

A UNIFIED RETRIEVAL METHODOLOGY FOR THE DMSP METEOROLOGICAL SENSORS¹

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ABSTRACT

An overview is presented for a unified retrieval methodology applicable to the data sets of the Defense Meteorological Satellite Program (DMSP) meteorological sensor payload. Desired quantities include temperature and water vapor profiles, surface temperature, cloud properties, precipitation, visibility, and those related to surface type such as snow cover, vegetation, and soil moisture. The hybrid retrieval approach employs both statistical and physical retrieval concepts. The approach exploits existing DMSP operational experience with statistical methods to provide a first guess capability. The first guess is upgraded, if necessary, using a physically based, simultaneous retrieval. Required cloud properties and surface type information are obtained by image processing high spatial resolution visible and infrared data from a colocated imager.

1. INTRODUCTION

The sensor payload of the Defense Meteorological Satellite Program (DMSP) spacecraft of the 1990's will consist of a visible/infrared imager (the operational linescan system or OLS), a microwave temperature sounder (SSM/T-1), a millimeter wave water vapor sounder (SSM/T-2), and a microwave imager (SSM/I). The current OLS imager provides high spatial resolution, global cloud imagery. Notably, all the other sensors are millimeter/microwave instruments. Of these microwave mission sensors, the SSM/T-1 and SSM/I are currently operational (Falcone and Isaacs, 1987). The SSM/T-2 is scheduled for launch in the early 1990s. The attributes of these sensors are summarized in Table 1. Meteorological data requirements tasked to this sensor complement include the acquisition of cloud information, temperature and water vapor profiles, precipitation, and surface properties. One important application of these data products is

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Table 1. DMSF Meteorological Sensors

Instrument	Frequency or Wavelength	Polarization (H or V)	FOV (km)	Response	NEAT (K)
SSM/T	50.5 GHz	H	200	surface	0.6
	53.2	H	200	T at 2 km	0.4
	54.35	H	200	T at 6 km	0.4
	54.9	H	200	T at 10 km	0.4
	58.825	V	200	T at 16 km	0.4
	59.4	V	200	T at 22 km	0.4
	58.4	V	200	T at 30 km	0.5
SSM/I	19.35	H and V	50	surface	0.6
	22.235	V	50	water vapor	0.6
	37.0	H and V	25	clouds, rain	0.8
	85.5	H and V	12.5	clouds, snow	1.1
SSM/T-2	90.0	V	100	surface, water vapor	0.6
	150.0	V	60	surface, water vapor	0.6
	183.31±1	V	50	water vapor	0.8
	183.31±3	V	50	water vapor	0.6
	183.31±7	V	50	water vapor	0.6
OLS	0.4-1.1 μ m		0.6	surface/clouds	-
	10.5-12.5 μ m		2.4	surface/clouds	-

global numerical weather prediction (Isaacs et al., 1986a). Current operational analysis procedures for the OLS, SSM/T-1, and SSM/I treat each sensor data stream independent of the others. OLS imagery is processed into global cloud property fields using an automated nephanalysis algorithm (Fye, 1978). The retrieval scheme for temperature sounding by the SSM/T-1 is based on regression of SSM/T-1 brightness temperature data against desired mandatory level temperatures (Rigone and Stogryn, 1977) and an analogous statistical approach is currently being used in the determination of meteorological parameters such as cloud liquid water content and precipitation (among others) from the SSM/I data (Lo, 1983). These approaches share a common heritage in the "D" matrix technique described by Gaut et al. (1975). Data from the SSM/T-1 and SSM/T-2 will be integrated together in a statistical retrieval of water vapor profiles (cf. Isaacs, 1987).

For a variety of reasons, the operational approach described above could be improved. The main criticisms are: (1) the lack of a multispectral perspective, (2) reliance on statistical retrieval approaches, which

produce retrieval fields with reduced variance properties, fail to treat inherent problem nonlinearities, and provide little opportunity to monitor retrieval quality, and (3) neglect of some physical aspects of the retrieval problem, such as the effect of cloud on millimeter wave brightness temperatures.

Recent advances in remote sensing retrieval theory have verified the significance of both multispectral/multichannel sensor data (that obtained from diverse spectral regions, i.e. visible, infrared, microwave, millimeter wave) (Susskind et al., 1984) and physically based retrieval techniques (Susskind et al., 1984; Smith et al., 1983, 1985) to enhance the accuracy of resultant sounding retrieval products. In a recent joint study undertaken by NASA and NOAA (Phillips et al., 1988), a physically based retrieval approach developed by NASA was shown to uniformly outperform NOAA's operational statistical retrieval technique. This has prompted NOAA to undertake evaluation of physical retrievals for operational implementation to achieve the National Weather Service (NWS) objective of 1K temperature sounding accuracy, i.e. equivalent to that of the MJCS requirement.

