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Progress Report

ATMOSPHERIC INFRARED SOUNDER

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Aircraft-based Measurements

Work continued on analysis of data from the TOGA-COARE experiment. Uplooking data from the 118-GHz radiometer is of good quality, and should provide a test for theoretical transmittances. There are some questions regarding *in-situ* measurements: the radiosonde profile from Townsville differs from the temperature measurements made by the ER-2. Unique high-resolution measurements of tropical cyclone Oliver were obtained from two overpasses.

The MIT Microwave Temperature Sounder was flown on NASA's ER-2 at Wallops Island in the CAMEX experiment during September and October. Other instruments similar to those that will be in the EOS payload were also on board. Although there were some malfunctions, including failure of a disk drive due to loss of pressurization, most of the flights produced useable data. We obtained uplooking data at both 118 and 53-54 GHz, which will be used to test and validate atmospheric transmission models. There also were underflights of the DMSP satellite and flights over convective activity near Florida.

Algorithm Development Activity

The preliminary version of the "microwave first-guess" algorithm for temperature and moisture was delivered to JPL.

In the iterative minimum-variance algorithm (described previously in the December 17, 1992 report) moisture retrievals from MHS make use of the retrieved temperature profile in calculation of weighting functions and in determining the saturation moisture capacity at each level. Simulations have been run to address the question of how important the temperature profile accuracy is to the moisture retrieval. Figures 1 and 2 show water vapor errors, expressed as a percentage of the ensemble mean, when the temperature profile is retrieved from AMSU brightness temperatures and when the actual temperature profile is used, respectively. The profile ensemble was the Phillips "a" set. Some moderate improvement is seen to occur in the layers from 500 to 850 mb in Fig. 2, compared with Fig. 1. This comparison is of interest because although the true temperature profile will not be available to the retrieval process when in operation, the AIRS-retrieved temperature profile will be, and it should be an improvement on AMSU alone.

Moisture retrievals from MHS were simulated in cloudy atmospheres. The Phillips ensemble of 100 profiles (set a) was used as the test dataset in these simulations. Between 700 and 850 mb, the water vapor was set to the saturation value determined from the temperature profile, and cloud liquid water was inserted, with a total weight of $6 \cdot 10^{-3}$ g/cm^2. Above and below the cloud layer, moisture was unchanged from the radiosonde profile. Brightness temperatures were computed for cloud cover of 25%, 50%, 75% and100% of the IFOV. Unity surface emissivity was assumed. Instrument noise was simulated by adding pseudo-random numbers to the brightness temperatures. The retrievals were done by the iterated minimum-variance algorithm. The TIGR ensemble of profiles provided the *a priori* statistics.

Comparison of the four cases showed that, overall, the effect of changing the percentage of cloud cover is small. Above the cloud, errors increase monotonically with cloud cover in the 600 to 700 mb layer but are unchanged in higher layers. There is a trend of slightly decreasing errors within the cloud layer as cloud percentage increases. A similar effect was found by Wilheit[1] as a function of cloud weight. The improvement seems to result from the fact that when the retrieval algorithm detects liquid water at any level, it pins the retrieved vapor profile to the saturation value determined by the temperature retrieval at that level. Below the cloud, in the 850 to 1000 mb layer, the minimum errors occur for 50% cloud cover. This case is shown in Fig. 3. The three profiles on the graph show the standard deviation of the ensemble; the rms error of layer-integrated water vapor retrievals, and the magnitude of the mean error. (The rms error includes the mean error as one component, and therefore is always larger than the mean.) Along the 1000 mb axis are plotted three X-symbols, which give the errors in the integral of water vapor through the atmosphere.

Artificial neural networks are computational paradigms for relating input vectors to output vectors via a sequence of inner vector products followed by non-linear transformations, usually sigmoidal. The result is a desired nonlinear relationship between the input and output vectors which generally has been computed with great efficiency. Efficient methods for determining the weighting coefficients to be used in these vector products have been developed. These coefficients generally converge in an iterative process to produce a unique minimum for a chosen performance metric, such as mean square retrieval error, over some training ensemble of meteorological conditions.

In a recent thesis,[2] Carlos Cabrera has applied these techniques to retrievals of humidity profiles from AMSU-A and -B spectral observations from space. This retrieval problem is challenging because it is highly nonlinear due to the dependence of the radiance weighting functions on the same humidity profile which is to be retrieved. It also can be singular when the local temperature profile is approximately isothermal, and this requires statistical regularization or some equivalent stabilization procedure.

