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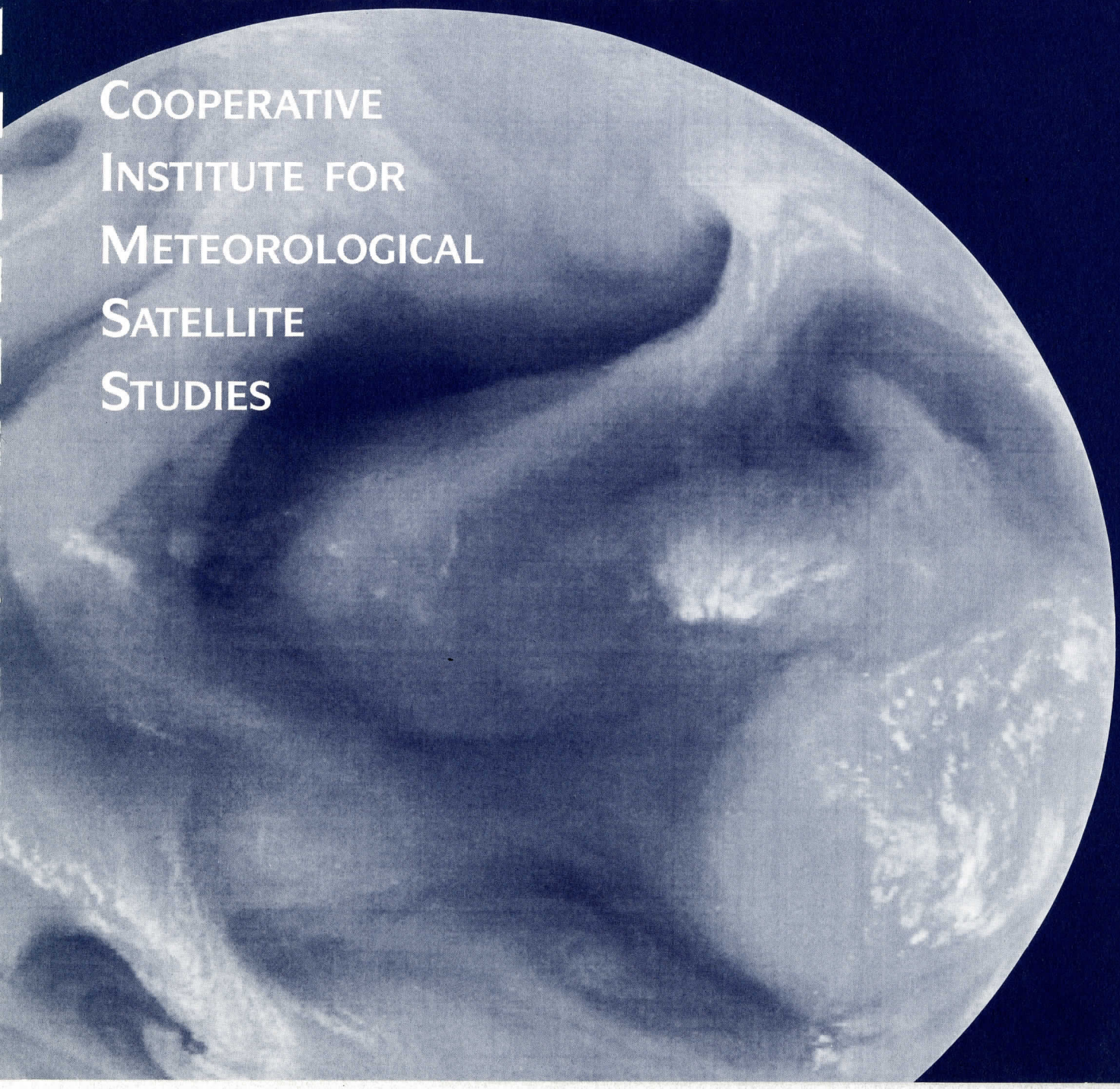
Final Report
NASA Grant NAG8-1320

Development of Atmospheric Retrieval Methodologies using Satellite Data from Microwave Sounding Instruments, With Complementary Imagery and Forecast Model Information

A REPORT from the

COOPERATIVE INSTITUTE FOR METEOROLOGICAL SATELLITE STUDIES



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Final Report
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Development of Atmospheric Retrieval Methodologies using Satellite Data from Microwave Sounding Instruments, With Complementary Imagery and Forecast Model Information

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I. Introduction

A. Background

The current combination of infrared and microwave instruments (AMSU/HIRS) on NOAA polar-orbiting platforms, versus the prior MSU/HIRS combination offers improved atmospheric temperature soundings using 14 microwave channels (sensitive to atmospheric and surface properties), and six water-vapor-sensing channels, sensitive to atmospheric water vapor and some also to surface properties. Infrared (HIRS) channels are sensitive to cloud presence and the amount of cloud water in the atmospheric column is evidenced to some degree in all of the microwave channels, depending on frequency. An excellent review of the characteristics of the current AMSU and HIRS instruments has been given by Jun Li et al. (2000)

The architect of the system that we use for retrieval of atmospheric temperature, moisture and microphysical quantities is John Eyre (U.K. Met. Service), who developed a so-called Statistical Interpolation (SI) retrieval method appropriate to HIRS/AMSU data (Eyre 1989) while a visitor to SSEC, as well as a method using infrared data to detect the and quantify certain characteristics of clouds (the so-called "minimum residual" method (Eyre and Menzel 1991). The atmospheric/cloud water retrieval algorithm (Eyre 1989) was theoretical, developed in the absence of real AMSU data, since a satellite version of the instrument was years in the future. This study showed promise for the new instrument suite, but used the forecast errors of the numerical models of the times to demonstrate the impact of the data, errors that have been significantly reduced in modern forecast models since that study of more than ten years ago.

