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USING MULTIPLE FIELDS OF VIEW TO DETERMINE CLOUD PARAMETERS IN A CLOUDY RADIANCE RETRIEVAL SCHEME

by

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ABSTRACT

This paper considers the advantages of the using multiple fields of view to specify the cloud top pressure for use in a TOVS retrieval scheme. It is discussed initially as a physical constraint applied in a 3-D analysis but the viewpoint taken is one of retrieval accuracy rather than as a more general NWP analysis problem where priorities and considerations may be different.

Because strong physical constraints on the retrieved field are already present to a large degree in the model background used, it is thought that full 3-D analysis will be of limited benefit except insofar as the reduction in measurement noise that it gives.

A strong physical constraint not available in this way is the consistency of the cloud top pressure between local soundings. A method of applying this constraint is presented and a practical implementation described. It is found that the constraint has beneficial effects on retrieval accuracy in a significant number of cases.

INTRODUCTION

TOVCFG is an iterative scheme for retrieving atmospheric parameters from cloud-contaminated TOVS radiances (see Eyre 1989 for details). An iterative method is required because the presence of cloud makes the relationship between radiance and atmospheric state highly non-linear and a solution to the inverse problem cannot be found analytically. TOVCFG employs Newton's Method to find the most probable atmospheric state given a forecast model background and the measured radiances. For TOVS sounding purposes the atmospheric state consists of temperature and humidity profiles, microwave surface emissivity, surface pressure and cloud top pressure and amount. Retrievals are made for each field of view (FOV) separately and as such they are effectively one dimensional (vertical) analyses of the radiance data. In the future we might hope that analyses of radiances would be done in 3 or even 4 dimensions and simultaneously with all other data in order that the information contained in them is fully utilised. Qualitatively, the strong correlation between background errors for a local group of soundings allows all the radiance measurements in the group to be used to estimate a single atmospheric state. Of course correlations are not unity and the measurements should be weighted appropriately (in a statistically optimum scheme) by a background error covariance which specifies these correlations. (They should also weighted by a measurement error covariance.)

We may expect most state variables to be slowly changing in the horizontal and, by implication, the corresponding background errors will be highly correlated over short distances. The exceptions are likely to be microwave emissivity, surface pressure (over mountainous terrain) and cloud amount.

Suppose we had a set of measurements at different frequencies for each sounding location. Then, with the horizontal correlation of background errors we would effectively have many more measurements of the state variables than from a single FOV. In fact the channels are the same at each sounding, and we do not have this luxury, we merely have duplicate measurements of the state which can be combined to reduce noise errors in the normal way. Unfortunately most significant radiance errors are of a systematic nature (especially in a local area) and such averaging will not be effective at noise reduction. For the state parameters with uncorrelated background errors in the horizontal, the 3-D analysis is equivalent to individual 1D analyses. In the vertical we are making different measurements and analysis is useful not to say essential.

Analyses can also be beneficial if there are physical constraints on the retrieved state fields. In 4-D analyses the model dynamics and physics provides a strong constraint. For example, a sounding analysed at model time zero may affect the model state and therefore the analysis of a sounding at some later time. Similarly in the 3-D case a sounding at one location can affect the analysis of a sounding at another location because atmospheric fields are only allowed to take on balanced or realistic forms; gradients must not be too high, curvature not too great etc. However, a large part of these physical constraints are already implicitly in the model background used: realistic dynamics and physics have produced the background field by integration from the previous analysis. One physical constraint not implicit in the background involves the parameters describing cloud conditions in the FOV. This is because the NWP model used (Fine Mesh) does not carry cloud explicitly (and is unlikely in the forseeable future to be able to specify cloud cover in the small area of a FOV). Physical constraints relating to these parameters are therefore not implied in the background field and there may be a strong case for 3-D analysis to apply them.

We can put no realistic constraint on the the cloud amount, n, found in FOV. If we knew we were observing a large cloud opaque cloud bank then there may be a case for setting n=1 for all such soundings. But generally the cloud amount in adjacent FOVs will be random and therefore unconstrained.