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[1] T. T. Wilheit, *J. App. Meteor.* v.29, pp. 508-515 (1990).

[2] C. R. Cabrera-Mercador, Neural Network Statistical Retrieval of Atmospheric Water Vapor from Microwave Radiometric Observations, S.M. thesis, Dept. of Elec. Eng., M.I.T. (August 17, 1993).

Figure 4 compares the performance (expressed as a troposphere-averaged error) of three-layer and four-layer networks as a function of the total number of weights which must be determined from the training set. A four-layer network (two hidden layers with 20 and 10 hidden nodes in succession) with 750 weights was chosen to do retrievals of relative humidity.

Our earlier technique for humidity retrievals was described by Kuo et al.[3]. It involves an iterative procedure employing both statistics and the physical equation of radiative transfer appropriate to the previous retrieval iteration. Not only is the neural network computational burden a small fraction of the other algorithm, the performance is better, particularly in the troposphere over land. Figure 5 shows the rms errors in retrieved relative humidity profiles for both the neural network and the Kuo et al. method. Note the improvement of several percent in relative humidity retrieval errors below 700 mb over land when the neural network is used; over ocean the two performances are more nearly comparable.

The neural network was trained on a global all-season subset of 1658 profiles selected from the TIGR ensemble. The results shown in Figure 6 for the training set and a small independent set of profiles are essentially the same. Over land the retrieval errors are approximately one percent higher than over ocean, for pressures greater than ~600 mb.

Preliminary analyses of the computations performed by these neural networks suggest that they are very similar in form to the retrieval functions computed by traditional linear statistical methods, but that they automatically adapt in a physically plausible way to the climate class of the sounding being processed. Thus far, the neural network simulations have not included any cloudy atmospheres.

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[3]C. C. Kuo, D. H. Staelin, and P. W. Rosenkranz, Statistical iterative scheme for estimating atmospheric relative humidity profiles, IEEE Trans. Geosci. Rem. Sens. (in press, 1993).

