ALGORITHM AND SOFTWARE DEVELOPMENT OF ATMOSPHERIC MOTION VECTOR (AMV) PRODUCTS FOR THE FUTURE GOES-R ADVANCED BASELINE IMAGER (ABI)

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ABSTRACT

Atmospheric motion vectors (AMVs), derived from the current GOES series of satellites, provide invaluable tropospheric wind information to the meteorological community. AMVs obtained from tracking features (i.e., clouds and moisture gradients) are used for: i) Improving numerical weather prediction (NWP) analyses and forecasts; ii) Supporting short term forecasting activities at National Weather Service (NWS) field offices; and iii) Generating tropical and mesoscale wind analyses.

The Geostationary Operational Environmental Satellites (GOES)-R Algorithm Working Group (AWG) Winds application team is working on development of algorithms and software for the generation of Atmospheric Motion Vectors (AMVs) from the GOES-R Advanced Baseline Imager (ABI) to be flown on the next generation of GOES satellites. The GOES-R series of satellites offers exciting new capabilities that are expected to directly benefit and improve the derivation and quality of the AMVs. These new capabilities include: continuous scanning with no loss of imagery due to eclipse or conflicting scanning schedules, higher resolution (spatial and temporal) imagery, and improved navigation. Improved cloud-top height assignments derived from the GOES-R ABI are expected to contribute to further improvement and utilization of the AMV products.

GOES-R AMV software development and testing is being done within a framework supports a tiered algorithm processing approach that allows the output of lower-level algorithms to be available to subsequent higher-order algorithms while supplying needed data inputs to all algorithms through established data structures. MSG/SEVERI, current GOES imager, and simulated ABI imagery are being used as proxy datasets for GOES-R ABI AMV development, testing, and validation activities. This talk will highlight the AMV algorithms and results from recent testing.

1. INTRODUCTION

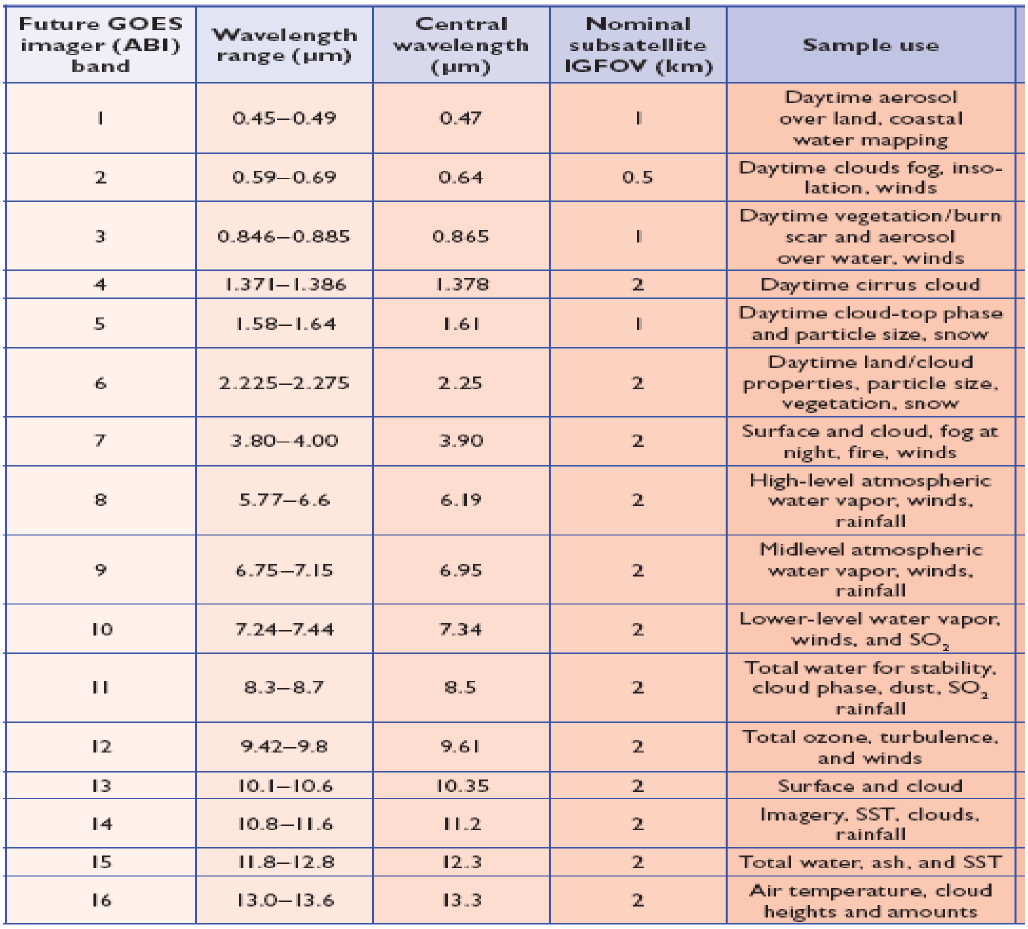
The GOES-R program is a collaborative development and acquisition effort between the National Oceanic and Atmospheric Administration (NOAA) and the National Aeronautics and Space Administration (NASA). The GOES-R series acquisition includes two spacecraft, GOES-R and GOES-S, five different environmental instrument suites, spacecraft launch services, ground systems, and the end-to-end systems integration to support GOES-R design, fabrication, testing, launch, and operations. The Instruments to be flown on GOES-R include the: Advanced Baseline Imager (ABI), Geostationary Lightning Mapper (GLM), Space Environmental In-Situ Suite (SEISS), Solar Ultra Violet Imager (SUVI), Extreme Ultra Violet / X-Ray Irradiance Sensors (EXIS), and Magnetometer (MAG). The current launch dates for GOES-R and GOES-S are December 2014 and April 16, 2016, respectively.

