView-2 datasheet) is a predecessor to WorldView-3 and only carries the WorldView-110 camera, which is the same main imaging instrument on board WorldView-3 but without any SWIR capability. WorldView-2 does acquire enough spectral information to enable cloud detection with the methodology we describe.

An initial investigation into the suitability of the WorldView-3 main imager for cloud physics research found it to have great potential (Wind et al., 2024). The first step in performing any sort of satellite-based work, whether it is studying cloud physics or land features, is distinguishing between clear sky and clouds. Landsat and Sentinel-2x provide a cloud mask variable. These sensors are also selective in scene acquisition and limit storage of cloudy scenes. The provided cloud mask variable has proven to be problematic in the past and needed regional correction (Supplemental figure S1). The cloud mask fails to identify some of the brighter parts of clouds, which leads to missing cloud property retrieval values at a significant enough scale that a correction needs to be applied. The spectral range of Landsat and Sentinel-2x is broad enough to permit application of MODIS-like spectral cloud masking tests without significant difficulty (Irons et al., 2012; Xi et al., 2019). Regionality of the selected subset of scenes allowed for manual selection of MODIS cloud mask spectral test regimes as needed (Ackerman et al., 2010).

Vantor has a proprietary cloud masking algorithm that is not made available to the public. The company releases a public cloudiness percentage for each scene. Using a single metric per scene obscures the variability of within-scene cloud dynamics and can be ambiguous, especially in polar regions with snow and ice. For example, Figure 1 shows two scenes with a 0% cloudiness rating despite obvious cloud contamination. Inaccurate cloud coverage estimates may be expected over snow or ice, the most challenging land cover classes for cloud detection using VNIR-only imagers. But neither of these scenes contains snow or ice. Cloud mask data can be purchased from Vantor, but the cost is such that the community at large opts out.

Some environments are more conducive to cloud masking than others. Well-vegetated surfaces and dark ocean scenes do not present a significant challenge in identifying most clouds; simple spectral thresholds perform admirably (Ackerman et al., 2010). Thin cirrus detection presents a challenge for all spectroradiometers in any environment, no matter what spectral channel set an instrument may have (Nguen et al., 2025). Any cloud-masking approach that relies on land and ocean surface conditions requires users to preclassify scenes, adding complexity. This process becomes especially cumbersome and error-prone if vegetation or ice cover is variable.



Even instruments with a wide spectral range, such as MODIS or VIIRS, experience difficulties with cloud masking in the Arctic due to inherent difficulties with ancillary data, which is required to perform scene preclassification for their cloud mask algorithms (Ackerman et al., 2010). These ancillary datasets are low resolution both temporally and spatially, on the order of tens of kilometers to 1 degree per grid point, and are not instantaneous, but rather temporal aggregates of as much as five days (Derber et al., 1991; Robinson et al., 2014). There are other options such as forecast models like GEOS-IT (Rienecker et al., 2008). While those models are initialized with observations, they are still models, adding uncertainty to the existing spatial and temporal resolution issues. Such datasets may be used by instruments such as MODIS or VIIRS with only minor impacts (Platnick et al., 2017), but they are unsuitable for an instrument like WorldView-3, where the entire complex scene would be described by a couple of points in the ancillary datasets. Temporal information cannot be used since geostationary platforms such as GOES-R or Meteosat do not provide usable coverage in the Arctic. Traditional spectral tests, such as those used by the MODIS cloud mask (Ackerman et al., 1998, 2010; Frey et al., 2008), rely on absorption by atmospheric water vapor. This does not work well in the Arctic, with well under 1cm of column precipitable water on average (Rinke et al., 2019). Arctic landscapes present exceptionally dynamic background environments where ice, snow, and vegetation coverage all change dramatically with the seasons. A significant built environment is also present (Manos et al 2026).

Even though the atmospheric water vapor amount is low, the Arctic is quite cloudy, with a monthly zonal cloud fraction at or above 60% (Figure 2, Achert et al., 2026). This high cloudiness, combined with seasonal lack of solar illumination, presents a challenge for URSI data utilization. High cloud cover and uncertain weather forecasts result in frequent cloud contamination in Arctic URSI imagery. Cloud cover is often falsely identified as snow/ice and vice-versa, thus confounding estimates of ground snow cover. Most areas of the Arctic have low population density and correspondingly limited opportunities for in-situ monitoring. Aircraft operations are challenging due to both weather and cost. Thus, URSI data is one of the best sources of high-resolution data for monitoring changes in the Arctic environment and a critical risk mitigation resource for local stakeholders as they adapt to changes in the Arctic ocean and landscape.

On average, 163 Arctic Worldview-3 scenes (a.k.a. catalog IDs) are collected each day during the Arctic summer. Manual examination is painstaking and exceptionally slow. An automated method of clearing clouds is essential for such continental-scale high-resolution monitoring of the Earth's surface. Conversely, automated cloud identification at high-resolution would be invaluable to the atmospheric research community. Having access to URSI-derived cloud microphysics gives us the ability to observe clouds at the earliest stages of their formation and inform our understanding of the processes that drive cloud evolution.

In this paper, we present a general-purpose cloud masking algorithm for use with the WorldView-3 and WorldView-2 main imagers, freely available to the community. This algorithm is fully automated and runs without user involvement or a priori information about scene content or atmospheric conditions. We present our algorithm results here, focusing on the most challenging of environments for cloud masking: the Arctic.

2. Data preparation

WorldView-3 separates the VNIR and SWIR acquisitions, which are recorded using different telescopes. There is a lag of a few seconds between acquisitions, resulting in slightly different observation angles. The VNIR channels are captured at 1.24m, and SWIR channels are recorded at 3.7m. This allows the satellite to optimize its data flow and acquire additional (SWIR) information on command. The SWIR data are delivered to the end-user in one continuous long swath, 15 km across and up to 100 km long. Due to the higher resolution, the VNIR data are delivered in a set of multiple smaller scenes to avoid large file sizes. Thus, multiple VNIR scenes fit into a single SWIR data record.



To harmonize the two products, the VNIR and SWIR images are projected to a common spatial grid and corrected for terrain-induced pixel displacement. The results are converted to top-of-atmosphere reflectance (Kuester, 2016) according to Vantor's documentation (Vantor, Inc., 2025) at the Polar Geospatial Center using the imagery-utils package (https://github.com/PolarGeospatialCenter/imagery_utils). Where possible, the data are then stacked into a 16-band integrated product in NetCDF-4 format. Image-level metadata (e.g., solar and view geometry) are converted to pixel-level grids and included in the NetCDF data stack. NetCDF-4 format is more appropriate for atmospheric science tools than the binary formats used in land surface remote sensing. This data unification was of utmost importance to the first version of our cloud identification algorithms, as it used a MODIS-like spectral thresholding paradigm, which involved combinations of VNIR and SWIR channels. The second version of the algorithm, called CM-URSI, operates only on VNIR channels and thus does not require the SWIR channels. However, when SWIR is available, unification makes the data ready for later use by CHIMAERA for retrievals of cloud optical and microphysical properties. We initially attempted to run CM-URSI on full 1.24m data. However, pixel value heterogeneity at native resolution presented excessive noise. Reducing VNIR resolution to 3.7m eliminated scene noise in CM-URSI retrievals.

