Microwave Integrated Retrieval System (MiRS)

Algorithm Theoretical Basis Document

Compiled by the

MiRS Integrated Product Team (IPT),
NPOESS Data Exploitation Project (NDE),
and Office of Satellite and Product Operations (OSPO)

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DOCUMENT HISTORY
DOCUMENT REVISION LOG

The Document Revision Log identifies the series of revisions to this document since the baseline release. Please refer to the above page for version number information.

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LIST OF CHANGES

Significant alterations made to this document are annotated in the List of Changes table.

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Version Number	**Date**	**Changed By**	**Page**	**Section**	**Description of Change(s)**
1.0	05/17/13	Grassotti	All	All	Original Document
2.0	09/01/15	Grassotti			Changes to document updates in MiRS v11.2
3.0	04/24/18	Grassotti			Changes to update current satellites/sensors and to add snowfall rate product
3.1	06/14/19	Grassotti	20	2.3.1	Fixed units typo in Table 2-1. Fixed values in Table 1-2 and Table 2-1

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1. INTRODUCTION

1.1. Product Overview

1.1.1. Product Description

Product description with sufficient detail so that the user understands how to use the product files. *(Document Object 34)*[1]
Writers: Algorithm Scientists.

The list of products generated by MiRS is summarized in Table 1-1. Also included is the list of heritage products, e.g., generated by MSPPS. "Standard" products are labeled those that have been routinely retrieved and for which extensive validation and testing has been done. Listed are the MiRS 1DVAR and derived products. MiRS 1DVAR products include the parameters that are part of the retrieval state vector. MiRS derived products are those generated using MiRS 1DVAR parameters as inputs and a post-processing procedure, e.g., a simple vertical integration of retrieved water vapor profile for computing TPW, or a new algorithm, e.g., for the estimation of SWE from the retrieved surface emissivities. Note in the table MiRS profiling capability, which is lacking in MSPPS.

[1] If Document Objects have been written, the indicated object should be directly inserted to satisfy each template instruction. Document Objects are described in the Algorithm Theoretical Basis Document Standards and Guidelines http://projects.osd.noaa.gov/spsrb/standards_data_mtg.htm

Heritage Products	MiRS 1DVAR Products	MiRS derived products
Standard Products		
Total Precipitable Water (TPW)	Atmospheric temperature profile (T)	Q-based TPW
Cloud Liquid Water (CLW)	Atmospheric humidity profile (Q)	NPCP-based CLW
Land Surface Temperature (LST)	Land Surface Temperature (LST)	IGP-based IWP
Emissivity at certain window channels	Emissivity vector (Em)	RP-based Rain Water Path (RWP)
Rain Rate (RR)		Em-based SIC
Ice Water Path (IWP)		Em-based First-Year SIC
Snow Water Equivalent (SWE)		Em-based Multi-Year SIC
Sea Ice Concentration (SIC)		Em-based SCE
Snow Cover Extent (SCE)		Em-Based Surface Type
		CLW,RWP&IWP-based RR
		Em-based SWE
		Em-based Snow Effective Grain Size
		Snowfall Rate (SFR)*

Table 1-1. List of heritage, advanced and derived MiRS products. *Note that the SFR is an optional product based on MSPPS heritage algorithms currently requiring availability of ancillary NWP data from the GFS model.

1.1.2. Product Requirements

State the requirements for each product, either explicitly or by reference to the project's requirements document, if available. Product requirements should include content, format, latency, quality. *(Document Object 1)*
Writers: Development Lead.

The MiRS was developed by the NOAA/NESDIS Center for Satellite Application and Research (STAR) as a major upgrade to the existing suite of microwave retrieval algorithms called the Microwave Surface and Precipitation Product System (MSPPS). MSPPS lacks profiling capability and is specific to a single instrument, the AMSU. Another objective for developing MIRS was to provide retrievals in all-weather and over all-surface conditions with the immediate benefits of extending the spatial coverage to critical areas such as active regions and using non-exploited measurements such as those made by surface-sensitive channels for temperature sounding.

MiRS is applicable to both existing and future microwave sensors. It is currently being applied operationally to the NOAA-18, NOAA-19, METOP-A and METOP-B AMSU/MHS suite, the DMSP-F17, DMSP-F18 SSMI/S sensor, to GPM GMI data, to SNPP and NOAA-20 ATMS measurements, and to Megha-Tropiques (MT) SAPHIR data. In addition MIRS has been applied to TRMM TMI, Megha-Tropiques (MT) MADRAS, and GCOM-W1 AMSR2 data in research mode. It could also be a system for Infrared (IR) sensors onboard the JPSS and GOES-R platforms. Having one retrieval system for a multitude of sensors is scientifically sound because the radiative transfer physics involved is by and large the same and the mathematical basis for the inverse problem is identical. The practical advantages of having one single system for a multitude of sensors are numerous. They include among others, the time and cost savings related to generating a retrieval algorithm for a new sensor, the optimal use of the information content and the consistent treatment of time series of satellite data for long-term trend monitoring and climate studies. MiRS is coupled with the Joint Center for Satellite Data Assimilation (JCSDA) Community Radiative Transfer Model (CRTM) which is valid in both microwave and infrared spectral regions, as well as in clear, cloudy and precipitating conditions and over all surface types.

Therefore, MiRS meets the following operational product requirements: temperature and humidity profiles in all-weather conditions, total precipitable water (TPW), land surface temperature (LST), surface emissivity, non-precipitating cloud water, ice/graupel, and rain profiles, as well as their integrated amounts (CLW, RWP, GWP), emissivity-based sea-ice concentration (SIC), sea ice age (SIA), snow water equivalent (SWE), snow effective grain size (SGS), snow cover extent (SCE), surface type classification (ST), a high resolution surface rainfall rate (RR), and snowfall rate (SFR). Quality control metrics and flags defining retrieval product quality are also provided.

For operational processing of NPP and NOAA-20 ATMS data in the NPOESS Data Exploitation (NDE) environment, and transitioned to the NOAA Office for Satellite and Product Operations (OSPO), the MIRS algorithm provides the capability to convert MiRS product files to the NetCDF4 format following the Climate and Forecast convention and STAR metadata standards.

In both processing environments, two product files are created for each set of input observations (e.g. granule or orbit). One file, referred to as the sounding products file (SND) contains temperature and humidity profiles. The second file, referred to as the imaging products file (IMG), contains primarily products more responsive to surface sensitive channels including TPW, LST, CLW, RWP, IWP, surface emissivity, SIC, SIA, SWE, SGS, SCE, RR, and SFR.

1.2. Satellite Instrument Description

Describe the attributes of the sensing system(s) used to supply data for the retrieval algorithm at a level of detail sufficient for reviewers to verify that the instrument is capable of supplying input data of sufficient quality. *(Document Object 28)*
Writers: Development Lead and PAL should collaborate.

The MiRS algorithm is used with a variety of microwave sensors. Currently, high resolution products are supplied using the NOAA Polar-orbiting Operational Environmental Satellites

(POES) AMSU/MHS (NOAA-18 and NOAA-19), the US Department of Defense (DoD) polar-orbiting satellites DMSP SSMI/S (F17 and F18), European Meteorological Operational Satellites (METOP) AMSU/MHS satellite (Metop-A and Metop-B), Global Precipitation Mission (GPM) GMI, Megha-Tropiques SAPHIR, the Suomi NPOESS Preparatory Project (SNPP) ATMS, and NOAA-20 ATMS.

The most recent instrument implemented in MiRS is the Advanced Technology Microwave Sounder (ATMS) aboard SNPP and NOAA-20. It is based on previous AMSU-A/B versions, but ATMS contains 22 channels that span the temperature and moisture sensing frequencies in its single design in a cross-track scanning fashion. The full instrument details are given in Table 1-2, and Table 1-3 provides a report of its projected technical performance.

SNPP and NOAA-20 both orbit at an altitude of 824 km with 97.1° inclination angle. The SNPP local node is at 1:30 pm, while that of NOAA-20 is 50 minutes later. ATMS is only one of five main instruments aboard the satellite, which include the Clouds and Earth's Radiant Energy System (CERES), the Cross-Track Infrared Sounder (CrIS), the Ozone Mapping and Profiler Suite (OMPS) and the Visible/Infrared Imager/Radiometer Suite (VIIRS). SNPP was launched on October 28, 2011 and is currently operated by NOAA.

The purpose of the SNPP mission is to extend observations of geophysical quantities important to monitoring long-term trends in climate, with specific relevance to the water and energy cycle. It was launched to serve as a transition between the POES satellites to the upcoming Joint Polar Satellite System (JPSS). NOAA-20 is the first of the JPSS series of satellites and was launched on November 18, 2017.