The 1989 study showed in a theoretical (no real or synthetic radiances were used) context that the model forecast errors of that time for temperature and moisture forecasts could be improved upon and there was the possibility of estimating column cloud water with an accuracy of about 0.2 mm from the AMSU. Retrieval of atmospheric profiles and cloud water was done simultaneously in Eq. 1 (below, to be explained). For a tabulation of the model standard errors and covariances used in this study, see Eyre (1990)

Later, less-theoretical studies were performed by Diak et al. (1992) and Wu et al. (1995). They were different in the sense that a real forecast model was used in experiments of Observing System Simulation (OSSE) mode. Control or "truth" forecasts were made to represent nature, which later were perturbed, using the spatial characteristics of the errors of real forecast model to simulate real forecasts (containing errors). So-called "forward" radiances generated from the control ("perfect") forecast were then used to try to eliminate the errors that were added. Our retrieval findings in this mode were very similar to the theoretical results of Eyre (1989), but again used the errors of the models of the early 1990s, error statistics that have been significantly improved upon at this writing.

Wu et al. (1995) used a similar OSSE procedure as Diak et al (1992), but added the assimilation of the retrieved cloud water amounts into subsequent model forecasts, finding most significantly that this assimilation reduced the so-called "spin-up" time for forecasts to generate precipitation and geographical accuracy of precipitation locations. Diak (19xx) and Huang and Diak (19xx) showed the sensitivity of various AMSU channels to the presence of cloud liquid water and the potential for detection and quantification using channel pairs.

B. Anticipated Complications using Real Data

While initial results of our HIRS/AMSU studies were encouraging, we anticipated certain complications that would arise with real data and almost certainly modify the accuracy of these theoretical and pre-flight results. Foremost among those is the influence of the microwave emissivity of the earth's surface, both ocean and land on low-level retrievals of any quantity. In both land and water cases, the emissivity of the surface is not well-known in relationship to the accuracy required to produce high-quality sounding results. For both water and land, the emissivity is frequency-dependent: for water there also wind speed dependence and other subtle relations to content. For land surfaces, soil moisture, vegetation land cover and smaller water bodies with a pixel can make the scene emissivity hard to quantify. If the emissivity is not properly estimated, there can be several degrees of brightness temperature difference between the forward estimates and real measurements used in so-called "physical" or "statistical-physical' retrievals that will cause erroneous retrieval results in the lower atmosphere. This will be elaborated on later.

Additionally, forecast errors have been significantly reduced in the past ten years. The RMS forecast errors that we use now in the SI retrieval scheme (Eq. 1) comes from a 50-km, 43–level mesoscale model (the CIMSS Regional Assimilation System, CRAS; Diak et al. 1998) are about half of those used in the initial experiments described. At 500 hPa, the CRAS has a twelve-hour RMS forecast error in temperature of about 0.7-0.8 degrees K for data-rich areas (varying slightly with season), indeed hard to improve upon with current sounders.

II. Retrieval Methodology- Clear and Cloudy Atmospheres

A simplified (linearized) mathematical form of the retrieval algorithm is adequate to elaborate on the characteristics of the SI retrieval system. The retrieval equation can be presented as:

$$X = X_b + C K^T (K C K^T + E)^{-1} (Tb_m - Tb(x_b))$$

It is called a "physical-statistical' system because a physical forward model of radiative transfer is used, but forecast error statistics come into play in several ways. Each capitol letter in this equation is matrix of one or two dimensions. X is a column vector representing quantities to be retrieved by the system: these can include temperate and humidity at various levels, as well as cloud liquid water. Other variable could be included. X_b is a guess of the retrieval quantities that may come from climatology, or more frequently in modern systems, a mesoscale forecast model. K is the so-called "forward" model (actually, here the derivatives of retrieve variables with respect to measured brightness temperatures) that enables measured increments in brightness temperature from those produced using the guess to be translated into the changes to the retrieval variables (e.g., temperature, etc.) from the guess.

C is a matrix of error covariances of the background information that serves two purposes in the retrieval scheme. The first is to provide a restraint on the retrieval if corrections to the guess are excessive compared to the statistical errors of the model. The second purpose of this covariance matrix is to relate errors at one atmospheric level to those at other levels, and also examine the relationship (inter-variable covariances) of errors between different variables (T versus moisture for example), which often are correlated. The C matrix acts to interpret how brightness temperature signals should be apportioned to variables in the vertical column (help to mathematically condition the system), and also

make corrections in variables that are statistically correlated to others, but perhaps not represented in measured brightness temperatures.

The last term in Eq. 1 [$(Tb_m - Tb(x_b))$], is the "signal" or forcing in this equation, the difference between measured brightness temperatures and those synthesized through the forward model using the "first guess" set of atmospheric variables, represented by X_b. Lastly, E, represents errors in the forward model and errors of measurement (instrument noise, for example. In practice, a slightly more complex, iterative version of Eq. 1 is used to solve the equation system.

III. A Realistic Approach to the Retrieval of Atmospheric Profiles and Cloud Liquid Water

A. General

Since our methodology requires the derivatives of brightness temperature with respect to retrieved quantities, we chose the RTTOV-6 forward radiance package, product of the U.K. Met. Office (Saunders et al., 1999) and a follow-up to the package use by Eyre (1990), that calculates these derivatives with respect to temperature, moisture, emissivity, level cloud water values and other quantities of interest. This forward model uses 43 atmospheric levels of information on atmospheric temperature, moisture, clouds and certain surface properties to calculated forward brightness temperatures in all HIRS and AMSU channels.

