SENSITIVITY STUDY FOR OPERATIONAL GOES AND PLANNED GOES-R SOUNDING BENEFIT USING REAL-TIME MOISTURE CONSTRAINTS

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Abstract

The current Geostationary Operational Environmental Satellite (GOES) sounding retrieval algorithm is underdetermined and requires a first guess for its solution. Conventionally, the first guess is derived from a model forecast for the time and location of the retrieval. In addition, it is logical to assume that other first guess knowledge would help in constraining the solution. That concept is the basis of this paper. In our study, the NOAA Community Radiative Transfer Model (CRTM) is used to assess the potential in improving the thermal retrieval profile by constraining total water vapour. Total water vapour is currently available in real time by independent observation and can be used in conjunction with the sounding retrieval processing. If it is established that this ancillary data is useful for improving sounding accuracy, arguments for additional types of these observations become more relevant.

The primary purpose of this work is to show that if current GOES (i.e., GOES 13, 14, and 15) sounding processing could be aided by total precipitable water (TPW) information, and by what degree. The technique was also run as a trial for GOES-R advanced baseline imager (ABI) soundings only to see what kind of benefit ancillary water information could offer in that context. Results show that the current operational GOES thermal profile uncertainty can be improved at several levels in the vertical, as well as near-surface, by constraining TPW. Furthermore, GOES-R thermal profiles, obtained using the planned GOES-R ABI infrared (IR) channel data, will benefit by up to three times more near the surface than the current GOES when using this constraint.

The paper reviews the methodology applying CRTM to this sensitivity study that incorporates CRTM forward model radiances, K-matrix, and an ensemble of perturbed soundings to assess the impact of thermal retrievals to total water. The results show Global Positioning System – meteorology (GPS-met), or other ground-based technologies that provide real-time knowledge of total column water vapour, can improve thermal satellite sounding retrievals.

INTRODUCTION

The thermal IR channels used in the GOES sounder are influenced to a significant degree by water vapour. This is shown by the radiance Jacobians (or weighting functions) with respect to water vapour (courtesy of Tim Schmitt, Cooperative Institute for Meteorological Satellite Studies, (CIMSS) in Figure 1.