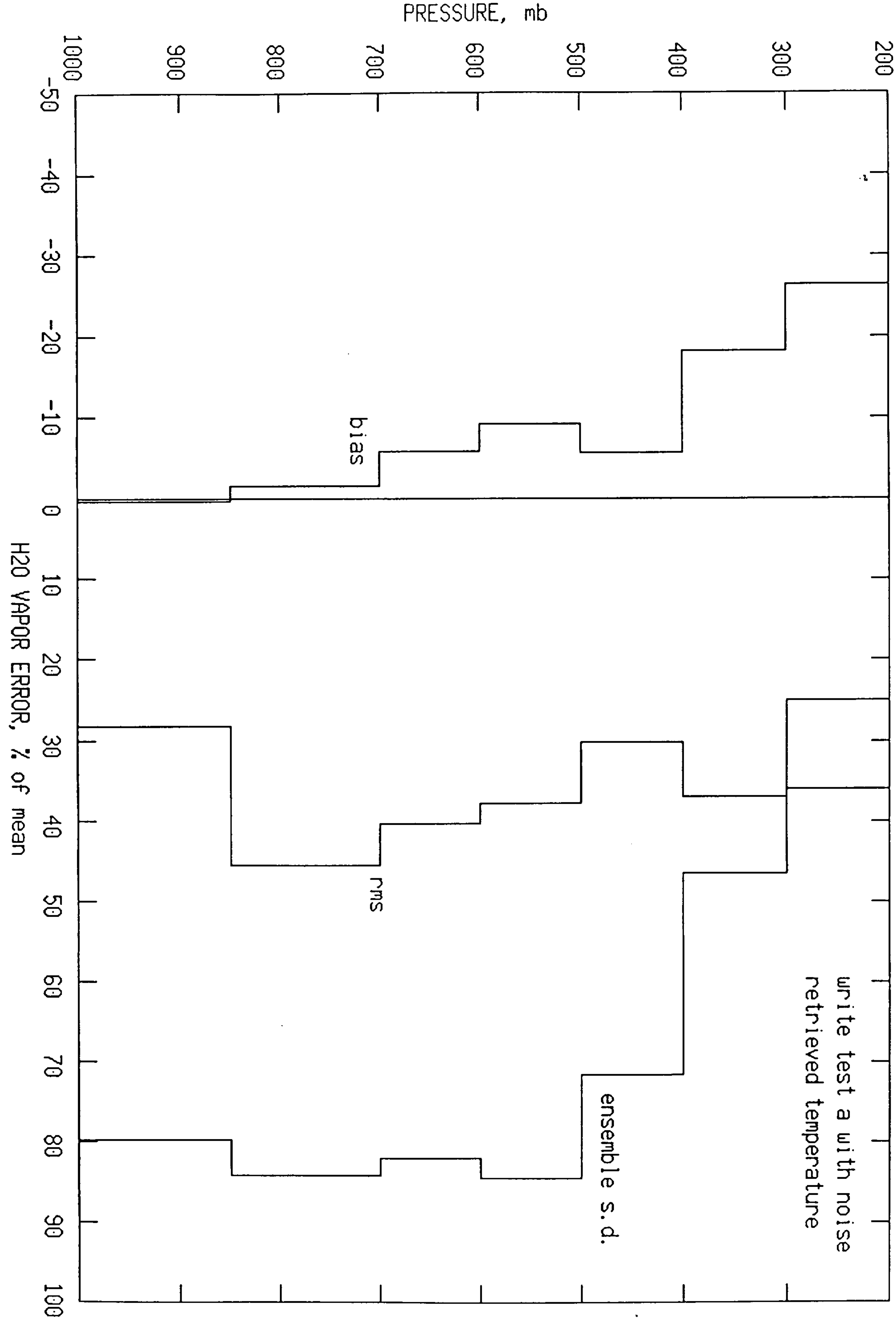

PRESSURE, mb
H2O VAPOR ERROR, % of mean
bias
rms
ensemble s.d.
write test a with noise
retrieved temperature