As is often the case, simulation studies are somewhat over-optimistic of the real results that are later obtained with real data and procedures; they are necessary, however, because if a simulation study does not work, the odds of a real system working are nil. This is exactly what we found when trying to simultaneously retrieve atmospheric profiles and cloud water amounts via Eq. 1 using real HIRS/AMSU data. As in the simulation studies, cloud top pressure and effective fraction (the area fraction times

the emissivity) were evaluated in a first pass using only two IR channels in the "Minimum Residual" method (Eyre and Menzel, 1989). Subsequent to this, all the channels were used to retrieve IR clouds, but using the results at the RMS errors of the Minimum Residual method to constrain changes to the cloud variables

The results of this procedure were that about three-quarters of the time when there were clouds, the system was numerically unstable, and when convergence was achieved, most often large and unrealistic changes were made to level values of temperature. Cloud fractions less than unity cause channel weighting functions that may have duplicate peaks, causing ill-conditioning in the retrieval matrix. Additionally, the forward brightness temperatures in the IR channels are extremely sensitive to cloud fraction and level (temperature), making the entire retrieval system extremely sensitive and not very stable more often than not under cloudy conditions.

Much better results, however, were achieved using the following procedure that separated clear versus cloudy retrieval philosophies. If clouds are detected by the Minimum Residual (infrared) method, we retrieve only cloud height and effective fraction using Eq. 1 and no atmospheric profile variables. If the retrieval of the cloud parameters is successful, we try a retrieval of level cloud liquid water, if the clouds detected are above a critical temperature (the approximate minimum for supercooled water). Detection of clouds below about 850 hPa was not reliable due to uncertainties in surface quantities translating into inaccurate forward radiances (used in the Minimum Residual method) and false cloud evaluation. Only clouds evaluated at 100 hPa above the surface, or lower pressure are considered valid. If no clouds are detected or the clouds pressure is above this surface minus 100 hPa value, we attempt a clear retrieval of certain levels of atmospheric temperature and moisture.

B. Cloud Liquid Water Approach

The RTTOV6 Radiative transfer model contains calculation of brightness temperatures (Tb's) and derivatives with respect to amount of cloud liquid water (CLW) at its various levels. IR detection of cloud is critical in positioning cloud top in the vertical. For retrieving level values of CLW, the standard errors and vertical covariances that are required by the retrieval method are very hard to estimate, since cloud variability is extremely high and CLW values are in general poorly researched. Through the literature and guidance of CRAS model cloud predictions, we chose 100 hPa as an average cloud depth and tried several covariance structures, one with a linear correlation cloud top to bottom (which will essentially produce a linear cloud water concentration through the cloud depth). The second was a Gaussian shaped cloud covariance set, peaking in the middle of the cloud depth and dropping off with a 50-hPa half-power depth, which proved superior. The level values of CLW were capped at 1.0 g/kg in the retrieval, an approximate threshold for light precipitation. With precipitation, our CLW radiative transfer (absorption-based) model is no longer valid, since scattering becomes relevant in the brightness temperatures.

III. Examples of Retrieval Results over Water and Land Surfaces

A. Temperature and Moisture Soundings

As has been much discussed in the literature, HIRS+AMSU clear soundings of temperature, while of decent accuracy, were not superior to the guess (forecast) values that they began with in the conventional-data-rich area (continental U.S) where our studies were run. Moisture soundings, however, were superior to the guess about 50% of the time. Seeing that both NCEP and the ECMWF have reported positive forecast impact, using ATOVS data in conventional-data-sparse regions, we presume that our region of emphasis had much to do with sounding results.

B. Cloud Liquid Water Estimates

Two case studies are shown in Figs. 1 through 4 of retrieval of clouds and microphysical quantities using combinations of HIRS+AMSU A/B channels. Both include land and water surfaces, and are typical of the results achieved in our studies estimating cloud water. HIRS channels, always required for cloud detection, were mid- and lower-atmospheric channels 4 through 8. AMSU-A channels were also mid- to low-level oxygen channels 5 through 9. In experiments where the AMSU-B was included, we used channels 18 through 20.

In the case studies shown, we compare the results of cloud quantification between results using HIRS+AMSU-A and HIRS+AMSU-A and B. In the color figures, black indicates no clouds detected by the IR minimum residual method, while gray indicates clouds at too low a temperature to confidently presume that they are water clouds and subsequently perform a CLW estimate. Both land and water surfaces are present in these two studies. Figures 1 (a-d) and 2(a-b) are for the case study of 4 February 2002 (NOAA-16 data), while Figures 3 (a-d) and 4 (a-b) are for 22 October 2000 (NOAA-15 data).

Figures 1 (a-c) are for the case study of 4 February 2002. Here, Figures 1B and 1B are identical, to show the identification of the cloud fraction by the minimal residual method. Figure 1A shows clouds identified by this IR method and CLW water quantified using only the AMSU-A channels mentioned above. As can be seen, comparing these figures with GOES IR and visible images at nearly the same time (Figures 2a-b), the minimum residual method does a relatively good job of identifying clouds, except for certain regions of low cloud, where this method (and similar methods such as the so-called "CO^2 Slicing Method" have problems. In Figure 1A, the CLW amounts retrieved (0-100 g/m**2) are physically realistic and in line with those produced by a model simulation of this synoptic situation. When the AMSU-B channels are added (Figure 1C), we

see an increased sensitivity to CLW amounts, especially over land surfaces. This is expected, since these 183 GHz channels have the most sensitivity to CLW, and enhance detection and quantification over land.