Even though CM-URSI only requires VNIR reflectance without the need for a priori data from other instruments, we still produce this georeferenced unified product for further downstream processing to create derived physical variables (Level 2) and, eventually, to pan-Arctic statistical gridded products (Level 3).

3. Description of Current Algorithm

Our first attempt at automating cloud masking from WorldView-3 (Wind et al., 2024) followed in the general vein of a traditional cloud masking algorithm based on spectral thresholds. We adapted CHIMAERA to perform retrievals of cloud top properties and MODIS-like cloud microphysics (Platnick et al., 2017) from WorldView-3. This initial approach performed reasonably well on the set of test scenes it was presented with. We quickly found that it had limits. It could only execute on WorldView-3 scenes that had all 16 spectral channels present. Furthermore, we found that the algorithm was confused by high SWIR reflectance over barren terrain. An altogether different approach was needed.

Changing tactics, we decided to improve the initial algorithm by adding additional spectral threshold conditions, again staying with the tried-and-true MODIS-like approach (Ackerman et al., 2010, Frey et al., 2008). However, all those approaches depended heavily on having a variety of a priori knowledge of surface properties. Meter-scale surface classification maps may exist for certain areas, but not globally. Moreover, seasonal changes in snow and ice cover, common in the Arctic, change the working conditions dramatically. The MODIS cloud mask algorithm becomes confused in the presence of snow and ice when ancillary data does not accurately capture it (Ackerman et al., 2010). Figure 3 shows a portion of a clear-sky Terra MODIS scene from January 28, 2025, 16:45UTC, with snow cover over a section of the Midwestern US. In this false-color RGB composite, any clouds, if present, would appear in shades of either yellow or pink depending on cloud thermodynamic phase. Because the snow was not well captured by one of the "state of the surface" ancillary datasets used by the MODIS cloud mask, some of that snow was identified as "cloud".

Given the very high spatial resolution of the WorldView imager, an effective cloud identification algorithm must be able to operate without any a priori knowledge about a pixel to be classified, especially in the Arctic. No data product could pre-identify floating sea ice, which changes by the hour at WorldView resolution. Depending on their size, individual sections of sea ice may be on the level of scene noise for an instrument like MODIS or be entirely subpixel. But they become major scene features at 3.7m resolution.

We observed that clouds tend to be spectrally flat in the VNIR range, especially between 550 and 900nm (Platnick et al., 2017), unlike more complex surfaces. Based on that observation, we



set out to examine sections of a set of 29 WorldView-2 and WorldView-3 scenes. 17 of those had all 16 spectral channels available. We used a variety of spectral-based criteria to create custom pixel groups for the scenes, selecting pixel populations of known classes for analysis. For example, for many scenes WorldView-3 channel 2 reflectance being less than 0.4 could be used to select barren land. A combination of WorldView-3 reflectance in channel 8 being less than 0.6, WorldView-3 reflectance in channel 3 being greater than 0.5 and WorldView-3 channel 2 reflectance greater than 0.6 was indicative of clear sky bright ice surface. Supplemental Table S1 shows the list of WorldView-2 and -3 scene IDs used in this study, though not every scene contributed to model creation. About half of the scenes are from Alaska, in the Utqiagvik area. Others are on or near Greenland during the Arctic Radiation-Cloud-Aerosol-Surface Interaction Experiment (ARCSIX) field campaign timeframe (ESPO ARCSIX, 2026, Schmidt et al., 2020).

The custom pixel groups were used to tease out any characteristic shapes in all-channel reflectance curves of clouds and various surfaces, according to our hypothesis. Figure 4 shows an example of the custom pixel groups selected from the WorldView-3 scenes. In this case, we designed our selections to identify only pixels containing a cumuliform cloud and pixels that contain only snow-free land surface. We aggregated pixel groups of the same feature class from different scenes to create combined feature class spectral profiles.

We focused on the 8 VNIR channels of WorldView-3, as those are the ones acquired for every scene. We then used a Python script to create histograms of measured reflectance in each band, normalized within the sample set, as a function of wavelength. We then fit quadratic functions to maximum counts for select sections of spectral channels. Figure 5 shows some examples of such plots. Panel a shows one of the models for a clear-sky snow-covered surface. With some minor variations, snow cover displays a generally convex curvature in the reflectance function. Panel b shows a typical spectral profile of a clear-sky land surface. A clear-sky non-snow profile is generally quite concave. Panel c shows a reflectance profile typical of a cloudy model with its characteristic flatness in the 550 and 900nm range. Each panel, in addition to a histogram of counts, shows the peak normalized reflectance plot (solid red line) and the three sectional fits in black, green, and blue, respectively. The number of samples used to generate each model is listed in the colorbar for each model plot.

Linear regression was insufficient to capture the behavior. Quadratic functions fit very well in addition to being computationally inexpensive. We did attempt higher-order polynomials as a single curve over the entire available spectral range. We found that this approach not only resulted in a poorer fit ($RMS > 0.3$, as opposed to $RMS < 0.1$ for piecewise quadratic), but also added significant computational requirements. After selecting the fit functions, we altered the initial sample sets and iterated on fitting to minimize histogram spread as much as possible, so as to improve the models' representation of measurements.

We created a set of nine such statistical models. These models were then added as a static lookup table to a Fortran program that performed the actual encoding of incoming pixels as "cloudy" or "clear". Table 1 shows the full listing of coefficients of these models in the current version of CM-URSI. The coding is performed by a variety of tests. Figures 6 and 7 show the full algorithm execution flow chart. The algorithm uses a sieve-style processing flow where pixels that exit a series of tests are not examined again.

The resulting raster includes individual model matches for the three sections of the spectral range (Table 1). There is also the net cloud mask score that shows the path taken through the flow chart. Additionally, dispersion in channels 5 and 8 is included. Dispersion measures may be useful for overall scene analysis, as discussed near the end of section 4. Finally, we provide the cloud detection confidence value, an integer between zero and five that indicates how confident we are in the detection result. A value of zero indicates no confidence at all, and five indicates the highest confidence. Figures 6 and 7 show how the confidence settings are derived as a function of the spectral tests applied in the algorithm. The same information is summarized in supplemental Table S2.



The CM-URSI code has a computational complexity of $O(n)$, where n is the number of pixels under consideration, and does not require significant computational resources to execute.

4. Results and discussion

In this section, we show some selected example results from running CM-URSI over a variety of complex scenes that can be challenging even for instrumentation with more spectral diversity. The complexity stems from scene backgrounds being snow/ice or a combination of land surface types that normally would require a priori scene classification before attempting any cloud detection.

CM-URSI can detect thin clouds over sea ice. Figure 8 displays an example of CM-URSI cloud detection results for a WorldView-3 scene from August 8, 2024, at 21:37:40 UTC. Panel a shows the true color image of the scene with thin stratocumulus clouds over a sea ice surface. Panel b shows the CM-URSI cloud detection result. The scene is almost completely cloudy and so would not be of much use to the land community, but very much of interest to the atmospheric science and radiation community. Thin clouds like these tend to be radiatively active and produce a net warming effect on the atmospheric column due to being generally colder than the surface. They allow solar radiation to penetrate down to the surface yet prevent some of the thermal radiation from leaving (Bennartz et al., 2013). These thin clouds are challenging to detect with traditional algorithms from moderate-resolution instruments, and their true extent across the Arctic is not well characterized. Now that we can detect this type of cloud, we may be able to study their extent and then quantify their radiative effects and impact on the Arctic environment.