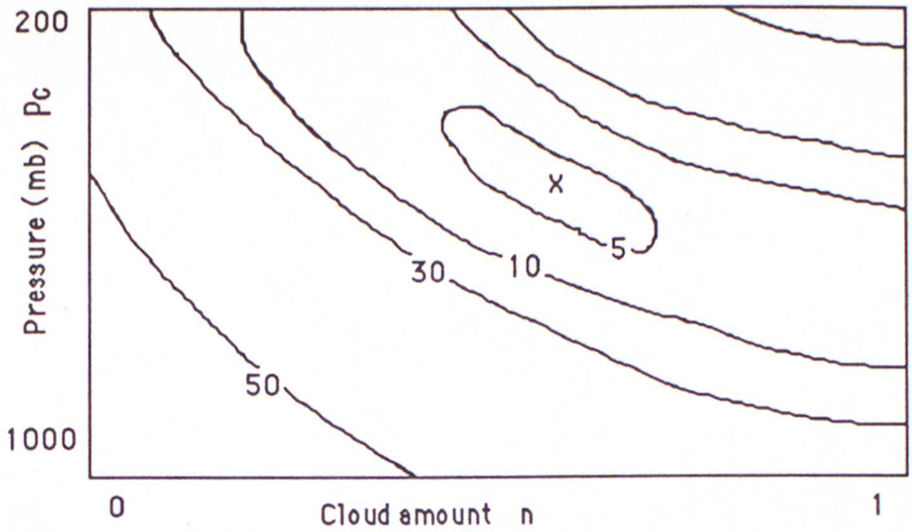
The cloud top pressure, P_C, is however correlated between FOVs. It is not the same for all FOVs but, for local FOVS, it is probably not too different. How tight the constraint can be is dependent on the type of cloud present: for stratus it can be very tight, for mixed layer cloud it must be loose. Information on cloud type is not generally available in real time TOVS processing especially where imagery data is not used, it is certainly not available in TOVCFG. Inevitably then, the constraint on P_c must be fairly weak, so will it be at all useful?

The next section describes how the initial estimates of the cloud parameters are obtained in TOVCFG and the ambiguity that arises between n and P_c. This ambiguity allows large compensating errors to exist in n and P_c especially when n is small or P_c high. It is possible then, that even a weak constraint on P_c may be effective.

FIRST GUESS CLOUD PARAMETERS

The model background does not contain a cloud amount or pressure, so they are set arbitrarily at 0.5 and 600 mb and with errors of 0.5 and 400 mb so that there is no effectively no constraint from the background values. TOVCFG then proceeds by solving for the most non-linear parameters first, namely the cloud, then for the weakly non-linear parameters as well, humidity and temperature. A refinement is an initial adjustment of the temperature and humidity by the microwave measurements which are transparent to most cloud. The cloud estimation proceeds as follows. Clear radiances and overcast radiances for cloud at all model pressure levels are calculated and the straightforward relationship between cloud amount n and the FOV radiances then allows an analytical solution for the n and P_c that best fit the measurements (with the temperature and humidity profiles fixed). The measurements used for this 'first guess' cloud estimation are just the HIRS longwave channels 7 and 8 (for a full discussion see Eyre 1989). For each possible n and P_c the calculated HIRS 7 and 8 values will differ from the measured values, the squared difference is often called the 'cost' or distance. Since we only have two parameters in this initial estimation we can actually draw this *Cost function* as a two dimensional field. A diagrammatic example for cloud conditions of 0.6 amount at 400 mb is shown in figure 1:

