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DETECTION AND CHARACTERIZATION OF SYSTEMATIC ERRORS IN ATMOSPHERIC MODELS

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1. INTRODUCTION

Numerical weather forecast models typically use three- or four-dimensional variational techniques (3-D or 4-DVAR) for data assimilation and model initialization. These and other traditional assimilation methods rely on error description to appropriately weight the observation in the analysis. Analyses provide an objective means to view the atmospheric state and initialize numerical forecast models. Such models are commonly used in operational meteorology for weather forecast guidance, as a definitive historical record of past meteorology, and a means to test new atmospheric models under "controlled conditions." Analyses are also used for climate research to study long-term trends and augment the climate record (Li et al. 2008; Seo et al. 2005).

Data assimilation methods typically assume that the distribution of observation and model errors are Gaussian and unbiased. This may not be true for all parameters under all circumstances, but until recently our ability to independently verify this assumption has been very limited. This is especially true of water vapor in the free atmosphere, which varies greatly in time and space. Since water vapor is central to almost all significant weather events and plays a critical role in climate processes, improved understanding of this parameter is critical for improving weather forecast accuracy and predicting changes in the Earth's climate. As a consequence, both weather forecasting and climatology are disciplines that stand to benefit greatly by identifying and correcting systematic moisture errors in observations, analyses, and models. For example, better understanding of the hydrologic cycle in General Circulation Models (GCMs), and the role water vapor plays in satellite cloud observations is increasingly relevant in climate work (Roebeling et al. 2009). Recent research at NOAA's Earth System Research Laboratory's (ESRL)'s Global Systems Division detects clear evidence of systematic errors in the analysis and prediction of atmospheric column total precipitable water (TPW) vapor in operational Numerical Weather Prediction (NWP) models over the continental U.S. Systematic errors in Geostationary Operational Environmental Satellite (GOES) water vapor products that may be related to these model errors have also been detected. This paper describes how these errors were discovered and how they appear to propagate with time.

2. LAPS AND THE ASSIMILATION OF SATELLITE DATA

During the 1980s, NOAA's Forecast Systems Laboratory (FSL); now the Global Systems Division (GSD) within ESRL conducted forecast exercises to test its workstation prototypes. Forecasters were burdened with the nearly impossible task of reviewing all national, regional and local, real-time, nonstop incoming data, made possible through new technologies, while forecast production schedules remained unchanged. Forecasters simply received too much data to be able to monitor all the conventional, new data, and meet their forecast obligations. In spite of advanced display technologies, this ever increasing data stream, often likened to a "firehose of data," remains true to this day although the situation has improved

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somewhat by better tools, one of which is the Local Analysis and Prediction System (LAPS).

Objective analysis of local data in conjunction with nationally disseminated data still presents a daunting problem. Conceived as a resolution to this challenge, LAPS was designed for the purposes of analyzing all local data in real time on an affordable computer workstation and using its own output fields to initialize local-scale forecast models as well as render visualizations to the forecaster that capture all available data, with each data source weighted relative to its respective error. To date, LAPS has been interfaced with several numerical models including the Regional Atmospheric Modeling system (RAMS) model, version 5 of the Pennsylvania State/National Center for Atmospheric Research Mesoscale Model, MM5, and most recently the Weather Research Forecasting (WRF) model using both Advanced Research WRF (ARW) and Nonhydrostatic Mesoscale Model (NMM) cores. A more detailed review of LAPS and its historical roots is available in McGinley et al. (1991). LAPS integrates all state-of-the-art data as they become routinely available to a field forecast office. Advanced data include Doppler reflectivity and velocity fields, satellite data including GOES infrared (IR) image data in Advanced Weather Interactive Processing System (AWIPS) format, and product data from National Environmental Satellite, Data, and Information Service (NESDIS), wind profiler data, dual-channel ground-based radiometer data, and automated aircraft reports. More recently ground-based Global Positioning System (GPS) derived zenith TPW is now incorporated into the LAPS moisture analysis.

A key feature of adapting LAPS to local data assimilation has been radar and satellite data. In the area of satellite data assimilation a number of approaches have been attempted for GOES moisture data. We have a variational interface that can assimilate raw sounder radiances, raw imager radiances, radiances approximated from eight-bit display image data, typically available on AWIPS, and most recently three-layer derived product water vapor assimilation.

After testing different approaches over several years, the derived product data was finally adopted as the primary satellite moisture product that we use. But there are even some adaptations that occurred in applying these data.

In the mid-1990s, the moisture module in the LAPS system became more based on one-dimensional variational minimization (1-DVAR) operating at each individual gridpoint to combine the diverse data sources that were added to the assimilation in the late 1990s and early 2000s. At about this same time, GOES-8 data products became available and it was assumed that these products would have minimal bias error due to the better onboard black-body calibration techniques available with the new satellite series. The variational system at that time dropped horizontal shape matching assimilation (Birkenheuer 1992) in lieu of directly using derived product TPW values in concert with other new moisture data sources such as GPS-derived (TPW), GOES direct radiance data through the use of a newer forward radiance model (now referred to as the community radiative transfer model, CRTM), and the inclusion of cloud information in the solution (Birkenheuer 1999).

Initially, the three-layer product was used directly for some time. We applied this as an absolute measure of water vapor for the three defined sigma levels in (each layer an integrated computation from the derived sounding profile). The computations of layer and total water from GOES were obtained from NESDIS and their operational suite of product data.

During this time we began assimilating TPW retrieved from GPS signal delays as another independent water vapor measurement in LAPS. The main point here is that GPS is also a satellite-based observing system but it is completely independent of GOES and other traditional meteorological satellite moisture measures that use the microwave or infrared bands.

3. GPS TPW MEASUREMENT AND ACCURACY

A summary of the techniques used by ESRL for about one decade to estimate TPW from GPS signal delays is available in Wolfe and Gutman (2000), and the rapid (near real-time) assimilation of these data into operational numerical weather prediction (NWP) models running at the National Centers for Environmental Prediction (NCEP) is described in

Smith et al. (2007). Provided funding, the system is planned to be transferred to the National Weather Service (NWS) for operational management in 2012.