One obvious challenge with cloud masking using only VNIR channels and without any water vapor channels is that thin cirrus clouds over non-ocean surfaces are very difficult to detect. That is an inherent drawback of any VNIR-only algorithm. However, thin cirrus clouds present a challenge to all cloud masking algorithms for passive sensors due to their signal being weak in every spectral channel.

While CM-URSI detects clouds when they are present, it must also properly deal with complex scenes where there are no clouds at all. CM-URSI generates a very small percentage of false positives in a control scene. Figure 9 shows the result. The WorldView-3 scene from June 16, 2021, at 22:38:38 UTC was selected because SWIR channel examination confirmed the scene did not contain any clouds. The scene background is complex, with both ocean and land surface present. Additionally, there is extensive snow/ice throughout. This scene would require preclassification of land cover types to use a traditional spectral cloud mask such as MODIS (Ackerman et al., 2010). CM-URSI does not require knowledge of scene background. The cloud mask result shows a very small percentage of false positives concentrated in a small coastal snow/ice area. Given the severe constraints under which CM-URSI operates, we consider this a very good result, again with the consideration that far more well-resourced cloud masking algorithms that have a priori scene classification and much more spectral information also give false positives. Land applications users would prefer to discard some clear pixels rather than risk retaining cloudy pixels. For atmospheric applications, clear pixels that were falsely identified as clouds fail attempts to retrieve their cloud optical and microphysical properties, and so are eliminated from any consideration that way. We provide multiple confidence levels to give users flexible options as to how to make their mask selections for various types of processing.

Another type of complex scene is one where bare ground, snow/ice, and clouds are present all together. CM-URSI successfully separates clouds from such a background. In Figure 10, we return to the WorldView-3 scene from May 26, 2015, at 22:16:39 UTC. Panel a shows the true-color scene. This scene has the SWIR channels present, so we can create a false-color RGB composite in panel b that allows us to distinguish between clouds (white) and snow/ice (red). The CM-URSI cloud mask, using only the VNIR channels, successfully distinguishes between clouds, land, and ground snow/ice. This kind of scene is a good example of data that would previously have been discarded for use in land applications due to a significant cloudiness percentage. Utilizing this



cloud mask, researchers can proceed with the usable pixels, as the clouds are all focused in one area. Moreover, by subtracting the cloud mask and focusing on the cloud-free area, it would be possible to use a simple VNIR reflectance thresholding technique to estimate snow cover. For atmospheric science, use of this scene would result in successful retrievals of cloud optical thickness and cloud effective radius. CM-URSI makes a scene valuable that would have been previously discarded. Additional CM-URSI cloud masking examples with complex scene backgrounds can be found in supplemental figures S3 and S4.

CM-URSI is constrained by being based on VNIR channels and thus is a daytime-only algorithm, having a requirement of sufficient solar illumination. We found that a sufficient solar zenith angle constraint to be 75° (a 15° solar elevation angle). This is a more severe constraint than is used by moderate-resolution spectroradiometers such as MODIS and VIIRS (Platnick et al., 2017). It may be possible to extend the CM-URSI application to larger zenith angles. Computer vision machine learning techniques, combined with using a large dataset of WorldView-2 and WorldView-3 data processed through CM-URSI as training data, may be able to aid detection in lower illumination conditions or with reduced spectral channels for certain types of clouds.

Additionally, during our analysis, we found that very high dispersion values that show through in the presence of clouds are associated with sea ice fields, and so the information may be useful for sea ice studies (Supplemental, Figure S2). More extended analysis and study of the associated research possibilities are outside the scope of this paper.

5. Validation

Validating the CM-URSI algorithm presents several unique challenges. Traditionally, cloud detection algorithms are best validated using lidar or radar. But the footprint of spaceborne lidar or radar is such that one of those footprints would cover a large portion, if not the entirety, of a WorldView-3 scene. This leaves in-situ instruments for attempting direct validation, and opportunistic aircraft observations or statistical studies for looking at area effects.

Ground-based zenith-pointing ceilometers are a common instrument used to measure instantaneous cloud cover at a station. We were able to use one such site located in Alaska. Airborne lidar is an instrument that can obtain cloud cover information along an aircraft flight line. There was no coordination between existing aircraft operations and WorldView-2/WorldView-3 since they were not the target of these airborne campaigns. Nevertheless, we were able to obtain an observation of opportunity during a recent aircraft field campaign in the Arctic.

We used the concurrent data from a ceilometer present at the Department of Energy North Slope of Alaska Atmospheric Research Measurements (DOE NSA ARM) site C1 located near Utqiagvik, AK (DOE website, 2026). The ceilometer is a zenith-pointing instrument that returns a measurement of cloud base height as a function of time (ARM, 1997). It returns whether clouds were detected and cloud base height if applicable. Unfortunately, the ceilometer data gives us only an instantaneous single sample for a single point in a scene. The ceilometer takes measurements every 17 seconds. Normally, that would be considered very high frequency, but 17 seconds is roughly equal to the amount of data acquired by WorldView-3 in a single scene. It is a point sample that can be compared instantaneously against a specific point in a WorldView-3 scene that corresponds to the coordinates of the site location.

Results of the comparison for WorldView-3 scenes over Utqiagvik, AK, are shown in Table 2. CM-URSI matched the ceilometer cloud detection very well (95% accurate). Of course, this is a very limited dataset, and more validation is needed, but initial results are encouraging. WorldView spacecraft do not acquire data in a predictable swath pattern, but the Utqiagvik Central ARM site is a long-running permanent facility in a town that is a frequent target for satellite acquisitions. Accordingly, we expect to see many more acquisitions of opportunity in the extended data record that will be useful for validation.

The High Altitude Lidar Observatory (HALO) (Nehrir et al., 2018) was deployed during the ARCSIX field campaign in Greenland on board the NASA DC-8 aircraft. There was no explicit



coordination with any WorldView spacecraft, as they were not the subject of any ARCSIX investigation. However, upon examination of both HALO flights and available WorldView scenes acquired during the ARCSIX campaign, WorldView-3 spacecraft intersected with HALO flight lines twice. We examined both of those scenes. Unfortunately, the technically more interesting transit across the WorldView-3 scene, ID 10400100991D5A00, was not useful. The time difference between WorldView-3 and HALO was too great, and HALO did not observe the same cloud field as WorldView-3. The second transit of opportunity happened on Jun 7, 2024, when the DC-8 passed across WorldView-2 scene ID 10300100FC0CA000. The overall scene is a clear-sky scene with a complex snow and ice surface. Because of the clear sky, the acquisition time difference of over an hour was not as important. HALO has a 100m footprint that covers many 3.7m WorldView pixels. We averaged the relevant WorldView pixels that fit HALO footprints and show the result in Figure 11.

These results are very limited and present only an initial attempt at validation of the CM-URSI algorithm. WorldView-3 and WorldView-2 data are not easily accessible due to licensing restrictions. The sheer data volume is such that it is not possible to process the dataset outside a large-scale facility. All analysis for this paper was performed on a single core of a Titan Vulcan X170 mobile workstation. Whereas the CM-URSI algorithm itself can be executed on as little as a K-12 classroom Chromebook computer, the storage requirements for WorldView series data are significant enough that coordination with larger storage and computing resources is necessary for processing more than a few dozen scenes.