Figure 1

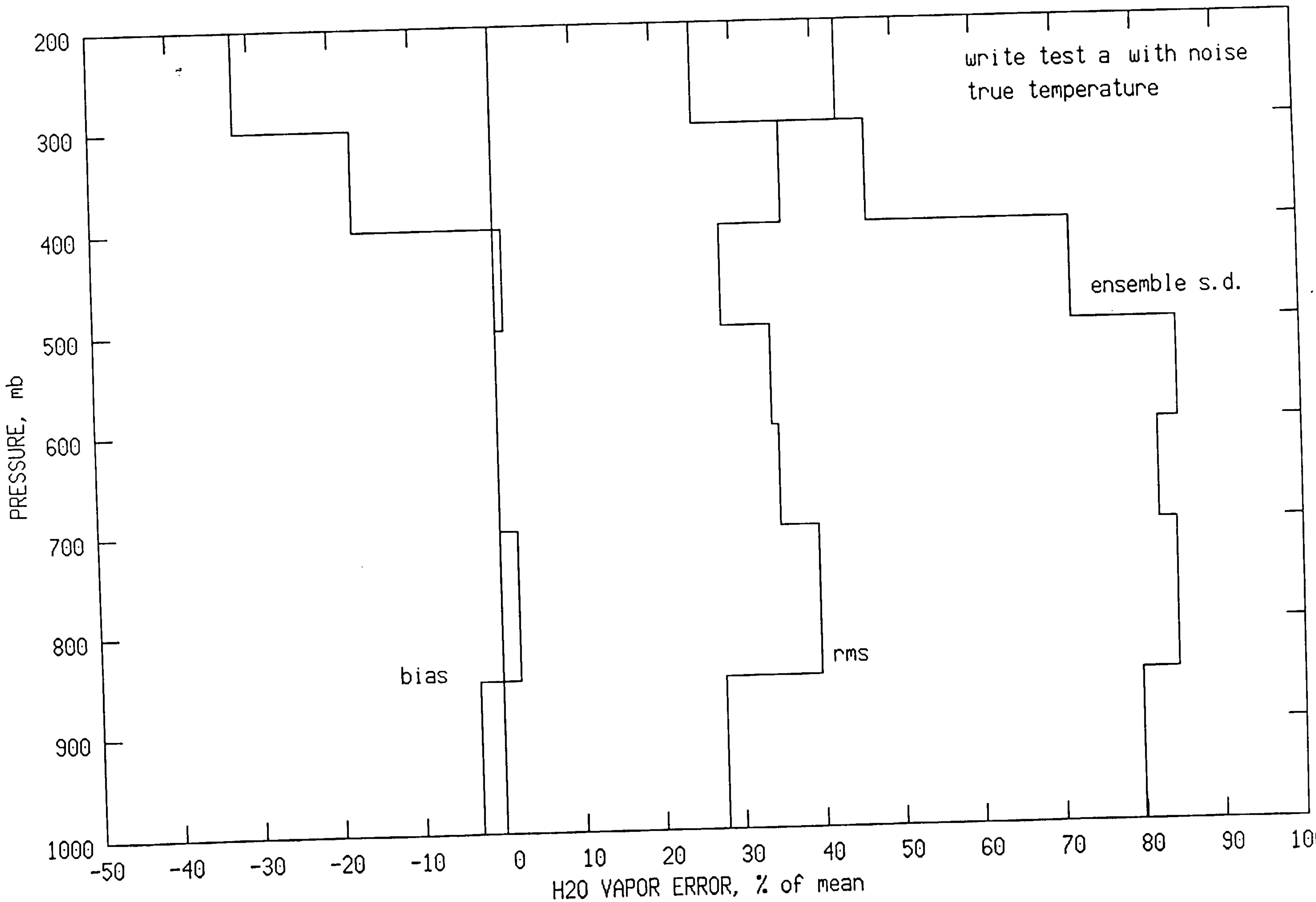

write test a with noise
true temperature
ensemble s.d.
rms
bias
PRESSURE, mb
200
300
400
500
600
700
800
900
1000
-50
-40
-30
-20
-10
0
10
20
30
40
50
60
70
80
90
100
H2O VAPOR ERROR, % of mean