Figure 1 Cloud parameter Cost function



We have shown a case where the minimum of the cost function corresponds to the true n and P_c and has a value of zero. That is we have fitted the measured radiances exactly with correct cloud parameters. In a real case there will be background[1] (profile) and measurement errors so that the minimum will neither be zero nor found at the true parameters. We have to accept that the true n, P_c may lie anywhere where the cost is below a certain value, ε, defined by these errors. Suppose that this cost level is shown by the shaded region in figure 2, then the range of possible cloud parameters can become large. Two cases are shown in figure 2. The left hand plot is for a large amount of cloud, the right hand one for a small amount, both with the same true cloud pressures. In both we can see the n-P_c ambiguity, decreasing n can be compensated by decreasing P_c, i.e. by having less but colder cloud. It is also clear that the ambiguity is greater for smaller cloud amounts. In the limit of small true n (or high P_c) then all values are possible because there is no effect on the radiances: zero cloud at any level has no effect; any amount of cloud at the surface has no effect. This is not to suggest that the cloudier FOVs are more useful because the cloud conditions are better defined: more cloud implies less radiance comes from the atmosphere and therefore the less information on the state parameters we really want to retrieve. It is possible to retrieve cloud parameters well from the cloudy FOVs, but not the temperature profile. Conversely, FOVs with very little cloud provide good profile retrievals, poor cloud retrievals. FOVs with intermediate amounts of cloud may give poor retrievals of both and it is with these that we hope the 3-D analysis of cloud pressure can help. If we know *a*

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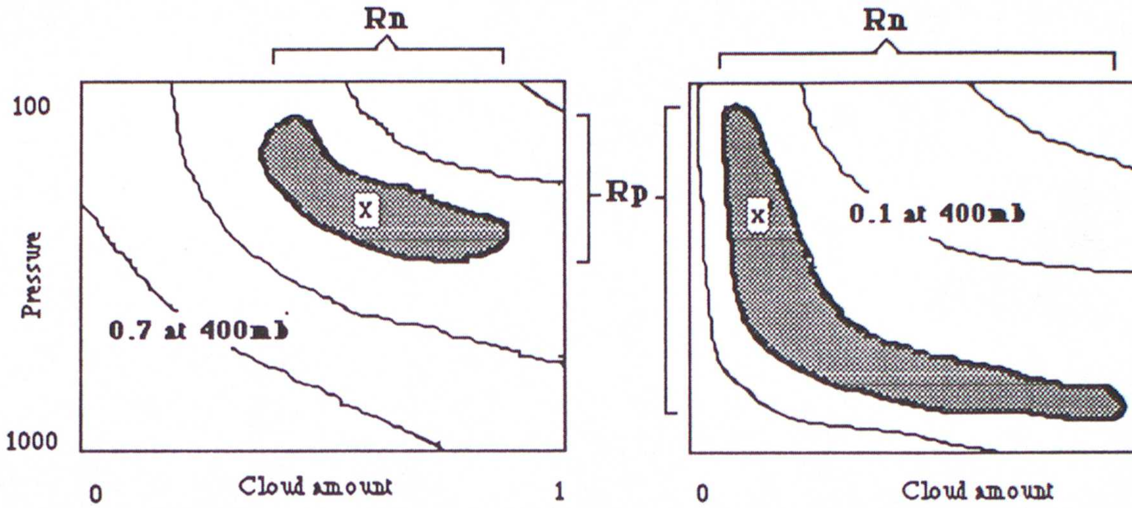
[1] the background appropriate to the cloud estimation is the original NWP model background modified by one iteration using only the MSU measurements.

priori that the cloud in each FOV is at a similar height then we can reduce the uncertainty in P_c in the less cloudy FOVs to the range of pressures common to all FOVs. The uncertainty in n will correspondingly reduce.

Figure 2: Cloud cost functions for small and large amounts of cloud



Rn = range of possible cloud amounts
Rp = range of possible cloud top pressures

A possible APPLICATION of the CONSTRAINT

The cost function referred to in the last section may be written as,

$$j^r = \sum_{i=7}^{8} \frac{1}{E_i}\left\{R_i\,(n,P_c) - R_i^m\right\}^2 \qquad 1.$$

where R_i is the radiance calculated in the i^{th} HIRS channel for n cloud cover at P_c. R_i^m is the measured value and E is the expected measurement and forward model error[2] . (j^r is proportional to the exponent of the gaussian probability of occurrence of the calculated and measured values when all errors are equal and uncorrelated.) We can write the cost function for all the M FOVs considered in the analysis as,

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[2] because the profile is constant during the cloud estimation, the forward model error should include the contribution from background errors. I.e. the cost of not fitting the measurements with the calculated radiances is reduced to allow for fact that the background profile is erroneous.