Channel	Central Frequency (GHz)	Polarization	Bandwidth (GHz)	Beamwidth (degrees)	NE∆T (K)	Calibration Accuracy (K)
1	23.8	V	0.27	5.2	0.7	1.0
2	31.4	V	0.18	5.2	0.8	1.0
3	50.3	H	0.18	2.2	0.9	0.75
4	51.76	H	0.40	2.2	0.7	0.75
5	52.8	H	0.40	2.2	0.7	0.75
6	53.596 ±0.115	H	0.17	2.2	0.7	0.75
7	54.50	H	0.40	2.2	0.7	0.75
8	54.94	H	0.40	2.2	0.7	0.75
9	55.50	H	0.33	2.2	0.7	0.75
10	57.2903	H	0.33	2.2	0.75	0.75
11	57.2903 ±0.115	H	0.078	2.2	1.2	0.75
12	57.2903	H	0.036	2.2	1.2	0.75
13	57.2903 ±0.322	H	0.016	2.2	1.5	0.75

14	57.2903 ±0.322 ±0.010	H	0.008	2.2	2.4	0.75
15	57.2903 ±0.322 ±0.004	H	0.003	2.2	3.6	0.75
16	87-91(88.20)	V	2.0	2.2	0.5	1.0
17	165.5	H	3.0	1.1	0.6	1.0
18	183.31±7	H	2.0	1.1	0.8	1.0
19	183.31±4.5	H	2.0	1.1	0.8	1.0
20	183.31±3	H	1.0	1.1	0.8	1.0
21	183.31±1.8	H	1.0	1.1	0.8	1.0
22	183.31±1.0	H	0.5	1.1	0.9	1.0

Table 1-2. ATMS Sensor Characteristics.

Key Parameter	Spec. Value	Projection	Basis
Cal Accuracy (K)	<0.75	<0.41	Analysis, with partial measurement validation
Nonlinearity (K)	<0.10	<0.088	Worst-case EDU measurement + analysis
Beam Efficiency (%)	>95	>95	Analysis, with partial measurement validation
Freq. Stability (MHz)	<0.50	0.45	Measurement + analysis
Pointing Knowl. (deg)	<0.05	0.044	Analysis
Mass (kg)	<85	75.4	Measurement
Power (W)	<110	91.0	Measurement
Data Rate (kbps)	<30	28.9	Measurement
Reliability	>0.86	0.88	Analysis

Table 1-3. Measures of ATMS Technical Performance.

2. ALGORITHM DESCRIPTION

2.1. Processing Outline

Full description of the processing outline of the retrieval algorithm. All key elements and sub-elements needed to convey a comprehensive sense of the algorithm should be included. The level of detail should be consistent with the current maturity of the software architecture (which will improve with each revision). A data flow diagram consistent with the software architecture is preferred. *(Document Object 13)*
Writers: Algorithm Scientists.

This section provides a description of MIRS components.
Figure 2-1 presents the basic conceptual diagram of the high-level MIRS blocks. The radiance processing is the interface with the inputs to MIRS, e.g., sensor data files and the inversion processing (1DVAR). It generates bias-free, ready-to-invert radiances or brightness temperatures that are used as main inputs to the inversion process. The inversion process generates retrieved EDRs from these bias-free radiances.

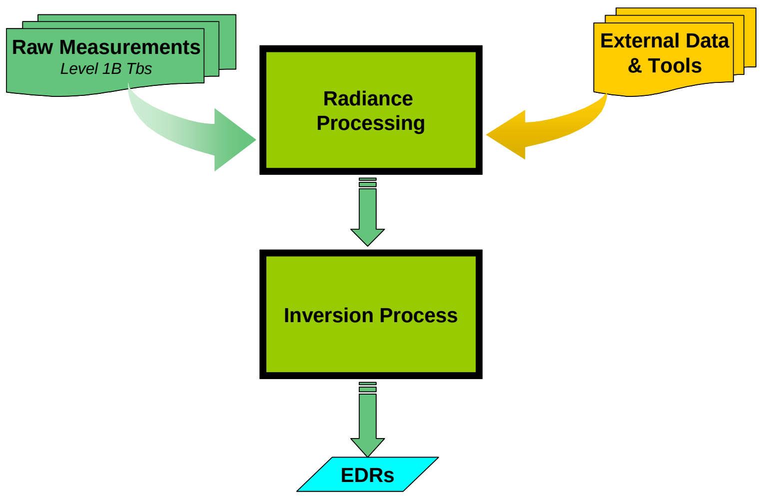

Figure 2-1. Overall conceptual diagram of the Microwave Integrated Retrieval System (MIRS) concept. Shown are the major components, the radiance and the inversion processing blocks.

Radiance Processing

The radiance processing is described here. First, raw sensor data are converted into MIRS internal format (rdr2tdr). Next, MIRS internal format sensor data are (optionally) antenna-pattern corrected (tdr2sdr), footprint-matched (fm) and bias-corrected. Note that the antenna pattern correction is optional and is not currently implemented in ATMS processing. This block also generates the noise files (NEDT) used for computing instrument noise matrix E. The noise values are assessed as part of the performance monitoring.

Footprint Matching

Footprint matching is the procedure that ensures that all channels for the retrieval view the same location on the Earth. The footprint matching is a sensor-specific application because every sensor has its own characteristics and viewing geometry.

For ATMS, the footprint averaging/resampling algorithm from the EUMETSAT ATOVS and AVHRR Preprocessing Package (AAPP) is used. As currently implemented, the lower frequency channels 1 and 2 (23 and 31 GHz) which have an original measurement beam width of 5.2 degrees are resampled to an equivalent beam width of 3.3 degrees. Channels 3 through 16 (50 through 88 Ghz) which have a beam width of 2.2 degrees, and channels 17 through 22 (165 through 183 GHz) which have a beam width of 1.1 degrees, are not averaged or resampled. Because the AAPP algorithm is used for ATMS measurements, the handling of input TDR files (granules) is slightly different than for other sensors. In order to apply the algorithm (96 footprints/scan line) the footprint matching algorithm normally requires several scan lines immediately before and after the current scan line currently being processed. Since ATMS granule files are small (12 scan lines per granule), the normal procedure is to automatically read in the granules immediately preceding and following the current granule file being processed. The exceptions to this would be (1) one or more missing granule files due to some technical problem, or (2) the first and last granules of the day being processed. In either of these cases, the AAPP footprint matching will simply “mirror” the first several and/or last several scan lines of the granule (as is normally done for the footprints at the edge of each scan line) to create a buffer of footprint values required for the successful execution of the algorithm.

Bias Removal

The bias removal is a procedure that applies a pre-computed bias offset (generated off-line prior to the algorithm software delivery) to the sensor measurements to produce ready-to-invert radiances. Bias removal is a generic term to define the removal of systematic differences between the forward operator and the actual measurements. The histogram adjustment method of bias correction is currently applied to ATMS data. This methodology removes bias by adjusting the histogram of the brightness temperature difference between simulated and actual measurements to make it centered about zero. This process reduces the sensitivity of measurements to clouds, precipitation and coastal contamination.

Inversion Processing

Figure 2-2 describes the conceptual organization of the inversion process. As shown, ready-to-invert measurements generated from the radiance processing are used as inputs to the heritage algorithms and MIRS 1DVAR, the latter referred to in the figure as “advanced”. The heritage algorithm products can optionally be used as first guess in the advanced retrievals. Note that this does not violate the mathematical requirement that the background errors and the instrumental/RTM errors be uncorrelated. This required condition is not violated because the regression algorithms are used as first guesses, not as background constraints.

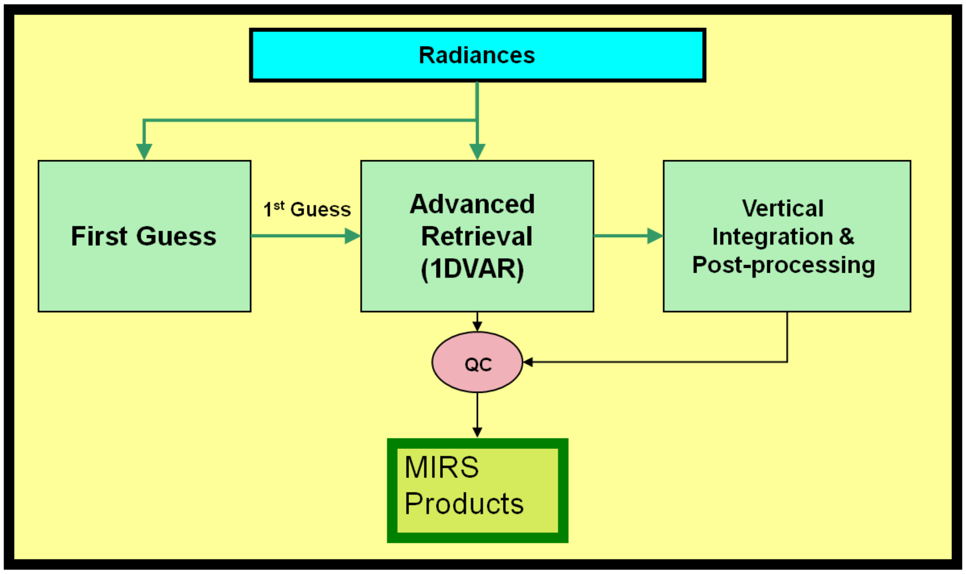

Figure 2-2. High-level diagram of the Inversion process block showing the MIRS concept of merging heritage, advanced and derived products.

The vertical integration and post-processing generates derived products from 1DVAR EDRs.