Certain challenges remain. Cirrus detection, possible in quite a few situations, is far from perfect, especially over snow/ice surfaces. The already weak signal from cirrus clouds becomes completely drowned out by the strong signal that snow/ice surfaces present in the VNIR range. The cirrus challenge is not unique to CM-URSI and is a well-known issue even for instruments that carry water vapor absorption and longwave infrared channels (Nguen, et al., 2025). The Arctic atmosphere has very low water vapor levels (Rinke et al., 2019), conditions that make water vapor absorption channels far less effective at differentiating cirrus from the ground.

The resolution of URSI instruments presents an additional challenge that is unique to URSI. We found that bare cliff sides, wet with meltwater and thus quite reflective, when observed from certain angles, can have a reflectance profile indistinguishable from that of a cloud. As we process more data and expand the cloud mask dataset both spatially and temporally, we can fine-tune the models to resolve some of the challenges presented by land surface structures.

6. Conclusions and Future Directions

Data from commercial ultra-high-resolution spaceborne imagers (URSI) present unique research opportunities for a wide variety of research communities. But differentiating between clouds and surface using these imagers presents a challenge due to their limited spectral range and lack of ancillary surface classification data at appropriate resolution. We developed an open-source community cloud masking algorithm for use with ultra-high-resolution spaceborne imagers, CM-URSI, that successfully overcomes the above challenges. Both initial validation against in-situ observations of opportunity and visual inspection indicate that the CM-URSI algorithm performs well in detecting clouds and clear sky.

The combination of CM-URSI processing path ID and cloudiness confidence levels gives users flexibility on how to interpret the cloud mask results to best suit their application. For example, one CM-URSI processing path, ID -15, combined with a land/sea mask appears to be able to detect broken sea ice even when the scene has very large amounts of thin-to-moderate cloud cover. And certain types of snow/ice and clouds can look spectrally ambiguous in the range covered by processing path ID -3. Thus, it could be beneficial to treat those pixels as “cloudy” for cloud applications because pixels that are truly not clouds will fail cloud effective radius retrievals, thus disambiguating the pixel set. Several other processing paths appear to uniquely identify certain scene features and may be useful in deriving further data products based on CM-URSI results.



This new cloud masking algorithm could support the development of an extensive ultra-high resolution cloud mask dataset from the commercial spacecraft data holdings at the Polar Geospatial Center. This holding is extensive in both temporal scale and spatial coverage, rivaling MODIS and VIIRS data records in length. The existence of such a dataset would allow for large-scale validation of CM-URSI results and lead to improvement in moderate-resolution imager cloud detection using methodologies similar to work described in Werner et al. (2018).

Future work should utilize concurrent acquisition pairs of WorldView-110 and CAVIS instruments as a source of validation data. CAVIS has additional spectral channels that would be helpful in verifying cloud detection, albeit at a lower resolution. It has the distinct advantage of being on the same spacecraft as the WorldView-110 camera. Observation timing and geometry issues are a major challenge to any validation and verification efforts. WorldView-110 and CAVIS concurrencies would have that challenge removed.

These results also show promise as a way to create a large training dataset for machine learning computer vision models that could key off the observed textures as well as the explicit spectral information. This would allow us to extend the cloud masking back in time to older commercial imagers that had fewer VNIR spectral channels than the WorldView series. The same type of machine learning approach could allow us to extend the WorldView cloud mask dataset to solar zenith angles greater than the current 75° limit.

It is our sincere hope that having the CM-URSI algorithm available will bring greater utilization of data from commercial spaceborne imagers by all research communities and the wide variety of stakeholders who could benefit from such use. Having this community cloud mask product will allow for studies that have not been attempted before due to the challenges presented by ground/cloud differentiation. As always, as more data is processed, there will be room for improvement, but with CM-URSI considered community software, such work is encouraged.

Data and software availability

All derived data products associated with this manuscript are freely available. Original Level 1 WorldView-2 and WorldView-3 data were acquired through the US Government Plus license of the Electro-Optical Commercial Layer contract between the National Reconnaissance Office and Vantor Holdings, Inc. The data are available to US federal employees and contractors and federally funded investigators through several avenues, including the Polar Geospatial Center, the NASA Commercial Satellite Acquisition Program, Vantor's G-EGD platform, USGS's Earth Explorer, and others. They can also be purchased directly from Vantor or via a reseller. The image identifiers have been included in this manuscript to assist in traceability and reproducibility.

The CM-URSI software is available free of charge on GitHub at the following link:
<https://github.com/galinawind/CM-URSI/>.

Author Contributions

Dr. Galina Wind is the developer of CM-URSI algorithm. She developed the retrieval methodology and performed all testing and validation.

Claire Porter performed the essential steps of obtaining and preparing the WorldView data. That involved format conversion, proper geolocation and reflectance computation so that WorldView-3 data was properly science-ready.

Dr. Anna Liljedahl is the Arctic environment specialist. She articulated community needs and directions in which our overall investigation would be of the greatest benefit. Without knowledge of those community needs, CM-URSI algorithm would have never been developed.

Competing Interests

The contact author has declared that none of the authors has any competing interests.



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589

<i>Model Name</i>	<i>WorldView -3 Channels</i>		
	1, 2, 3, 4	3, 4, 5, 6	4, 5, 6, 7, 8
<i>Model Coefficients</i>			
<i>Land 1</i>	73.1, -88.1, 25.4	-9.0, 22.5, -11.7	68.0, -82.2, 23.6
<i>Land 2</i>	124.6, -145.6, 41.5	-18.4, 35.4, -16.1	116.6, -146.0, 44.4
<i>Ice dark</i>	-32.0, 27.0, -4.5	0.3, -6.3, 3.9	1.9, -9.5, 5.3
<i>Ice middle</i>	-32.0, 28.2, -5.2	-13.9, 14.1, -3.2	-10.0, 7.7, -0.7
<i>Ice bright</i>	-46.8, 44.0, -9.5	-39.0, 52.1, -17.2	-11.3, 11.3, -2.4
<i>Cloud dark</i>	32.4, -45.9, 15.6	1.4, -5.0, 2.3	18.9, -27.2, 9.3
<i>Cloud middle</i>	4.5, -22.0, 10.5	-47.8, 71.0, -26.4	51.6, -62.5, 18.2
<i>Cloud bright</i>	-49.0, 35.6, -4.6	-39.9, 59.5, -22.2	92.7, -119.2, 37.7

590 *Table 1: Listing of CM-URSI quadratic spectral fit model coefficients and channel regions where*
 591 *each model is used.*

592



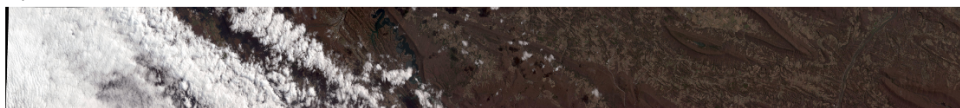
<i>Observation Date/Time</i>	<i>NAS ARM ceilometer cloudy</i>	<i>CM-URSI cloud detected</i>
2015-04-11	Yes	100% cloudy (CM confidence = 5)
2016-05-11	No	0% cloudy (CM confidence = 0)
2021-06-16	No	0% cloudy (CM confidence = 0)
2024-08-26	No	95% clear (CM confidence=1)
2024-09-04	Yes	100% cloudy (CM confidence = 5)
2024-09-09	Yes	100% cloudy (CM confidence = 5)