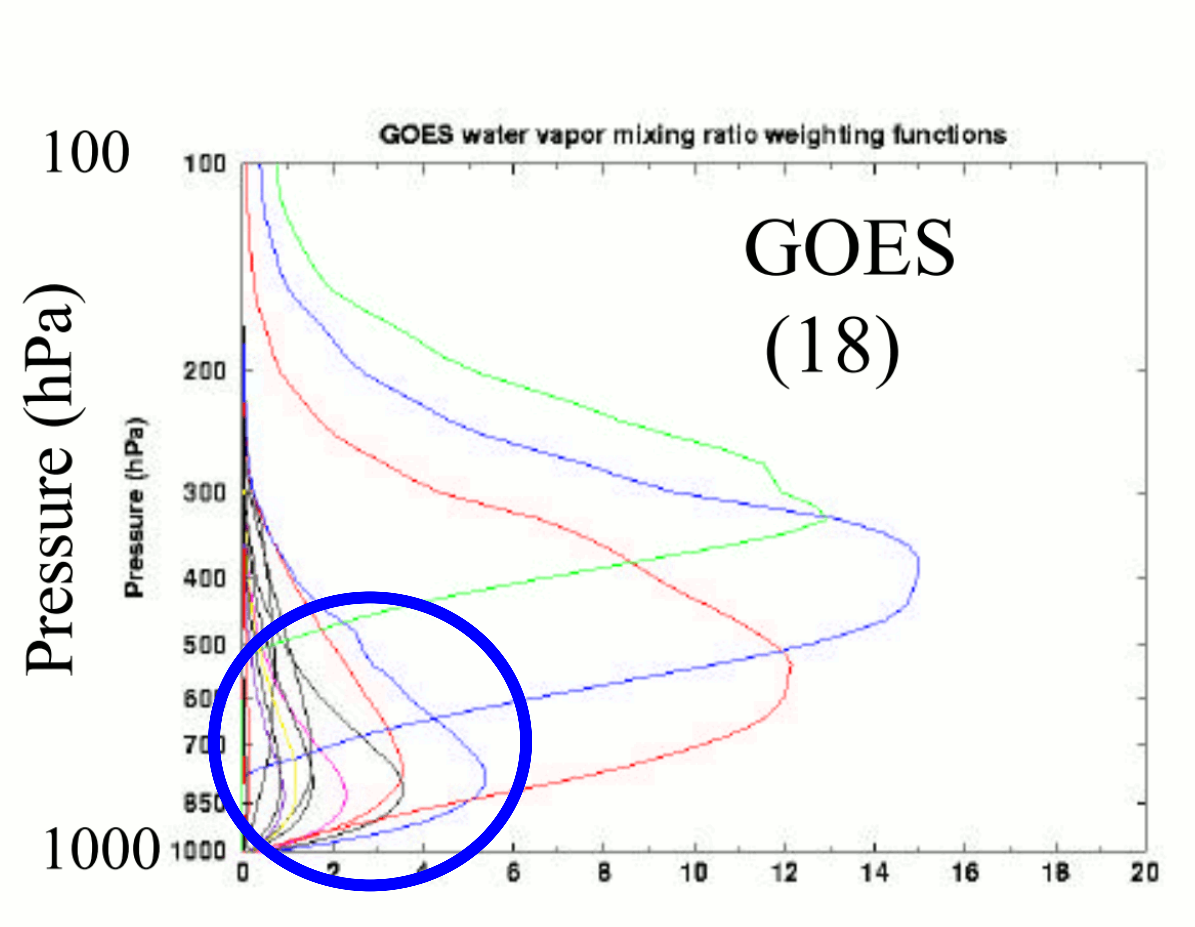

Figure 1: **Courtesy of Tim Schmit (CIMSS) from his presentation showing the water vapour mixing ratio weighting functions of all 18 GOES IR sounder channels. Three prominent peaks are water vapour channels designed for sounding moisture, the other channels (circled and not enumerated) are the other channels, mostly thermal, illustrating that they also are affected to a lesser, but still significant degree by water vapour.**

The three water vapour channels are clearly evident as prominent. The balance of the IR channels is also seen to have a water vapour influence to a lesser degree, but nonetheless still a significant effect. It is this response that improved knowledge of water vapour in the retrieval process could assist in producing a more accurate thermal retrieval by this instrument.

Such ancillary water vapour data are available from ground-based instruments such as GPS-met, which provides a zenith measure of TPW every 30m, and has been used to validate satellite retrievals (Rama Varma Raja et al. 2008). This paper describes a method to ascertain a rough estimate of the thermal sensitivity of a sounding thermal profile with knowledge of the TPW applied to modify the entire moisture column in a proportionate manner. This adjustment scales the profile to match the observation, thus preserving the profile shape.

This same technique is then applied to GOES-R ABI IR channels to ascertain the sensitivity for that application. This is a secondary goal of our work.

TECHNIQUE

The approach to perform the sensitivity test centred on the manner that one might modify a sounding with knowledge of TPW. Since TPW provides no indication of moisture distribution, a given moisture profile is scaled higher or lower to allow the integrated moisture from the input *a priori* sounding to match the TPW value, thereby preserving profile shape and matching the sounding first guess with the

TPW observation. The sensitivity for the thermal implications of this adjustment can best be shown in Figure 2.

