2.4 ASSESSING THE USEFULNESS OF AIRS RADIANCE OBSERVATIONS IN A 4D-VAR ASSIMILATION SCHEME USING A LIMITED AREA MESOSCALE MODEL AND A FAST RADIATIVE TRANSFER ALGORITHM

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1. INTRODUCTION

Difficulties in quantitative precipitation forecasting (QPF) are well known in the meteorological community. QPF accuracy is dependent on many factors including the reliability of microphysics schemes to reasonably parameterize precipitation formation; model resolution; seasonal factors; and initial condition uncertainty (ICU). The project discussed in this paper ultimately aims at improving the prediction of QPF by reducing the impact of ICU for short-term regional forecasts by assimilating radiance data obtained from the Atmospheric Infrared Sounder (AIRS) using the variational method, or four dimensional variational data assimilation (4D-Var).

There have been various projects that have aimed at reducing the impact of ICU in QPF by utilizing various techniques. Xu et al. (2001) attempted to do this by using a short-range ensemble forecasting technique, where the ensemble members were constructed using an adjoint model. More ambitious projects include Kuo et al. (1993) where a Newtonian nudging technique was used to develop a method of assimilating remote sensing data of precipitable water fields to improve model initialization. Kuo, et. al (1996) also sought to improve precipitation forecasts by assimilating precipitable water data obtained from a GPS satellite using a variational method.

Variational data assimilation, as introduced by Le Dimet and Talagrand (1986) has many advantages over other data assimilation techniques. The two most striking features is the method's ability to assimilate indirect observations into a numerical model (such as satellite radiance data), and the ability of the model to continuously assimilate observational data when generating an optimal initial condition. Using this method to assimilate indirect observations to improve short-term QPF should help to reduce the impact of ICU and provide the model with an optimal initial analysis.

On 4 May, 2002, NASA launched the Aqua satellite into sun-synchronous orbit 705.3 km above the earth's surface. Several state of the art visible, infrared, and microwave sensors were flown on Aqua, including the Atmospheric Infrared Sounder (AIRS) (Aumann, et al. 2003). AIRS was built with the goal to provide atmospheric temperature soundings retrieved from the instrument's radiance data with an accuracy of 1 K within 1 km layers. The instrument senses 2378 spectral channels simultaneously over a spectral range from 3.7 to 15.4 μm, collecting global observational data twice daily with a spatial resolution of 13.5 km. It is believed that assimilating this data, via the variational method into a mesoscale model, will help improve short-term QPF.

Prior to any 4DVAR assimilation utilizing AIRS data, several tasks need to be performed. First, a radiative transfer model must be selected that has

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the capability of simulating radiance values for a given domain for each of the AIRS spectral channels; second, the adjoint of this model must be developed and tested; third, any bias and/or outliers between the calculated and observed radiance fields must be identified; and lastly, an adjoint sensitivity study must be performed in order to ascertain which spectral channels will be most useful when attempting to improve the model QPF.

In the following sections an assessment of the potential usefulness of AIRS data in attempting to improve QPF will be discussed. In section 2, the AIRS radiative transfer algorithm (AIRS-RTA) will be introduced along with an overview of the observational data and the initial test case used for this assessment. Section 3 will outline the results from a comparison of RTA-calculated radiances with AIRS observations, including identification of any bias and/or outliers and their possible sources. Section 4 will include a brief discussion on the development of the AIRS-RTA adjoint model, along with an overview of the adjoint sensitivity analysis and its preliminary findings. These topics will be followed by a summary and a discussion on the project's future work.

2. AIRS-RTA AND AIRS RADIANCE OBSERVATIONS

2.1 *AIRS Radiative Transfer Algorithm*

In order to assimilate any indirect observations, such as radiance data, an observation operator is required that is capable of mapping model-produced parameters to the observation space and in the same form as the observations.