Advanced Algorithm (*1DVAR*)

The 1DVAR approach to retrievals is referred to as “advanced” since it is more optimal compared to heritage algorithms and it incorporates a sophisticated forward operator (missing in heritage algorithms) that fully assimilates sensor radiance measurements. It is schematically represented in Figure 2-3. The forward operator is based on the Community Radiative Transfer Model (CRTM) developed by the Joint Center for Satellite Data Assimilation (JCSDA). The CRTM produces the simulated radiances Y as well as the Jacobians K. The iterative loop is ended when convergence is reached. The unconstrained cost function is used as a metric for deciding if convergence has been reached.

$$\chi^2 = [Y^m - Y(X)]^T E^{-1} [Y^m - Y(X)]$$

Convergence is reached when $\chi^2 <= 1.0$. The iterative loop is also ended if the convergence criterion is not met within seven iterations.

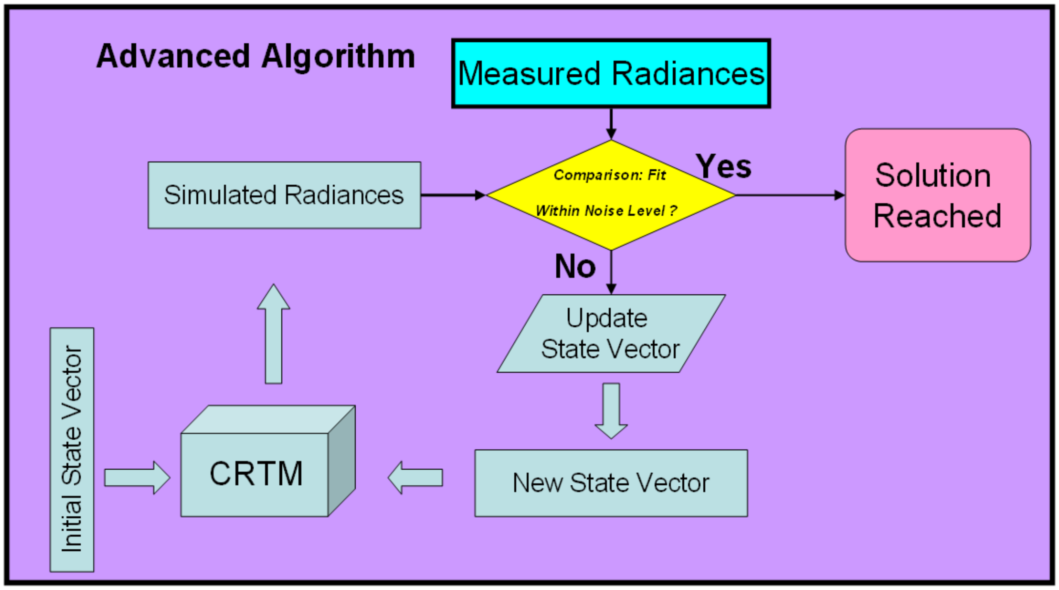

Figure 2-3. General description of the 1DVAR retrieval iterative system. The Initial state vector (or first guess) starts the iterations, the update of the solution takes place at each iteration depending on the local derivatives, simulated brightness temperatures, etc (see text). The solution is reached when the final simulations are fitting the measurements within the noise level. CRTM is used to generate the simulated measurements.

Vertical Integration and Post-Processing

The products generated by 1DVAR are utilized in a post processing stage to generate derived products, as shown in Figure 2-4. This post-processing can take the form of a simple vertical integration e.g. to derive TPW by vertically integrating the water vapor profile Q, or an algorithm, e.g., to derive the surface properties of snow cover and sea ice based on the 1DVAR retrieved parameters of surface emissivities and skin temperature.

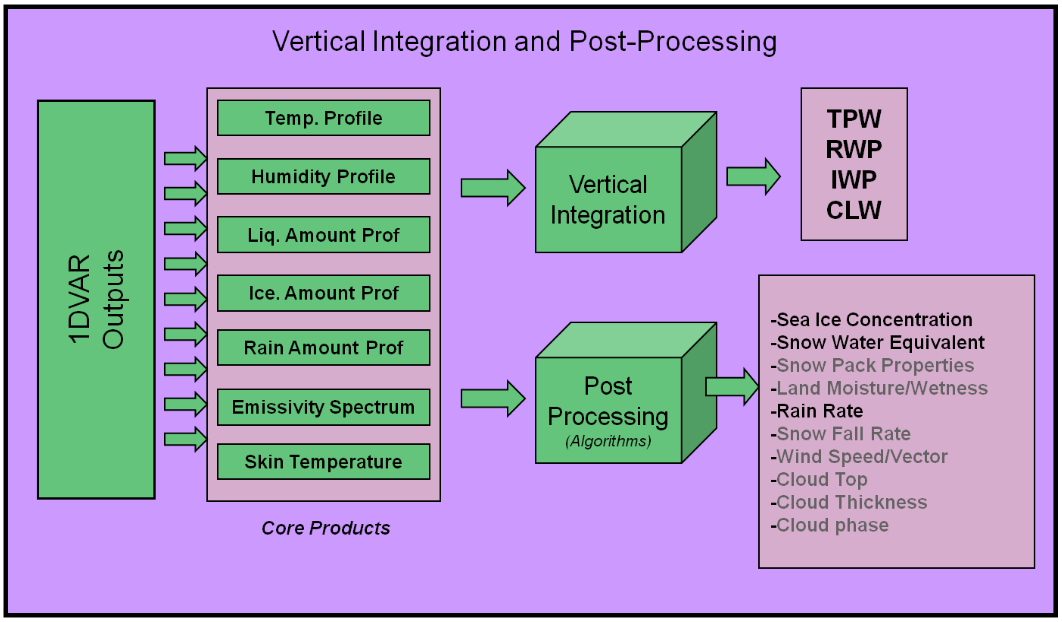

Figure 2-4. Schematic diagram of the MIRS main and derived products.

To summarize, the derived products generated by vertically integrating the corresponding MIRS core retrieved products are: total precipitable water (TPW, from the retrieved water vapor mixing ratio profile), rain water path (RWP, from the retrieved rain water profile), ice water path (IWP, from the retrieved ice water profile), and cloud liquid water (CLW, from the retrieved cloud water profile).

Also related to the hydrometeor retrievals described above is the retrieval of surface rainfall rate (RR) which is derived from a post-processing algorithm which operates on the vertically integrated products CLW, RWP, and IWP. The algorithm to derive rain rate takes advantage of the physical relationship found between atmospheric hydrometeor amounts and surface rain rate. As shown in the equations below, the MIRS rain rate algorithm uses a multi-linear regression approach that requires integrated CLW, IWP, and RWP (in mm), and a set of regression coefficients corresponding to each hydrometeor in order to retrieve the instantaneous rain rate in mm/hr over ocean and land. The regression coefficients are static components in the algorithm that have been determined based on an off-line training. Snowfall rate (SFR) is retrieved using an externally developed algorithm.

Post-processing of the retrieved emissivity spectrum relies on the development of an offline-computed catalog of emissivity spectra for a multitude of values of the parameters to be derived. The post-processing stage is then a simple look-up-table procedure that searches for the catalog pre-computed value that corresponds to a spectrum that matches closely with the retrieved one.

The MIRS derived products generated by post-processing the core retrieved emissivity spectrum and skin temperature are: snow water equivalent (SWE), snow grain size (SGS), total sea ice concentration (SIC), and sea ice age (SIA). The SWE and SGS product retrieval uses the retrieved surface emissivities as inputs and a catalog of surface emissivities and snow pack properties derived off-line from a one-layer Dense Media Radiative Transfer snow emissivity model. The retrieved MIRS emissivity spectra are compared with those from the catalog to find the closest match. The SIC product uses MIRS retrieved surface emissivities and skin temperature as inputs and a catalog of surface emissivities and ice fractions derived off-line from emissivity spectra of pure water and ice surface types (first year and multi-year ice). The retrieved MIRS emissivity spectra are compared with those from the catalog to find the closest match and compute SIC and SIA.

2.2. Algorithm Input

Full description of the attributes of all input data used by the algorithm, including primary sensor data, ancillary data, forward models (e.g. radiative transfer models, optical models, or other model that relates sensor observables to geophysical phenomena) and look-up tables. Do not include file formats; these will be documented elsewhere. *(Document Object 14)*
Writers: Algorithm Scientists.

The MiRS algorithm requires a number of data files to operate properly. The data files needed and their purpose are listed below.

Input Data: ATMS Radiometric Data (single granule)

Contents: Radiometric measurements (brightness temperatures).

Format: HDF 5

Number of Files: 1

Static/Dynamic: Dynamic

Input Data: ATMS Geolocation Data (single granule)

Contents: Earth-based latitude and longitude of radiometric data.

Format: HDF 5

Number of Files: 1

Static/Dynamic: Dynamic

Input Data: Radiometric Bias Correction

Contents: Bias corrections to be applied to radiometric measurements of all non-precipitating scenes. The bias corrections are based on the histogram adjustment method and are a function of both channel and scan cross-track scan position.

Format: Ascii

Number of Files: 1

Static/Dynamic: Static

Input Data: Radiative Transfer Model Error

Contents: Estimated random error of the radiative transfer model used in MiRS. The errors are a function of channel.