$$J^r = \frac{1}{M} \sum_{m=1}^{M} j^r_m \qquad 2.$$

We can write the physical constraint on P_c as a cost function or 'pressure penalty':

$$J^p = \frac{1}{M} \sum_{m=1}^{M} \left\{P_m - P_{bar}\right\}^2 \frac{1}{\sigma_P^2} \qquad 3.$$

where P_m is the cloud top pressure estimate for the m^{th} FOV, P_{bar} is the mean value for all FOVs and σ_p is the expected spread of the pressures in the group. (This formulation assumes that the group is small enough that σ_p is appropriate to all members, with a large group the P_{bar} could be replaced by P_0 for some central FOV, and σ_p could be a function of distance.) The total cost function can now be written,

$$J = J^r + J^p = \frac{1}{M} \sum_{m=1}^{M} \left[j^r_m + \left\{P_m - P_{bar}\right\}^2 \frac{1}{\sigma_P^2} \right] \qquad 4.$$

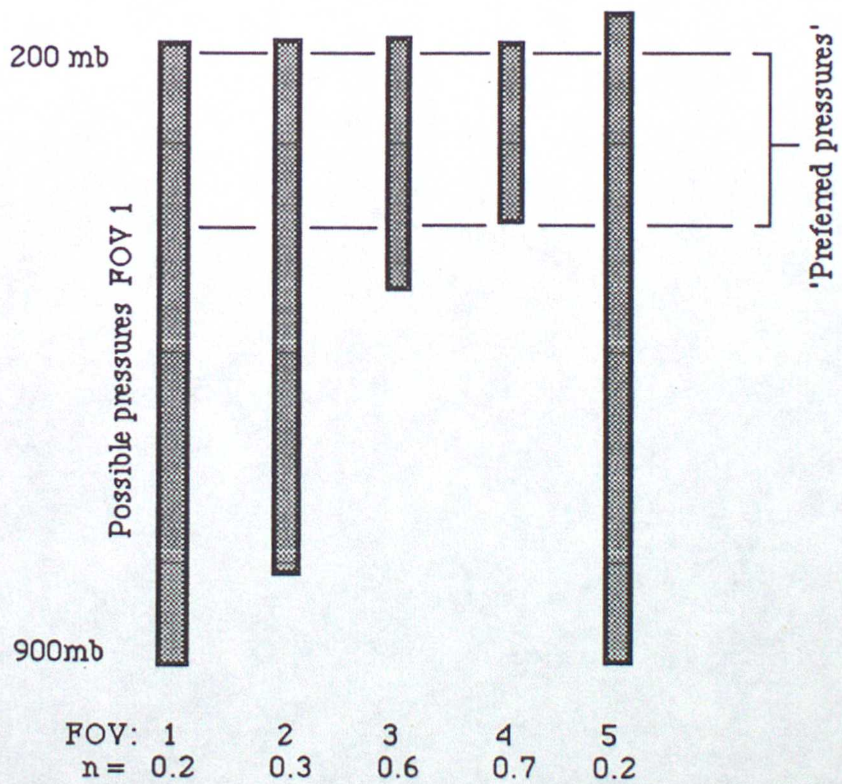
and can be minimised with respect to the M cloud amounts and pressures. Note that in the limit of high σ_p, i.e. no physical constraint, the solution reduces to individual FOV cloud estimation. Equation 4 would be minimised iteratively, first finding the n_m and P_m without the constraint to obtain a starting point. There are several considerations if equation 4 is to be minimised. Initially n_m and P_m could be found without a constraint since there would be no mean pressure. The iteration would then be allowed to proceed until convergence defined by negligible further changes in n_m and P_m. E and σ_p must be specified reasonably well if only to preserve the relative size of the two terms in the cost function. σ_p may be set to achieve different things. Set to accommodate most spreads of cloud heights (i.e. large) it will then apply a loose constraint but one which should operate everywhere. However it may be desirable to apply the constraint to those cases where there is more uniform cloud and therefore a good case for it. σ_p should then be small. This runs the risk of forcing erroneous cloud pressures on FOVs that genuinely have cloud at a different height to the rest of the group. However, it should be possible to check the individual j^r term as the iteration proceeds and where it gets too large, i.e.$> \varepsilon$, remove the FOV from the analysis. This is a form of quality control.