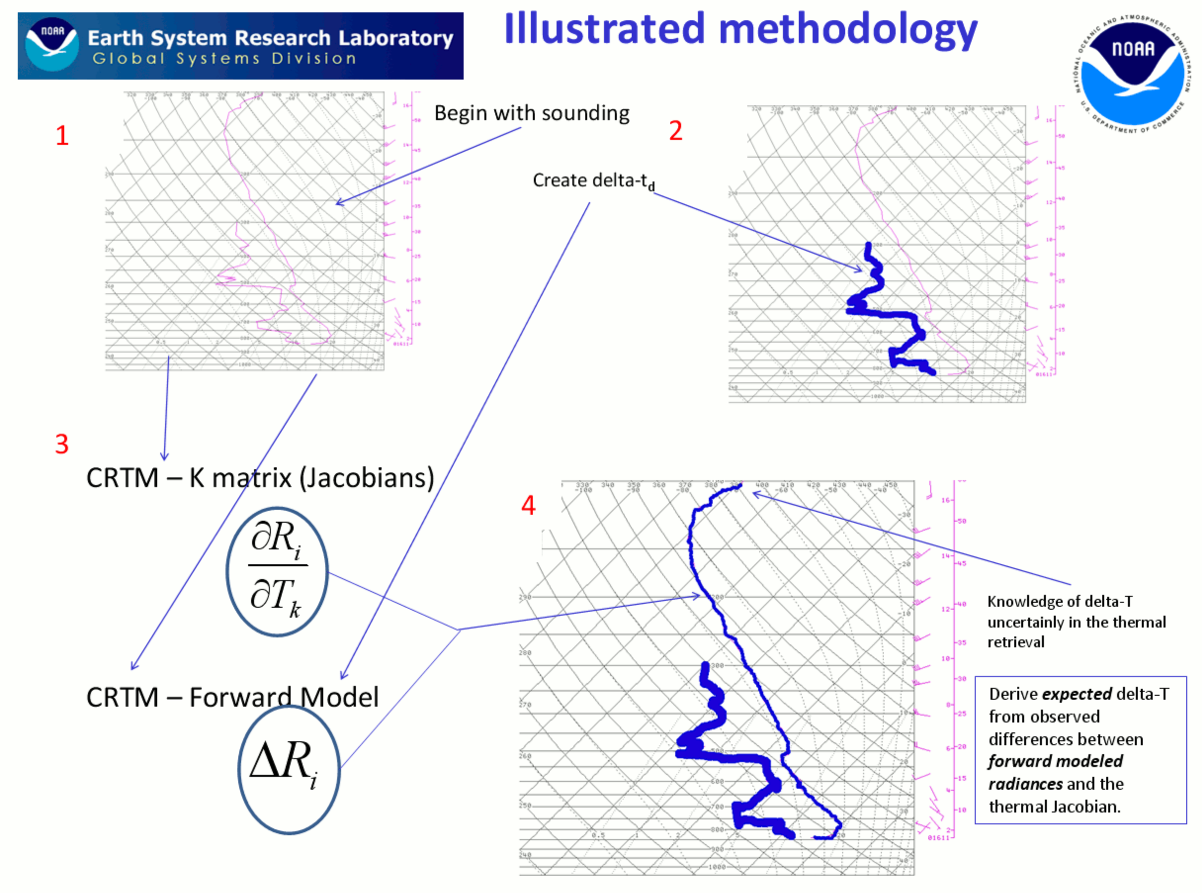

Figure 2: **Slide illustrating the procedure to determine the approximation for the thermal uncertainty profile from a given uncertainty in the moisture profile of a sounding by using the Community Radiative Transfer Model.**

Figure 2 shows a step-by-step process to go from a given sounding, assigning it a perturbation in moisture, and inferring from that an uncertainty in the thermal profile. Beginning at step-1 with one random sounding, one can dry the moisture profile, expressed by dewpoint temperature (T_d), by taking the product at all levels with 0.99 (1% drying). This then creates a second sounding, step-2 highlighted with a thickened moisture profile to indicate that it has been modified by a 1% drying at all levels (reduced by ΔT_d). Drying the profile guarantees that we will never saturate sounding step-2 by perturbation. We now have two soundings steps-1 & 2 with which to compute a thermal uncertainty. This is indicted in the figure as step-3. Here there are two steps, first to take the initial sounding, step-1 and using the CRTM, generate a K-matrix. The subset of the K-matrix Jacobians provides the partial derivatives in radiance R, with respect to temperature (T), with all *i* channels and *k* sounding levels. We can also (step-3-lower part) take the two soundings from steps-1 & 2, and run each through the CRTM's forward model to produce a set of channel radiances from each, then difference those, which gives us a ΔR for all *i* channels.