To address these issues, an alternative retrieval scheme has been developed. The approach outlined below is by no means statistically optimal. However, it does attempt to address the difficulties cited above and, in particular, integrates available data sources in a unified, multispectral retrieval constrained by radiative transfer principles.

2. RETRIEVAL APPROACH

The retrieval approach for the DMSP illustrated in Fig. 1 employs physical considerations and allows for the incorporation of all data sources. Recognizing potential operational constraints, an attempt has been made to build on the attributes of the existing DMSP retrieval capability and experience. The microwave sensor data, T_b^0 , is employed with the "D" matrix statistical retrieval to provide first guesses for the desired parameters, P^0 : temperature, $T(p)$, and water vapor profiles, $q(p)$, surface emissivity, ϵ_s , and temperature, T_s . Simulated brightness temperatures, T_b^n , are then evaluated to examine the consistency of the first guesses with the observations. The forward problem calculation (denoted by F in Fig. 1) is accomplished using the RADTRAN simulation code (Falcone et al., 1982) as modified by Isaacs et al. (1985). RADTRAN is a

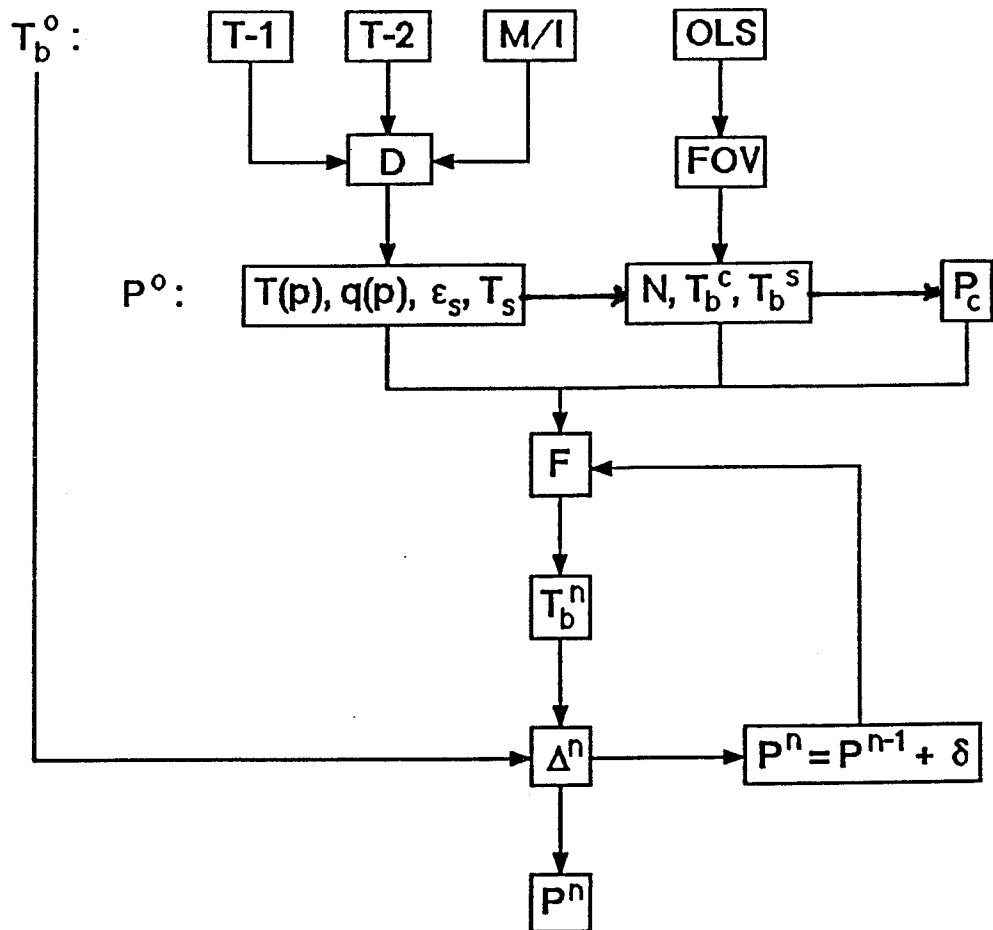


Fig. 1. Schematic of unified DMSP retrieval scheme.

line-by-line calculation. For operational application a computationally efficient microwave band model such as Eyre and Woolf (1988) should be employed. When the residuals, Δ^n , (i.e. differences between simulated and observed brightness temperatures) are small, the process terminates. However, when residuals are larger than a preset tolerance (usually determined by the sensor noise equivalent brightness temperatures (NEAT) and scene noise), the procedure goes on to adjust the first guess profiles. This adjustment is accomplished by using the residuals in a simultaneous physical retrieval.