The estimation of the excess path length or signal delay introduced by the refractivity of the neutral (non-dispersive) lower atmosphere is tantamount to discerning the change in the speed of light through the atmosphere due to the presence of water vapor (Wolf and Gutman 2000). The determination of water vapor-induced "signal delay" is used to derive a value for the zenith "equivalent" integrated water. Unlike satellite sounder retrievals, the distribution or vertical profile of water vapor cannot be directly measured using GPS techniques alone; only the sum total can be computed. However there is a good match in the asynoptic measuring abilities of GPS, GOES, and other conventional and experimental water vapor observing systems as described in Revercomb et al. (2003) and other more recent publications.

Even though the satellite observations using radiometric techniques and GPS use different techniques to compute TPW, one would expect that the end result of comparing these independent TPW estimates should be approximately the same and the differences should be more or less random. The GPS measurement requires no external calibration and ultimately depends on the accuracy of the atomic clocks in space and on the ground. Systematic errors in GPS measurements of position and time are thought to come from mismodeling the elements of the GPS error budget as defined in (1).

$$P = R + c(\Delta T - \Delta\tau) + \Delta ion + \Delta trop + \Delta multi + \varepsilon \quad (1)$$

where:
P = measured pseudorange
R = the geometric range to the satellite
c = the speed of light
ΔT and $\Delta\tau$ = errors in the receiver and satellite clocks
Δion and $\Delta\ trop$ = ionospheric and tropospheric signal delays
$\Delta multi$ = errors introduced by multipath
ε = receiver noise.

Given that our ability to estimate the pseudorange (i.e. the product of the speed of light in a vacuum and the difference between the arrival time of the radio signal the time the signal was transmitted) is constantly improving,[1] it is reasonable to assume that our estimates of the tropospheric signal delays and water vapor retrieved from these delays will continue to improve over time.

While other water vapor sensing systems (e.g. radiometers, LIDARs, and in situ systems including chilled mirrors and tunable diode laser spectrometers) are known to be more precise than GPS, all except GPS require external calibration. What GPS lacks is the ability to reveal the vertical distribution of moisture. As a consequence, one can easily envision a composite global observing system (at least for water vapor) that uses GPS for temporally invariant calibration of brightness temperature or estimates of TPW derived from IR satellite radiance, and other satellite, ground-based or in situ observing systems. These systems could provide precise estimates of PW at different vertical levels in the atmosphere.

One example of the utility of this independent measure is the recently exploited ability to identify and ferret out bad batches of rawinsonde observations (RAOBs). We see this illustrated in Fig 1; the good tracking between RAOB integrated water collocated with GPS TPW data, and the identification of a "bad batch" of RAOBs that was then pulled from operational use after noting the discrepancies with RAOB data.

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[1] The reason for this is that as the accuracy of the atomic clocks improves (i.e. ΔT and ΔT become smaller), our ability to measure lengths based on the relationship between frequency and wavelength improve. As more satellites are launched, and the number of receivers on Earth increase, the estimates of the geometric range to each satellite (the satellite orbits) improve. Increasing the number of frequencies of the signals transmitted by the satellites improves estimating the ionospheric signal delay, which is frequency dependent. Even if there are no significant reductions in multipath errors or receiver noise, the precision of the tropospheric signal delay estimate is now approximately 5 mm which is equivalent to less than 1 mm of precipitable water vapor in the total atmospheric column.