The observation operator selected for this work is the Stand-alone AIRS Radiative Transfer Algorithm (SARTA). SARTA was specifically designed for use with AIRS data and as such is capable of simulating radiance values for a specified domain at all 2378 AIRS spectral channels. SARTA is computationally fast, having been designed to generate radiance values as a convolution of the AIRS spectral response functions (SRF) with monochromatic radiances, where the monochromatic radiances are calculated using parameterized transmittances and reflected downwelling radiation (Strow and Hannon, 2002). The radiative transfer algorithm used by SARTA takes the following form:

$$R_i^{AIRS} = \int R_v SRF_i(v)\,dv\,, \qquad (1)$$

where R_v is the monochromatic radiance leaving the top of a non-scattering atmosphere, and $SRF_i(v)$ is the AIRS spectral response function (SRF) for channel *i*. The SRF for each channel is known, therefore, the monochromatic radiance is the term that needs to be calculated. SARTA uses the following formula to calculate this radiance term:

$$R^i = \varepsilon_v B_v(T_s)\Im_s^{eff} + \sum_{l=1}^{l_s} B_v(T_l)\left(\Im_{l-1}^{eff} - \Im_l^{eff}\right) \qquad (2)$$
$$+ R_{i,refl.th.}^{eff} + H^v(\theta_{sun})\rho_{solar}\Im_s^{eff}\,.$$

SARTA incorporates four source terms in its radiative transfer equation: (1) surface emission, (2) atmospheric emission, (3) downwelling atmospheric emission reflected by surface, and (4) reflected solar radiation) in its radiative transfer equation; and is evaluated using input data interpolated to 100 atmospheric layers (Strow and Hannon, 2002).

2.2 *AIRS Observations and Initial Test Case*

The radiance data collected by the AIRS instrument provides information on different atmospheric parameters and surface characteristics. For example, within the spectral range of 650.33 cm^{-1} to 755.33 cm^{-1}, there exist many CO_2 sensing channels from which atmospheric temperature can be derived. Most of the surface characteristics (surface skin temperature, etc.) are derived from the spectral range of 2394.03 cm^{-1} to 2664.14 cm^{-1} . The majority of the atmospheric water vapor channels lie in the 1310.18 cm^{-1} to 1605.05 cm^{-1} spectral range (Pagano[2] et al., 2002)

In order to assess the usefulness of AIRS radiance data in a 4D-VAR assimilation scheme, it was necessary to select a simple test case for which simulated radiances can be compared to observational radiances obtained from AIRS. The case selected for this project involves a strong, mid-level moisture gradient in association with a cold front over the southeastern United States on 11 July, 2003.

This case was selected due to its simplicity; there is no measurable precipitation associated with the system at the verification time selected (1800 UTC). In addition to this, the existence of the mid-level moisture gradient provides an excellent measure as to how well the observations do in detecting the atmospheric water vapor, and also how accurately the mesoscale model and the radiative transfer model (RTM) perform in handling the atmospheric moisture.

Figure 1 displays actual AIRS brightness temperature (BT) data for the southeastern region at 1800 UTC (spectral channel 1740 at 1513.83 cm^{-1}). The AIRS observations show a distinct gradient in the BT field across this region (possibly the result of a mid-level moisture gradient).

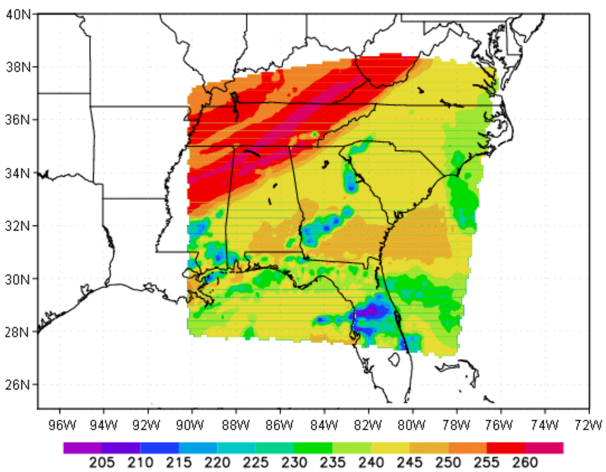

Figure 1--Simulated BT from AIRS observations at 18z 11 July, 2003. Spectral channel 1740 (1513.83 1/cm) shown.