Finally, using the chain rule, we can arrive at step-4 in Figure 2. This is accomplished by dividing the ΔR_i values by the Jacobian (1), which renders an approximate set of $\Delta T_{i,k}$ at all levels for all different channels. The mean ΔT_k is then obtained by averaging all channel dependent $\Delta T_{i,k}$ values over all 18 GOES sounder channels (2).

$$\Delta T_{i,k} \approx \frac{\Delta R_i}{\partial R_i / \partial T_k} \quad (1)$$

$$\overline{\Delta T_k} = \sum_{i=1}^{18} \Delta T_{i,k} / 18 \qquad (2)$$

In order to approximate a reasonable thermal sensitivity from perturbing moisture, several thousand random soundings were run through the above computations to determine corresponding sets of $\Delta T_{i,k}$. These were then averaged to render vertical thermal sensitivity. Equations 1 and 2 were similarly modified to average over only 7 IR channels in the case of GOES R ABI.

DATA USED TO COMPUTE THE SENSITIVITY

In order to produce a comprehensive measure of average ΔT_k sensitivity, a set of "real" random soundings were used to produce a mean average result. The data selected for this were soundings from the ECMWF nature run (Chevallier et al. 2006). Of these, we selected 3508 soundings that extended from all parts of the world (all latitudes) and times of day, but were constrained such that the lowest sounding level terminated between 913 and 1023 hPa. This study did not include differences in surface. Thus, it needs to be kept in mind that the lowest level represents air temperature uncertainty.

SENSITIVITY FINDINGS

Results of these computations are shown in figure 3, with the overall average uncertainty in the thermal profiles of the current GOES (blue) and GOES R ABI (green).