Cloud or precipitation in the field-of-view (FOV) of the microwave sensors can be problematic. Precipitation will generally preclude soundings of temperature and moisture and the determination of surface properties.

Quality control flags for precipitation (as well as precipitation amounts) can be obtained from the SSM/I statistical retrieval (Lo, 1983; Jin and Isaacs, 1987). Isaacs and Deblonde (1987) have discussed the potential impact of cloud on statistical millimeter wave water vapor retrievals and evaluated the sensitivity of these channels to cloud presence. Cloud fields from the DMSP OLS (using an appropriately spatially averaged subset of visible and infrared imagery) aid in cloud/no cloud discrimination. To determine first guess cloud properties within the FOV necessary to accomplish the physical retrieval step, the high spatial resolution OLS imager data is utilized. Image processing of this data within the relatively larger microwave footprint provides first guess cloud coverage, N , and equivalent brightness temperatures (EBTs) for cloud top and surface, $T_b^{C,S}$. Once cloud coverage is assessed, visible/infrared imagery data for cloudy areas can be used to accomplish desired nephanalysis including cloud cover, height, layers, and type information. Cloud top brightness temperature along with the first guess temperature profile yields a first guess cloud top pressure, p_c . Over the oceans, cloud properties derived from the OLS imager data are supplemented by information on cloud integrated liquid water content (ILWC) available from the SSM/I. Cloud ILWC provides a parameterization of cloud optical thickness and emissivity. These cloud properties are required to treat the effect of cloud on the SSM/T-2 sensor data and therefore are input to the forward problem.

There is significant information available in cloud free regions as the result of the FOV analysis. Cloud free imager data can be applied to the determination of visibility, surface type, vegetation, and snow cover. While not directly applicable for NWP purposes, these data are of interest for optical propagation and background discrimination purposes.

3. STATISTICAL (FIRST GUESS) RESULTS

The integrated scheme described above has been tested in simulation assuming cloud free conditions. These results are described in the next two sections. First guesses for temperature profile, integrated water vapor profile, surface temperature, and emissivity are based on a statistical retrieval employing SSM/T-1, SSM/T-2, and SSM/I data. Data was simulated for these sensors using the RADTRAN microwave radiative transfer code (Falcone et al., 1982) and ensembles of midlatitude and tropical atmospheres from a radiosonde data set consisting of a total of 400 soundings. Sensor noise was introduced by sampling Gaussian distributions

with zero means and standard deviations equal to the NEAT for each channel given in Table 1. Scene noise was ignored as were the spatial averaging effects of differing sensor FOVs. Emissivity values were calculated from an ocean surface reflectance model assuming calm seas (Isaacs et al., 1989). The resultant values were varied assuming a Gaussian distribution with the calculated value as mean and an assumed standard deviation. While surface emissivity per se is not a required meteorological parameter, it provides information on surface winds and sea ice over the ocean, and vegetation, soil moisture, and snow cover over the land (Isaacs et al., 1986b). The surface temperature was set equal to the 1000 mb atmospheric temperature.

The temperature (a) and water vapor (b) retrieval results for various instrument combinations are shown in Figs. 2 and 3, for midlatitude and tropical cases, respectively. Shown are fraction of unexplained variance (FUV) values for each instrument combination. Perfect retrievals have an FUV of 0.0 while those which perform no better than climatology have FUVs of 1.0. (FUVs greater than 1.0 mean that climatology is better than the retrieval.) Fig. 2 shows that the combination of T-1 and T-2 data provide a more accurate integrated water vapor profile than the use of T-2 data alone. Especially note the potential improvement in temperature profile retrieval near the surface obtained when combining SSM/T-1 data with that from the SSM/T-2 or SSM/I. The importance of the SSM/I data combined with the SSM/T data for surface parameter retrievals is also reflected in the surface temperature and emissivity results. These results are shown in Table 2. These midlatitude results can be compared to those for the tropics (Fig. 3). Due to the smaller variance of tropical temperature profiles near the surface compared to midlatitude counterparts, there is little advantage to the combined data set. However, in the tropics the combination of SSM/T and SSM/I data still provide the most accurate retrievals of surface emissivity.