3. COMPARISON OF CALCULATED AND OBSERVED BRIGHTNESS TEMPERATURES

3.1 *Methodology*

In order to compare the observed BTs obtained from AIRS with those calculated by the AIRS-RTA, the RTM is linked to a mesoscale model and its data interpolated to the observation space.

The model used in this study is the Pennsylvania State University / National Center for Atmospheric Research fifth-generation Mesoscale Model (MM5). The MM5 is a limited-area non-hydrostatic model which uses a finite-differencing scheme (Dudhia et al., 1993) This model can be used to predict atmospheric motions on a variety of scales ranging from a few hundred meters to thousands of kilometers. The latest version of the MM5 (version 3) is used in this project to produce forecasts of meteorological fields. The MM5 has the ability to run with multiple nested grids (although only one grid is used here) as well as the capability to utilize a number of different physical parameterization schemes.

Several alterations were made to the AIRS-RTA in order for it to use MM5 fields as input. Once these changes were made and a translation subroutine installed, the AIRS-RTA was able to produce simulated radiances for a specified MM5 domain. In order to compare the simulated radiance values with the AIRS observations point-by-point, the RTM-produced radiances are interpolated from the model space to the observation space using a simple linear interpolation scheme.

Cloud contamination is a serious obstacle when dealing with infrared sounders and AIRS is no exception. In order to deal with this problem, the MODIS cloud mask (produced with the EOS science team's institutional algorithm) was obtained from the DAAC for each AIRS time period. The MODIS cloud mask (MOD35) is available at 1km resolution over the AIRS swath for both day and night passes. Although the quality of the MODIS cloud mask varied between day and night and land and ocean over the southeastern U.S. (Haines et al. 2004), its performance is generally quite good with greater than 80% of the cloud conditions being properly detected. The MODIS cloud data was interpolated to the AIRS swath and used to determine the percent cloud cover for each AIRS field of view (on average about 225 MODIS points were used for each AIRS footprint). Additionally, the MODIS cloud top pressure (MOD06) values were used to obtain a mean cloud top pressure for each AIRS footprint using the cloud mask information. This approach allowed us to consider three situational parameters for the selection of "cloud-free" AIRS data for each footprint: 1) a cloud/no cloud determination (33% AIRS pixel covered by cloud threshold), 2) a varying threshold (0-100 percentage), and 3) channel selection based upon cloud height (cloud top pressure). The first and simplest parameter indicates if a grid point is either 100% clear or not. Understandably, this field leaves very few viable grid points from which to do an analysis. The second parameter indicates the percentage of the grid point that contains clouds. The last parameter, and the one used for this study, indicates the vertical level of the highest cloud top over the specified grid point. This parameter allows one to increase the amount of AIRS data (channels) used in the cloudy regions by using only those whose weighting functions peak above the clouds. This parameter works because each spectral channel senses radiances from varying vertical levels in the atmosphere. The weighting function for AIRS channel 309 (738.48 cm^{-1}), for instance, peaks