Format: Ascii

Number of Files: 1

Static/Dynamic: Static

Input Data: Regression Coefficients for Geophysical First Guess

Contents: Precomputed regression coefficients used to generate a geophysical state vector (i.e. temperature, water vapor, cloud water, skin temperature, total precipitable water, and emissivity) used as a first guess for the 1dvar iterative retrieval. Separate files are stored for each geophysical parameter and surface type.

Format: Ascii

Number of Files: 24 (6 parameters x 4 surface types)

Static/Dynamic: Static

Input Data: Background Mean and Covariance Statistics

Contents: Precomputed mean and covariance statistics of all geophysical parameters to be retrieved in MiRS. The eigenvectors or empirical orthogonal functions (EOFs) of the covariance matrices are also contained in the file. The means, covariances, and EOFs are used as fundamental constraints in the 1dvar iterative retrieval. Separate files are maintained for atmospheric (temperature, water vapor, skin temperature, cloud water, rain water, and ice water) and surface (emissivity) parameters. At run time users can specify one of two options for the use of the mean geophysical background for temperature, water vapor, skin temperature and cloud water: (1) a surface-type based mean background based on global NWP analysis data averaged over each of the four major surface types defined in MiRS (ocean, ice, land, snow), or (2) a spatially and temporally variable climatology derived from one year of gridded NWP analyses. This dynamic mean background varies with latitude, longitude, month and time of day. Option (1) above is stored in an ascii file, while the dynamic background used in option (2) is stored I a large binary file. Both options use the same covariance statistics.

Format: Ascii and binary

Number of Files: 3

Static/Dynamic: Static

Input Data: CRTM coefficients

Contents: Files which contain the optimized spectral and tau coefficients needed for the sensor-specific radiative transfer calculations in CRTM.

Format: Binary

Number of Files: 2

Static/Dynamic: Static

Input Data: Snow Water Equivalent Climatology

Contents: Files which contain the mean snow water values from an archived SSMI-based climatology. These are used as an a priori constraint in the snow water and snow grain size post-processing algorithm.

Format: Ascii

Number of Files: 2

Static/Dynamic: Static

2.3. Theoretical Description

2.3.1. Physical Description

Comprehensively describe the sensor physics and the associated geophysical phenomenology key to the product retrieval. *(Document Object 15)*
Writers: Algorithm Scientists.

The Advanced Technology Microwave Sounder (ATMS), flown on the Suomi-NPP satellite, is a cross-track scanner with 22 channels. Channel selection and frequencies are similar to the heritage AMSUA/MHS sensors flown on the NOAA and Metop polar-orbiting series of satellites. Channel frequencies are chosen to provide sounding of atmospheric temperature, water vapor and cloud, hydrometeors such as rain and ice water, as well as retrieval of surface characteristics. Table 2-1 summarizes the ATMS channels and passband characteristics, instrument noise, and beam widths.

Channel Number	Center Frequency (GHz)	Band width (GHz)	Sensitivity (NEDT) (K)	Accuracy (K)	Beam width (degrees)
1	23.8	0.27	0.7	1.0	5.2
2	31.4	0.18	0.8	1.0	5.2
3	50.3	0.18	0.9	0.75	2.2
4	51.76	0.4	0.7	0.75	2.2
5	52.8	0.4	0.7	0.75	2.2
6	53.596±0.115	0.17	0.7	0.75	2.2
7	54.4	0.4	0.7	0.75	2.2
8	54.94	0.4	0.7	0.75	2.2
9	55.5	0.33	0.7	0.75	2.2
10	57.2903	0.33	0.75	0.75	2.2
11	57.2903±0.115	0.078	1.2	0.75	2.2
12	57.2903	0.036	1.2	0.75	2.2
13	57.2903±0.322	0.016	1.5	0.75	2.2
14	57.2903±0.322 ±0.010	0.008	2.4	0.75	2.2
15	57.2903±0.322 ±0.004	0.003	3.6	0.75	2.2
16	87-91(88.20)	2.0	0.5	1.0	2.2
17	164-167	3.0	0.6	1.0	1.1
18	183.31±7	2.0	0.8	1.0	1.1
19	183.31±4.5	2.0	0.8	1.0	1.1
20	183.31±3	1.0	0.8	1.0	1.1
21	183.31±1.8	1.0	0.8	1.0	1.1

22	183.31±1.0	0.5	0.9	2.0	1.1

Table 2-1. ATMS channels and passband characteristics.

Figure 2-5 shows the ATMS atmospheric weighting functions for all 22 channels based on a U.S. Standard Atmosphere. The weighting functions provide a synthesis of how the atmospheric state at each vertical layer (primarily through absorption/emission) contributes to the observed upwelling radiance at the top of the atmosphere for each channel.

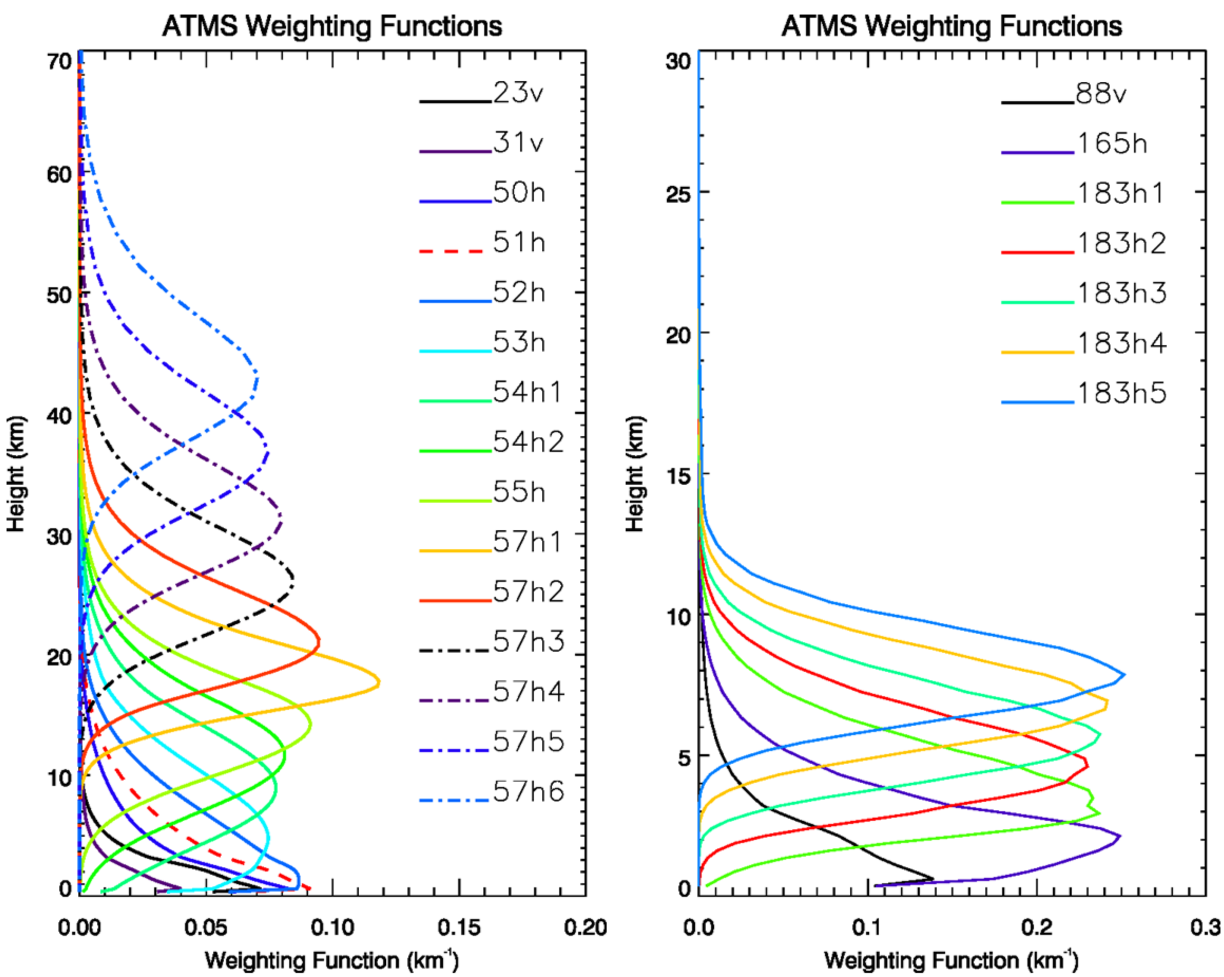

Figure 2-5. ATMS weighting functions.

Non-gaseous constituents can also impact measured radiances, in particular cloud and precipitation-size hydrometeors via absorption and scattering of upwelling radiation. Figure 2-6 shows the modeled impact of cloud, rain and ice on over-ocean brightness temperatures in the range from 1 to 300 GHz, with the spectral range covered by ATMS highlighted. Note that the impacts have a spectral dependence, and that this dependence differs between cloud, rain and ice. This characteristic allows the MiRS algorithm via the Jacobians (brightness temperature sensitivities) to extract information on the hydrometeor type and amount within the variational retrieval.