4. PHYSICAL RETRIEVAL RESULTS

4.1 Theory

Statistical first guess results, P^0 , are assessed for consistency with the brightness temperature observations, T_b^0 , by calculating a set of nth guess synthetic sensor data, T_b^n . The RADTRAN algorithm is employed as the forward problem generator, F. Adjustments to the first guesses are accomplished using the brightness temperature residuals Δ^n and physical

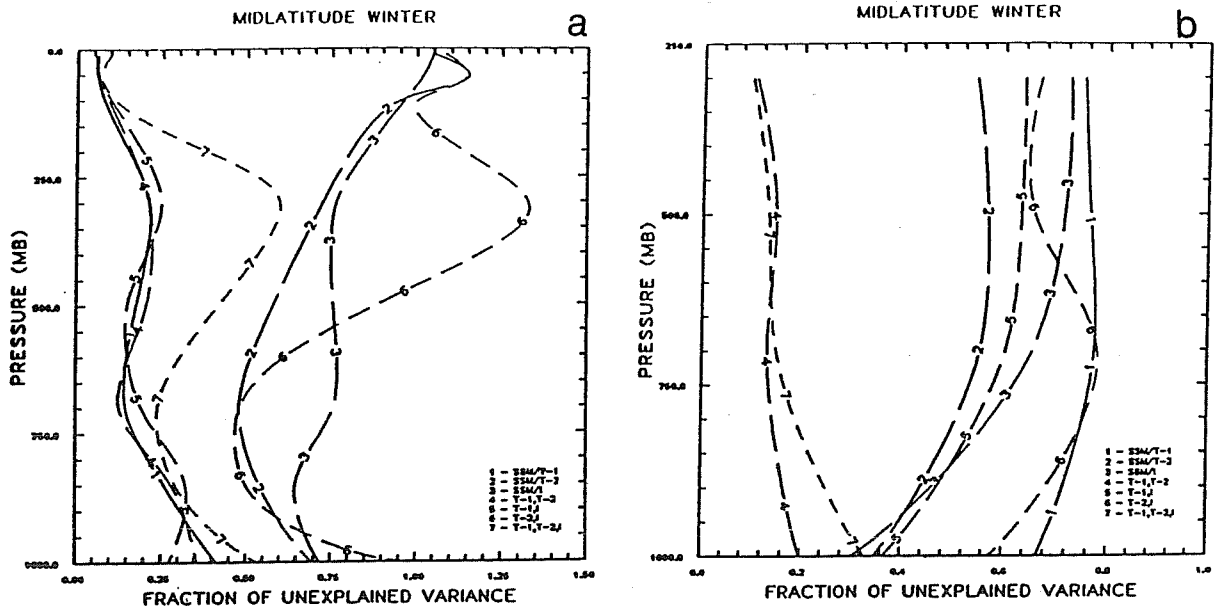


Fig. 2. First guess retrieval FUVs for various sensor combinations (midlatitude statistics).