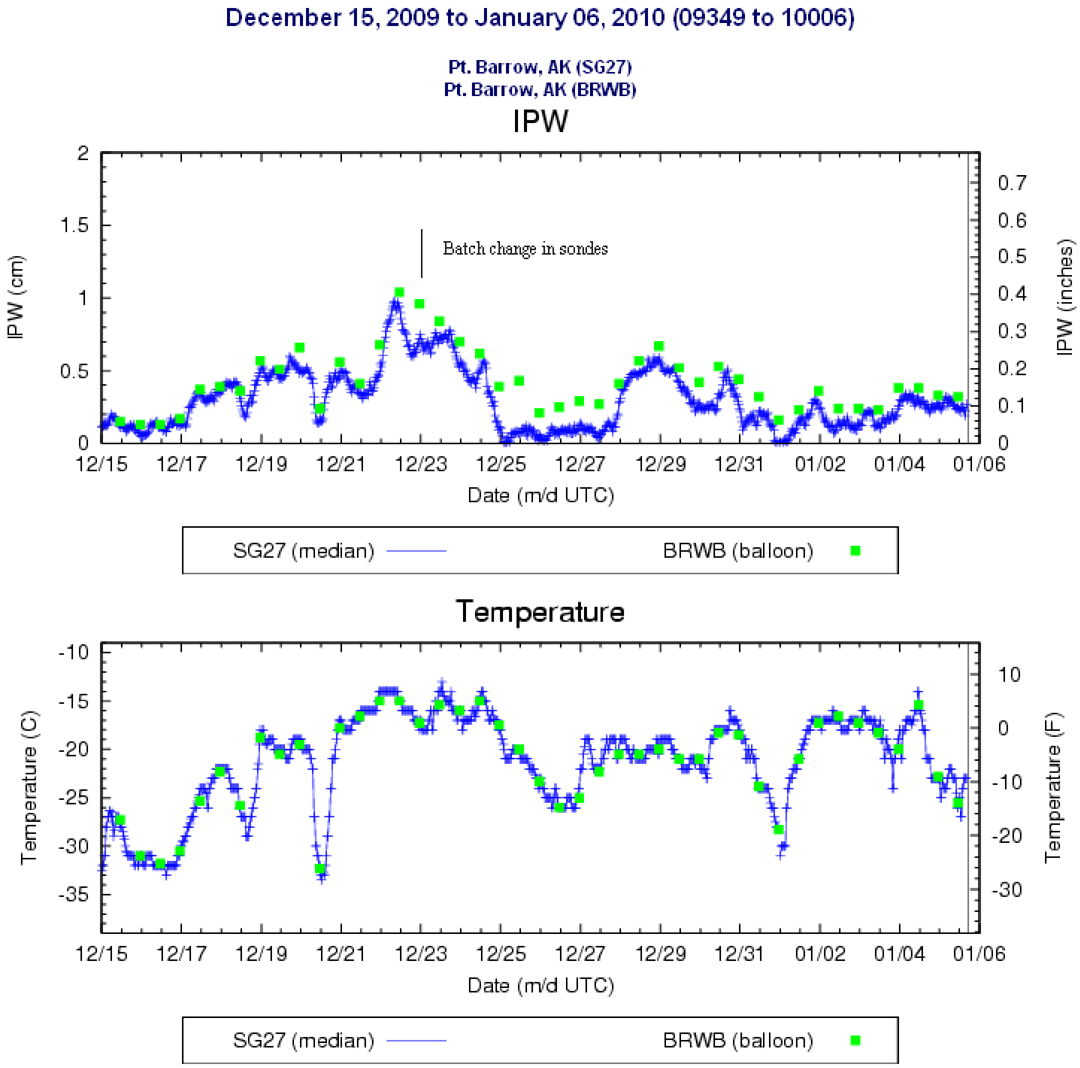

Fig 1. Compares GPS median measurements (blue) with green RAOB launch data for Pt. Barrow AK. Top figure shows integrated precipitable water (IPW), [virtually the same as TPW] from RAOB and GPS, the lower plot shows the comparison with surface temperature. Around 12/23 (denoted on the figure), a new batch of rawindsondes is put into service. Immediately a discrepancy is seen between GPS and RAOB data. The batch was subsequently removed from use on 1/04 and the integrated precipitable water (IPW); again matches between RAOBs and GPS IPW/TPW measures.

4. GPS AND GOES MOISTURE ASSIMILATION, RECONCILIATION, AND SOLUTION

With GPS data available, we began examining the two independent TPW data sets (GPS and GOES) and made some observations that were difficult to explain given the information about the assumed accuracy of GOES observations that are available in peer-reviewed literature.

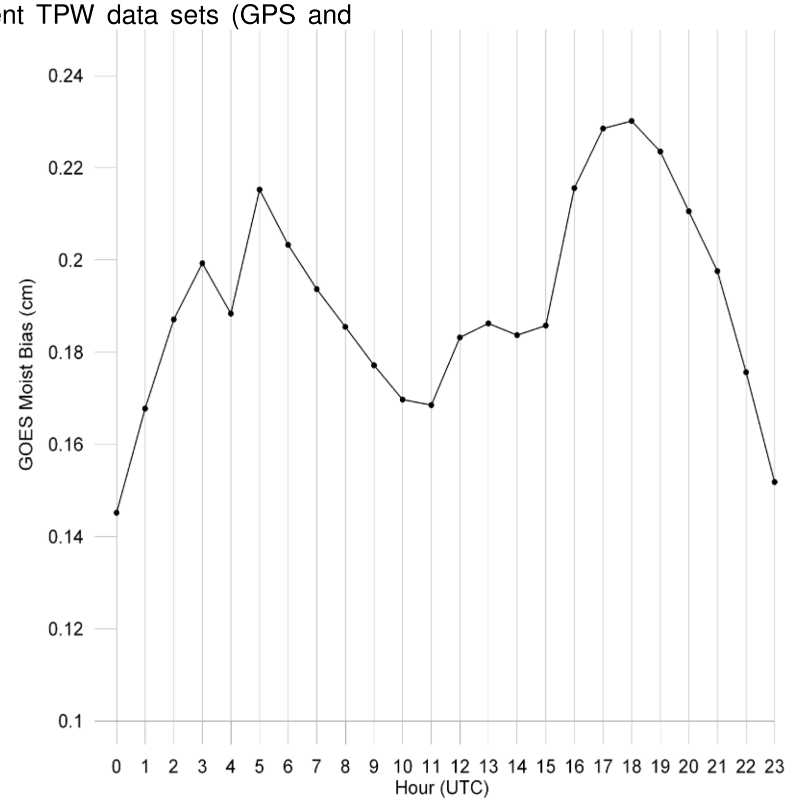

Fig. 2 The hourly bias plot of GOES [defined here using GPS TPW as "truth"] was our first clue that operational GOES vapor product data was not representative of a-synoptic water vapor. The reason for this is presumed to be due to model dependence on RAOB data for updates in water vapor truth, or perhaps because the GOES product was "tuned" to RAOB data (limited to synoptic times). This analysis reveals that, aside from the overall moist bias in GOES, the GOES product data bias degrades between synoptic times.

At this stage two paths could be pursued to deal with the discovered moist bias; we chose to go in both directions. The first path to establishing better accuracy was a bit more elegant, and that was to variationally minimize a solution that best matched horizontal gradients from the satellite field in the variational scheme while simultaneously maintaining agreement with absolute measures of water vapor (RAOB/GPS/saturated cloudiness),. This had the advantage of capturing the spatial detail in the satellite imagery while ignoring bias (since the derivative of constant bias is zero). This approach has worked well for routine satellite water vapor assimilation and is the current methodology used in our operational system. (Birkenheuer et al. 2006).

The second approach was to attempt a correction of the product data and led to the foundation for this paper. A simple scaling and exponential fit of the data to collocated GPS data points was used as a correction function (Birkenheuer et al. 2008).

$$G_c = aG^b \qquad (2)$$

where G_c are the corrected GOES moisture values, G are the initial product values as received from NESDIS, a is a scaling term and b is a power term, both dimensionless. The b term removes curvature from the paired measurements, while the scaling term helps to move the linear agreement to the 1:1 line. The selection of this fitting equation was made such that no absolute bias offset was defined.