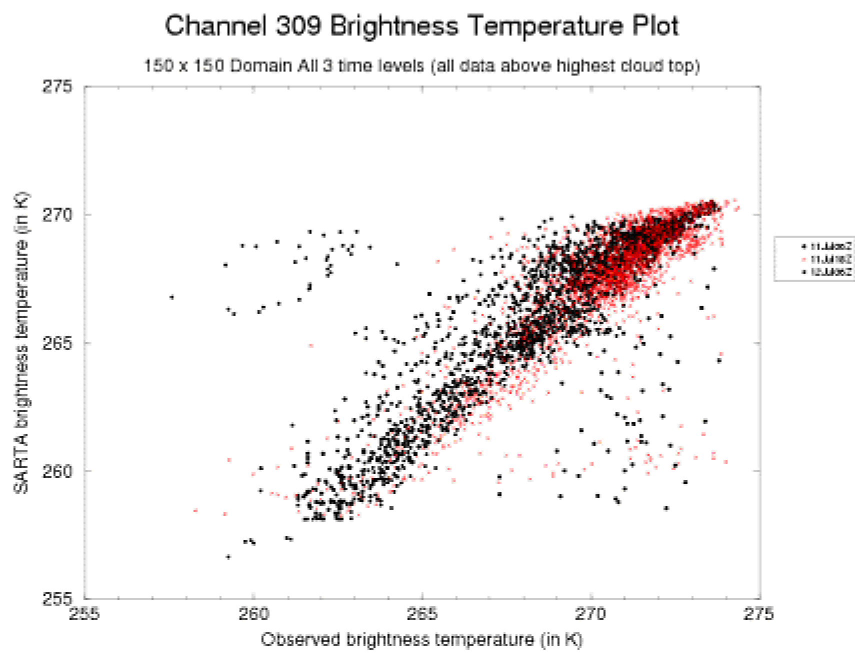

Figure 2--Brightness temperature comparison for AIRS spectral channel 309 (738.48 1/cm)

near the 700-mb level. Therefore, if the highest cloud top for a grid point is at the 900-mb level, then this channel should be relatively unaffected and the grid point is utilized for that channel.

As previously stated, the MM5 model is used to produce input data for the AIRS-RTA. For this analysis, a 36-hr forecast was produced by the MM5 and was initialized at 00:00 UTC 11 July, 2003. The grid used is 150 x 150 x 35 and has a 20-km resolution. The physics utilized include the Dudhia explicit moisture scheme, the Grell cumulus convection scheme, and the Blackadar PBL. Three time-levels were investigated for this study, two nighttime views and one daytime view. Each MM5 time-level was matched as closely as possible to the actual observation time. The time periods used include 06:00 UTC 11 July, 18:00 UTC 11 July, and 06:00 UTC 12 July. These each correspond to the observation times of 08:00 UTC 11 July, 19:00 UTC 11 July, and 07:00 UTC 12 July, respectively.

A subset of the 2378 AIRS spectral channels has been selected by the AIRS science team for their geophysical parameter retrievals. A subset 10 of the 275 AIRS team channels is used in this study to investigate any possible bias and/or outliers present in either the model or observational data. In no way should this study be seen as representative performance of all 2378 channels; a future study will investigate the bias and RMS errors for all channels produced by the RTM.

Table 1 displays the channels selected for this analysis along with each channel's absorbing gas, wave number, and level of maximum sensitivity (see section 4).

Table 1:

Channel ID	Wavenumber (1/cm)	Primary Absorbing Gas	Level of Max Sensitivity
309	738.48	CO2	700 mb
375	759.58	CO2	800 mb
843	937.91	H2O (window channel)	960 mb
1142	1074.48	H2O	850 mb
1740	1513.83	H2O	330 mb
1793	1563.01	H2O	300 mb
1852	1605.05	H2O	400 mb
2123	2401.91	CO2	990 mb
2197	2500.60	H2O (window channel)	1000 mb
2377	2664.14	H2O (window channel)	1000 mb

3.2 *Results*

The following scatterplots represent the comparison between observed and calculated BTs over the specified MM5 domain. The x-axis represents the observed BT values while the y-axis represents the calculated BT values. All three time-levels are included in the scatterplots (black dots indicate nighttime data, red dots represent the daytime data set).

a. *Channel 309 (738.48 cm^{-1})*

As seen in this scatterplot (figure 2), the AIRS-RTA seems to do an adequate job of simulating the BT values across the domain for this channel. Channel 309 is a midlevel CO_2 absorbing channel,