The successful development of Level-2 product algorithms is critical to the success of the GOES-R program, for meeting NOAA mission goals, and ultimately for meeting user community needs. Given the importance of the Level-2 product algorithms, the GOES-R Algorithm Working Group (AWG) was formed to lead the development of all Level-2 product algorithms from the various instrument suites and deliver these algorithms to the GOES-R ground segment. The GOES-R AWG is comprised of thirteen product application teams with one of them being the winds application team. The winds application team is responsible for the development of the AMV algorithms. There are also three cross-cutting GOES-R AWG support teams that support the development of GOES-R ABI proxy datasets, lead L1B and Level-2 calibration/validation activities, and support algorithm software integration activities.

This paper focuses on the development of algorithms and software for the generation of Atmospheric Motion Vectors (AMVs) from the GOES-R Advanced Baseline Imager (ABI). The GOES-R series of satellites and the ABI offers exciting new capabilities that are expected to directly benefit and improve the derivation and quality of the AMVs. Section 2 describes the ABI and many of its specifications and new capabilities. Section 3 provides a description of the GOES-R AMV algorithm and software development approach being taken. In Section 4 the GOES-R ABI proxy datasets being used in AMV algorithm development efforts are described. Finally, in Section 5 the AMV algorithm components developed to date are described, along with some results from early testing.

2. GOES-R ADVANCED BASELINE IMAGER (ABI)

The ABI has been designed to address the needs of many users of geostationary data and products (Schmit, et al, 2005) It will offer more spectral bands (to enable new and improved products), higher spatial resolution (to better monitor small-scale features), and faster imaging (to improve temporal sampling and to scan additional regions) than the current GOES imager. The spatial resolution of the ABI data will be nominally 2 km for the infrared bands and 0.5 km for the 0.64-μm visible band. Table 1 provides a summary of the 16 spectral bands that will be available on the ABI and their intended uses. Those channels that are expected to be used in AMV feature tracking, at least initially, include the 0.64um, 3.90um, 6.19um, 6.95um, 7.34um, and 11.2um bands.



Future GOES imager (ABI) band	Wavelength range (μm)	Central wavelength (μm)	Nominal subsatellite IGFOV (km)	Sample use
1	0.45–0.49	0.47	1	Daytime aerosol over land, coastal water mapping
2	0.59–0.69	0.64	0.5	Daytime clouds fog, insolation, winds
3	0.846–0.885	0.865	1	Daytime vegetation/burn scar and aerosol over water, winds
4	1.371–1.386	1.378	2	Daytime cirrus cloud
5	1.58–1.64	1.61	1	Daytime cloud-top phase and particle size, snow
6	2.225–2.275	2.25	2	Daytime land/cloud properties, particle size, vegetation, snow
7	3.80–4.00	3.90	2	Surface and cloud, fog at night, fire, winds
8	5.77–6.6	6.19	2	High-level atmospheric water vapor, winds, rainfall
9	6.75–7.15	6.95	2	Midlevel atmospheric water vapor, winds, rainfall
10	7.24–7.44	7.34	2	Lower-level water vapor, winds, and SO_2
11	8.3–8.7	8.5	2	Total water for stability, cloud phase, dust, SO_2 rainfall
12	9.42–9.8	9.61	2	Total ozone, turbulence, and winds
13	10.1–10.6	10.35	2	Surface and cloud
14	10.8–11.6	11.2	2	Imagery, SST, clouds, rainfall
15	11.8–12.8	12.3	2	Total water, ash, and SST
16	13.0–13.6	13.3	2	Air temperature, cloud heights and amounts

Table 1: Summary of the wavelengths, resolution, and sample use of the GOES-R ABI bands. Circled are those bands that are expected to be used for feature tracking.

The ABI will scan approximately 5 times faster than the current GOES imagers. This brings opportunities and flexibility for the collection of more observations that will enable user needs to be better met. At the present time, there are two anticipated scan modes for the ABI. The first is a flexible scanning scenario that will provide one scan of the Full Disk (FD), three scans (5 minutes apart) of the Continental United States (CONUS), and 60 scans (30 seconds apart) over a selectable 1000 km ×1000 km area every 15 minutes. The second mode is continuous full disk scanning where full disk coverage is obtained every 5 minutes. In practice, some combination of both modes may be used. For example, three sequential FD images that are 5 minutes apart may be taken every hour for the generation of AMVs. The flexible scanning mode would then be used for the rest of the hour.

Significant improvements in the performance of the image navigation and registration are expected with GOES-R. These improvements are expected to translate to more accurate AMVs. Table 2 shows the image navigation and registration specifications (3σ) in black for the GOES-8-12, GOES-13/O/P, and GOES-R series of satellites. In red are computed image navigation and registration performance statistics for GOES-12 (using four 1-week periods of residual data from 2005 and 2006) and for GOES-13 (using two days from special collection period in December 2006) based on the standard deviation of the residual differences calculated from satellite image navigation and registration (INR) data. It is clear from this table that the image navigation and registration performance has improved with each new series of GOES satellites. The GOES-13 image-to-image registration accuracy, for example, is substantially improved over its predecessors and approached the GOES-R specifications, which represent even a further improvement.

	GOES 8-12	**GOES 13,O,P**	**GOES-R**
	KM D / N	**KM D / N**	**KM D / E**
ABSOLUTE NAVIGATION	**4.0 / 6.0 (4.5 /5.0)**	**2.3**	**1.0 / 1.5**
WITHIN IMAGE	**1.6 / 1.6**	**2.0**	**1.0**
I-TO-I (RD)			
5-7 MIN	**-- (2.3 / 2.3)**	**-- (0.6/0.6)**	**0.75 1.0**
15 MIN	**1.5 / 2.5 (2.8 / 3.2)**	**1.3 (1.0/1.3)**	**0.75 1.0**
90 MIN	**3.0 / 3.8**	**1.8**	**0.75 1.0**
24 HR	**6.0 / 6.0**	**4.0**	**--**

Table 2. Image navigation and registration specifications (3σ) in black for the GOES-8-12, GOES-13/O/P, and GOES-R series of satellites. In red are computed image navigation and registration performance statistics for GOES-12 and GOES-13 (Computed values courtesy of G. Jedlovek; NASA/MSFC)

Higher spatial, spectral, temporal resolution, together with increased radiometric performance and improved navigation/registration performance, of the GOES-R ABI is expected to result in better target selection, improved feature tracking and target height assignment. In addition, new opportunities for applications of very high-resolution (spatial & temporal) winds in severe storm environments and feature tracking of volcanic ash and dust are expected.