The method of solution for (1) was variational analysis. This was chosen because it has an advantage over traditional linear least squares determination of coefficients *a* and *b*.

The variational method minimizes the following simple functional:

$$J = \sum_{i=1}^{N} (G_{ci} - GPS_i)^2 \qquad (3)$$

where J is minimized via iteration using the Powell (1962) method by modifying coefficients *a* and *b* from (1) and summed over all of the data (N points) consisting of paired (i) GOES and GPS data. The “best fit” (and lowest J value) therefore forced all of the corrected GOES measurements to be as close as possible in magnitude to GPS. The variational method puts direct linear weight on the water amount differences. Thus, small differences (less than one, even if they described large amounts of water) likely carry almost insignificant weight in determining the result, while ever increasing values of moisture discrepancies would proportionally more strongly influence the correction terms.

Thus, we created correction data for use by NESDIS and any product user who would want to apply the data with an hourly bias correction. The correction algorithm was able to maintain the intercept at zero and correct both linear and minor nonlinear bias. The following figures show the dramatic reduction in hourly bias, both in terms of hourly plots and overall scatter with respect to paired GPS data.

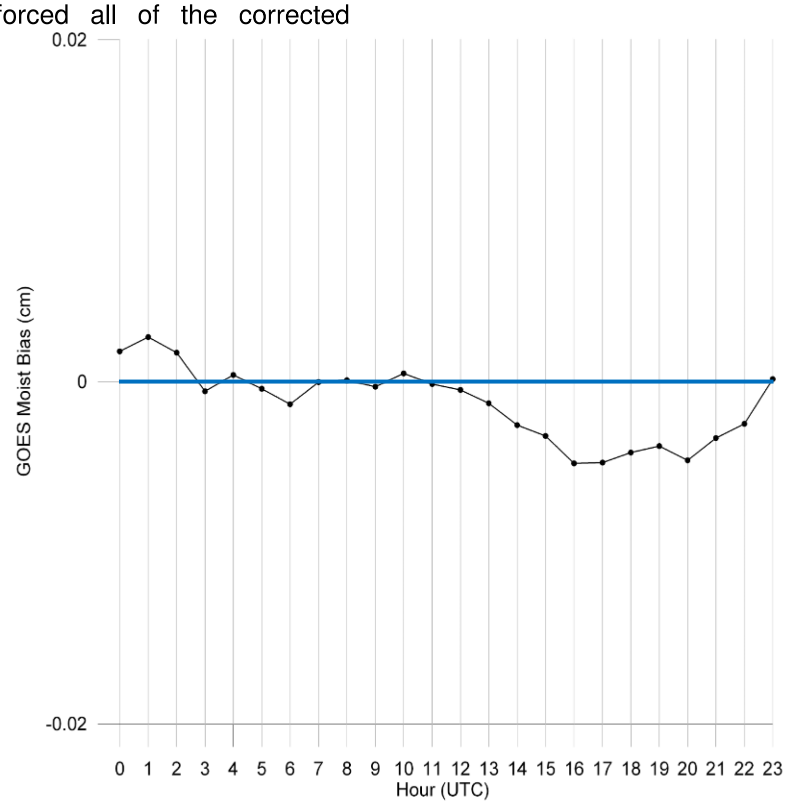

Fig. 3 After correction the bias was very close to the zero line.

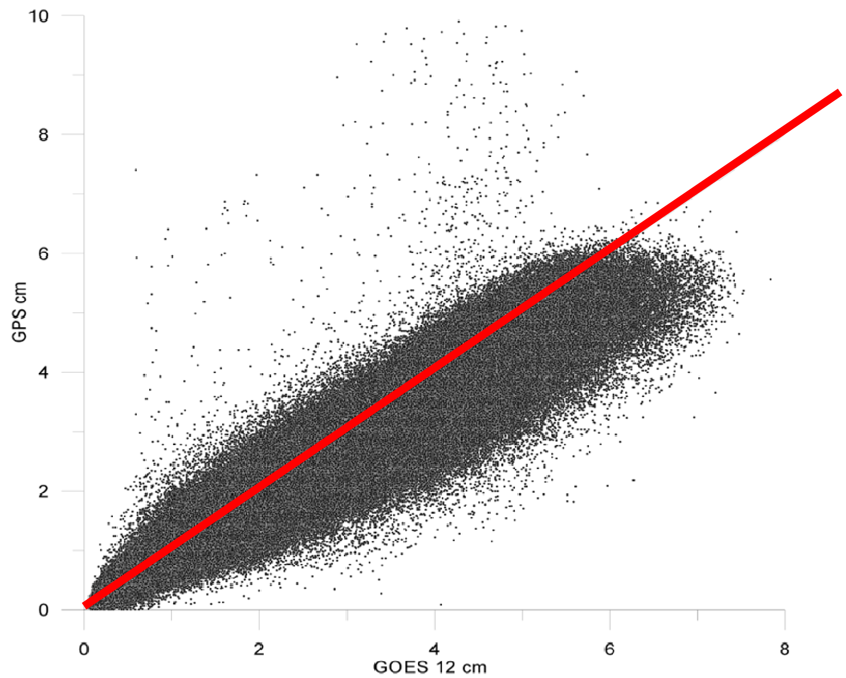

Fig. 4 The initial scatter plot of ~1.8M paired GPS and uncorrected GOES 12-derived TPW data. No quality control was applied, the few outliers seen above the main cluster represent an insignificant number of points overall.