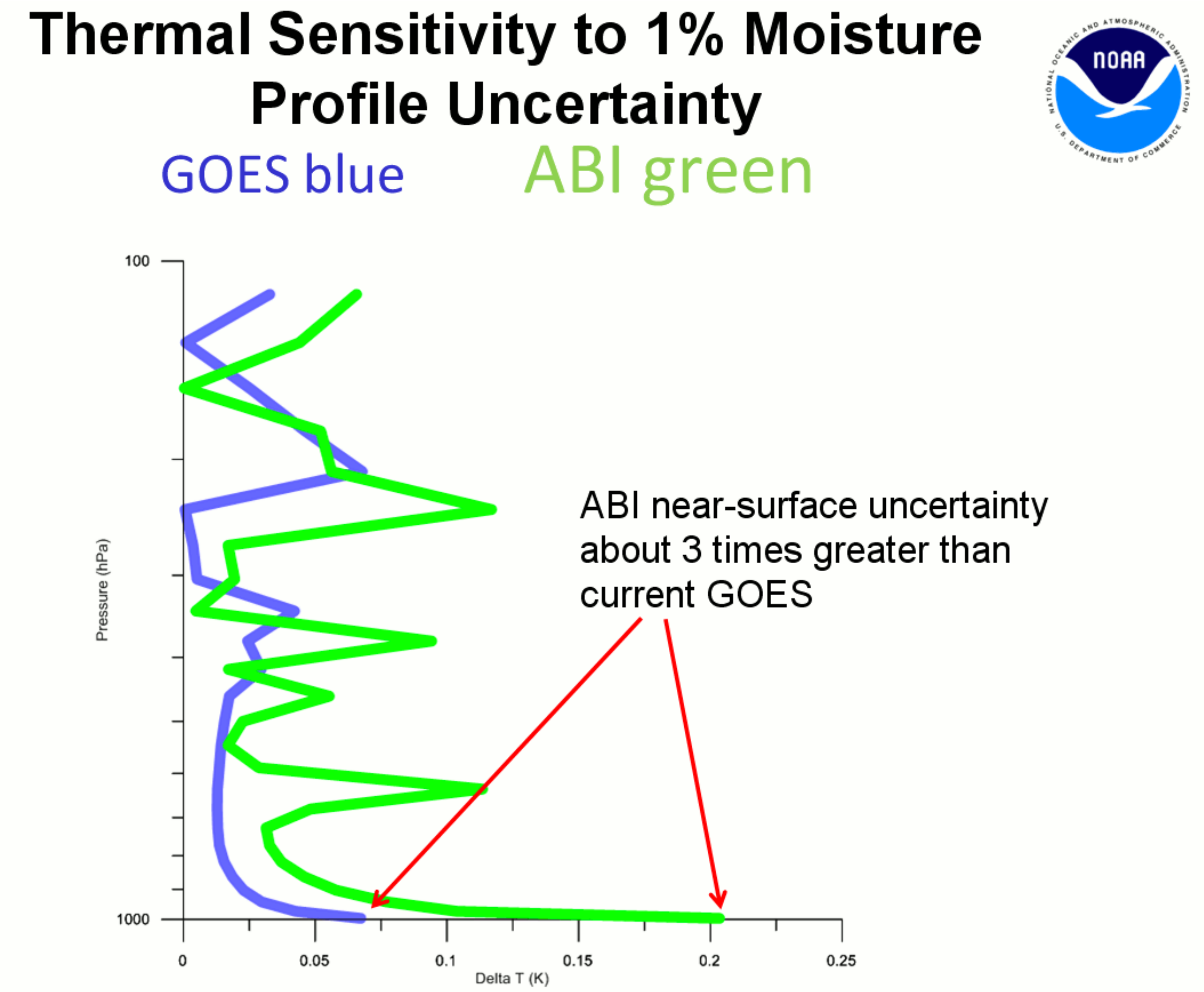

Figure 3: **Thermal uncertainty, Delta T (K), in the sounding thermal profile as a function of pressure (hPa) owing to a 1% TPW uncertainty. As anticipated, current GOES is less affected by moisture than one would see in GOES-R ABI thermal retrievals. Sensitivity in the low atmosphere is shown to be about 3 times greater in GOES-R than current GOES.**

IMPLICATIONS OF THE SENSITIVITY TO WATER VAPOUR UNCERTAINTY

The above computations (figure 3) show the relationship of a 1% water vapour uncertainty to temperature profile. However, to gauge the true nature of this result, one must relate this to some kind of “typical” moisture uncertainty encountered in nature.

To get some estimate of this impact, one random case was lifted from a WRF model run covering Oklahoma and parts of North Texas during the late summer of 2013. This was a morning case not associated with any other case study, severe weather, or other significant weather. However, this was an abnormally moist summer for this area and there was more water vapour than is typical for this region at this time of year. In this sense, even though differences between first guess and observed data are substantial, it represents a case where knowledge of the true water vapour would be of great help in improving a thermal profile. Figure 4 shows a scatter plot of observed TPW (cm) against the integrated first guess water vapour profile that would be used for an *a priori* first guess.