The story with the second situation (22 October 00) is much the same, and the figures parallel those from the first case of 4 February. We see that that the AMSU A+B combination is most effective in quantifying CLW amounts (Figure 3C [HIRS +AMSU- A/B], versus Figure 3A [HIRS +AMSU-A], again the difference most noticeable for land surfaces, where the sensitivity of brightness temperatures to CLW is greatly enhanced with the addition of AMSU-B channels. Again, the CLW amounts are physically realistic for this type of synoptic system

IV. Conclusions

In work sponsored by a prior NASA grant, we demonstrated the sensitivity of AMSU channels to CLW through simulation studies prior to launch of the instrument, as well as the effect of atmospheric retrievals in Observing System Simulation Experiments. Since that time, forecast quality has substantially improved, and it is doubtful whether HIRS+AMSU retrievals can make a contribution to temperature forecasts in conventionally-data-rich regions such as the continental United States, although the likelihood of improvements in moisture forecasts is somewhat more probable.

In experiments sponsored by this grant, we have shown the potential to retrieve CLW amounts. Verification of this quantity is very difficult, since the data on CLW amounts is very sparse. The values we have retrieved, however, are consistent with those produced by fairly sophisticated cloud models. Results are based on an absorption model of radiative transfer, and thus are best for mid-level (water clouds). Since results also depend to the ability of IR channels to detect cloud, the quantification of low-level clouds is also compromised. Improved quantification of the surface

emissivity and temperature, especially in microwave channels, would improve the accuracy of evaluation. We suggest that the best use for this CLW information is for the initialization of mesoscale models at synoptic times in combination with rawinsonde data, when the temperature and moisture state of the atmosphere is relatively well-depicted by these rawinsonde profiles, and thus much of the "signal" in the brightness temperatures (measured minus "forward" values would likely come from the presence of clouds.

IV. Publications from Grant NAG8-132

Burns, B. A., X. Wu and G. R. Diak, 1997: Effects of precipitation and cloud ice on brightness temperatures in AMSU moisture channels., Int. J. Rem. Sens., 35, 1429-1437.

Wu, X, B. B. Burns and G. R. Diak, 1996: Water vapor retrievals using SSM/T2 data. Eighth AMS Conference on Satellite Meteorology and Oceanography, Jan. 28-Feb.2, 1996, Atlanta, GA.

Burns, B. B., X. Wu and G. R. Diak, 1995: Model-derived brightness temperature in AMSU moisture channels for various precipitation structures: Comparison of two radiative transfer formulations. Proc 1995 International Geoscience and Remote Sensing Symposium, Florence, Italy 10-14 July, 1995, Vol II, 876-878..

V. References

Diak, G. R., M. C. Anderson, W. L. Bland, J. M. Norman, J. R. Mecikalski, and R. M. Aune, 1998: Agricultural management decision aids driven by real-time satellite data. Bull. Amer. Meteor. Soc. 79, 1345-1355.

Diak, G. R., M. C. Anderson, W. L. Bland, J. M. Norman, J. R. Mecikalski, and R. M. Aune, 1998: Agricultural management decision aids driven by real-time satellite data. Bull. Amer. Meteor. Soc. 79, 1345-1355.

Diak, G. R., 1994: A note on the relationship of a microwave "effective cloud fraction" derived from a minimum residual method to the column cloud water amounts for non-precipitating clouds. J. Atm. Ocean. Tech., 12, 960-969.

Eyre, J. R. 1990: The information content of data from satellite sounding systems: A simulation study. Q. Jour. Roy. Met. Soc., 116, 401-434.

Eyre, J. R. and W. P. Menzel 1989: Retrieval of cloud parameters from satellite sounder data: A simulation study. J. Appl. Meteor, 28, 267-275.

Huang, H. L. and G. R. Diak, 1992: Retrieval of non-precipitating water cloud parameters from microwave data: A simulation study, J. Atmos. Ocean Tech., 9, 354-363.

Saunders, R. W., M. Matricardi and P. Brunel, 1999: An improved fast radiative transfer model for assimilation of satellite radiance observations. Quart. J. R. Met. Society., 125, 1407-1425.

Wu, X., G. R. Diak, C. M. Hayden and J. A. Young, 1994: Short-range precipitation forecasts using assimilation of simulated satellite water vapor profiles and cloud liquid water. Mon. Wea. Rev., 123, 347-365.

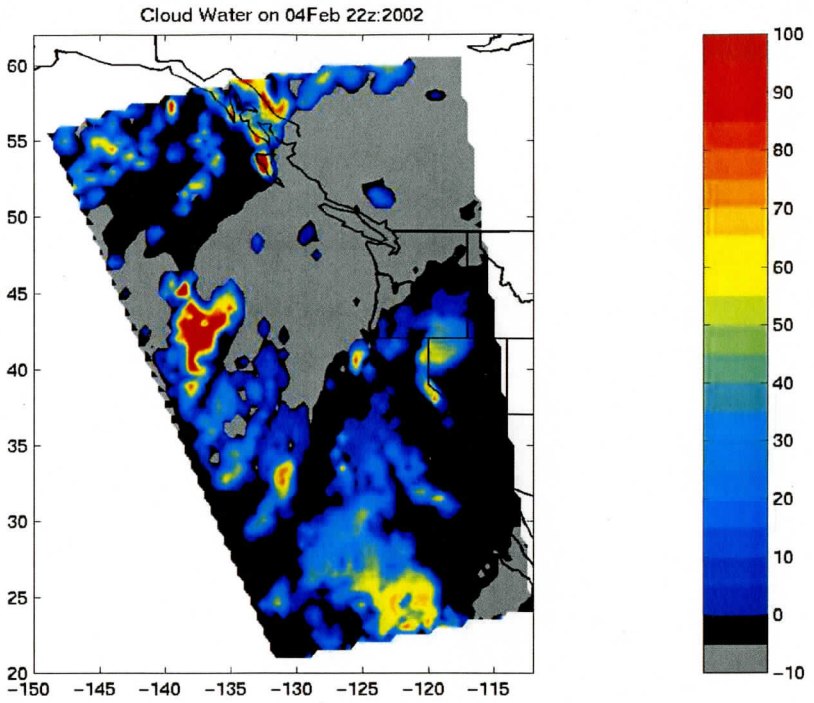
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Fig. 1A