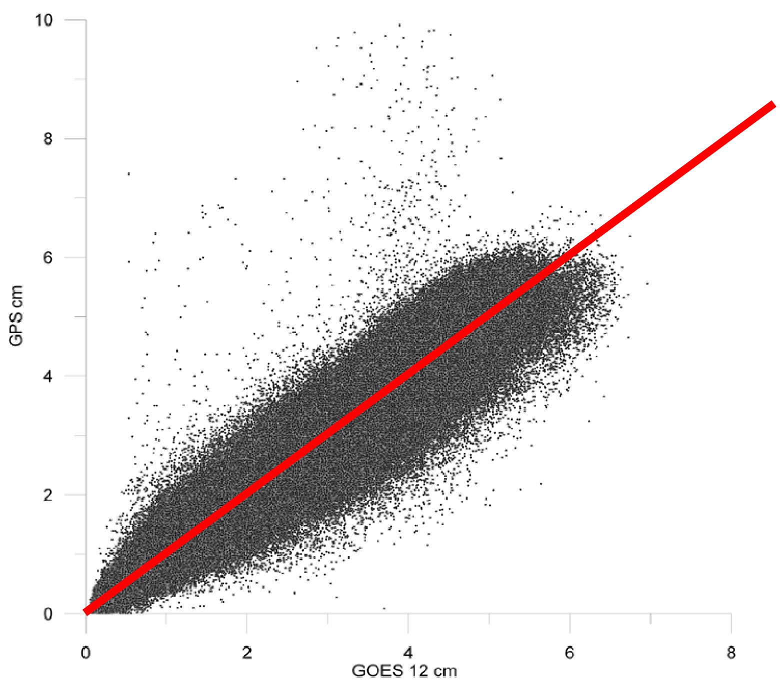

Fig. 5 The same scatter plot after applying the hourly correction coefficient to all data. A successful shift of the GOES data to drier values was achieved along with an unforeseen narrowing of the scatter (not shown) at the moist end. The result was also seen to reduce RMS. This was likely due to the correction of the tendency to increase moist bias at high moist values, in effect "straightening" the observed curvature in bias at these levels.

The second approach also led to another unforeseen observation. About two years ago, the correction coefficients were plotted by hour. Initially they had only been viewed in tabulated form and once plotted it was evident that a pattern emerged (Birkenheuer et al. 2008). A diurnal signal was detected as there appeared to be a random feature to the data during dark hours but during daylight the coefficients changed in a regular manner. More important, a second observation was made between the GOES-East and -West coefficients. Though the coefficients were not as high in value for the western satellite, the same temporal response was observed and it was offset in phase. The phase shift roughly corresponded to the difference in "time zone" between the spacecraft subpoints and thereby the time difference in when the daylight periods began and ended for the fields of view of each spacecraft. We obviously had some kind of daylight response to the water vapor retrieval that we could not explain.

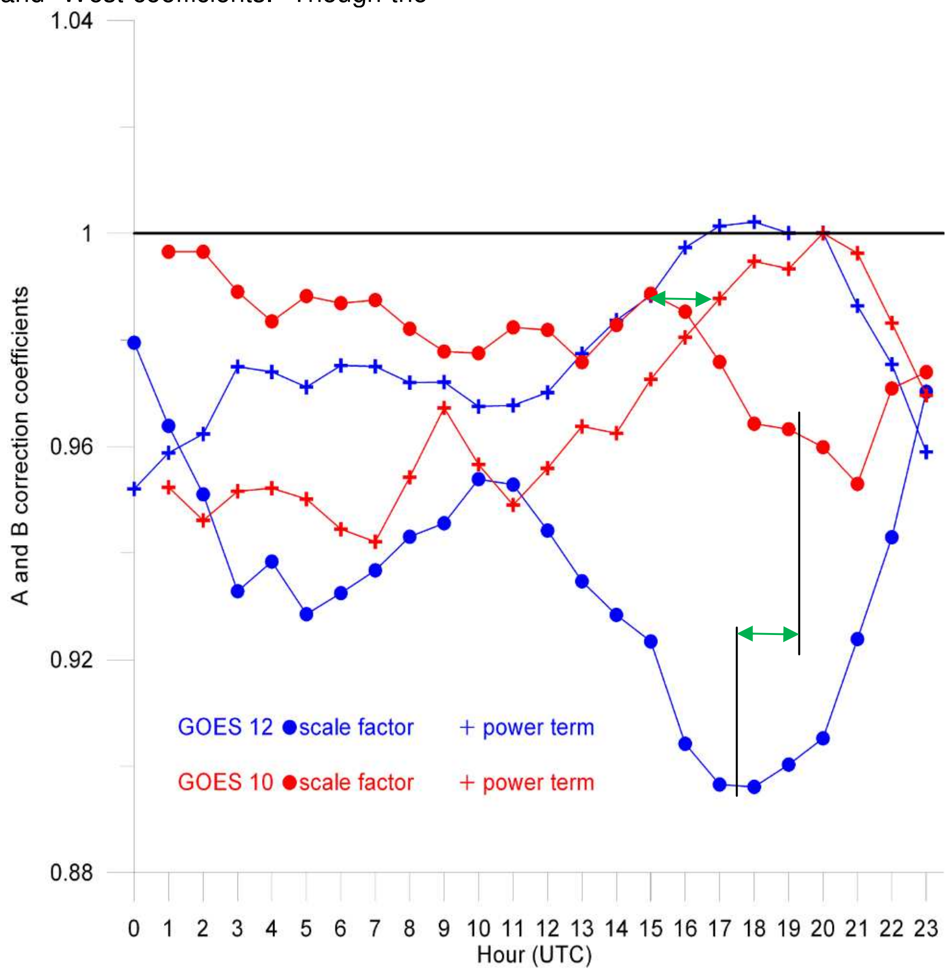

Fig. 6 Systematic errors were revealed through the examination of plotted correction coefficients. Here we see a clear daytime effect in both GOES-East and -West data. We also see that the "onset" of this response appears offset or phase delayed and that it roughly corresponds to the time zone difference between the two satellites (green arrows, for both scaling and power terms). The fact that this is shorter than the actual time zone difference might be explained by observation location. GOES West satellite data are paired with GPS data to the east of that satellite's subpoint (135 degrees west), while GOES East was viewing pairs primarily west of its subpoint at 75 degrees west.