593
 594 *Table 2: Comparison of CM-URSI cloud detection results with the North Slope Alaska DOE ARM*
 595 *site ceilometer at Utqiagvik, AK (Site C1). The ceilometer is a ground-based instrument that*
 596 *captures a zenith-pointed measurement of cloud cover every 17 seconds. 17 seconds is roughly the*
 597 *size of a single WorldView-3 VNIR scene. Thus, unfortunately, only a single measurement is*
 598 *captured per scene.*
 599
 600

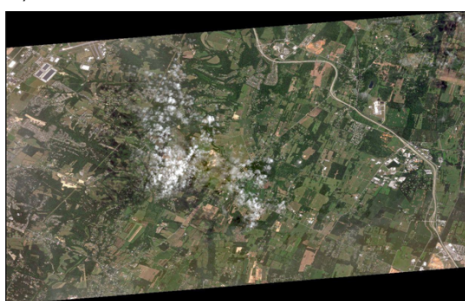


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602
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a) WV-3 scene ID 10400100B511F900



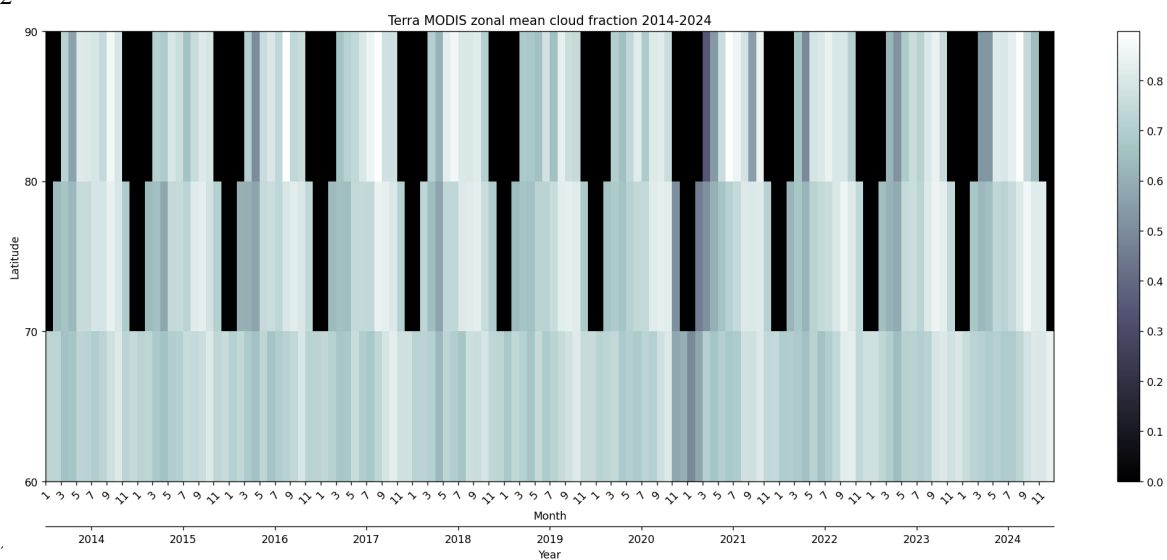
b) WV-3 scene ID B0400011002DA810



604
605 *Figure 1: Example WorldView-3 scenes illustrating Vantor's proprietary cloud mask's drawbacks.*
606 *Panel a) shows a mosaicked set of scenes acquired between State College, PA, and Martinsburg,*
607 *WV, on 03.10.2026 at 16:15:15 UTC. Panel b) is a scene acquired just south of Martinsburg, WV,*
608 *on 07.13.2026 at 16:10:48 UTC. The Vantor metadata lists both of these scenes as having 0% cloud*
609 *cover.*
610
611