Figure 2

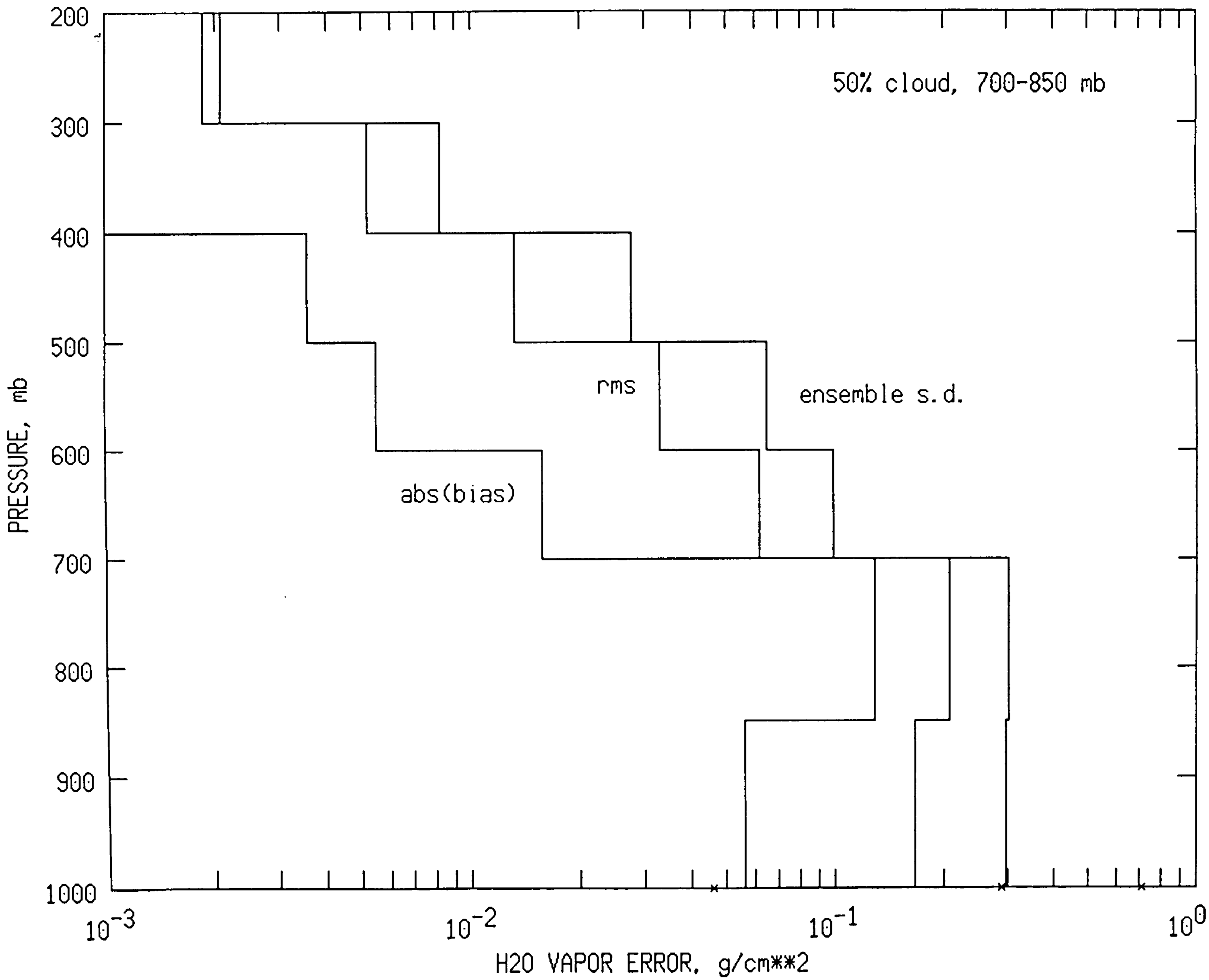

50% cloud, 700-850 mb
PRESSURE, mb
200
300
400
500
600
700
800
900
1000
rms
ensemble s.d.
abs(bias)
10^{-3}
10^{-2}
10^{-1}
10^{0}
H20 VAPOR ERROR, g/cm**2

Figure 3

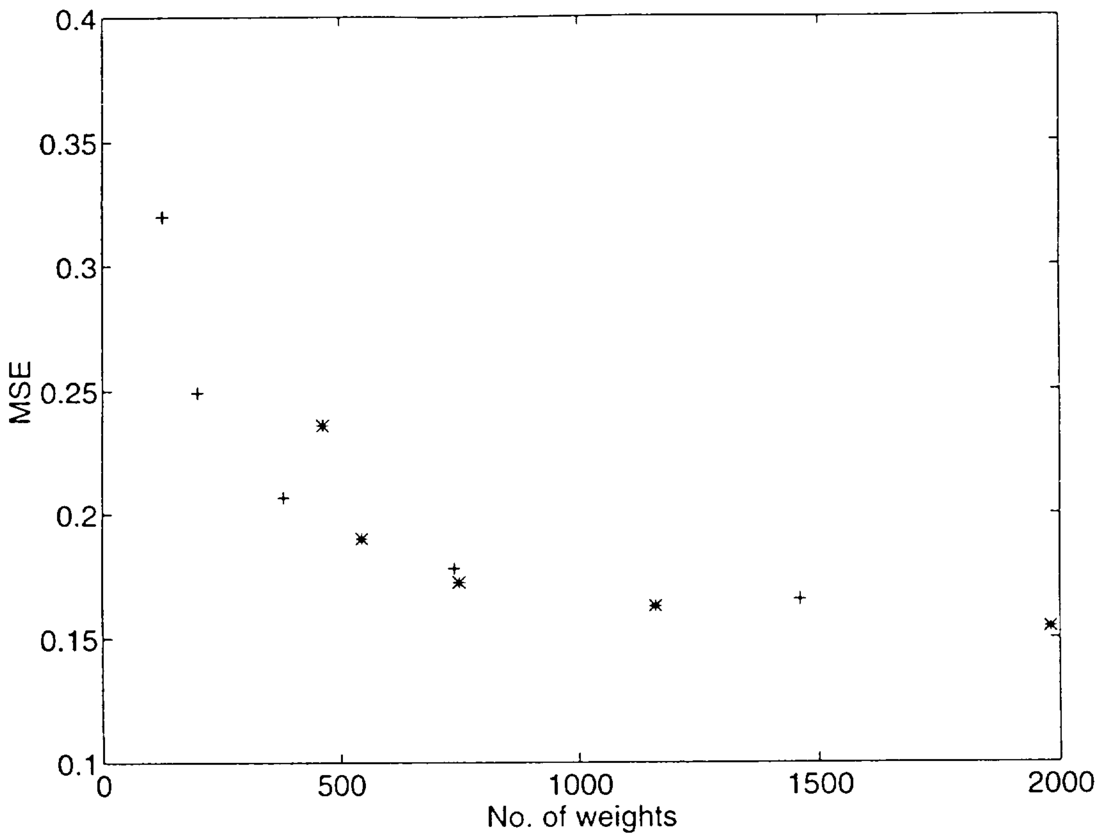
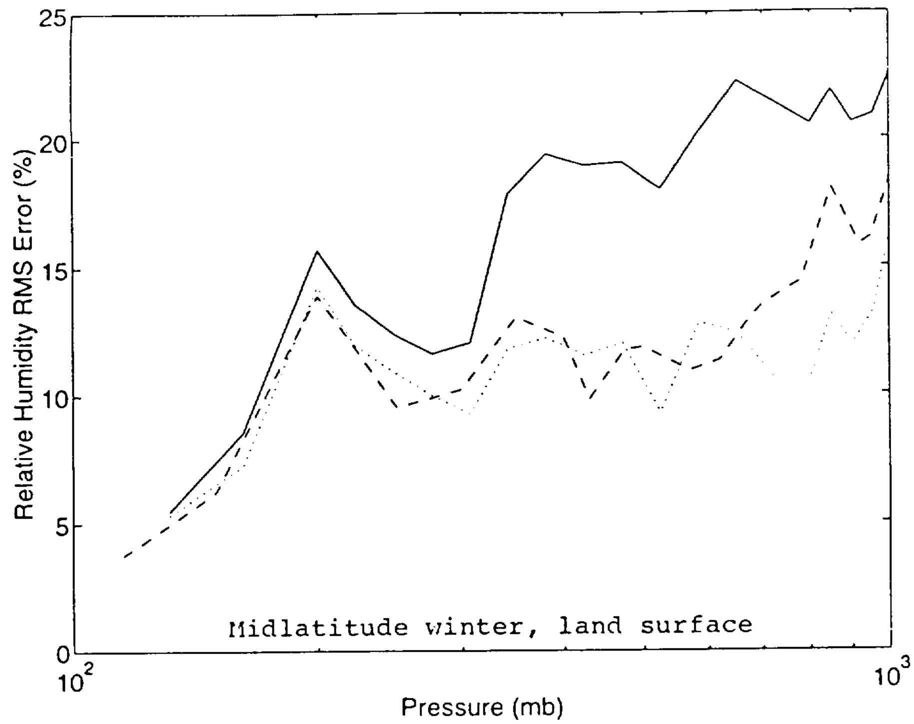