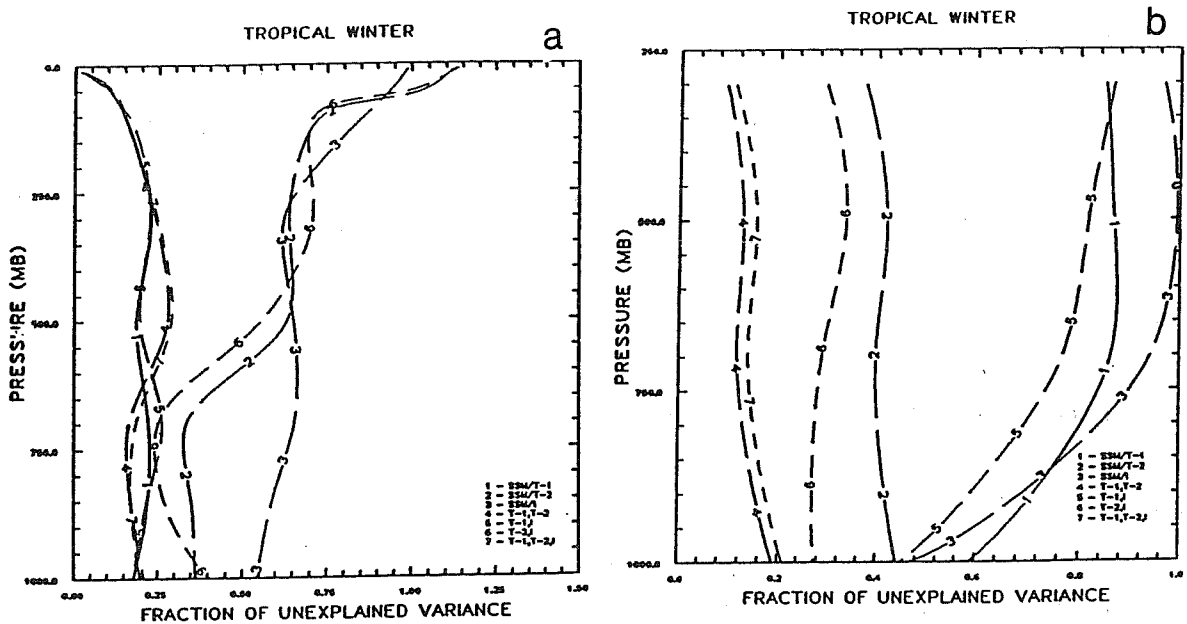


Fig. 3. First guess retrieval FUVs for various sensor combinations (tropical statistics).

Table 2. Standard deviation of first guess retrieval errors for surface emissivity and temperature

PARAM.	SSM/T1	SSM/T2	SSM/I	1&2	1&I	2&I	1,2&I	P S.D.	P MEAN
MIDLATITUDE STATISTICS									
T _S	4.4223	5.6669	5.7308	4.1072	3.5782	6.6991	5.0054	6.8623	277.7990
ε _S	0.0201	0.0219	0.0188	0.0171	0.0128	0.0235	0.0185	0.1232	0.8041
TROPICAL STATISTICS									
T _S	2.2754	3.2836	3.9874	2.4830	2.2967	3.4474	2.4270	5.4435	296.2430
ε _S	0.0173	0.0252	0.0116	0.0137	0.0092	0.0119	0.0108	0.1232	0.8041

retrieval concepts based on both Susskind et al. (1984) and the simultaneous retrieval method of Smith et al. (1985). Monitoring residuals also provides the means to quality control each retrieval.

The radiative transfer equation for microwave frequencies is:

$$T_{b\nu} = [\epsilon_S T_S + (1 - \epsilon_S) \int_0^{P_S} T(p) d\tau'_\nu] \tau_\nu(P_S) + \int_{P_S}^0 T(p) d\tau_\nu \quad (1)$$

where

$$\tau_\nu(p) = \exp \left[- \int_0^p k(\nu, p') dp' / \mu \right] \quad (2)$$

and

$$\tau'_\nu(p) = \exp \left[- \int_p^{P_S} k(\nu, p') dp' / \mu \right]. \quad (3)$$

Here, μ is the cosine of the path zenith angle, τ_ν and τ'_ν are the upward and downward transmission functions, respectively, and p_S is the surface pressure. Specular surface reflection is assumed.

Differentiating equation (1) with respect to the desired variables U, T, T_s and ε_s and dropping the frequency indices, one obtains:

$$\Delta^n = \frac{\partial T_b}{\partial \epsilon_s} \delta \epsilon_s + \frac{\partial T_b}{\partial T_s} \delta T_s + \frac{\partial T_b}{\partial T} \delta T + \frac{\partial T_b}{\partial U} \delta U \quad (4)$$

where:

$$\frac{\partial T_b}{\partial \epsilon_s} = [T_s - \int_0^{p_s} T(p) dr'] r_{p_s} \quad (5)$$

$$\frac{\partial T_b}{\partial T_s} = \epsilon_s r_{p_s} \quad (6)$$

$$\delta T \frac{\partial T_b}{\partial T} = r_{p_s} (1 - \epsilon_s) \left\{ \int_0^{p_s} \delta T dr' \right\} + \int_{p_s}^0 \delta T dr. \quad (7)$$

$$\begin{aligned} \delta U \frac{\partial T_b}{\partial U} &= (\epsilon_s - 1) [T_s - \int_0^{p_s} T(p) dr' + r_s T(0)] \frac{\partial r_s}{\partial U} \delta U \\ &+ \int_0^{p_s} \left[\frac{\partial r}{\partial U} + r_s (\epsilon_s - 1) \frac{\partial r'}{\partial U} \right] \delta U dT \end{aligned} \quad (8)$$

Parts of δU (∂T_b/∂U) have been obtained using integration by parts. Note that (∂r(p_s)/∂T) and the variation with respect to surface pressure have been ignored.