These observations led to speculation regarding the cause of the daytime effect. One idea was that the sunlight had an effect on the retrieval algorithm and this might be modifying measured radiance. After discussing these data with the satellite team at the Cooperative Institute for

Meteorological Satellite Studies at the University of Wisconsin-Madison Space Science and Engineering Center (CIMSS), they designed a new algorithm that is now under test with improved surface emissivity. This new algorithm reduces the moist bias compared to the operational algorithm studied above. Though better than the current (operational NESDIS) algorithm, when compared to GPS data, it did not appear to address all of the problems.

Another possible explanation for some of these effects could relate to the choice of the forecast model background. In this case, Global Forecast System (GFS) forecasts are used as an *a priori* first guess in the undetermined satellite retrieval processing. This "first guess" is minimally perturbed so as to create a slightly modified thermal and moisture profile that when used in a forward radiance model, generates synthetic satellite radiances that better match observed radiance. Higher-quality, "first-guess" profiles used in this processing will result in less chance for incurring solution error. Thus, the chapter was opened on examining model agreement with GPS data and the main theme of this paper.

5. GFS POSSESS A "CHRONIC" MOIST BIAS

Our observations did not solve the satellite water vapor problems that we had encountered, but they revealed that GFS model forecasts are too moist and this fact might be relevant for climate interests, if not for the sake of modeling in general. It is prudent to understand why something is going on in a model that may otherwise be taken for granted, not understood, or even perceived. In our working with the GFS model, the background model used for satellite retrieval processing first guesses, we discovered that the overall moisture trends against GPS were: a) too moist, and b) increasing with time; at an unrealistic pace. The fact that the model contains more moisture than observed with a system like GPS, leads us to believe that this could contribute to moist biased retrievals. We show here that GPS-met water vapor assimilation can improve the description of vapor in some models. The GFS, that lacks GPS assimilation, is shown to be consistently moist biased.

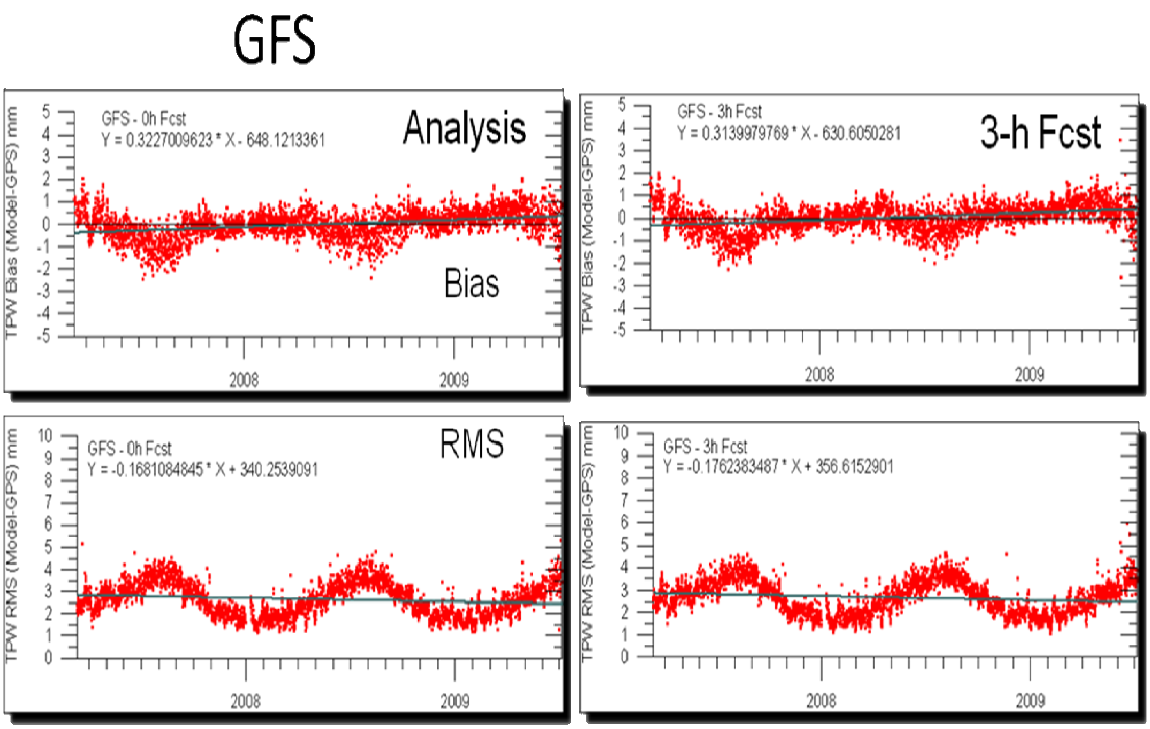

Fig. 7 The GFS 00-hr and 03-hr forecast trends over an approximate two-year period show a steady, discernable increase in moist bias compared to GPS. Of the three models studied here, we see the

greatest changes over time. The RMS error for both the forecast and the initial times show a cyclical characteristic with better agreement in the dry months (expected) and the highest uncertainty during the convective seasons.

We also examined the NAM and the RUC models. Neither of these models demonstrated the increasing trend in moisture we see in the GFS.