Figure 4. Performance vs. cost of three-layered (+) and four-layered (*) neural networks in a global retrieval experiment. The cost of the networks is given in terms of the number of weights.



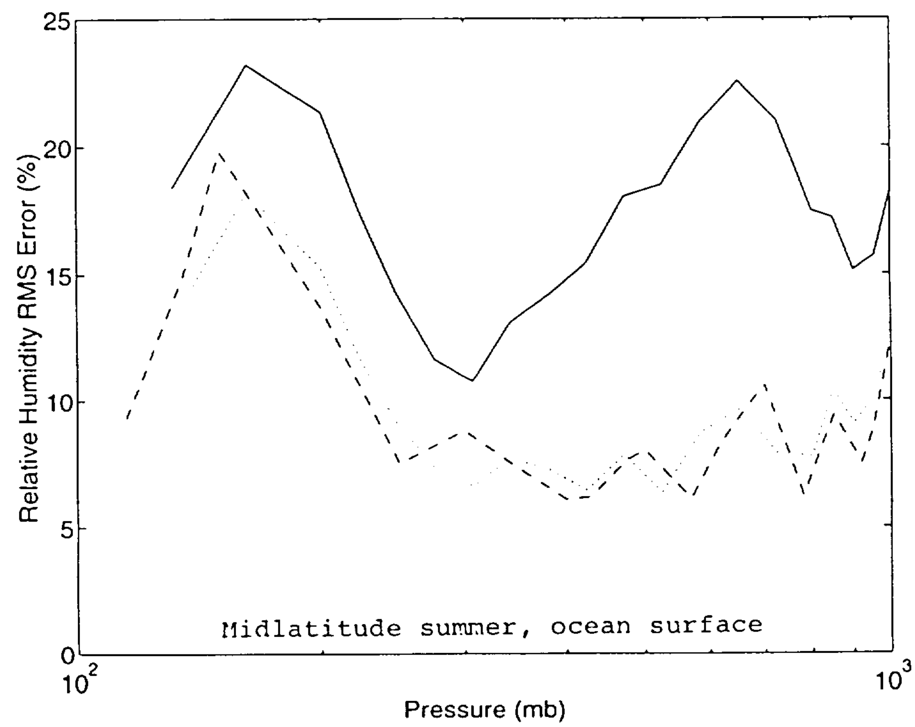


Figure 5. Comparison of the neural network retrieval and the iterative retrieval. The performance of the neural network is indicated by the dotted curve and the iterative retrieval by the dashed curve. The solid curve is the *a priori* standard deviation of the validation ensemble.