A PRACTICAL SCHEME

The 'pressure penalty' method of applying the constraint outlined in the last section has not been tested here. The uncertainties in the cost function weights and the need to investigate a robust minimisation scheme and quality control suggested that initially a simpler implementation was needed. The method used we might call the 'preferred pressure' method.

The projection of the shaded regions in figure 2 onto the pressure axis give the possible cloud pressures for the FOV. A large range of pressures is found for small cloud amounts, a small range for large cloud amounts. The method matches the possible pressure ranges to find those 'preferred pressures' which are compatible with each FOV in the group. This is shown diagrammatically in figure 3.

Figure 3: 'Preferred pressure' method



Five FOVs are shown, all with a consistent cloud height. Possible pressures for each FOV are shown by a vertical bar, example cloud amounts are given and the set of preferred pressures is indicated. n_m and P_m are found by minimising the cost function within the range of preferred pressures and for each FOV separately. In this way the information on P_c in the cloudiest FOVs is conferred to the less cloudy whilst allowing for inevitable variation in cloud top pressure. Establishing the cost level ε which defines the possible pressures is an analogous problem to that of E and σ_p described in the previous section except that here only the combined effect is required. Nevertheless, calculating the cost level from the available information (measurement, background errors and spread in P_c) is non-trivial and open to interpretation in the same way that σ_p is. For the experiments described here the cost level was set empirically to obtain plausible possible and preferred pressure ranges.

The method can in principle allow for groups containing one or more FOVs which have different cloud heights (non-homogeneous). There may not be a set of preferred pressures for such a group, and in this work, where this happens we resort to individual unconstrained estimation. A more sophisticated version could identify the homogeneous members of the group and subject just these to the constrained estimation. There will, however, be cases where preferred pressures are found for non-homogenous groups and the constraint will be applied to some FOVs inappropriately. However, since the estimate obtained from minimising the cost function subject to the constraint will still have a cost $< \varepsilon$, it is effectively no less reliable than the estimate from the unconstrained minimum. We therefore expect the constrained minimisation to produce better estimates of the cloud parameters when the constraint is valid, and estimates as reliable as the unconstrained solution when it is not.

IMPLEMENTATION with the CATHIA data set

The scheme was tested using the CATHIA data set supplied by the Centre Meteorologie Spatiale. CATHIA comprises high quality colocated radiosonde, TOVS and AVHRR data from the NOAA-7 and NOAA-9 satellites though only NOAA-9 data were used here. Each radiosonde in the set is colocated with between 8 and 12 TOVS soundings immediately surrounding the sonde location. The set was designed to represent all types of cloud conditions and is therefore well suited to testing the cloud analysis. One limitation is the lack of a forecast background profile needed by the inversion scheme. This was circumvented by generating profiles from the radiosonde with error characteristics given by the background error covariance used in the retrieval. The retrieval accuracies shown later are therefore optimistic in that real forecast profiles do not have errors defined exactly by this covariance. However, the removal of a source of retrieval error not directly connected to the cloud estimation problem is unlikely to invalidate results and may, in fact, clarify them somewhat.

The CATHIA colocations provide a straightforward way of defining the groups needed. The crucial cost level was obtained completely empirically by seeing how the preferred pressure ranges formed with different values. Table 1 shows the preferred pressures for the NOAA-9 groups as an underlined number; the cost level that gave this was 5 $(mw.st^{-1}.cm.m^{-2})^2$. The number itself shows how many FOVs for that group had that pressure selected by the original unconstrained estimation. Consequently, a non-zero figure that is not underlined represents the FOVs where the estimated pressure changed when the constraint was applied. The number of these for each group is indicated in the right hand column and totalled below. The exception to this is where no constraint was applied because no preferred pressures were found (indicated by bold face **0** in the change column). For example, the fifth row reading <u>07</u>1000.... means that the preferred pressures were the uppermost two levels, i.e. 150 and 200 mb, and that the 1D estimate gave 7 FOVs at 200 mb and 1 at 250 mb. The 1 at 250 mb was moved by the 3D estimate to be either 200 or 150 mb (depending on which had the lower cost).