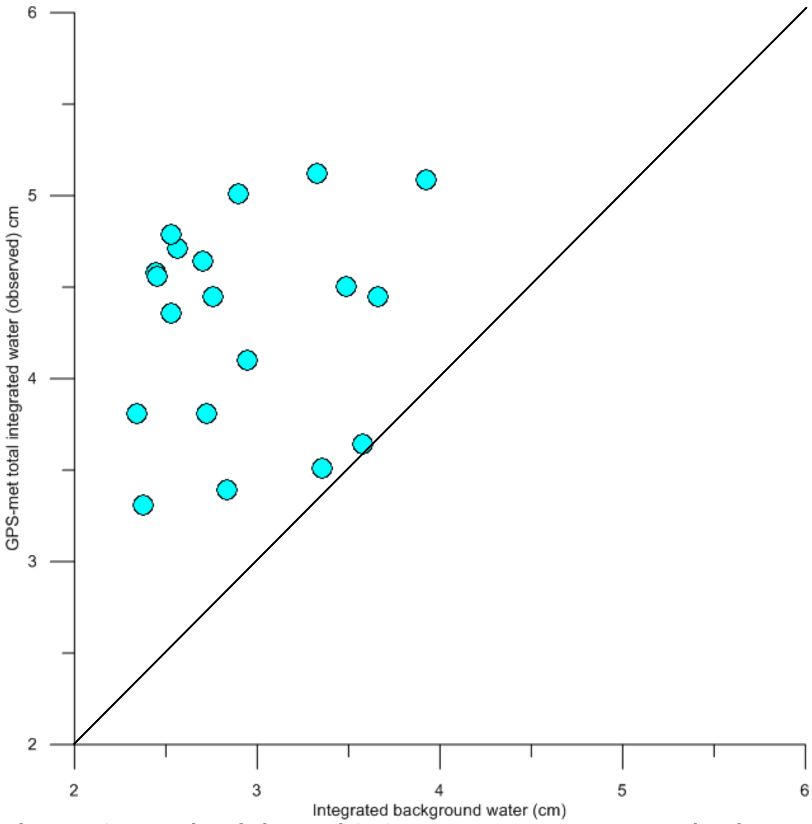

Figure 4: **Scatter plot of observed GPS-met TPW measurements against integrated background water (cm). In all cases for this instance, observed water was greater than integrated.**

The data above can be cast into a form that can be directly related to the sensitivity results.

Figure 5 is a histogram of the same data only showing binned frequency of the percent change applied to the background model so it matches observed TPW.

Percentages were computed as,

$$Percent \;\; Deviation = \frac{|(O-I)|}{O} \; (100)\,, \tag{3}$$

where *O* is the observed TPW (cm), and *I* is the integrated total water from the background first guess (cm).

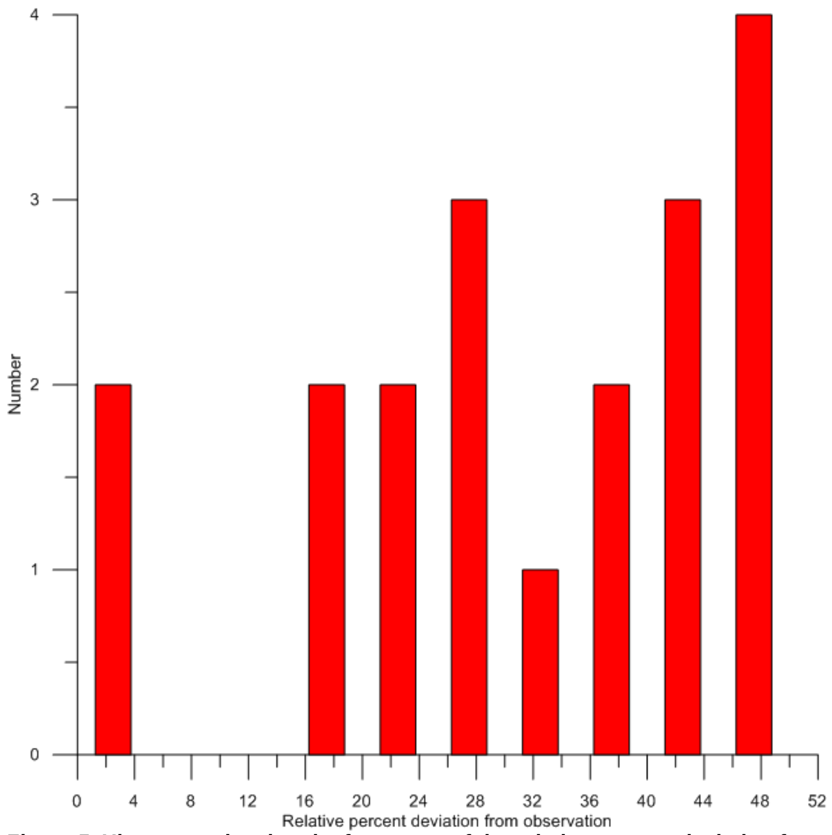

Figure 5: **Histogram showing the frequency of the relative percent deviation from observation for the points shown in figure 4.**