3. GOES-R AMV ALGORITHM AND SOFTWARE DEVELOPMENT APPROACH

GOES-R AMV software development and testing is being done within a common processing framework that supports a tiered algorithm processing approach that allows the output of lower-level algorithms to be available to subsequent higher-order algorithms while supplying needed data inputs to all algorithms through established data structures. This is illustrated in Figure 1. The framework efficiently provides routine services to algorithms that are easily plugged into the framework. The reading in and handling of calibrated/navigated radiances and ancillary data are performed by the framework. These data are then loaded into established data structures that can be accessed by all algorithms. Other established data structures enable the output of the lower-level algorithms to be accessible by higher-level algorithms.

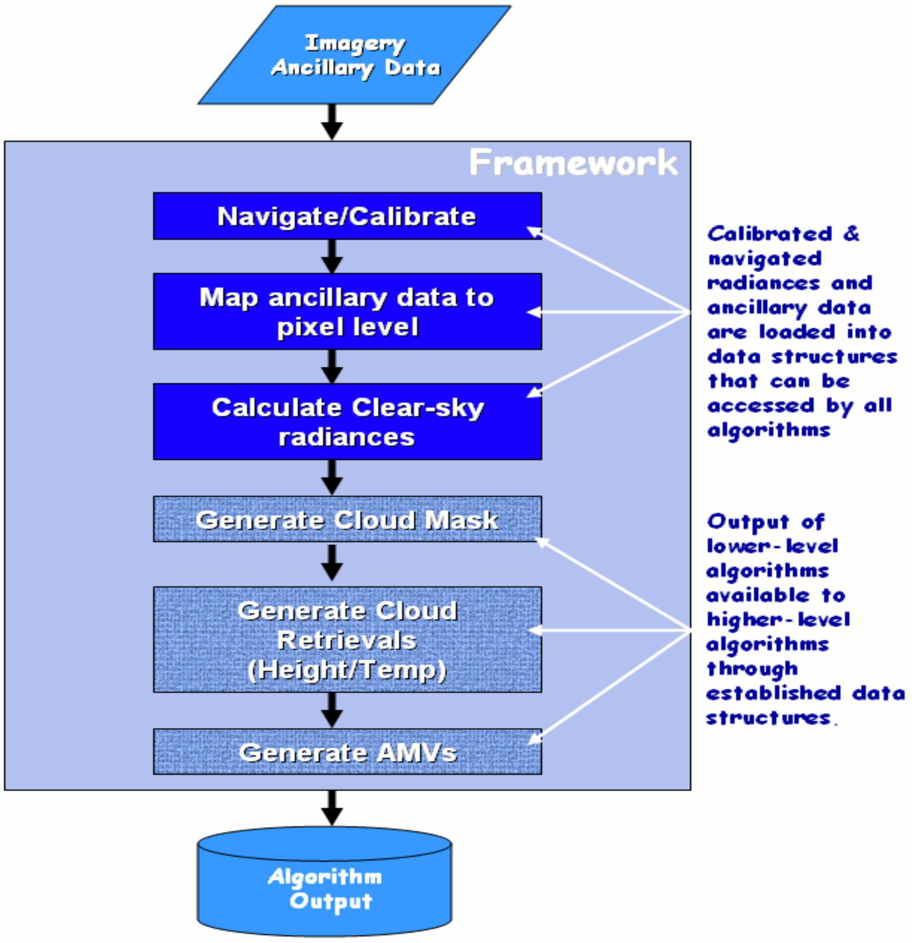


Figure 1. Processing framework has been developed to support a tiered algorithm processing approach.

While we are leveraging and building upon existing target selection/quality control, feature tracking, and quality, and quality control algorithms used operationally today at NESDIS, there are some important differences. For example, the target selection and height assignment will rely on utilization of pixel level cloud mask and cloud height products generated upstream via algorithms delivered by AWG cloud application team. More details on these various AMV algorithms are presented in Section 5.

4. GOES-R ABI PROXY DATASETS

Meteosat Second Generation (MSG) SEVERI instrument, the current GOES-imager, and simulated ABI data are all being used as proxy datasets for GOES-R ABI AMV development, testing, and validation activities. The SEVIRI imager on MSG offers 11 ABI channels at 3km horizontal resolution with a temporal resolution of 15 minute for full disk coverage making it the best proxy data available today for our needs.

A comprehensive database of Meteosat-8 SEVERI imagery, all ancillary data needed by the AMV algorithms, and validation datasets needed to validate the AMV algorithm output has been constructed. The entire full-disk Meteosat-8 SEVERI imagery (all channels at 15 minute temporal resolution) is available for August 2006 and soon to be for January 2007. The ancillary datasets needed to derive AMVs include short-term global forecasts from the National Weather Services (NWS) National Center for Environmental Prediction (NCEP) Global Forecast System (GFS), global topography, coastline mask, and a snow/ice mask, for example. Validation datasets collected include: rawinsondes, GFS analyses, and AMVs generated from current operational NESDIS AMV algorithms. Figures 2a shows a false-color image of Meteosat-8 SEVERI on 04 August 2006 at 1215 UTC and Figure 2b shows Cloud-drift AMVs derived from a Meteosat-8 SEVERI image triplet centered at 12:15 UTC on 04 August 2006.

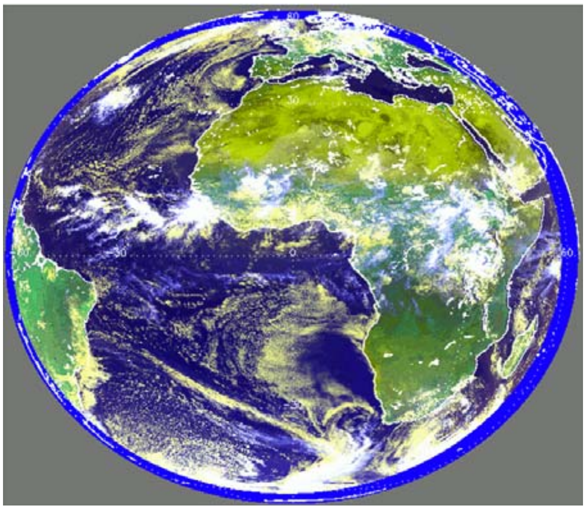


Figure 2a. False color image of Meteosat-8 SEVERI on 04 August 2006 at 12:15 UTC.