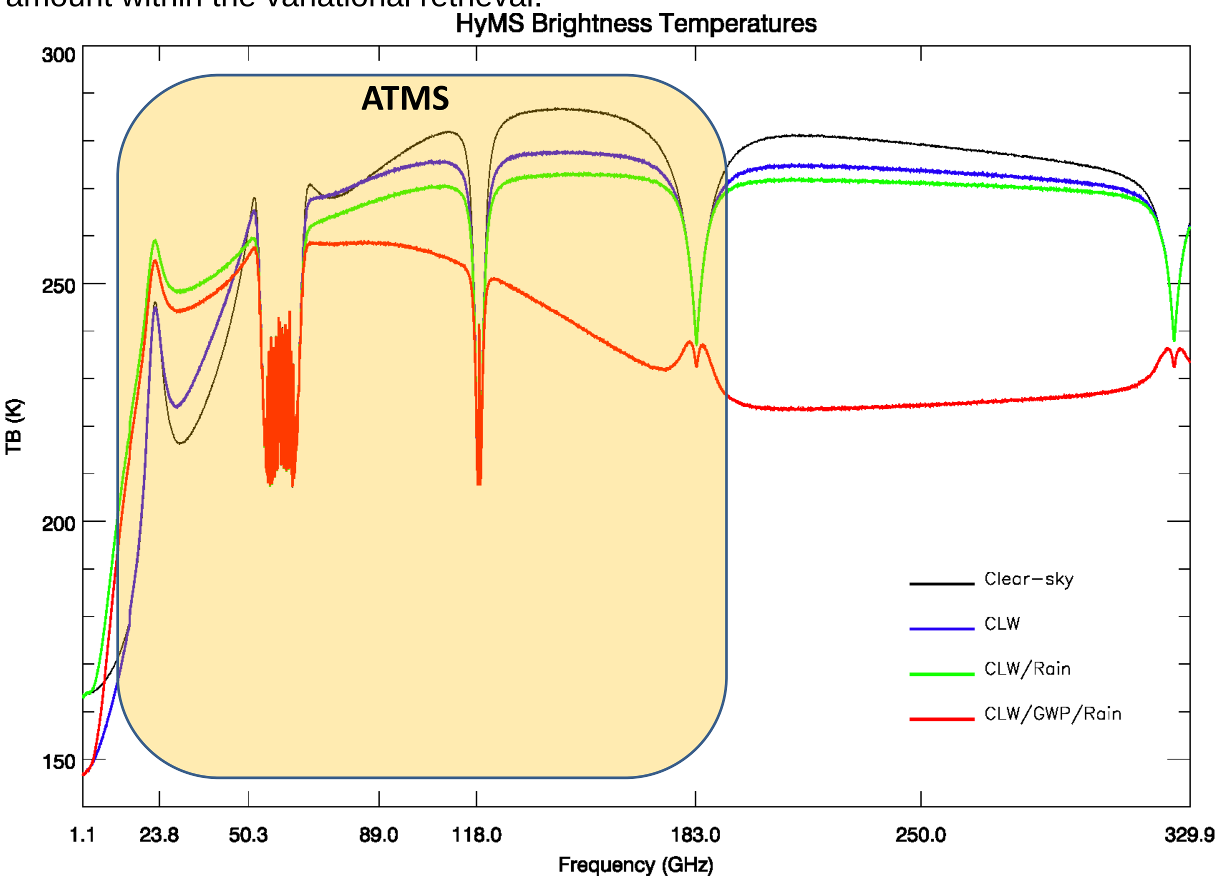

Figure 2-6. Impact of cloud ice and rain in simulated brightness temperatures in the range 1 to 330 GHz. The shaded area indicates the spectral range of the ATMS channels.

In addition to the impact of atmospheric conditions on upwelling radiances, surface characteristics also modulate observed radiances via changes in surface emissivity, which can be highly variable and dependent on polarization, frequency, satellite zenith angle, and surface type. Over bare ground, characteristics such as soil moisture, soil type, soil moisture, and vegetation type affect emissivity, Over cryospheric surfaces, characteristics such as snow depth, snow grain size, and sea ice age influence emissivity. Over ocean, surface roughness (driven largely by surface wind speed, salinity, and surface temperature affect the emissivity spectrum.

Figure 2-7 and Figure 2-8, which are based on the model results of Weng et al. (2001) show the dependence of the microwave surface emissivity spectrum on surface type for both vertically and horizontally polarized radiation.

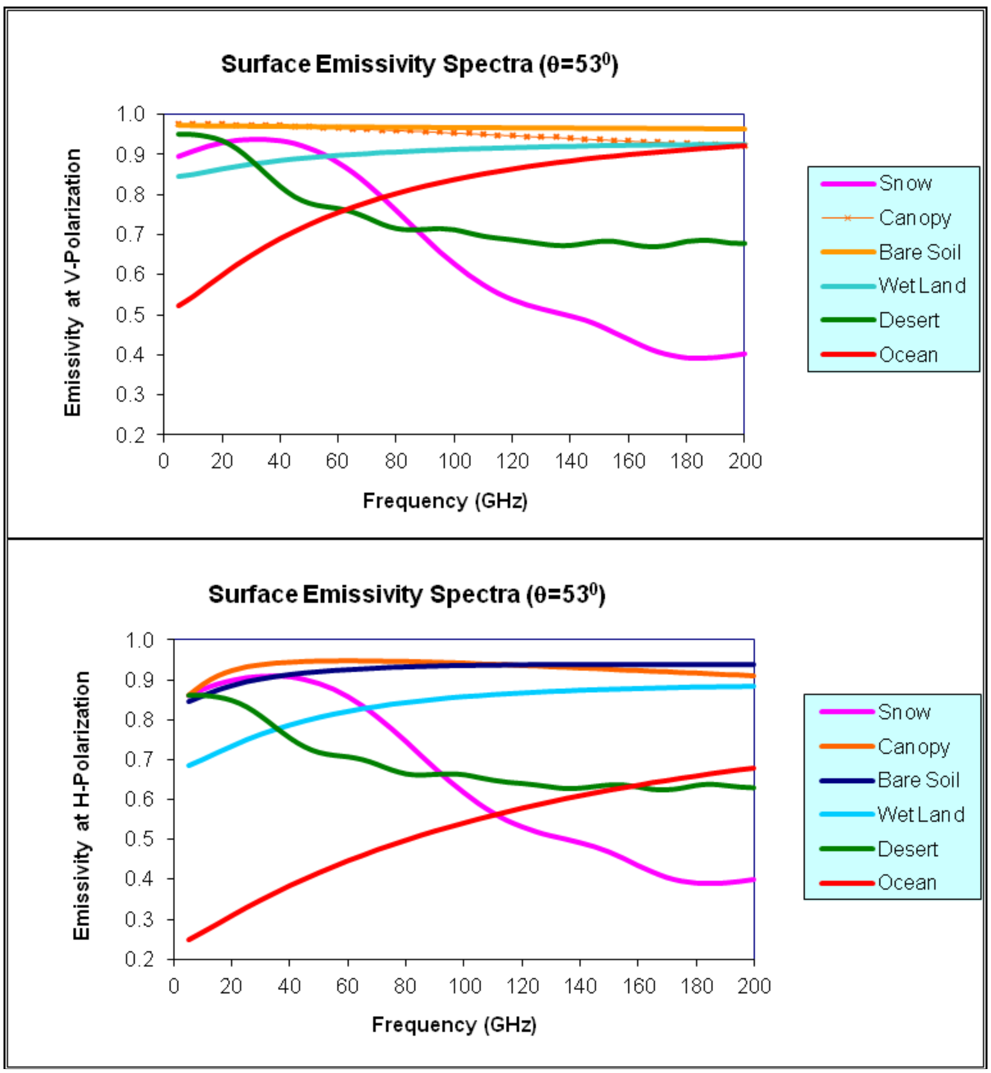

Figure 2-7. Modeled emissivity spectra at V-pol (top) and H-pol (bottom) as a function of land and snow surface types (Weng et al. 2001).

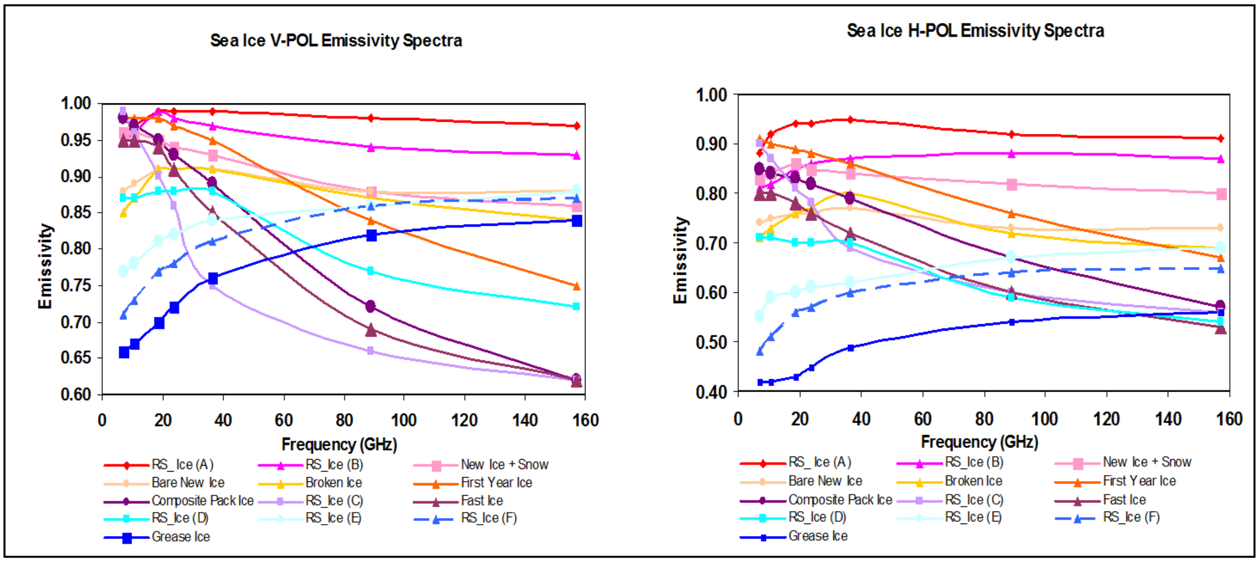

Figure 2-8. Emissivity spectra at V-pol (top) and H-pol (bottom) as a function of sea ice types (Weng et al. 2001).