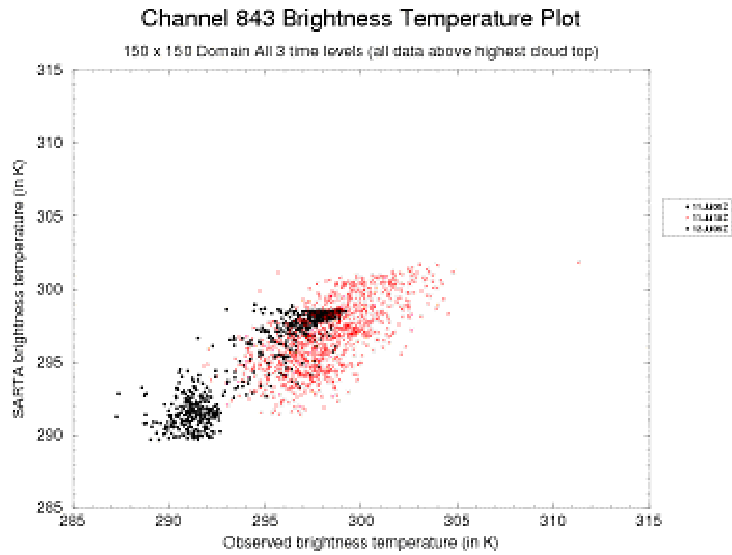

Figure 3--Brightness temperature comparison for AIRS spectral channel 843 (937.91 1/cm)

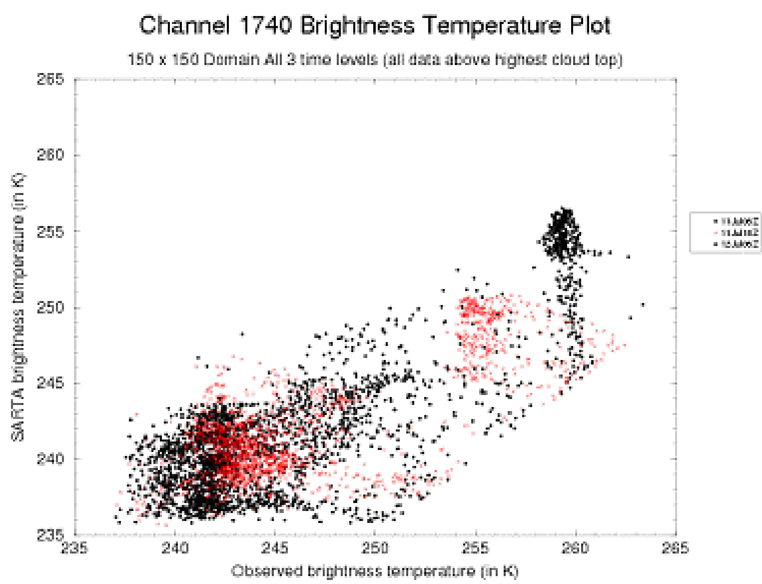

Figure 4--Brightness temperature comparison for AIRS spectral channel 1740 (1513.83 1/cm)

which is good for atmospheric temperature retrievals. There exists a rather pronounced cold bias in the model simulation, which does not seem time-dependent; and many of the model's BTs are colder than the observations by 4-7 degrees. The slope of the best-fit line is near unity, indicating a relatively constant bias with temperature (over the region) for this channel, but the bias must be removed before any assimilation is to be done. The data points which are far-removed from the best-fit line are outliers and likely caused by some residual cloud contamination.

b. Channel 843 (937.91cm^{-1})

AIRS channel 843 (figure 3) is a surface channel used by the AIRS team to generate surface property and water content retrievals. For this and other surface channels, the cloud mask filtered out any grid point where any amount of cloud was detected. For this channel, almost no bias is detected, and very little spread is seen in the data, however, the results for individual days show significant variation. The AIRS observations show a larger range of temperatures than does the RTA, which is probably do to the lack of variation in the MM5 surface temperature fields.

c. Channels 1740 (1513.83 cm^{-1})

Channels 1740, figure 4, is located in a spectral band of channels that are highly sensitive to water vapor, and as such the scatterplot shows greater disagreement than the previous plots. This is understandable since most numerical models have a difficult time with accurately simulating the atmospheric moisture profile. There exists a definite cold-bias in these results and a fair amount of spread in the data from the best-fit line.