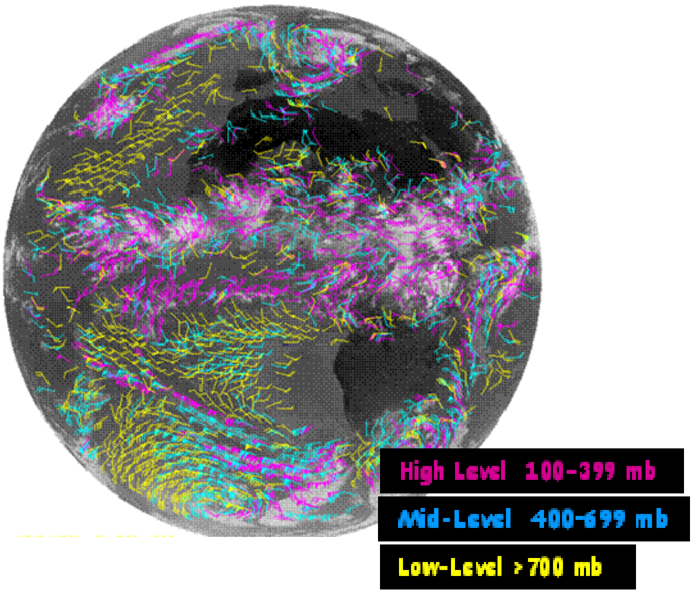


Figure 2b. Cloud-drift AMVs derived from a Meteosat-8 SEVERI image triplet centered at 12:15 UTC on 04 August 2006.

All of these August 2006 data have been staged and are being used for GOES-R AMV algorithm development activities. These same datasets are also being used by the GOES-R AWG Cloud Application Team for the development of a number of pixel-level cloud products that include: cloud mask, cloud type, cloud height, cloud phase, and cloud optical and microphysical properties. Presently, the Cloud Application Team is actively using CALIPSO and CLOUDSAT data for their pre-launch cloud retrieval algorithm validation activities using the August 2006 SEVERI dataset. When co-located with SEVIRI, CALIPSO and CLOUDSAT are serving as a vital validation source for GOES-R cloud algorithms. Active interactions between the Wind Application and Cloud Application teams occur since the AMV target height assignment algorithm relies on using several of the pixel-level cloud products to generate representative target scene heights.

Simulated GOES-R ABI imagery is also being used for GOES-R AMV algorithm development, testing, and validation activities. AWG Proxy Team members at CIMSS have developed the capability to provide high

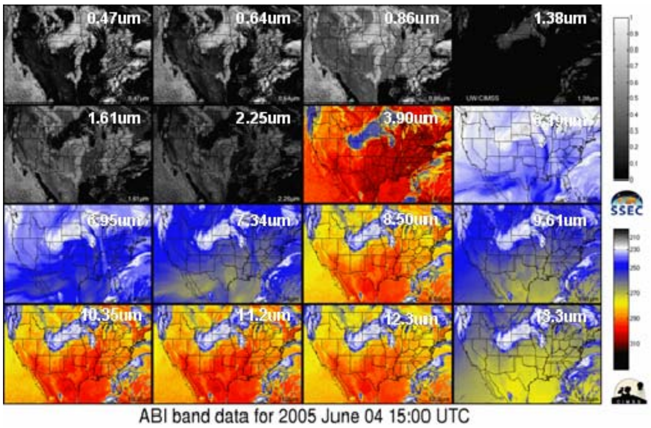


Figure 3a. Simulated GOES-R ABI data for all 16 Bands for 04 June 2005 15:00 UTC.

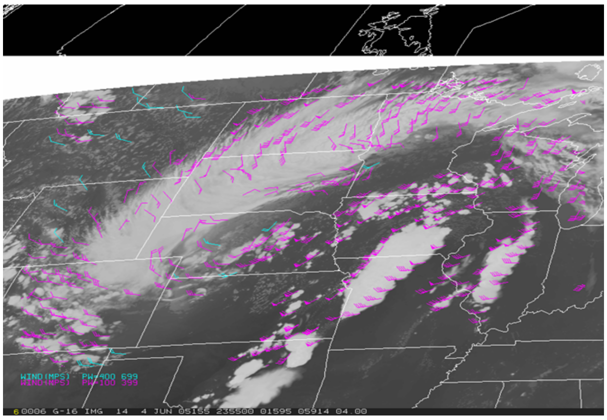


Figure 3b. Cloud-drift AMVs derived from a simulated GOES-R ABI band 14 (11um) image triplet centered at 00:00 UTC on 04 June 2005

fidelity simulated datasets at 2km horizontal resolution and at 5 minutes temporal resolution for 04 June 2005. Figure 3a shows simulated GOES-R ABI imagery for each of the 16 ABI bands. Figure 3b shows an example of cloud-drift AMVs derived from a simulated GOES-R ABI image triplet centered at 00:00 UTC on 05 June 2005. AMV algorithm sensitivity studies are planned using these simulated datasets.

The simulated GOES-R imagery are also being used in tandem with the GOES-R Analysis Facility for Instrument Impacts on Requirements (GRAFIIR) system that enables instrument impacts (noise, calibration errors, striping, etc) to be imposed on the simulated data. These simulated data are then used to derive AMVs and a variety of GOES-R Level-2 products that are then assessed to determine the impact of the instrument effects on the performance of these products. Wanzong et al, 2008, discusses the performance of AMVs when various amounts of noise were added to simulated GOES-R ABI radiance datasets.