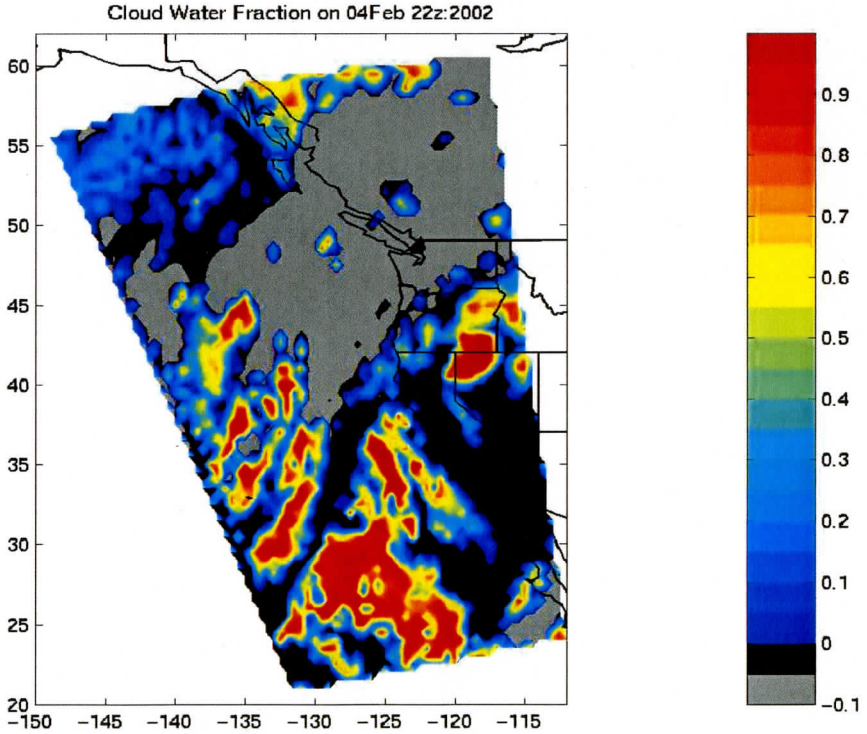
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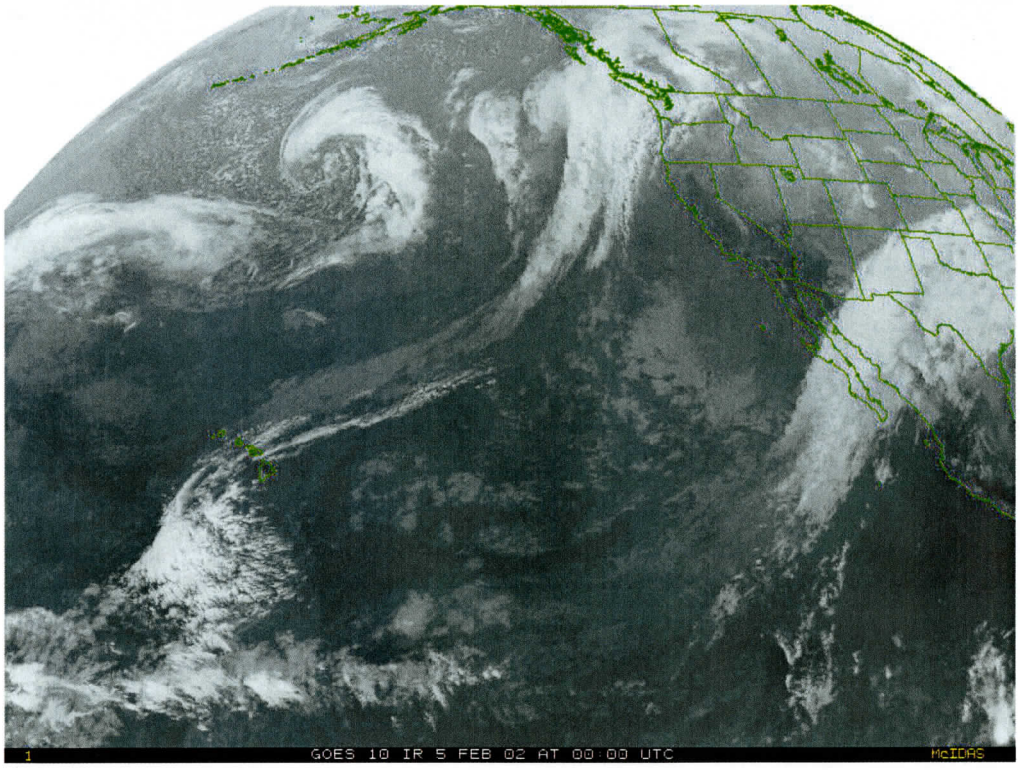
Fig. 1B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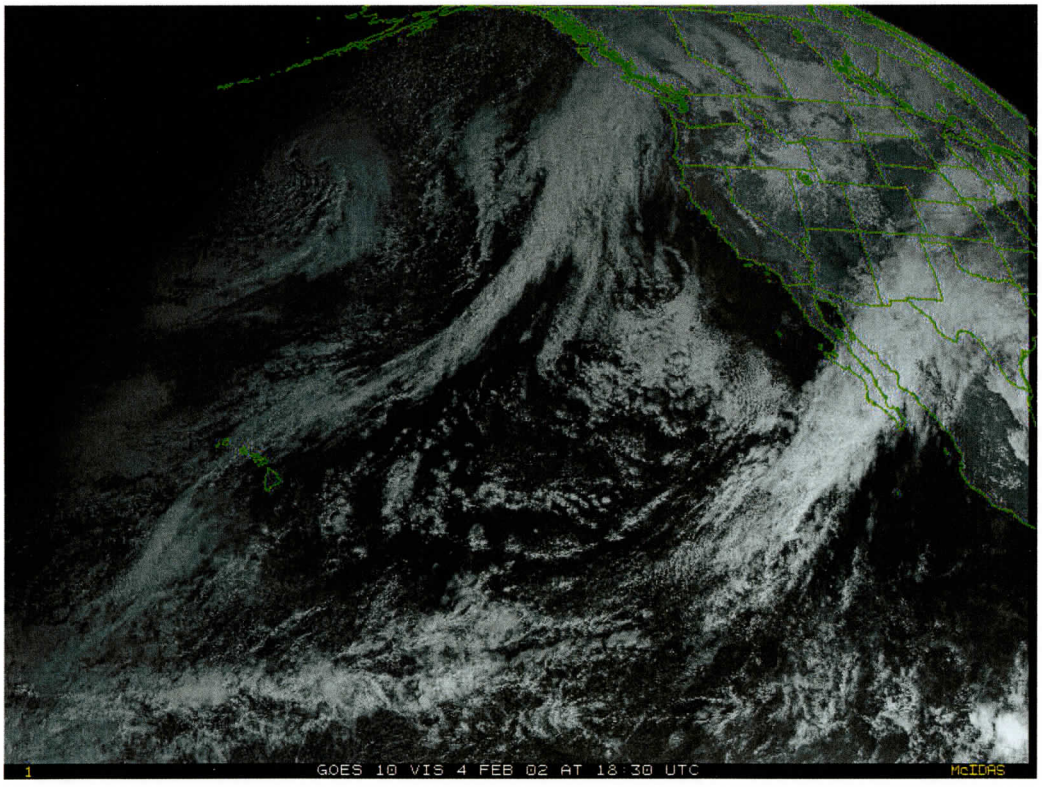
McIDAS