The MiRS algorithm utilizes this sensitivity of the observed radiances to the retrieved geophysical parameters, which is embodied in the Jacobian matrix computed by the CRTM forward model, to obtain self-consistent retrievals of all official products.

2.3.2. Mathematical Description

Comprehensively describe the mathematics used by the algorithm, including all assumptions, simplifications, approximations. *(Document Object 16)*
Writers: Algorithm Scientists.

MiRS is based on the one dimensional variational retrieval (1DVAR) approach. The inversion is an iterative physical algorithm that optimally extracts the information content present in the measurements. It performs the retrieval in a consistent fashion, with the end result being a set of geophysical parameters or Environmental Data Records (EDRs) that are computed simultaneously and, when used as inputs to the forward model, would nominally fit the measured radiances to within the noise level. The retrieval is performed in a reduced space by using Empirically Orthogonal Function (EOF) decomposition to allow a more stable inversion, a faster retrieval and to avoid the null space. MIRS is coupled with the Joint Center for Satellite Data Assimilation (JCSDA) Community Radiative Transfer Model (CRTM) which is valid in both microwave and infrared spectral regions, in clear, cloudy and precipitating conditions and over all surface types.

The mathematical basis for the inversion problem is to find a vector X, in this case, a set of geophysical parameters, given a vector of measurements Y^m, in this case a vector of radiometric data (radiances or brightness temperatures). Several techniques are available, the suitability of which mainly depends on the nature of the inversion problem. These techniques have different names but generally result in the same mathematical expressions. Among the names found in the literature are: maximum probability solution (MPS), one-dimensional variational retrieval (1dvar), Bayesian algorithm, Optimal Estimation Theory, etc. Two important assumptions are made, namely, the local-linearity of the forward problem and the Gaussian nature of both the geophysical state vector and the simulated radiometric vector around the measured vector. With these assumptions, the mathematical problem can be formulated as a minimization of the following cost function:

$$J(X) = \left[\frac{1}{2}(X - X_0)^T \times B^{-1} \times (X - X_0)\right] + \left[\frac{1}{2}\left(Y^m - Y(X)\right)^T \times E^{-1} \times \left(Y^m - Y(X)\right)\right] \quad (1)$$

where X_0 and B are the mean vector and covariance matrix of the vector X respectively. E is the measurement and/or modeling error covariance matrix. Y is a forward operator capable of simulating a measurements-like vector. The left term represents the penalty in departing from the background value (a-priori information) and the right term represents the penalty in departing from the measurements. The solution that minimizes this two-termed cost function is sometimes referred to as a constrained solution. The minimization of this cost function is also the basis for the variational analysis retrieval. The solution that minimizes this cost function is easily found by solving for:

$$\frac{\partial J(X)}{\partial X} = J'(X) = 0 \quad (2)$$

which has the following iterative solution:

$$\Delta X_{n+1} = \left\{BK_n^T\left(K_n B K_n^T + E\right)^{-1}\right\}\left[\left(Y^m - Y(X_n)\right) + K_n \Delta X_n\right] \quad (3)$$

where *n* is the iteration index, *K* is the matrix of partial derivatives of Y with respect to the state vector X (Jacobian) and ΔX is the departure from the background value. At each iteration *n*, a new optimal departure from the background is computed given the current geophysical and radiometric departures. The derivatives and the covariance matrices (error/modeling covariance and the geophysical covariance) are also computed. This is an iterative-based numerical solution that accommodates slightly non-linear problems or parameters with slightly non-Gaussian distributions. MIRS performs the retrieval in one loop.

The whole geophysical vector is retrieved as one entity, ensuring a consistent solution that fits the radiances. The constraints are in the form of the measurements as well as the assumed a-priori information. In the retrieval scheme used by MIRS, the departure from the measured radiances is normalized by the noise level (NEDT) impacting the measurements and the uncertainty in the forward modeling, making it possible to sometimes use the signal of a particular channel when the geophysical signature (through the derivative) is stronger than the noise (leading to a useful signal-to-noise level), and some other times dismiss the same channel when the signal in question is within the uncertainty/noise level. The departure from the background is also scaled by the uncertainty placed on the background. This makes it harder for the retrieval to depart from the background information if it is deemed accurate. The source of these backgrounds can vary from simple climatology (loose background errors) to NWP forecast fields (tight errors in the temperature background).

Retrieval in Reduced Space Using Empirical Orthogonal Functions (EOFs)

The retrieval in MIRS is performed in EOF space through projections back and forth between the original geophysical space and the reduced space. This is done mainly because the information contained in the radiances is not enough to fully constrain the ill-posed problem of inverting atmospheric profiles and surface optical properties from the limited set of radiances. The strong natural correlations that sometimes exist between the parameters to retrieve create a potential for instability in the retrieval process, which could be reduced significantly by performing the retrieval in an orthogonal space.

Additional advantages of performing the retrieval in EOF space are:

- Time saving: smaller matrices to manipulate and invert.
- Consistent way to tune the retrieval to different instrument configurations: one with many channels requires more EOFs while a limited set of channels would require a smaller number of EOFs for the retrieval of a particular parameter.

2.4. Algorithm Output

Describe the output data products - not format - at a level of detail to determine if the product meets user requirements. *(Document Object 17)*
Writers: Algorithm Scientists.

The list of products generated by MIRS is given in Table 2-1. Both core and derived MIRS 1dvar products are listed. MIRS core products include the parameters that are part of the retrieval state vector. MIRS derived products are those generated using MIRS 1dvar parameters as inputs and a post-processing procedure, e.g., a simple vertical integration of retrieved water vapor profile for computing Total Precipitable Water (TPW), or a new algorithm, e.g., for the estimation of Snow Water Equivalent (SWE) from the retrieved surface emissivities. All sounding products are produced on a vertical pressure grid consisting of 100 layers. Imagery and sounding products refer to those products that are stored in the IMG and SND netCDF output files, respectively.

Observational Parameter	Imagery Product	Sounding Product	Core or Derived Product
Atmospheric Temperature profile (T)		X	Core
Atmospheric Water Vapor profile (Q)		X	Core
Total Precipitable Water (TPW)	X		Derived from retrieved profile
Land Surface Temperature (LST)	X		Core
Surface Emissivity Spectrum (Em)	X		Core
Sea-ice Concentration (SIC)	X		Derived from emissivity
First-year sea-ice Concentration (FYI)	X		Derived from emissivity
Multiyear sea-ice Concentration	X		Derived from emissivity
Snow Cover Extent (SCE)	X		Derived from emissivity
Snow-Water Equivalent (SWE)	X		Derived from emissivity
Snow Grain Size	X		Derived from emissivity
Integrated Cloud Liquid Water (CLW)	X		Derived from retrieved cloud profile
Integrated Ice Water Path (IWP)	X		Derived from retrieved ice profile
Integrated Rain Water Path (RWP)	X		Derived from retrieved rain profile
Rainfall Rate (RR)	X		Derived from CLW, IWP, RWP
Snowfall Rate (SFR)	X		External algorithm

Table 2-2. MIRS 1DVAR core and derived products.

An expected benefit of using MIRS is the self-consistency of the retrieved EDRs as the 1dvar formalism requires the simulated radiances derived using the retrieved geophysical scenes as input, to fit the observed radiances to within the known uncertainty of the measurements.

2.5. Performance Estimates

2.5.1. Test Data Description

Description of data sets used for V&V, including unit tests and system test, either explicitly or by reference to the developer's test plans, if available. This will be updated during operations to describe test data for maintenance. *(Document Object 31)*
Writers: Development Testers

Details of the data sets used for validation and verification as part of the code unit tests can be found in the following NOAA Enterprise Product Lifecycle (EPL) artifacts from the MiRS Test Readiness Review (TRR), the Code Unit Test Review (CUTR), and the System Readiness Review (SRR), which are located on the password-protected section of the MiRS website. Users should contact the algorithm developers for this information.