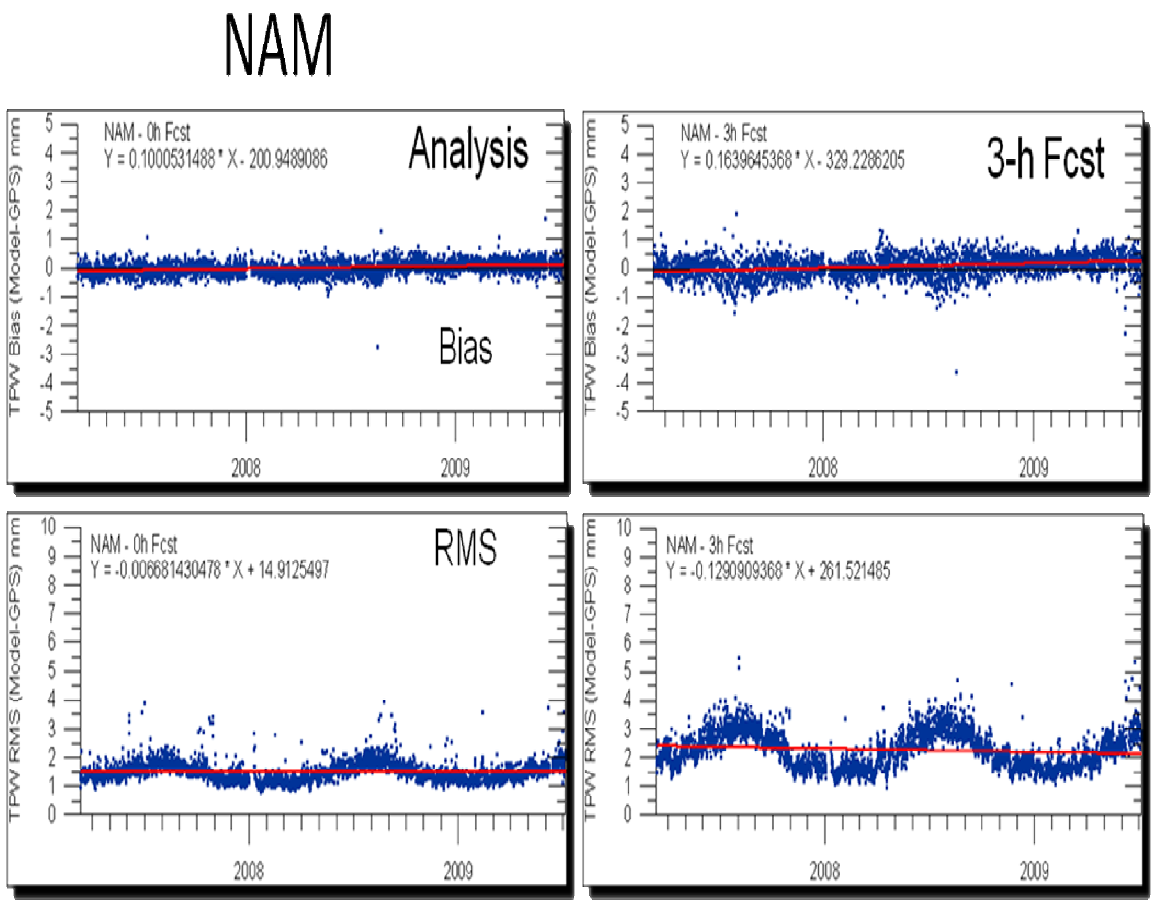

Fig. 8 In the above NAM analysis and forecast covering the same period as the GFS figures, we see the bias is very near zero with zero change for both the 00-h and 03-h forecasts. The GPS-compared RMS figure is near 2.5mm. Data appear to remain constant over the course of the two+ years shown. This is the operational NAM model and it does include GPS in the assimilation scheme. Unlike the GFS, the cyclical RMS is stronger in the 3-h forecast over the analysis time. This would suggest that we are analyzing well at convective times, but moisture is not as well tracked by the forecast. In fact, the magnitude of this uncertainty at 3h is very close to the GFS.

Finally, we examined the RUC model.