5. GOES-R AMV ALGORITHM DESCRIPTIONS AND RESULTS FOM EARLY TESTING

This section describes the current state of the various algorithms used to derive AMVs. These algorithms include target selection, target height assignment, feature tracking, and quality control. Preliminary results from some early testing are presented as well.

5.1 Target Selection

For GOES-R ABI, the heritage target selection algorithm used in the current operational GOES AMV processing is for the most part retained (Neiman et al, 1997). The size of the target scene used in current testing is 15x15 pixels. The size of the target scene ultimately chosen will be based on results from additional testing. The central image of the image triplet is used to find and select prospective targets. Gradient magnitudes are derived at each pixel in the image and the maximum gradient within each target scene is determined. A 4-point centered difference algorithm that spans 5 pixels in the north/south and east/west direction, is used to compute the gradient magnitudes. Figures 4a shows an image of GOES-12 11um pixel-level gradient magnitude used in target selection. A significant amount of structure is observed in this figure. Dark areas reveal where the gradient magnitudes are largest. These areas occur along cloud edges and even in the interior of clouds. These areas are prime locations for potential targets. For reference, Figure 4b shows an image of the corresponding GOES-12 11um brightness temperatures used to calculate the gradient magnitudes.

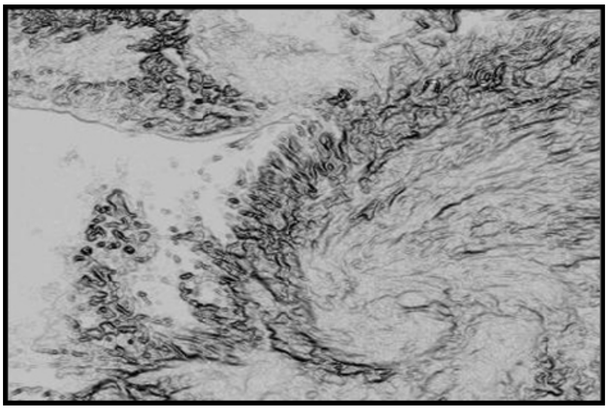


Figure 4a. Image of GOES-12 11um pixel-level gradient magnitudes used in target selection

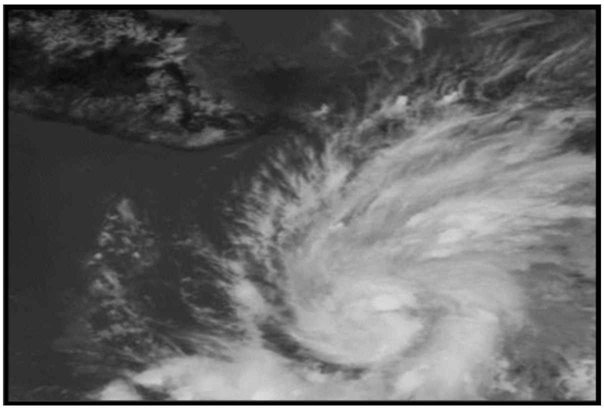


Figure 4b. Image of corresponding GOES-12 11um brightness temperatures

If the computed gradient is of sufficient magnitude (currently 4K), then the target scene is re-centered at the maximum gradient, after which, quality control (QC) is applied to the target scene. The following quality control tests are performed on each target scene before determining a representative height for each:

- ☐ Exclude earth edge
- ☐ A minimum number of cloudy pixels must exist in the target scene (currently set 10%)
- ☐ Exclude unreasonable values

- ❒ Perform a spatial-coherence analysis (Coakley and Bretherton, 1982; Neiman et al, 1997) to find coherent signals
- ❒ Perform cluster analyses on mean 3x3 radiances passing spatial coherency to look for and exclude multi-deck cloud scenes (Neiman et al, 1997)

5.2 Target Height Assignment

Heights are assigned to those targets that pass target selection criteria. Upstream pixel-level cloud-top heights within the target scene are used to arrive at a representative target height that is hoped to be consistent with and has ties with the feature being tracked. The use of these upstream pixel-level cloud heights to arrive at a representative target height is a large paradigm shift from the way in which target heights are done now in the current operational GOES AMV processing.

The GOES-R AWG cloud application team is responsible for the selection, development, and validation of the cloud-top height algorithm to be used for the GOES-R ABI. The GOES-R ABI provides an opportunity to combine the sensitivity of the 13.3 μm CO_2 channel to cloud height with the sensitivity of the 11 μm and 12 μm window channels to cloud microphysics and therefore improve upon the performance of the current operational imager cloud products. To this end, the cloud application team has chosen to use an optimal estimation (or 1D-Var) framework (Rodgers, 1976) to maximize the impact of selected ABI channels (currently the 11 μm, 12 μm, and 13.3 μm channels) to retrieve cloud-top height and cloud microphysical properties. Figure 5a shows an image of the retrieved cloud-top pressures derived from the 1-D VAR cloud retrieval algorithm. Plans call for tests involving use of the water vapour bands to increase the algorithm's sensitivity to thin cirrus. CALIPSO observations and state-of-the-art scattering models are used to derive forward model and first guesses for the 1D-Var retrieval algorithm. Error estimates of the retrieved cloud information are provided and will be evaluated when validating the quality and performance of the AMV products.

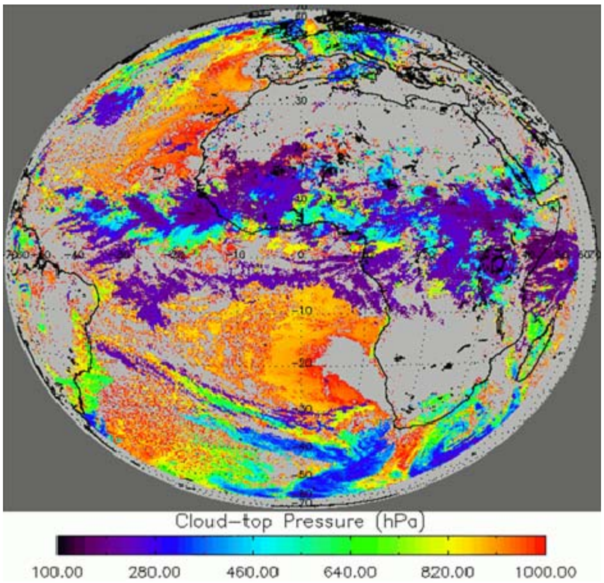


Figure 5a. Image of Meteosat-8 retrieved cloud-top (mb) on 04 August 2006 at 12:15 UTC