Overall, the AIRS-RTA and MM5 appear to do an adequate job of simulating the BTs over the specified domain in comparison to the AIRS observations for these 3 channels. The outliers have been identified in further study as being the result of residual cloud contamination and will be removed before any 4D-Var assimilation. There appears to be a substantial cold bias in most of the channels investigated here. This bias is likely caused by errors in the MM5 input fields, and could be a result of the model producing too much moisture over the specified domain.

Figures 5a and 5b display the MM5-produced relative humidity fields for 12:00 UTC 11 July, 2003 at two pressure levels (500 mb and 850 mb). Figures 5c and 5d display the same fields at the same pressure levels as the MM5 figures but for radiosonde data from 12:00 UTC 11 July, 2003. Notice the difference in the magnitude in the RH fields between the observations and the MM5 model results, especially for the 850 mb level. It appears, from these results, that the MM5 is producing more near-surface moisture than what actually existed at this time. Also, the MM5 seems to be under predicting the moisture values at 500; this may provide some explanation for the cold bias in AIRS channel 309, and certainly in the water vapor channel shown here.

Further study is planned in this area to determine the root cause of the bias seen in these channels. In addition to this, a full investigation of all 2378 AIRS spectral channels will be done to find the RMS errors and the bias of each channel when comparing AIRS-RTA BTs to that obtained from the AIRS observations. This study will be used to obtain bias-correction coefficients which will be applied to any future 4D-Var assimilation.

4. DEVELOPMENT OF THE AIRS-RTA ADJOINT MODEL AND PRELIMINARY SENSITIVITY ANALYSIS RESULTS

4.1 *Development of the AIRS-RTA Adjoint Model*

In order to conduct any 4D-Var assimilation, it is necessary to derive the adjoint of the nonlinear AIRS-RTA. The actual process of deriving this model is actually two-fold; first, the *tangent linear* (TGL) model of the AIRS-RTA is found by taking the first order Taylor expansion around the nonlinear AIRS-RTA solution. The *adjoint* (ADJ) model is then derived as the transpose of the tangent linear model.

The nonlinear AIRS-RTA can be expressed by the following equation:

$$R = H(\mathbf{x}). \tag{3}$$

Where H is the observation operator, $\boldsymbol{x}$ is the state vector, and R is the solution (in this case, the radiance values). The TGL-RTM can therefore be expressed as the following:

$$\delta R = \mathbf{H}(\mathbf{x})\delta\mathbf{x}. \tag{4}$$

Where $\mathbf{H} = \frac{\partial H}{\partial \mathbf{x}}$ is the tangent linear of the observation operator, $\delta\mathbf{x}$ is the perturbation to the