55 FOVs, about 20%, have a different cloud pressure as a result of the constraint though 14 of the 32 groups had no preferred pressures. 9 of these 14 groups were classified in CATHIA as mixed cloud type; this classification is given in the last column of table 1. Overall, if we consider the use of the constraint an indication of single layer cloud and no constraint to indicate mixed layer, then the scheme 'agreed' with the CATHIA classification for 20 groups and 'disagreed' for 9 (2 groups have an ambiguous CATHIA class). Probably a more sophisticated scheme could have identified homogeneous subsets in many of the mixed layer groups and the constraint could have been applied more often. Of course, we could have achieved the same with a cost limit higher than 5 mw^2 but the preferred pressure ranges would have become wider and consequently the number in the *change* column correspondingly smaller. We re-emphasis: this method is very empirical. It is interesting to note that many of the changes are from the lowest pressure level allowed in TOVCFG (950 mb i.e. second column from right in table 1) to higher levels.

VALIDATION

The broad agreement with the CATHIA group classification indicates that the constraint is being applied in appropriate cases. A more detailed validation is required to establish whether applying the constraint is of any use.

A validation of the cloud estimates, although the most direct measure of success, was not possible; good cloud estimates are hard to come by. Two estimates were available: the classification of cloud type and cover by CMS which is in the CATHIA data set and an estimate from the AVHRR data. The human estimate from CMS was made from examination of the AVHRR imagery in a rectangular box large enough to accommodate the HIRS FOV. Consequently, the estimate is not of the actual FOV coverage. Additionally, the cloud amount defined in TOVCFG is an effective amount which allows for semi-transparent clouds. For example, a FOV fully covered with cirrus with a transmission of 0.5 would have a TOVCFG n of 0.5. The human estimate would be 1. This is a problem also with AVHRR. Estimates from the image data can be

Table 1: underline 0 0 5 2 = preferred pressure with cost limit @ 5 mw²

Pressure levels: 150 mb........................1000 mb	no. in group:	Changes: (0=no constraint)	CATHIA mixed ?
0 0 0 0 0 0 0 1 1 3 0 1 0 0 0 0 2 0	8	2	
0 0 0 0 0 0 0 0 0 0 1 0 0 2 3 0 2 0	8	0	
0 0 0 0 0 1 0 0 0 0 0 1 2 4 1 0 0 0	9	0	
0 3 0 2 0 0 1 0 0 2 0 0 0 0 0 0 2 0	10	0	
0 7 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	8	1	?
0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 8 0	9	8	
0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 0 5 0	8	0	√
0 2 0 0 3 1 0 2 0 0 0 0 0 0 0 0 0 0	8	0	√
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8 0	8	0	
0 0 0 3 2 2 0 0 1 0 0 0 0 0 0 0 0 0	8	3	√
0 0 2 4 1 1 0 0 0 0 0 0 0 0 0 0 0 0	8	4	√
0 1 0 0 0 0 1 2 0 1 1 1 0 0 0 0 2 0	9	3	
0 0 0 0 0 0 2 2 3 2 0 0 0 0 0 0 0 0	9	0	
0 3 0 0 0 0 0 0 0 0 0 0 0 0 0 3 2 0	8	0	√
0 1 1 0 0 1 0 0 0 0 0 1 0 0 0 0 5 0	9	5	
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.9 0	9	0	
0 2 0 0 0 2 2 1 0 0 0 0 0 0 0 0 1 0	8	6	?
0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 6 0	8	6	√
0 3 1 1 0 0 0 0 0 0 0 0 0 0 0 0 4 0	9	0	√
0 2 1 2 0 0 1 0 0 0 0 0 2 0 0 0 1 0	9	3	
0 0 0 0 0 0 0 0 0 1 0 0 0 2 2 1 2 0	8	0	
0 0 0 0 0 0 0 0 0 1 2 1 2 0 1 0 2 0	9	0	
0 2 1 0 0 0 0 0 0 0 0 0 0 1 0 0 5 0	9	0	√
0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 6 0 0	8	0	
0 0 0 0 0 1 0 0 1 0 0 0 0 0 1 1 4 0	8	0	√
0 4 4 2 1 0 0 0 0 0 0 0 0 0 0 0 1 0	12	0	√
0 0 1 1 2 5 0 0 0 0 0 0 0 0 0 0 0 0	9	7	√
0 1 0 0 1 1 0 0 0 0 0 0 0 0 0 0 5 0	8	0	√
0 0 0 0 0 0 0 0 0 0 0 0 0 7 0 0 1 0	8	0	
0 0 0 0 0 0 0 0 0 0 0 0 0 2 7 0 0 0	9	7	
0 6 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0	9	0	√
0 0 0 1 1 0 0 0 0 1 0 0 0 0 0 0 6 0	9	0	
Total:	276	55	