The quantities δU and δT are expanded in series of the eigenvectors of the covariance matrices (EOFs) of U and T, with N_u and N_t terms, respectively.

$$\delta U(p) = \sum_{j=1}^{N_u} A_j \phi_j(p); \quad \delta T(p) = \sum_{j=N_u+1}^{N_u + N_t} A_j \phi_j(p) \quad (9-12)$$

$$\delta T_s = A_{N_u + N_t + 1}; \quad \delta \epsilon_s = A_{N_u + N_t + 2}$$

Upon substitution of (9-12) into (4) a linear equation in the coefficient A_j is obtained:

$$\Delta^n = \sum_{j=1}^{N_u + N_t + 2} A_j \Phi_j \quad (13)$$

where the Φ_j 's are functions of the terms in equations (5-8). The desired difference terms, δ , in the relaxation equation:

$$p^n = p^{n-1} + \delta \quad (14)$$

are available by solving (13) for the A_j 's.

The ridge stabilized, least squares solution is given by:

$$A = (\Phi^T \Phi + \sigma H)^{-1} \Phi^T \Delta^n \quad (15)$$

where σ is the ridge parameter and the diagonal elements of the H matrix are the inverse of the fractional variance due to each EOF.

4.2 Physical retrieval results

Results of the physical retrieval for the tropical temperature and integrated water vapor profiles are shown in Figs. 4a,b, respectively. The statistical first guesses described in the previous section are employed and the necessary EOFs of temperature and water vapor are evaluated from the radiosonde data set used in the generation of the first guess retrieval statistics. Physical adjustment of the temperature profile results in a slight increase of RMS error in the vicinity of the tropopause and a small improvement in accuracy near the surface. The tropopause problem is attributable both to EOF truncation representation errors and the generally weak contribution functions in this region. There is a much more noticeable improvement on the accuracy of water vapor results. Retrieval

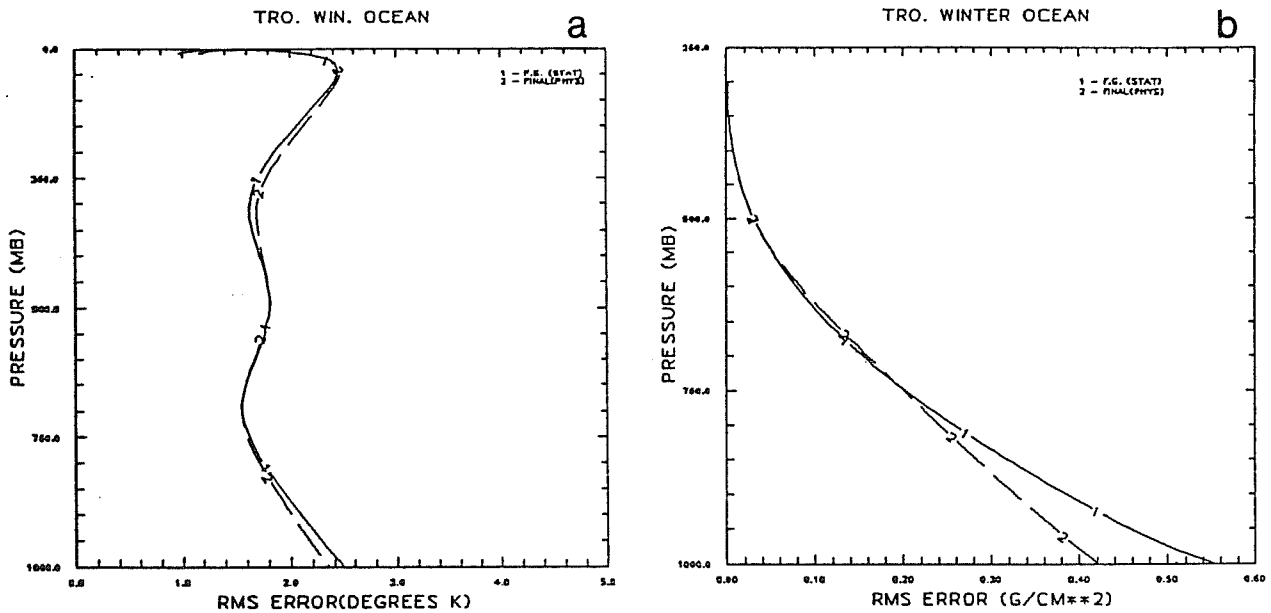


Fig. 4. Physical retrieval results for the tropics.

of low level moisture is considerably improved by the physical adjustment applied to the statistical first guess results. This is understandable since the physical retrieval process directly treats the inherently nonlinear dependence of channel brightness temperatures on water vapor which is not well represented by the first guess linear regression.