Fig 2A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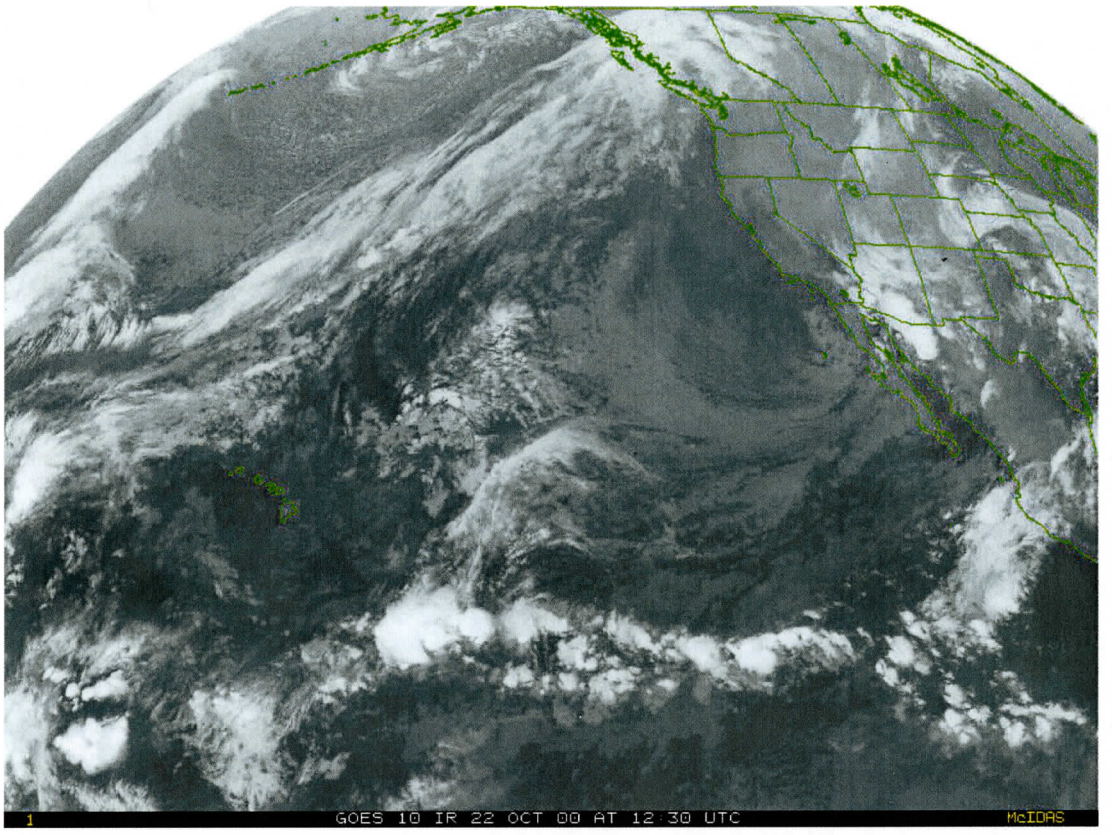
McIDAS