Figure 5b. Comparison of AMV height distributions between the new GOES-R and current GOES AMV height assignment algorithms for 04 August 12:15 UTC

Deriving a representative height for each target from available pixel-level cloud-top information is currently based on the following approach. A 1-D histogram of the 11 μm channel brightness temperature values is first constructed. The cloud-top pressures associated with the coldest 25% of the cloudy and probably cloudy pixels (as determined from pixel-level cloud mask) are sorted so that the median cloud-top pressure can be extracted. The median pressure is determined. This pressure then serves as the representative height for the target scene. Figure 5b shows a comparison of AMV height distributions between the new GOES-R and the current GOES AMV height assignment algorithms for the Meteosat-8 on 04 August 2006 12:15 UTC case. There is reasonable agreement between the two distributions. Both distributions are bi-modal with the GOES-R distribution showing a sharper more defined peak at upper levels. At low levels, the GOES-R height distribution shows more heights at higher pressures. This behaviour is a result of improved low cloud height assignment in regions where a low-level temperature inversion exists.

The presence of low level temperature inversions causes problems for the retrieval of low level cloud heights. Low level temperature inversions are common over ocean in the vicinity of sub-tropical high pressure systems that are characterized by the existence of an extensive stratocumulus deck. In these situations, the retrieved cloud-top pressure can be in error in excess of 200mb since the cloud-top temperature can be found at two locations in the temperature profile. In these situations, the cloud height solution adopted for GOES-R ABI is to use a slightly modified version of the approach used for MODIS (Minnis et al, 1992). If a low level temperature inversion is identified (through use of a NCEP GFS forecast temperature profile), then the GFS forecast surface temperature is assigned to a surface air parcel that is then lifted and cooled at the dry adiabatic lapse (9.8K/km) until its temperature matches the cloud temperature. The level at which this occurs is then used to assign the cloud height. Figure 6 illustrates the impact of this approach on the performance of low level AMVs. The low level AMVs are shown in yellow with their accompanying heights after the low-level height correction is made. It is clear that these heights are in very good agreement with the GFS forecast winds at 900mb (shown in violet). The original AMV heights (before the correction was applied) were in the 700-750mb range which clearly led to large differences in speed and direction between these AMVs and the GFS winds at these levels.

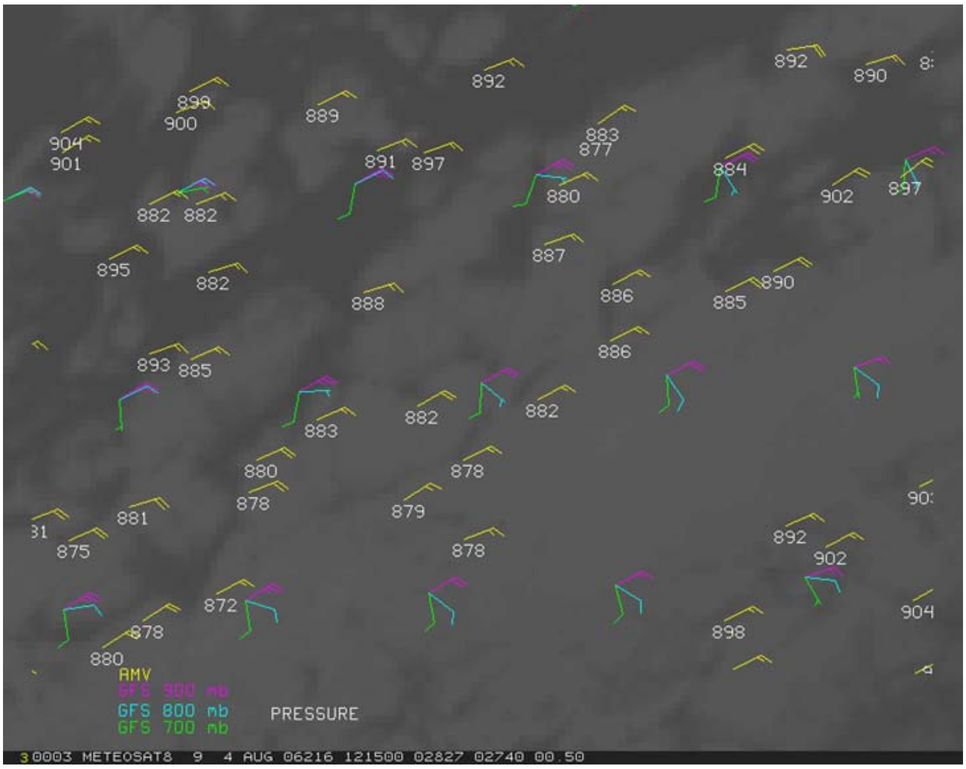


Figure 6. Meteosat-8 Low-level cloud-drift AMVs (in yellow) and their associated heights (in white) after applying a low-level height correction as a result of the presence of a low level temperature inversion. GFS forecast winds at 900mb (violet), 800mb (cyan), and 700mb (green) are shown.

5.3 Feature Tracking

The feature tracking algorithms that will be available for the derivation of GOES-R AMVs include the Sum of Squared Difference (SSD) and the Cross Correlation (CC) algorithms. These are the two heritage algorithms that are currently being used to derive AMVs for the current GOES, MODIS, and AVHRR instruments.

New software has been written for both algorithms and both have been tested using image triplets. The use of an image pentad is possible and will be tested in the future. For GOES-R, feature tracking will be done with 16-bit real brightness temperature values as opposed to with 8-bit integer grey-scale values, which is done with GOES, MODIS, and AVHRR today.