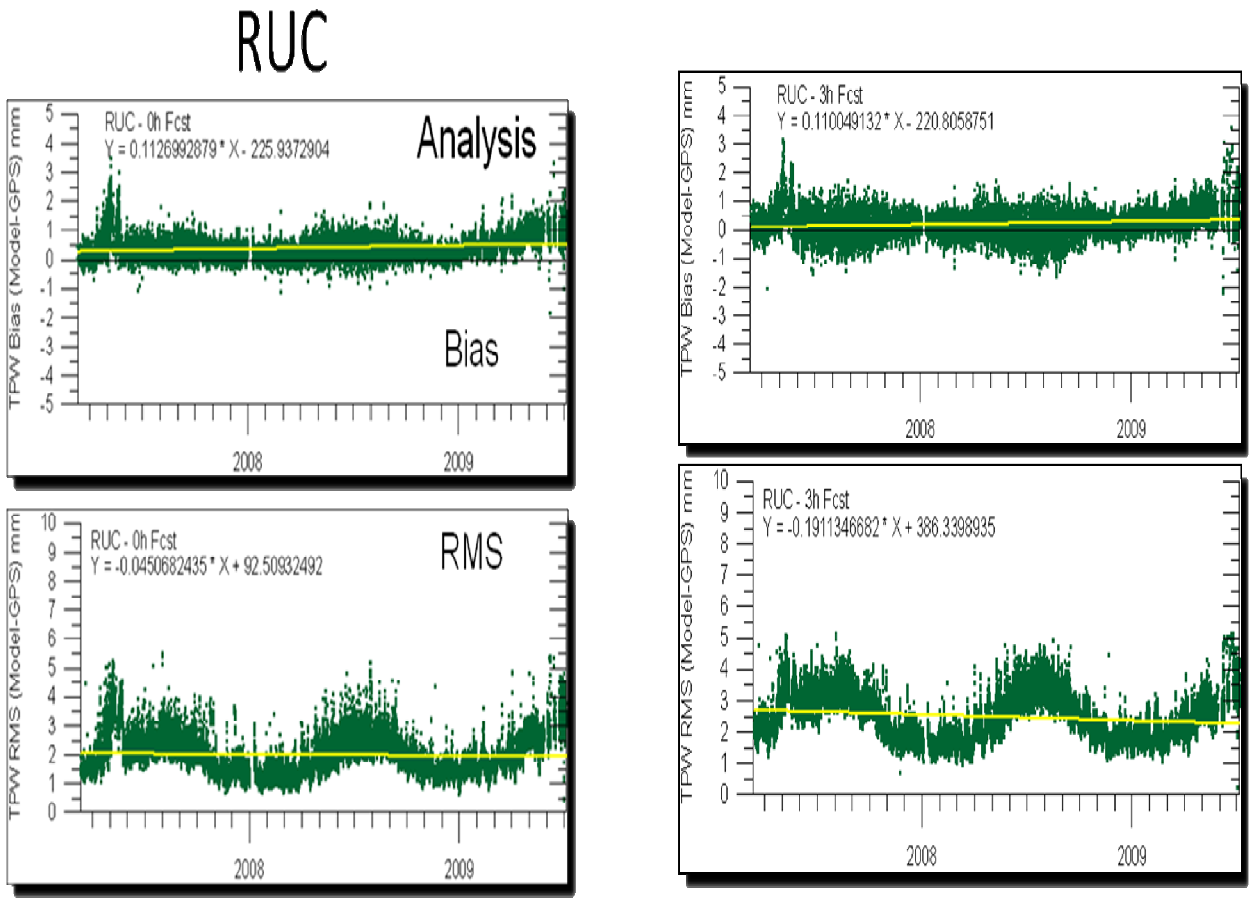

Fig. 9 The RUC result is similar to the NAM but with slightly more moist bias showing at time 00. Also a slightly increasing bias in the 3-hr forecast accumulating over the past couple of years. Like the NAM, this system is assimilating GPS data. We feel that the increasing bias in time is due to a concurrent assimilation of radar data which started after GPS assimilation. We have not yet determined if the radar assimilation is deemed to be in its most optimal form as of yet, since it is still under development.

6. THE IMPLICATIONS FOR CLIMATE STUDIES

For the purposes of climate record and GCM experiments, moisture budget will play an ever increasing role of importance since this greenhouse gas is so complex in its behavioral relationship to thermal changes. Thermal-driven phase changes not only simply add or subtract the vapor load in the atmosphere, but contribute to clouds, ice, and liquid water on the surface which interact with incoming and outgoing radiation at long and short wavelengths. This is generally understood to be the complicating nature of water vapor, moving it to the top of the list of several significant climate-impacting substances. The ability to at least get the vapor "right" in a model is one good first step to getting the other relevant water-related characteristics in the model correct. Along with this, a poor description of moisture may bring questionable impact to any analysis of record or climate predictions.

Moist bias in the satellite retrieval first guess will make for a more difficult solution given an underdetermined problem. Generally the algorithms used for deriving thermal and moisture profiles start with a model forecast as a first guess and minimally perturb these profiles to achieve a match between modeled and observed satellite radiance. On the current

GOES spacecraft there are about three IR channels that contribute to moisture information with weighting functions at low (sfc-700hPa), middle (700-500 hPa), and high (above 500 hPa) atmospheric levels. Therefore, it is critical that the first guess contain the profile detail in these layers, or the resulting profile may be unrepresentative. Given the GOES R Advanced Baseline Imager (ABI) will be underdetermined for sounding retrieval work in the same way as the current GOES where model error in thermal and moisture character will be critical. Why is this important for climate research? Geostationary satellite soundings may wind up in climate records focused on local climate; certainly spaceborne radiometry currently has direct bearing on climate records (Chen et al. 2007; Town et al. 2007), including geostationary (GOES R) Goldberg (2009), (Wang et al. 2009). This is certainly the case for polar data but potentially for GOES as well. Thus, if this does happen and the GFS model is in some way responsible for a bias, it needs to be reconciled; at least that is our philosophy.

Recommendations of this work are to globally expand the temporal nature and density of a surface-based GPS network. This will serve several purposes. It will augment the QC of radiosonde networks, contribute to better satellite analyses of moisture (when assimilated in models), and will improve forecasts serving both forecast meteorology and climate. At this time ESRL is striving to move a sustained GPS meteorology program (GPS-met) into the NWS for operational use. In addition, we are working on an international level to expand the global ground- and water-based network. To this end we have collaborated with efforts in Africa, Japan, Korea, Europe, and we look to include perhaps Mexico in the near future. We are not only exploring expansion of ground-based systems, but looking to expand capability over large bodies of water. For example, we are establishing the first “permanent” sites on off-shore oil platforms in the Gulf of Mexico with the cooperation of oil companies in 2010. It is also conceivable that platforms can be located on ocean freighters, research, and naval vessels.

7. SUMMARY AND CONCLUSIONS

We have demonstrated that the model first guess can be improved with knowledge gleaned from GPS water vapor data and this can improve both the retrievals and the analysis of water substance. Retrievals will benefit by way of a better *a priori* model first guess. Analysis will improve simply by acquiring more accurate water information.

Relevance for climate is directly related to improved water representation in models and analyses. At least one global model (GFS) has been shown here to contain an unrealistic bias that is increasing with time. Such drift if left unchecked will only obscure the truth that can be derived from GCM climate model simulations.

Assimilation of GPS-met data into current CONUS and smaller scale models is shown here to have positive impact on reducing if not eliminating water bias (NAM). We urge the modeling community to seek ways to incorporate GPS-met data into other models that have relevance to climate research.

Satellite data play a key role in long-term global climate monitoring and analysis of trends. It is therefore important to understand the weaknesses observed in utilizing these data in other meteorological applications (even local-scale modeling of something like convective initiation) since they may have direct relevance to climate science in the future.

To apply the concept of “Analysis of Record” to remotely sensed observations (i.e., satellite data) for quality climate work, will require the ability to verify the accuracy of the observations that were analyzed to independently validate the accuracy of the analysis. Another approach is to direct more focus on assimilating satellite gradients in an analysis to ignore bias.

GPS (along with other independent measures) provide an excellent measure as an independent data source to quantify the hourly and annual bias and RMS of remotely sensed data that drive climate records, including the quality control of conventional data such as radiosonde. We have demonstrated that satellite data can be used more effectively by utilizing GPS-met data in routine operations in addition to improving our meteorological models and analyses.

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