5. PROCESSING OF IMAGERY DATA FOR CLOUD PROPERTY RETRIEVAL

In cloudy areas, cloud coverage and cloud top height first guesses are necessary for the physical retrieval step (Equation 1 is modified). Colocated with the microwave sensors aboard the DMSP spacecraft, the Operational Linescan System (OLS) provides both visible and infrared imagery at high spatial resolution. There is considerable information regarding cloud field properties available from this data (Isaacs and Barnes, 1987). With much higher spatial resolution, the visible and

infrared data from the OLS imagery can be used to characterize the uniformity of the much larger microwave footprints. In those areas where the contributions from the atmosphere to microwave brightness temperature are small (i.e., nonprecipitating situations), visible or infrared data is able to provide guidelines on the uniformity of the surface observed within a field-of-view. When clouds obscure portions of the microwave field-of-view, the imager data provides the complementary capability of cloud property determination. We exploit this capability to support the millimeter wave retrievals in a manner analogous to that recently described by Liu et al. (1988) for infrared temperature retrievals. However, in addition to providing cloud coverage data for profile retrieval purposes, imager data is also employed for nephanalysis and the determination of other required parameters.

Classically, techniques to infer FOV non-uniformity have been referred to as texture analysis methods. A number of approaches can be used for texture analysis including: (a) examination of the spatial power spectrum of an image through Fourier decomposition, (b) edge enhancement, and (c) spatial coherence. We have chosen the spatial coherence approach (Coakley and Bretherton, 1982) for the determination of both cloud and surface properties from OLS data. The statistics evaluated are the local mean (\bar{I}) and local standard deviation (LSD) of radiance (or gray shade) values. The LSD is calculated for $n \times n$ sets of pixels.

A plot of LSD_k vs. \bar{I}_k gives the cloud coverage fraction within the microwave footprint and the EBT of the surface and effective cloud top. Figs. 5 a,b illustrate LSD_k vs. \bar{I}_k frequency plots for a partially cloudy microwave FOV over the ocean evaluated using GOES visible and infrared imagery. The spike in the visible result (Fig. 5a) denotes the surface reflectance value due to clear visible pixels. The higher reflectivity, signatures with nonzero standard deviation result from partially cloudy pixels. In the infrared data (Fig. 5b), the highest and lowest EBTs correspond to the surface and cloud top emission, respectively. Distinguishing between surface and cloud top temperatures i.e. T_b^S and T_b^C , provides the capability to measure cloud coverage, N , and identify cloud layers. The cloud top EBT is used with the first guess temperature profile to obtain the first guess effective cloud top pressure, p_c . Isaacs et al. (1988) have demonstrated FOV characterization for this purpose using high resolution DMSP OLS infrared data to determine cloud