- http://www.star.nesdis.noaa.gov/smcd/mirs/meetings/meetingTRR20110119/MiRS_TRR_NPP_ATMS_2011-01-19_Final.pptx
- http://www.star.nesdis.noaa.gov/smcd/mirs/meetings/meeting20110526/MiRS_CUTR_NPP_ATMS_2011-05-26_Final.pptx
- http://www.star.nesdis.noaa.gov/smcd/mirs/meetings/meeting20120419/MiRS_SRR_NPP_ATMS_2012-04-19_Final.pdf

2.5.2. Sensor Effects

Characterize sensor effects that may contribute to retrieval error. Include the following effects if relevant:

o Flowed-through effects of sensor noise (radiometric, thermal, or other) on the quality of products, using text and graphics (scatter plots, image displays, etc.).

o Flowed-through effects of calibration errors (radiometric, including structured scenes and response versus scan, or any sensor biases) on the quality of products, using text and graphics.

o Flowed-through spatial and spectral error effects (pointing and geolocation errors, apodization, modulation transfer function (MTF), point-spread function (PSF), out-of-band (OOB) response, near-field stray light, Earth shine, solar contamination, polarization, cross talk, etc.) on the quality of products, using text and graphics.

o Flowed-through effects of un-modeled or neglected geophysical phenomena on the quality of products, using text and graphics.

(Document Object 18)
Writers: Algorithm Scientists.

A summary of uncertainties in sensor and model-simulated measurements and their estimated impacts on retrieval parameters is shown in Table 2-3 below.

Error Source	Handling in MiRS	Limitation	Estimated Impact
Sensor Noise	Computed from standard deviation of sensor warm target temperature values in each granule. Included in combined radiometric uncertainty matrix in 1dvar inversion.	Relies on on-board warm target measurements. May not include all noise sources. Same value applied for all scan positions.	Generally small relative to normal geophysical variability, with impact on temperature estimates less than 1 K, and on water vapor of less than 10 % (random errors).
Calibration Errors	Uses off-line estimate of radiometric bias based on differences between observed and simulated brightness temperatures. Bias corrections which are channel and scan position dependent are applied to each scene prior to retrieval.	Overall bias correction/estimate is a combination of sensor and forward model errors. Bias correction is developed using clear over-ocean scenes and may not be representative to precipitating or non-ocean scenes. Bias correction assumes quasi-linear behavior of the combined sensor/model bias and does not account for more complex sensor-based artifacts such as polarization cross-talk due to reflection from satellite itself extending into measurements at higher scan angles.	Variable, but could impact temperature estimates by 1-4 K, and water vapor estimates by 10-20 % in some cases (systematic errors).
Modeling Errors	CRTM forward model accounts for absorption/emission of all relevant species, including cloud water droplets. Scattering effects due to precipitation size liquid and frozen hydrometeors is also accounted for.	Scattering currently assumes a fixed hydrometeor particle size distribution. Scattering from snow is not turned on.	Variable, but could impact ice and rain water path estimates by up to 50 % in some cases (random and systematic).

Table 2-3. Summary of sensor and modeling effects on MiRS retrievals.

2.5.3. Retrieval Errors

Accuracy of products, as measured by V&V testing, and compared to accuracy requirements. Refer to relevant test reports. *(Document Object 39)*
Writers: Algorithm Scientists and Development Testers should collaborate

Product Accuracy

Description of MIRS ATMS post-launch product validation activities were described in the Validation section. Table 2-4 summarizes the MiRS retrieval performance in terms of accuracy and precision for the official products, along with accuracy objectives. For some products (e.g. temperature and water vapor profiles) only selected layers are shown. For certain hydrometeor products (e.g. ice and rain water) a reliable reference data set is not available. However, the performance results for surface rain rate can be considered an indirect measure of the ice and rain water performances since the rain rate is derived directly from these products.

Further details and examples of validation results can be found at the official MiRS website `https://www.star.nesdis.noaa.gov/mirs/index.php`

Retrieval Product	Precision	Accuracy	Accuracy Specification
Temperature (300 mb), ocean (K)	1.9	0.7	1.
Temperature (300 mb), land (K)	1.6	0.7	1.5
Temperature (500 mb), ocean (K)	1.5	-0.4	1.
Temperature (500 mb), land (K)	1.5	-0.1	1.5
Temperature (900 mb), ocean (K)	2.2	1.2	2.0
Temperature (900 mb), land (K)	4.3	0.8	2.0
Water Vapor (300 mb), ocean (%)	53.	4.	20.
Water Vapor (300 mb), land (%)	56.	3.	20.
Water Vapor (500 mb), ocean (%)	51.	-6.	20.
Water Vapor (500 mb), land (%)	56.	18.	20.
Water Vapor (900 mb), ocean (%)	20.	-3.	20.
Water Vapor (900 mb), land (%)	34.	-4.	20.
Total Precipitable Water, ocean (mm)	2.5	1.5	1.0
Total Precipitable Water, land (mm)	2.2	1.7	2.5
Cloud Liquid Water, ocean (mm)	0.10	-0.03	0.03
Land Surface Temperature (K)	7.0	3.0	4.0
Emissivity (23.8 GHz Vpol), land	0.02	0.01	0.020
Emissivity (50.3 GHz Hpol), land	0.03	0.01	0.015
Emissivity (165.5 GHz Hpol), land	0.04	0.01	0.015
Rain Rate, ocean (mm/h)	0.5	0.05	0.10
Rain Rate, land (mm/h)	0.5	0.03	0.05
Sea Ice Concentration (%)	15.0	-5.0	10.0
Snow Water Equivalent (cm)	5.0	-2.0	3.0

Table 2-4. Summary of MiRS ATMS product performance based on validation activities. Unless otherwise stated, results are for combined clear/cloudy conditions.

Organize the various error estimates into an error budget, presented as a table. Error budget limitations should be explained. Describe prospects for overcoming error budget

limitations with future maturation of the algorithm, test data, and error analysis methodology. *(Document Object 19)*
Writers: Algorithm Scientists.

Error Budget

Estimated errors in MiRS retrievals are summarized elsewhere in the product accuracy section. In Table 2-5 we summarize the primary areas where identified errors might be reduced, and the means by which that could potentially accomplished. Testing and implementation of such mitigation strategies would depend on project resources, and a full evaluation of the impacts upon algorithm performance, including on both retrieval accuracy and required IT resources.

Error Source	**Magnitude of Retrieval Impacts**	**Mitigation Strategies**
Sensor Noise	• T: less than 1 K • WV and other parameters: less than 10 %	Footprint averaging to lower resolution would lower noise impact, but this option limited by operational requirements.
Sensor Bias	• T: up to 1-4 K • WV and other parameters: 10-20 %	Current scan-dependent biases in ATMS SDRs are being investigated by cal/val team and if a physically-based mitigation approach is developed, the MiRS algorithm can easily switch from processing TDRs to SDRs.
Forward Model Bias	• T: up to 1-4 K • WV: up to 10-20 % • RWP and IWP: up to 50 % • All other parameters: 10-20 %	• Currently a single set of bias corrections are applied. Mitigation approach could consider development of air mass-dependent bias corrections that explicitly account for impact of geophysical state on forward model biases. • Other biases may be related to assumptions made in the scattering module of CRTM, including the assumption of fixed hydrometeor particle size distribution parameters. More recent versions of CRTM allow user specification of these parameters and the retrieval might be designed to make use of this.
A priori Background Error	• T: locally up to 5-10 K • WV: up to 20-40 % • All other parameters: 10-20 %	A single global climatology, stratified by surface type, is used as the a priori background. Retrieval errors can be amplified in situations far from the climatological means. Development of a spatially and temporally varying a priori background can potentially reduce retrieval errors as the background state is closer to the truth during the 1dvar minimization.
Core Retrieval Algorithm Errors	Emissivity: up to 10-20 %	Core EDRs are retrieved in terms of EOF basis functions rather than directly in geophysical space. For some parameters the orthogonality constraint of the EOFs may not be sufficient to assure physically realistic, particularly the emissivity spectrum, which is prone to being a "sink" into which errors in other core parameters are projected. Alternative functional representations that impose a higher degree of smoothness may mitigate this behavior.
Postprocessing Algorithm Errors	Rain Rate: up to 50 % Snow Water Equivalent: up to 50-75 % (5-10 cm) Sea Ice Concentration: up to 50-75 %	• For rain rate the post processing algorithm assumes a fixed relationship between core retrieved hydrometeors and surface rain rate, stratified by land and ocean. Development of distinct relationships based on classification of precipitation into stratiform or convective type may help adjust the relationships based on the geophysical state. • Snow water is derived from the core retrieved emissivity spectrum, which utilizes a subset of the window channel retrievals in combination with look-up table generated by a physical model. The algorithm could be adjusted to 1) utilize higher frequencies which might enhance the sensitivity to lower snow water amounts, 2) use empirically-based, rather than physically-based relationships that might address uncertainties in the physical model. • Both snow water and sea ice emissivity spectra are retrieved assuming a surface-dependent a priori background spectrum. This background is based on the preclassified surface type and misclassifications can sometimes lead to corresponding errors in the retrieved spectra. Improvements to the preclassifier to reduce misclassification or to allow for mixed surface types near snow or ice edges might lead to improved emissivity spectra and, hence, to the derived snow water and sea ice concentration.

Table 2-5. Summary of MiRS retrieval error estimates and possible mitigation approaches.