612

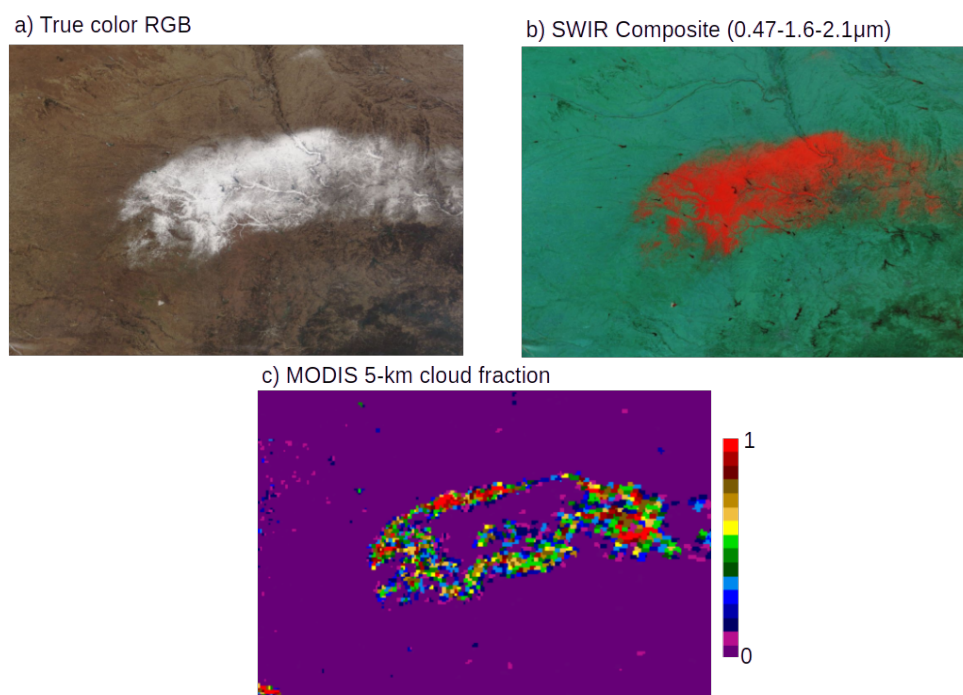


613

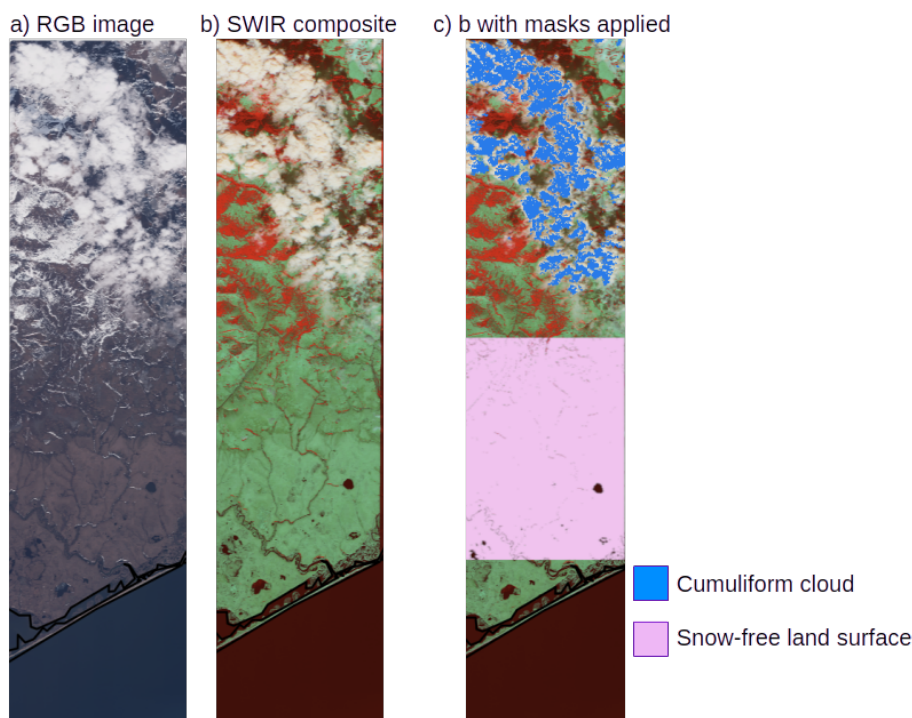
614 *Figure 2: 10° zonal 1°x1° spatially aggregated mean daytime cloud fraction from Terra MODIS for*
 615 *the operational period of WorldView-3 spacecraft. Black areas correspond to periods of polar*
 616 *darkness. This high cloudiness, combined with seasonal lack of solar illumination, presents a*
 617 *challenge for URSI data utilization.*

618

619



620
 621 *Figure 3: An example of Terra MODIS Data Collection 6.1 cloud mask confusion from 2025, day*
 622 *028, 16:45 UTC in the SE section of the granule. Panel a) shows the true-color RGB image of a*
 623 *clear sky scene with snow on the ground. Panel b) shows the SWIR composite image using the 0.47,*
 624 *1.6, and 2.1 µm bands. In this composite, bright red indicates snow/ice. Clouds would appear either*
 625 *pink or pale yellow. Panel c) shows the 5km resolution MODIS cloud fraction. Because ancillary*
 626 *scene pre-classification does not capture this snow, the spectral cloud mask algorithm treats the*
 627 *scene as being snow-free, becomes confused, and maps the snow as clouds, though there are no*
 628 *actual clouds present.*
 629



630
 631 *Figure 4: A WorldView-3 scene from May 26, 2015, at 22:16:39 UTC. Panel a) shows the true-*
 632 *color RGB image. Panel b) shows the MODIS-style (470, 1600, 2100nm) false-color SWIR*
 633 *composite that clearly differentiates the snow/ice from clouds. Panel c) shows the scene with*
 634 *custom pixel screening groups identified. The identification areas were defined with the end goal of*
 635 *avoiding cross-contamination as much as possible. It is difficult to make a spectrally-based mask*
 636 *for the cloud in this scene. Doing the same for the snow-free land proved to be a challenge, so a*
 637 *purely geometric form was used. The contents of these pixel class groups inform the reflectance*
 638 *profile models for the CM-URSI algorithm.*
 639

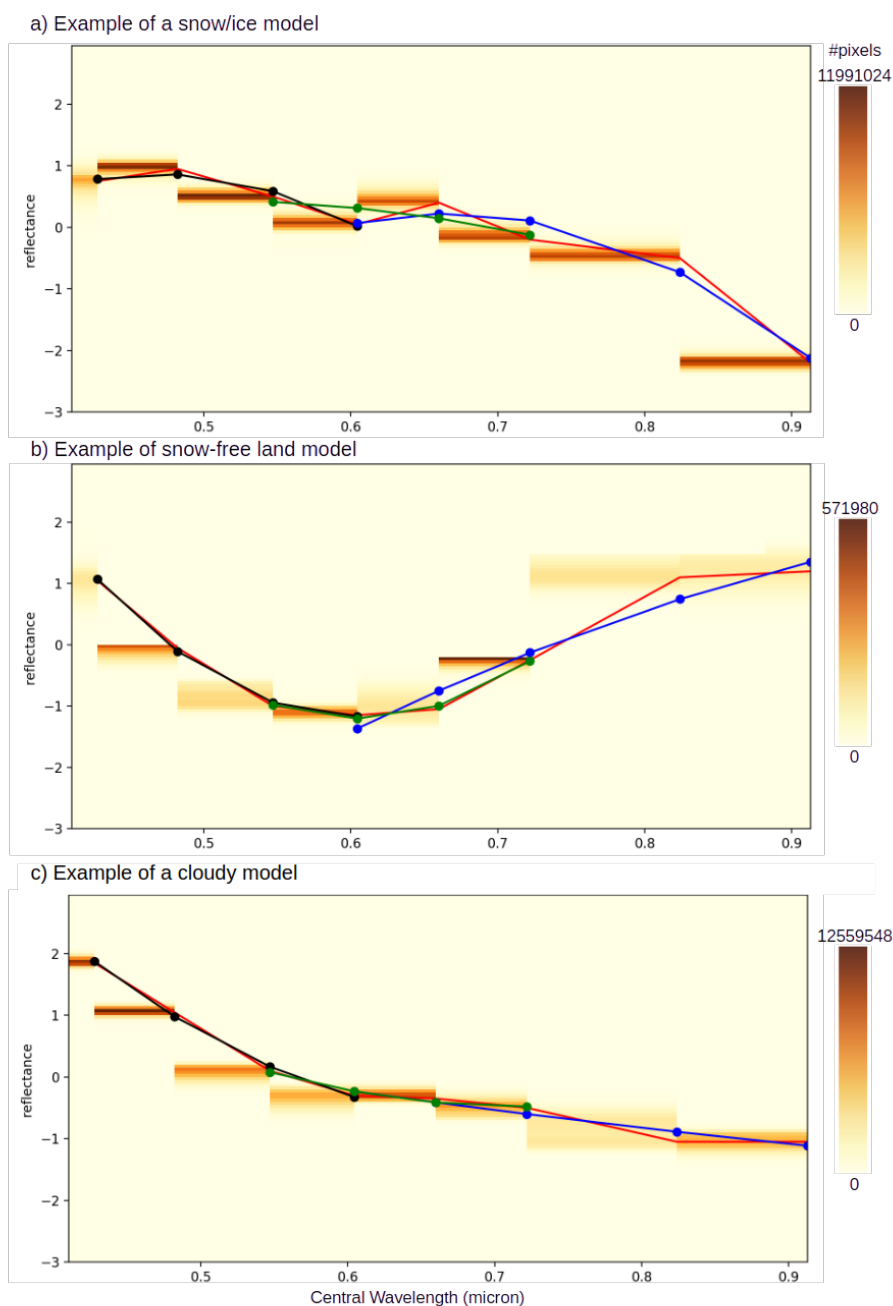


Figure 5: Normalized reflectance histograms (oriented along the Y axis) and fit curves (oriented along the X axis) as a function of WorldView-3 central wavelength for three models used by CM-URSI. Panel a) shows the "snow/ice high" model. Panel b) shows the "snow-free land low" model. Panel c) shows the "low reflectance cloud" model. Black curves are the fit for channels 1-4, green curves are the fit for channels 3-6, and blue curves are the fit for channels 4-8. The red curve shows the maximum-count reflectance of each reflectance histogram.