Fig 2B.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McIDAS

Fig. 4A

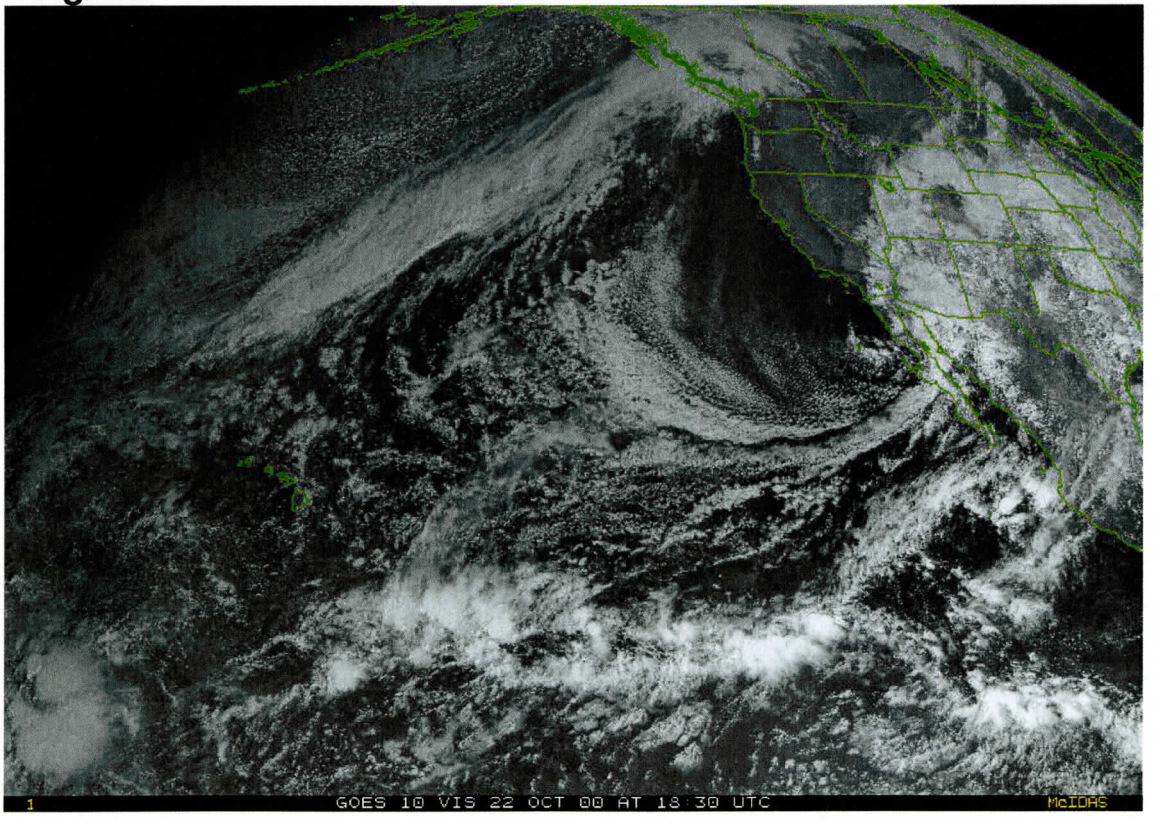
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Fig. 4B

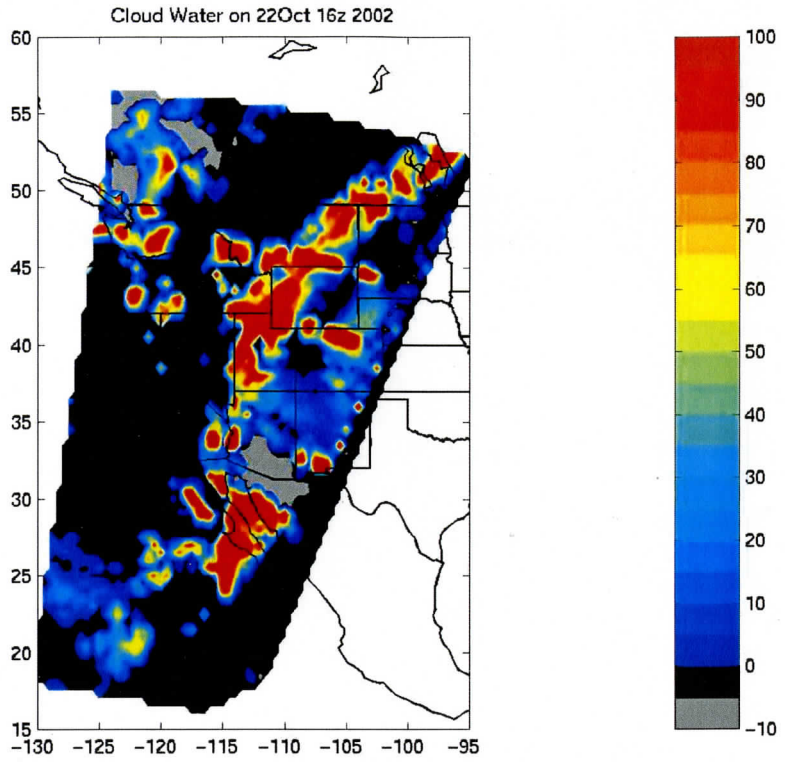
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Fig 3C