Figure 5 shows that the frequency of occurrence for data plotted in figure 4 is not preferential in any deviation range, but is fairly flat up to 48% for this case. If we apply a ~40% "error" with the sensitivity in the mid- to low-atmosphere of the current GOES, we infer a thermal retrieval uncertainty of (0.0125K/%) (40%) = 0.5K, and near the surface, possibly more important for stability computations, a near surface 0.07K/% uncertainty using 40% would lead to 2.8K. A 2.8 or 3K uncertainty in the thermal retrieval at low levels is substantive.

CONCLUSIONS

First, this study does not indicate the quality of thermal retrievals to the fullest extent. It must be kept in mind that only one aspect, moisture, is examined here as a state variable to affect the thermal accuracy of a sounding retrieval. There are other parts to the retrieval problem that likely play an equal or even more significant role in thermal accuracy. What this study does do is show us that if we constrain moisture to a greater degree than current algorithms presently do, and that the constraint is applied by shifting (scaling) the full vertical moisture profile of the *a priori* first guess sounding to align with observed TPW, that an improvement to thermal soundings computed using data from the current GOES sounder can be realized, especially in the low troposphere. This paper also does not address the situation where moistening the *a priori* sounding causes part of the profile to saturate. If this were to occur in the scaling procedure, additional moistening would be forced to occur at other levels, either above or below the saturation levels. This does not detract from the findings here. It points out that these results are approximations to the many different ways that TPW could be applied to a first guess, and that this study is only based on one method with fundamental restrictions. An extensive observing system experiment (OSE) with well-defined methodologies on handling TPW in the first guess might well be warranted based on this initial study.

Of all of the results shown here, the low level improvement to GOES sounding retrieval thermal accuracy is probably the most significant. Thermal error, coupled with moisture uncertainty (not discussed in this paper) will affect stability computations and stability products, especially at low levels, and can be improved by utilizing TPW and augmenting the first guess. An improvement on the order of 3K in the low atmosphere could possibly be realized in cases where observed total water is 40% out of agreement with the first guess profile. This magnitude of disagreement has been observed between nature and WRF forecasts, even though ostensibly extreme, its occurrence is considered plausible. Improvements to the derived retrieval products, implied by the correction of low-level thermal retrieval error, directly enhances severe weather forecasting and the monitoring of convective initiation, since they are some of the first real-time observation indicators of active-weather potential in the pre-convective environment presented to a forecaster.

The example used here, drawn upon for departures from truth, may not be representative of the average improvement one might see in using real-time GPS data in retrieval application. However, it should be pointed out that this is just the type of environment where this application may be the most helpful, one in which the environment is far more moist than provided by the first guess.

Finally, regarding ABI soundings, one can use the data in this paper to ascribe the moisture uncertainty to ABI thermal soundings. Whether or not ABI soundings will actually be produced has yet to be seen. However, if they are generated, we can expect that ancillary bulk water measurements can play a more significant role in improving ABI thermal retrievals than we see with current GOES. This could be on the order of three times greater in the low atmosphere, plus, some major improvements at discrete levels in the mid- to upper- troposphere.

REFERENCES

Chevallier, F, S. Di Michele and A. P. McNally, 2006: Diverse profile datasets from the ECMWF 91-level short-range forecasts, *NWP SAF Document No. NWPSAF–EC–TR–010*

Rama Varma Raja, M.K., S.I. Gutman, J.G. Yoe, L.M. McMillin, and J. Zhao, 2008: The validation of AIRS retrievals of integrated precipitable water vapor using measurements from a network of ground based GPS receivers over the contiguous United States. *J. Atmos. Ocean. Technol.*, **Vol. 25**, No. 3, pp. 432–444