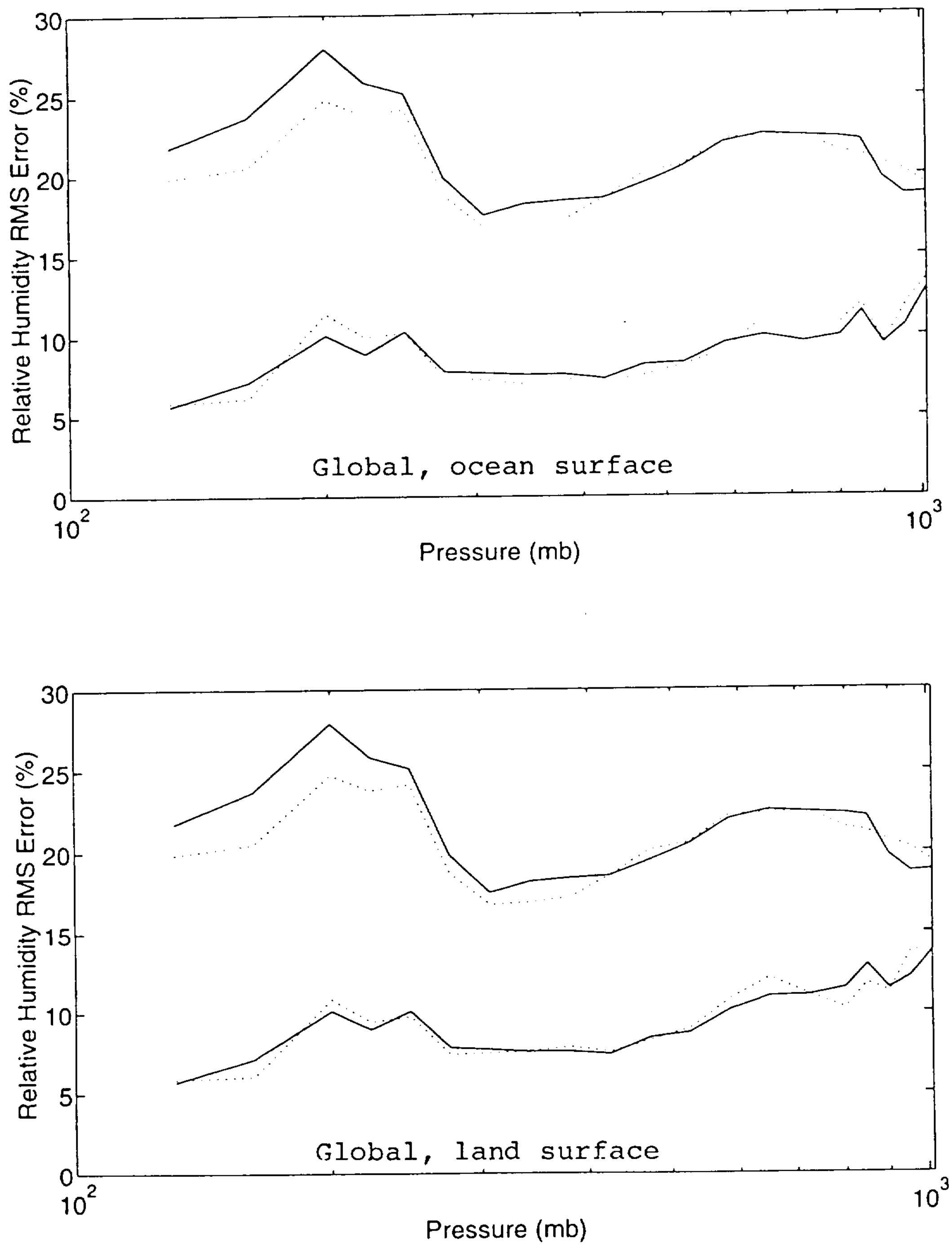


Figure 6. Relative humidity global rms errors of the neural network retrieval over land and ocean. The solid curves show *a priori* and *a posteriori* uncertainties of the training sets, and the dotted curves show the corrsponding errors evaluated on validation sets.

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15. Supplementary Notes

16. Abstract

This report summarizes the activities of AIRS Team Members P. W. Rosenkranz and D. H. Staelin during the last half of 1993.

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