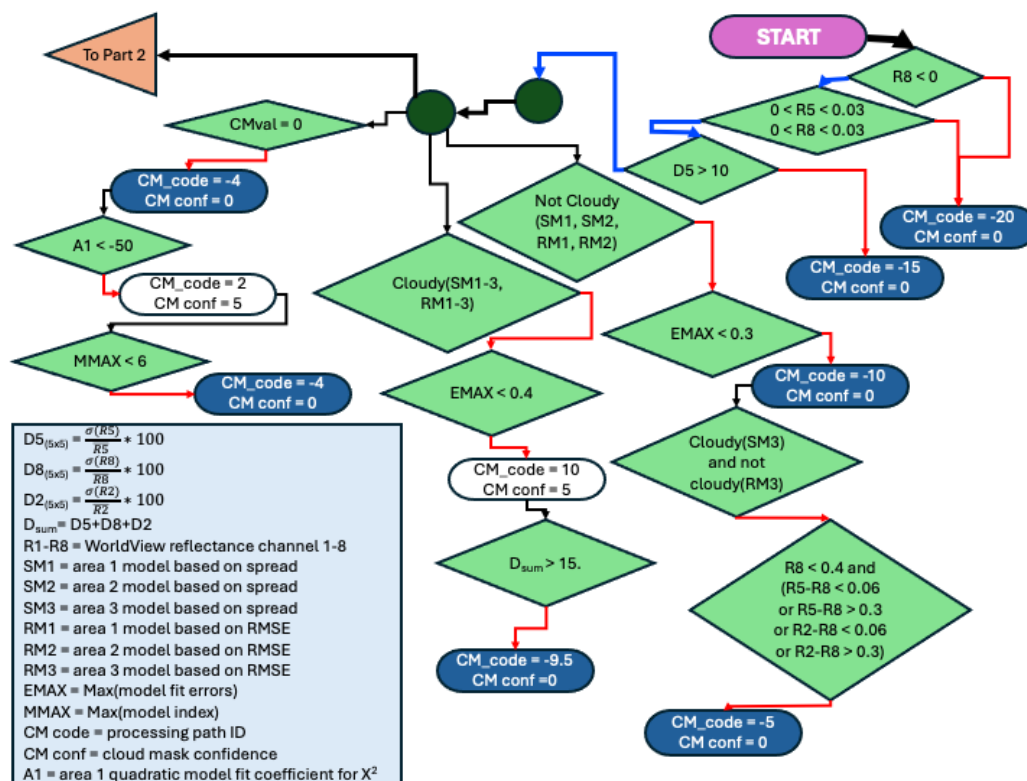


Figure 6: The first section of the CM-URSI algorithm flowchart. This chart shows the initial reflectance bypass tests that may decide a pixel's class before any of the more complex spectral profile fitting occurs. The first two of the spectral profile chain test sets are also present. If a decision is not made at any of these stages, the processing path then follows to part 2, shown in Figure 8. Red arrows indicate a positive test result, and blue indicates a negative result. Black means the transition is unconditional.

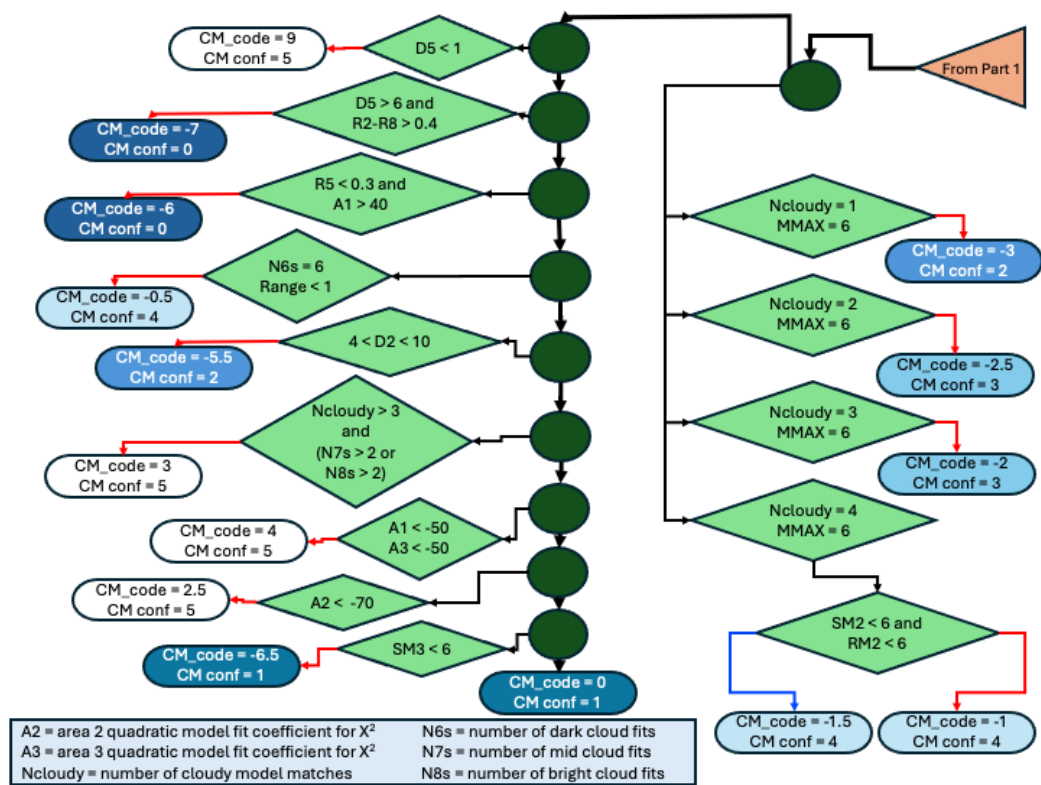
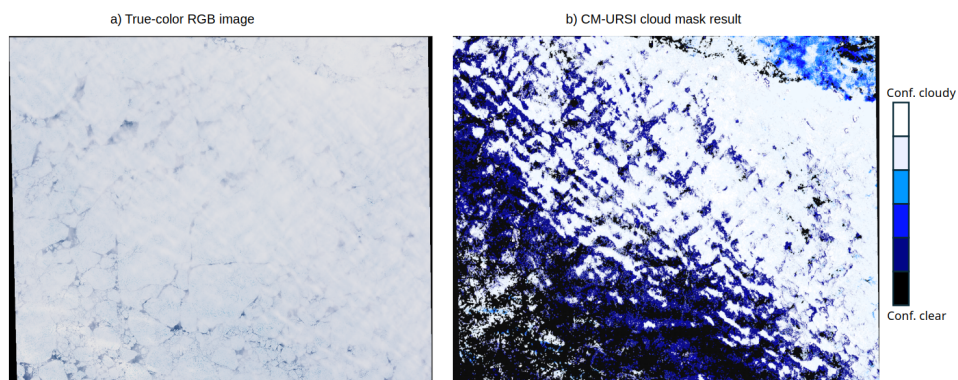