To minimize the computational expense and speed up the processing, the GFS model forecast winds are used to help guide the search process. Specifically, the search is confined to an area centered on the forecast displacement of the target. This is illustrated in Figure 7. The scene that maximizes the correlation (or minimizes the difference) between the target and search windows is labeled as the match. Two sub-vectors are generated in the tracking process, one vector for the backward time step and one vector for the forward time step. Each match must exceed a minimum correlation threshold and accelerations exceeding 10m/s are not permitted. The final vector is computed from an average of the two sub-vectors.

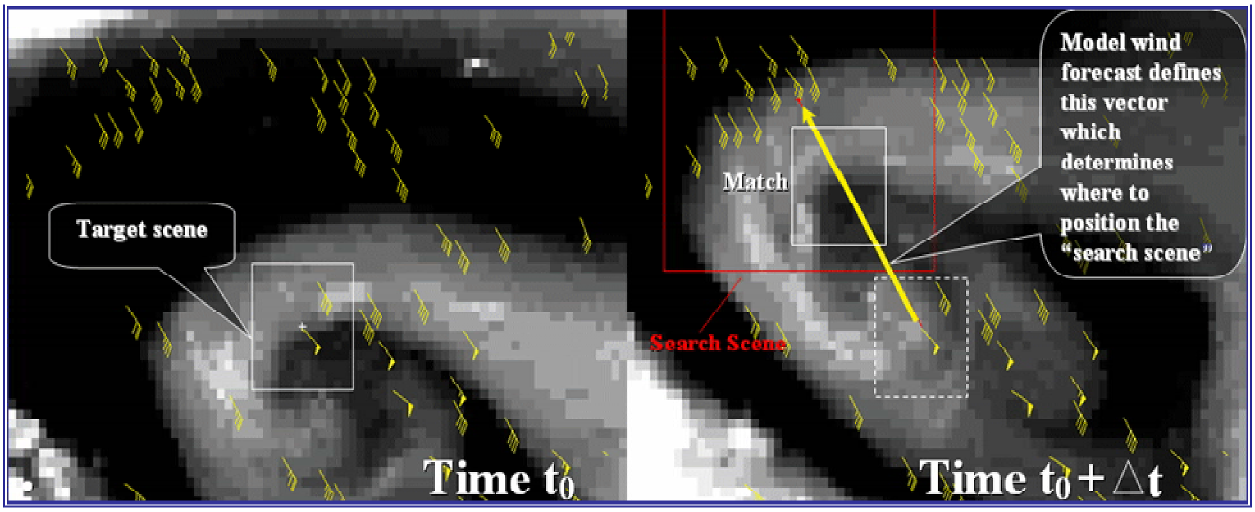


Figure 7. The GFS model forecast wind (defined by yellow vector), whose origin is located at the center of a target scene (solid white box at time t_0 and dotted white box at time $t_0+ \Delta t$) is used to position the search scene (red box at time $t_0+ \Delta t$). The feature tracking algorithm processes the data in the search scene to find the matching feature.

5.4 Quality Control

Careful quality control of AMVs is critically important for their subsequent use in NWP data assimilation systems. Automated QC checks of AMVs occur during their production to eliminate unacceptably poor vectors. This is achieved by examining the temporal consistency of the vectors (acceleration checks), the spatial consistency of the vectors (buddy checks), and comparisons of the AMVs against a short-term NWP forecast winds. Quality indicators (QI) are then appended to the AMVs in order to provide users of these data the ability to intelligently select those AMVs that provide the optimal impact in their operational environment. The Recursive Filter Function (RFF), EUMETSAT QI ((Holmlund, 1998), and Expected Error (EE) (LeMarshall et al., 2004) are three approaches used in NESDIS operational AMV processing today that assign quality indicators to derived AMVs. For the future GOES-R AMV processing, the EUMETSAT QI and Expected Error (EE) algorithms are expected to be used to assign quality indicators. The RFF algorithm is not being considered at this time.

Some limited testing involving the execution of the QI and EE algorithms on AMVs generated from Meteosat-8 SEVERI data. Figure 8 shows the distribution of QI scores, with and without use of the forecast, for the Meteosat-8 IR cloud-drift AMVs generated for the 04 August 2006 12:15 UTC case. Inspection of the QI distribution (without use of the forecast) shows that about 60% of the AMVs have QI scores in excess of 90. This is a very good result, especially when contrasted against similar results for GOES-12 IR cloud-drift AMVs where only 40-45% of the AMVs have QI scores in excess of 90. The higher image registration performance of the Meteosat-8 satellite is believed to be the primary reason for this result.