2.6. Practical Considerations

2.6.1. Numerical Computation Considerations

Describe how the algorithm is numerically implemented, including possible issues with computationally intensive operations (e.g., large matrix inversions, truncation and rounding). *(Document Object 21)*
Writers: Development Programmers.

All MiRS codes involved in producing the core and derived products are written in Fortran-90. Computationally intensive operations which involve issues of machine precision in MiRS are primarily the matrix inversion operations, which use double precision variables when necessary, and in the forward model, CRTM, which is not officially part of MiRS algorithm. However, with respect to the forward model, the computational intensity is also reduced, since MiRS uses a 2-attempt approach in which the first retrieval attempt uses a forward model calculation with no scattering processes, and is therefore much faster than a simulation in which scattering is included. In MiRS, only if the first attempt fails to converge is scattering turned on and the retrieval restarted. Since precipitating areas, which correspond to most of the non-convergent cases, represent less than 10 percent of the observed scenes globally, computational time is reduced and products are produced within operational latency requirements. Finally, at the script level MiRS is designed to take advantage of multi CPU systems in two ways: first by utilizing the chopp feature which can split a single granule into multiple sub-granules which can then be processed in parallel on multiple processors, and secondly, if run with more than one granule in the working directory, individual granules are sent to different processors since the 1dvar processing of one granule is independent of another and granules may be processed in any order. Outside of the MiRS algorithm, the NDE operating environment is likely to implement load balancing to optimize throughput in order to keep up with the real-time data flow.

2.6.2. Programming and Procedural Considerations

Describe any important programming and procedural aspects related to implementing the numerical model into operating code. *(Document Object 22)*
Writers: Development Programmers.

All MiRS codes are already fully mature in that all models and algorithms have already transitioned to operational quality code, and the same code structure has been running operationally for several years at NOAA on other operational satellite/sensor combinations. Programs and procedures are written in a modular fashion with all sensor-specific information passed as variables. This should simplify any updates or additions that may be made to the MiRS codes in the future.

2.6.3. Quality Assessment and Diagnostics

Describe how the quality of the output products and the retrieval itself is assessed, documented, and any anomalies diagnosed. *(Document Object 23)*
Writers: Algorithm Scientists.

The MiRS retrieval process has several built-in methods of quality assessment and product validation. They range from quality flag parameters produced in the retrieval files to continuous comparison of the products to a variety of external sources.

The quality metrics provided in the MiRS output files include values for chi square (χ^2) rms and the forward operator (Y^{fwd}) as well as a detailed quality control (QC) structure. The QC structure rates the quality of the retrieved products for each given location and gives specific details on any noted problems. For example, the structure indicates the presence of precipitation and whether the products are physically reasonable, or if there were problems with the measured input data. The QC structure is provided in both the EDR and DEP output files, and is mostly the same between the two. However, the version in the DEP files may be altered depending on any additional information raised by the post-processing steps.

The QC metric and the overall MiRS convergence rate percentage are monitored over time to detect anomalies in data quality. Likewise, the NEDT of the sensor inputs is also monitored to identify any potential problems or abnormal behaviors that would alter the expected retrieval quality.

The MiRS products are assessed and validated through comparison with external analysis and models, which are generated and monitored daily. To evaluate changes in radiometric bias and calibration, the forward operator is used with ancillary NWP data (both the GDAS and ECMWF analysis) to generated simulated brightnesses that are compared to the input brightness temperatures for the MiRS retrieval. Products retrieved with the ECMWF simulations are also compared to the MiRS outputs to detect outliers.

For products monitoring, the MiRS outputs are compared to collocated products from a variety of sources. The GDAS and ECMWF analysis products are also used for this assessment for a subset of the retrieved results, which include total precipitable water (TPW), skin temperature, emissivity, surface pressure as well as profiles of temperature and water vapor. In addition, the MiRS retrievals are contrasted with the microwave products generated by the heritage Microwave Surface and Precipitation Products System (MSPPS) algorithm for AMSU-MHS.

MiRS products are also validated and assessed for quality using external retrieved products and observations. The NOAA Products and Validation System (NPROVS) supplies HIRS skin temperature and daily radiosonde data for continual product comparison. CloudSat retrievals are also useful for monitoring the bulk of the hydrometeor outputs. For individual cryospheric products, validation is performed against AMSR-E snow and sea ice, the NOAA National Weather Service's National Operational Hydrologic Remote Sensing Center SNODAS snow analysis and the SSMI/S sea ice product.

For the specific precipitation products, an assortment of sources is available for comparison. The MiRS rainfall product is evaluated using the NCEP Stage IV precipitation analysis as well as collocated data from the Tropical Rainfall Measurement Mission (TRMM) retrievals, both the 2B31 rainfall rate and the 2A12 hydrometeor profile product. The International Precipitation Working Group (IPWG) provides carefully validated "ground truth"-based references in the form of rain gauges and rain radar observations for comparisons over three specific regions, which include the United States, South America and Australia. Finally, the NOAA/NCEP Climate Prediction Center (CPC) offers a precipitation product for MiRS validation over the US region.

For further quality assessment, the MiRS retrieved products are also inter-compared for all fields between the various sensors of operation. Any anomalies detected in this method and the other various comparisons and validations are noted, and the MiRS science team is alerted for further investigation and documentation.

2.6.4. Exception Handling

List the complete set of expected exceptions, and describes how they are identified, trapped, and handled. *(Document Object 24)*
Writers: Development Programmers.

2.7. Validation

Describe how the algorithm has been or should be validated at a level of detail appropriate for the current algorithm maturity. *(Document Object 26)*
Writers: Algorithm Scientists.

3. ASSUMPTIONS AND LIMITATIONS

Figures used in Section 3 should be numbered Figure 3-1, Figure 3-2, etc.

Tables used in Section 3 should be numbered Table 3-1, Table 3-2, etc.

3.1. Performance Assumptions

Describe all assumptions that have been made concerning the algorithm performance estimates. Note any limitations that apply to the algorithms (e.g., conditions where retrievals cannot be made or where performance may be significantly degraded. To the extent possible, the potential for degraded performance should be explored, along with mitigating strategies. *(Document Object 20)*
Writers: Algorithm Scientists.

3.2. Potential Improvements

Describe potential future enhancements to the algorithm, the limitations they will mitigate, and provide all possible and useful related information and links. *(Document Object 25)*
Writers: Algorithm Scientists.

As with any scientific algorithm, improvements can be anticipated as technology improves, computational resources increase, and scientific and technical understanding advances.

The following areas are those currently identified as those where an improvement in one or more of the MiRS output products are most likely. An improvement may be an increased accuracy of an already-retrieved product, or an addition of a new retrieval product.

Surface Emissivity Spectrum

The MiRS algorithm currently retrieves the emissivity spectrum directly as part of the core 1dvar retrieval, using the Jacobians of the brightness temperature with respect to emissivity returned by the CRTM. A degree of smoothness is imposed upon the retrieved spectrum through the use of EOFs as basis functions, and through the background error covariance structure. However, because the EOFs are designed to efficiently explain the dominant modes of variability of the overall training set, in some cases, the smoothness imposed by the EOF basis functions does not always adequately remove inter-channel variations for individual retrieved spectra that may be induced by inter-parameter crosstalk (e.g. between water vapor and emissivity), or uncertainties in the forward and Jacobian calculations. Work is underway to determine if an alternate representation of the emissivity spectrum other than EOFs may result in retrieved spectra that are less sensitive to these effects using, for example, an analytic or polynomial function representation. Implementation within the 1dvar would require a fast and efficient means of transforming the Jacobians at each iteration into the space defined by the functional representation. This implies that whatever the choice of function, its analytic derivative needs to be easily calculable.

Dynamic Bias Correction

The bias corrections used in MiRS are based on a histogram approach, using near-global sets of over ocean, clear-sky brightness temperature observations and collocated simulated observations using NWP model fields as input. This is done, in part, because the confidence in specifying the true atmospheric state in cloudy and/or precipitating conditions is deemed too low to form the basis of a robust bias correction in these conditions. However, this leads to the possibility that the bias corrections applied in these conditions may not be optimal, and prone to certain systematic errors. It is possible that if the hydrometeor states can be better-specified, either with field campaign measurements, or by developing simulated datasets, then a set of air mass-dependent bias corrections could be developed that could account for biases in the forward model that do depend on the actual atmospheric state. Implementation of an air mass or dynamic bias correction should be straightforward within MiRS.

Handling of Hydrometeor Size Distributions

In the current implementation of MiRS, hydrometeor size distribution parameters are held fixed, and only the actual hydrometeor amounts are retrieved. However, the hydrometeor absorption and scattering properties have an important dependence on both the mean and variance of the hydrometeor distribution, as well as the hydrometeor amounts. Research has shown some correlation between hydrometeor amounts and aspects of the size distribution, indicating that a hybrid approach could be considered, in which the distribution parameters are potentially updated within CRTM at each iteration based on some relationship to the current value of the hydrometeor amount at each layer. If implemented in the form of a look-up table approach, this would not be unduly complicated or costly in terms of computational resources.

4. REFERENCES

Jensen, K. A. and McNamara, D., 2011a, Algorithm Theoretical Basis Document Standards and Guidelines, http://projects.osd.noaa.gov/spsrb/standards_data_mtg.htm

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