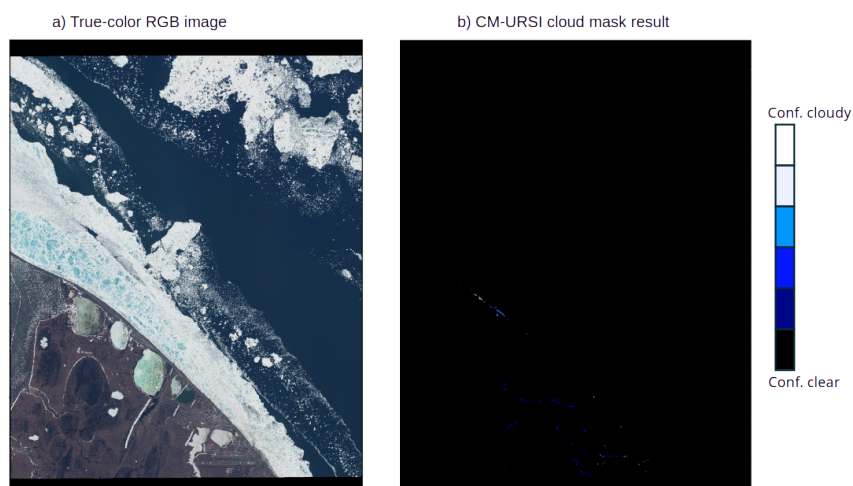
Figure 7: The second section of the CM-URSI algorithm execution flow chart, showing the final pixel tests. Notice that the algorithm avoids explicit spectral tests whenever possible. Traditional spectral tests do not work well in a VNIR-only environment and thus cannot contribute in a reliable way. “Range” in this case is the difference between the lowest and the highest reflectance in the profile, divided by reflectance in WorldView-3 channel 8. Red arrows indicate a positive test result, and blue indicates a negative result. Black means the transition is unconditional.



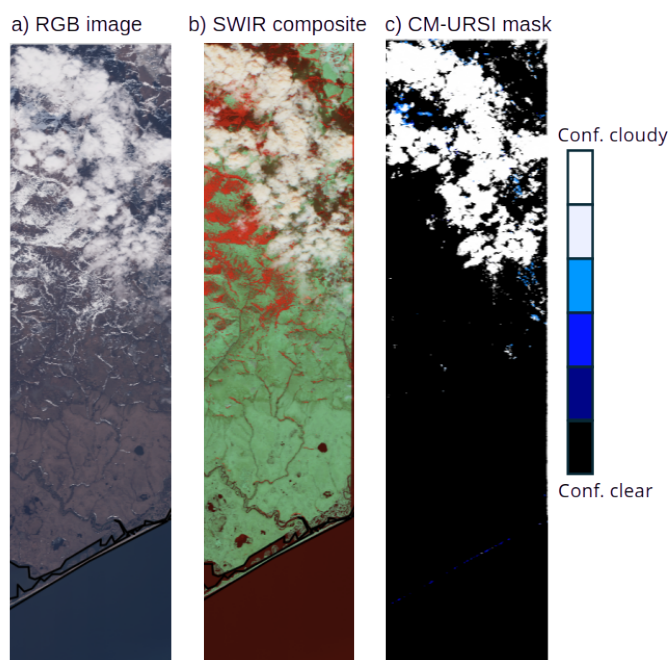
666



667 *Figure 8: A cloud detection example from WorldView-3 with the CM-URSI algorithm. Panel a)*
668 *shows the true-color RGB scene from the WorldView-3 imager acquired on Aug 08, 2024, at*
669 *21:37:40 UTC. Panel b) shows the CM-URSI cloud masking result for this scene, distinguishing*
670 *cloud pixels from sea ice pixels.*
671



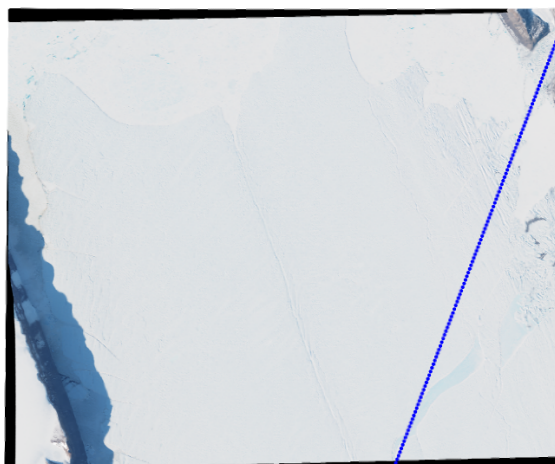
672
 673 *Figure 9: A CM-URSI cloud masking control case showing a WorldView-3 scene near Utqiagvik,*
 674 *AK, from Jun 16, 2021, 22:38:38 UTC, centered on 71.35°N, 156.73°W. Panel a) shows the true-*
 675 *color RGB scene. Panel b) shows the CM-URSI cloud masking result. There are no actual clouds*
 676 *present in this scene, and CM-URSI results include very few false positives. Everything that*
 677 *appears white in this particular scene is lake/sea ice.*
 678



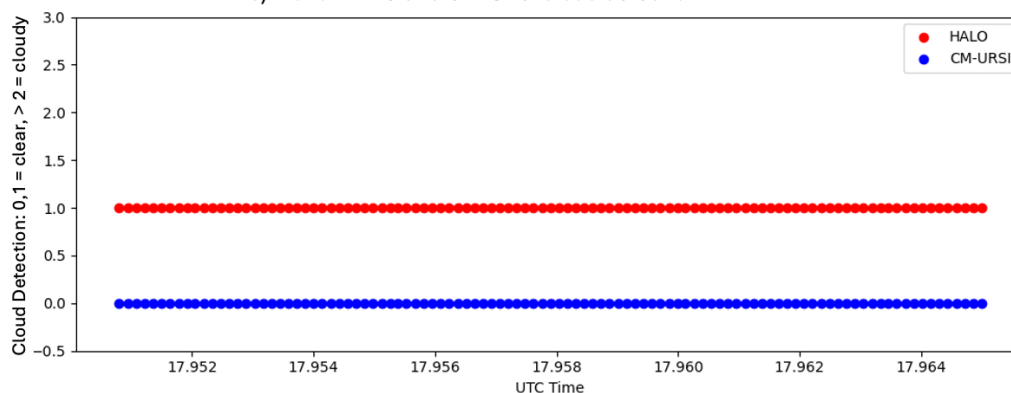
679
 680 *Figure 10: CM-URSI cloud masking example. WorldView-3 2015-05-26 22:16:39 UTC, centered at*
 681 *64.57°N, 164.50°W off the southern coast of Alaska. Panel a) shows the true-color image. Panel b)*
 682 *shows the SWIR composite. There is a significant amount of snow/ice in the scene, visible as bright*
 683 *red in the SWIR. Panel c) shows the CM-URSI cloud mask. CM-URSI allows us to confidently*
 684 *separate clouds from the ground snow and ice.*
 685



a) True-color RGB image with HALO path overlay



b) Plot of HALO and CM-URSI cloud detection



686
 687 *Figure 11: Validation that CM-URSI does not mistake snow/ice surfaces as clouds. Panel a) shows*
 688 *the DC-8 flight path overlaid on top of the WorldView-2 scene acquired on Jun 7, 2024 19:33:31*
 689 *UTC, centered at 81°N, 61.5°W, over the sea ice directly east of Ft. Conger, Nunavut. Panel b)*
 690 *shows the comparison of concurrent CM-URSI and HALO observations for the flight path. The X-*
 691 *axis shows UTC of HALO observations. The scene is clear sky, so the 90-minute time difference*
 692 *between observations is not a factor. The scene background is complex, with snow/ice throughout.*
 693 *CM-URSI agrees with HALO that the scene is cloud-free within the flight path.*
 694