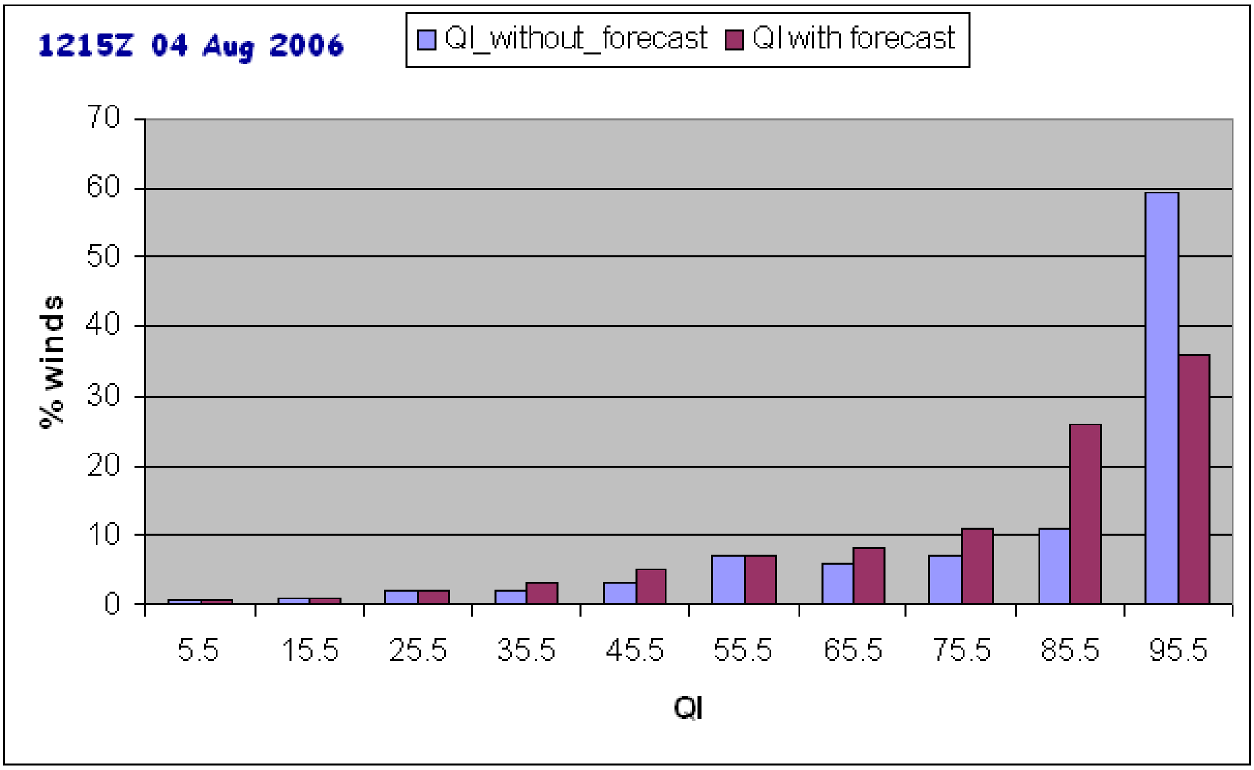


Figure 8: Distribution of QI scores, with and without use of the forecast, for the Meteosat-8 IR cloud-drift AMVs generated for the 04 August 2006 12:15 UTC case

Testing of the Expected Error (EE) algorithm in support of GOES-R AMV activities are described in Berger et al, 2008. The focus of this testing is to characterize the performance of the EE algorithm in a number of different regimes (ie., slow, fast wind regimes) and to optimize its performance (addition of predictors; thresholds).

6. PRELIMINARY VALIDATION RESULTS

Full disk Meteosat-8 IR cloud-drift AMVs have been generated at 00Z and 12Z for the period August 2-9, 2006 and collocated with 00Z and 12Z rawinsonde observations. Table 3 below shows the comparison statistics between collocated Meteosat-8 IR cloud-drift AMVs, GFS forecast winds, and rawinsonde wind observations for high levels (100-400mb), mid levels (400-700mb) and low levels (> 700mb). The collocation criteria used was: 1 hour (temporal), 150km (horizontal), and 25 mb (vertical). Only AMVs with a Quality Indicator greater than or equal to 80 have been included in these statistics. Overall, these statistics look quite good. Overall, the magnitudes of the various statistical metrics are on par with what is observed with the current operational GOES IR cloud-drift AMVs. At low levels, the AMVs outperform the GFS model winds. At mid levels, the AMVs exhibit a rather significant slow speed bias. This slow speed bias is almost certainly related to AMV height mis-assignments. This will need further investigation.

High Levels (100-400mb)	**Sat vs Raob**	**GFS vs Raob**	**Raob**
RMS Difference (m/s)	7.74	7.13	
Normalized RMS	0.40	0.37	
Mean Vector Difference (m/s)	6.27	5.89	
Speed Bias (m/s)	-0.79	0.44	
Mean Speed (m/s)	18.66	19.88	19.44
Absolute Directional Difference (deg)	12.22	13.16	
Sample Size	2009	2009	2009
Mid Levels (400-700mb)	**Sat vs Raob**	**GFS vs Raob**	**Raob**
RMS Difference (m/s)	5.43	4.30	
Normalized RMS	0.42	0.34	
Mean Vector Difference (m/s)	4.38	3.55	
Speed Bias (m/s)	-1.52	-0.37	
Mean Speed (m/s)	11.31	12.45	12.82
Absolute Directional Difference (deg)	13.04	13.66	
Sample Size	968	968	968
Low Levels (700-1000mb)	**Sat vs Raob**	**GFS vs Raob**	**Raob**
RMS Difference (m/s)	4.96	5.11	
Normalized RMS	0.53	0.55	
Mean Vector Difference (m/s)	3.51	3.70	
Speed Bias (m/s)	-0.45	-0.19	
Mean Speed (m/s)	8.82	9.09	9.28
Absolute Directional Difference (deg)	14.46	15.64	
Sample Size	795	795	795

Table 3. Comparison statistics between Meteosat-8 SEVERI IR cloud-drift winds, GFS model winds, and collocated rawinsondes at 00Z and 12Z for the period 02 August – 09 August 2006. Only AMVs with a Quality Indicator greater than or equal to 80 have been included in these statistics.

7. SUMMARY, FUTURE PLANS, AND OPPORTUNITIES

The GOES-R ABI is an improved imager that is expected to bring improvements to the AMV products. Over the past year, the GOES-R AWG Winds Application Team has made significant progress developing the AMV algorithms and software for the future GOES-R ABI. Current GOES imagery, Meteosat-8 SEVERI imagery, and simulated GOES-R ABI imagery are being used extensively for pre-launch algorithm development and validation activities. GOES-R AMV software development and testing is being done within a framework that supports a tiered algorithm processing approach. Several of the AMV algorithms used operationally today at NESDIS are being leveraged. New approaches for assigning heights to cloudy targets are being developed and tested. These involve the use of pixel level cloud heights, computed upstream of the AMV algorithm, to assign a representative height to the target.

The near term focus is on validating the performance of the current state of the GOES-R ABI AMV algorithms. Adjustments will be made the algorithms as needed based on the validation results. Future work that is planned is to perform feature tracking with the visible, short-wave IR, and water vapour bands and to assess the performance of the resulting AMVs. Other activities that will be explored as part of the GOES-R Risk Reduction program include:

- ❐ Generation of AMVs using non-heritage channels (1.38μm, 8.5μm, and 9.6μm).
- ❐ Applications of very high-resolution (spatial & temporal) winds in severe storm environments that take advantage of well navigated, higher spatial and temporal ABI imagery
- ❐ New applications involved with feature tracking of volcanic ash and dust

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