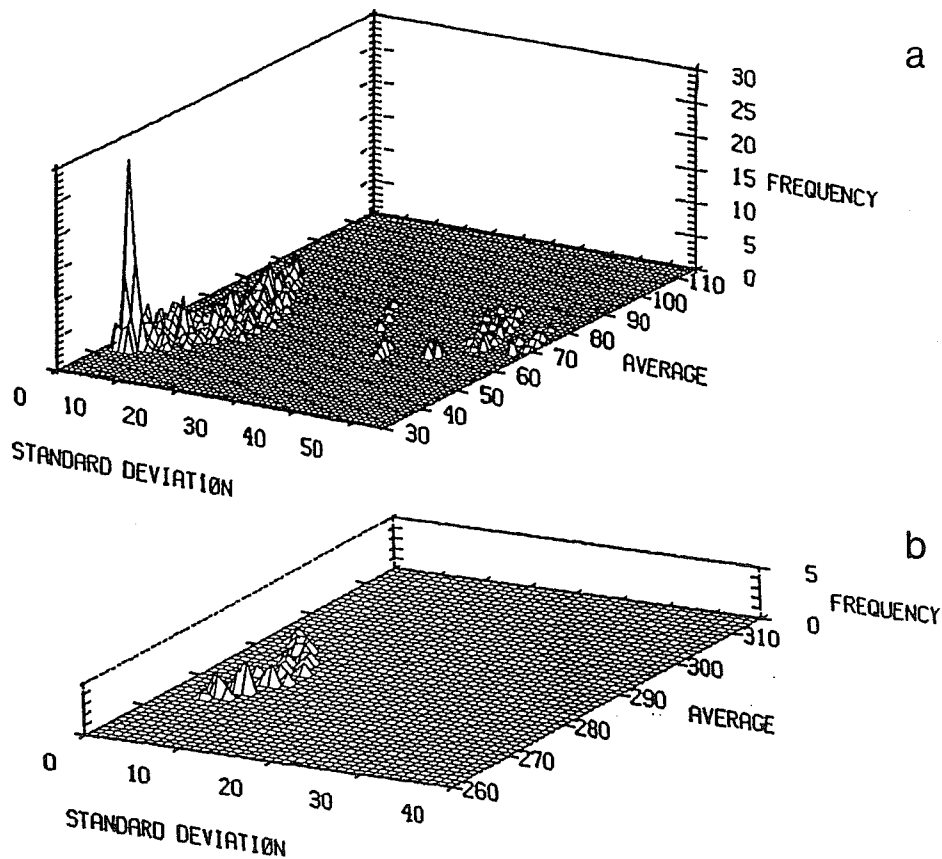


Fig. 5. Spatial coherence results for partially cloudy microwave field-of-view using: (a) visible and (b) infrared GOES imager data.

properties within SSM/I footprints. Another approach is to incorporate a sophisticated cloud property analysis scheme (i.e. type, levels, etc.) such as that of Garand (1988). This essentially incorporates the neph-analysis as part of the retrieval scheme and provides the added spinoff of water vapor first guess fields from the cloud imagery (Garand, personal communication).

There are additional benefits to processing the multispectral imagery data available for each FOV. In addition to cloud property characterization, there are requirements for obtaining precipitation amounts, visibility, and a variety of parameters related to surface type including snow cover, sea ice coverage and type, soil moisture, and vegetation.

Precipitation rate information is inherent in the microwave brightness temperature fields of the SSM/I. Jin and Isaacs (1987) have simulated the

sensitivity of SSM/I polarized brightness temperatures to rain rate, the presence of vertical inhomogeneities including temperature gradients and ice layers, and various underlying surfaces. Spencer et al. (1989) have demonstrated that precipitation signatures can be obtained over land and ocean and that gross vertical structure information is available from examining low and high SSM/I frequency data. Additionally, the significance of high spatial resolution infrared imager data in locating convective cells has been studied (Adler and Negri, 1988). Thus, for precipitation determination, SSM/I and OLS data sets will be combined in the FOV analysis procedure with first guess temperature and moisture fields from the statistical retrieval.

When fields-of-view are determined to be cloud free, there is interest in characterization of optical propagation and surface type related information. Visibility is dependent on aerosol loading. Over the ocean, visible sensor radiances can easily be related to aerosol optical thickness and visibility due to its low reflectance (Isaacs and Vogelmann, 1988). Over variable reflectance land surface an alternative technique based on analysis of spatial power spectra changes with aerosol loading can be employed (Mekler and Kaufman, 1982). Data on surface type can be inferred from visible information (e.g. snow cover) as well as microwave signatures. Isaacs et al. (1989) have compared SSM/I data with a variety of type dependent surface emission models to validate this approach.

6. CONCLUSIONS

This paper prescribes a unified retrieval approach tailored to the DMSP meteorological sensor suite. All of the available data is utilized in a multispectral sense. The existing operational statistical retrieval capability is exploited to provide parameter first guesses. First guess derived brightness temperature simulations are then compared with the original data and adjustments, based on sensor channel residuals, are made to the first guesses as required. A physically based simultaneous retrieval provides the appropriate parameter adjustments. Results of a retrieval simulation calculation illustrate the improvements possible to the statistical first guesses by utilizing all sensor data multispectrally and to the first guess parameters by employing the physical adjustment step. Recognizing the potential effect of clouds on the millimeter wave data, a method is outlined to introduce required first guess cloud information by image processing visible/infrared imager data. This procedure

provides the opportunity to characterize the uniformity (both atmospheric and surface) of the relatively large microwave FOV. This provides potential insights into both cloud and surface type classification with implications for determining their emissivities.

While the retrieval approach outlined has been formulated as a stand alone system, its most important application may be to provide data for use in a numerical weather prediction model. In this context it is noted that modifications to the procedure outlined are desirable. Operationally, for example, it may be advantageous to obtain some first guess elements such as the temperature and moisture profiles from model predicted fields. Furthermore, in the context of a prediction model application, forecast error covariances may be used as constraints on the adjustment process (Eyre, 1988). These changes are not inconsistent with the retrieval described and should in fact improve its effectiveness. Furthermore, the method provides estimates of each retrieval's accuracy.

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