made in at least two ways. By identifying and counting cloudy pixels in the HIRS FOV the estimate will be similar to the human one and will be over or under depending on whether the tests for cloud contamination are more or less stringent (see Saunders 1988). Another method with AVHRR is to establish the cloud top radiance, R_o, from fully cloudy pixels (tests are available, see previous reference) and also the clear radiance, R_c. The cloud amount then follows from the expression for the FOV radiance R:

$$R = n R_o + (1-n) R_c \qquad 5.$$

Two assumptions made here make the estimate unreliable: that the cloud is opaque so that R_o contains no contribution from the underlying atmosphere; that the cloud is flat so that the pixels used for R_o are typical of the whole cloud top. If the cloud is at all transparent R_o will be too high and the cloud amount too large. If the cloud is not flat it may be that the fully cloudy pixels will be biased towards the central higher parts leading to an underestimate of the mean cloudy radiance. AVHRR estimates are therefore most accurate for opaque flat clouds which are mostly found at low levels. TOVS cloud estimates, conversely, are best for high cloud. Similar problems arise with AVHRR estimates of cloud top pressure.

Scatter plots of the AVHRR and TOVS estimates were not encouraging and certainly any subtle improvement in the TOVS estimates would be hard to see. It is conceivable that with carefully selected FOVs the AVHRR estimate could provide a ground truth for TOVS cloud under certain conditions. AVHRR *can* measure the clear radiance in a FOV very well because there are no transparency problems and, away from coastlines, the scene is usually homogeneous, particularly over the sea. Some indirect validation of the cloud may well be possible by comparing this clear radiance with the clear HIRS 8 radiance after the full retrieval process has finished. Of course, this will include all the effects of the inversion rather than just the cloud estimation and it is not a validation of state parameters. It may nevertheless be interesting.

The validation presented here also includes the effects of the inversion but it is a validation of state parameters. The CATHIA radiosondes have been used to obtain mean and rms errors (strictly differences) of the retrieved temperature profiles. Apart from the distance of the retrieved product from the cloud estimation process there is the additional problem of colocation error between the sounding and the sonde. This is less of a problem than is usual because many of the sondes in CATHIA were released especially to coincide with the satellite overpass. Figure 4 is the standard deviation of retrieved temperature profiles with respect to the sonde profile for just the 55 cases where the cloud estimate changed significantly with the constraint.