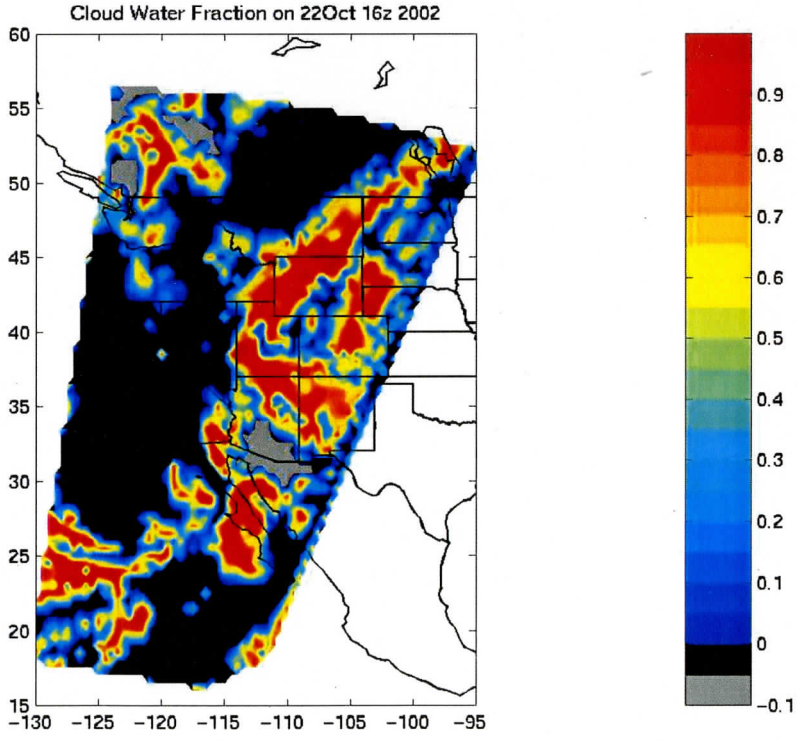
Cloud Water Fraction on 22Oct 16z 2002
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Fig. 3D

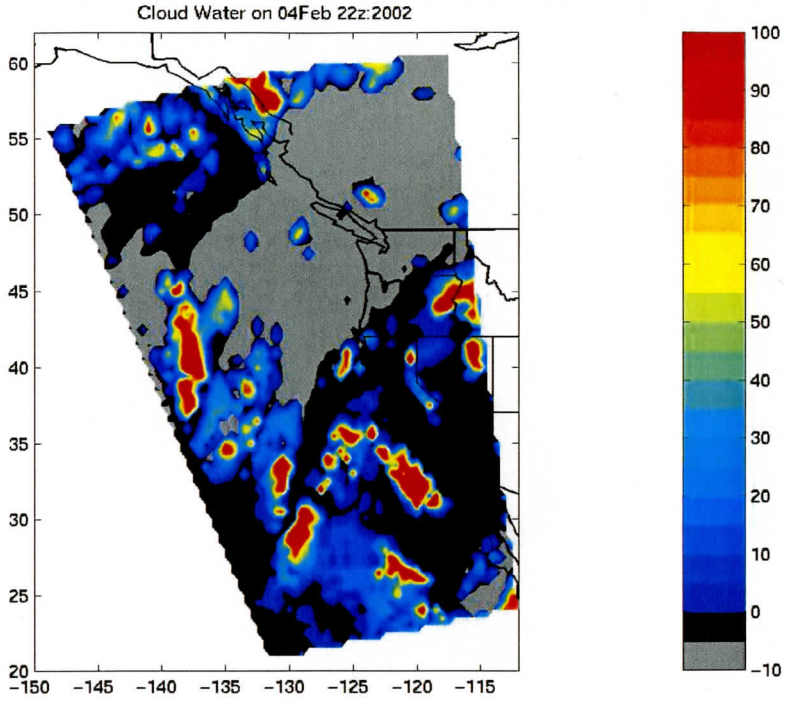
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Fig. 1C

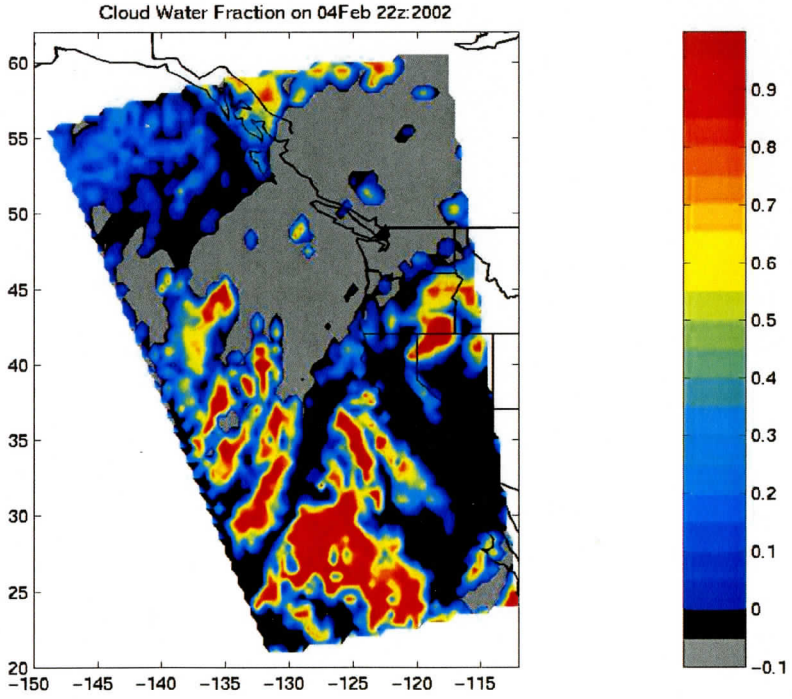
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Fig. 1D