Figure 4: Standard deviation of retrieval errors

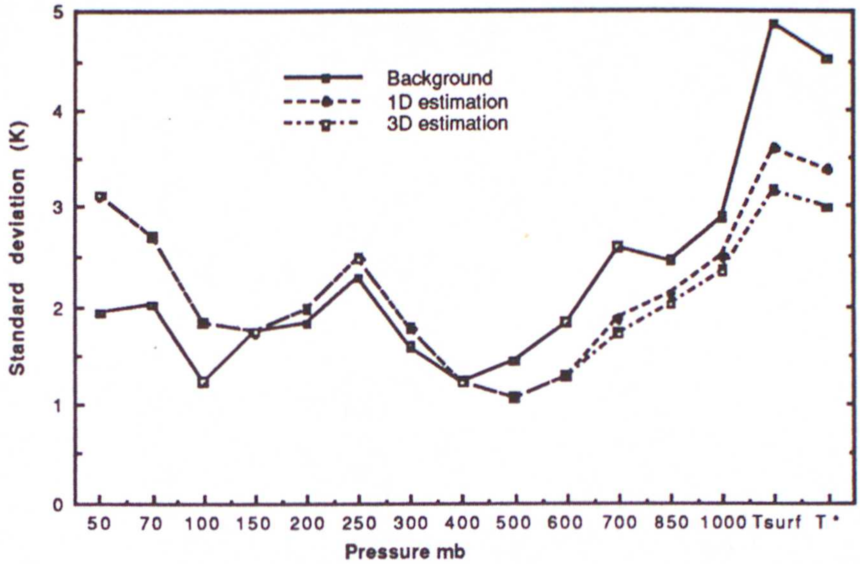
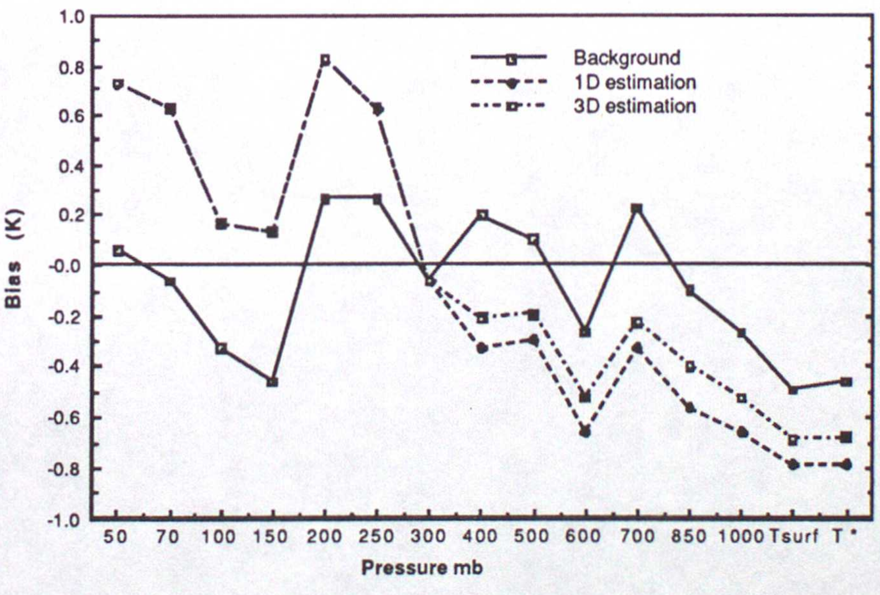


Figure 5: Mean retrieval error



The background accuracy is shown for reference and it is interesting that for most tropospheric levels the retrievals the retrievals are more accurate for both the 1D and 3D (unconstrained and constrained) cloud estimation. Other experiments with TOVCFG on real data fail to give results as good as this but, as mentioned earlier, results here are optimistic because of the exact specification of the background error covariance.

The increase in accuracy of the retrieval when the constraint is applied is very apparent especially at levels below 600 mb. It is at low levels that we might expect most gain because the 1D cloud errors here are larger than at high levels (see Eyre 1989). The gain in accuracy is around 0.1 K rising to 0.5 K at the surface. Figure 5 is the mean retrieval sonde difference and shows similar improvements with the constrained cloud estimates. A reduction in negative bias of around 0.1 K is found up to 400 mb.

SUMMARY

The use of multiple FOVs to aid the estimation of cloud parameters for a non-linear TOVS retrieval scheme has been discussed as a physical constraint in a limited 3D analysis of the data. Cloud parameters that are well defined in cloudy FOVs are used to constrain the parameters and therefore to aid the profile retrieval in less cloudy FOVs. One semi-rigorous ('pressure penalty') method of applying the constraint was outlined and a more *ad hoc* and simpler ('preferred pressure') method was described and tested on semi-real data (measurements were real but the background was simulated). The scheme's classification of groups of soundings as to whether they had single or mutli-layer cloud was largely successful as judged by independent human classification.

The impact on temperature retrieval accuracy in cases where the constraint was applied was small but significant: the same impact in real situations, where retrieval and background accuracies are very similar, would be very welcome. This has not been tested here.

The constraint could only be applied to 18 of the 32 groups because we insisted that it applied either to all group members or none at all. It is likely that the pressure penalty method would be able to identify sub-groups and apply the constraint more often - if 40% of soundings were to benefit from the constraint it would be a significant gain. We think the pressure penalty method would be generally more flexible and powerful than the preferred pressure method and is likely to be the subject of any future development.

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