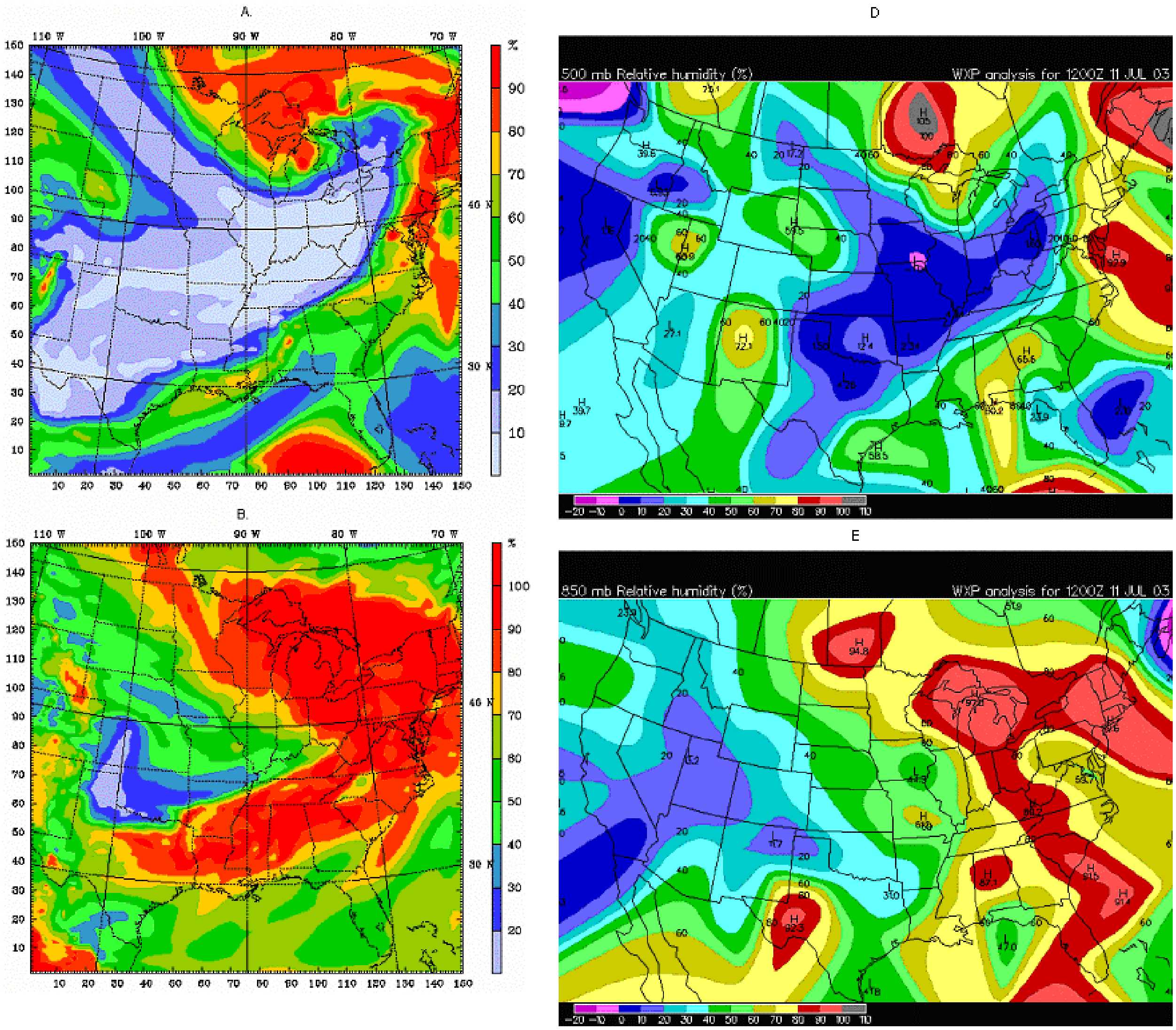

Figure 5--Relative humidity plots, all plots made from data valid at 12z 11 July, 2003: fig 5a displays RH from MM5 data at 500-mb level; fig 5b displays RH from MM5 data at 850-mb level; fig 5c displays RH from observations at 500-mb level; and fig 5d displays RH from observations at 850-mb level.

state vector, and δR is the perturbed radiance value. To derive the TGL-RTM, the nonlinear model code must be differentiated line-by-line with respect to the input variables.

Once the TGL-RTM has been derived and validated, the ADJ-RTM can be found. The ADJ-RTM is simply the transpose of the TGL-RTM (if the TGL-RTM contains calculations involving complex numbers, the complex conjugate must first be found then the transpose operation can be done). The ADJ-RTM can be expressed as the following:

$$\delta \mathbf{x}^* = \mathbf{H}^*(\mathbf{x})\,\delta R^* . \tag{5}$$

Where all the terms superscripted with a * are adjoint variables. $\mathbf{H}^*$ is the adjoint operator which acts on the forcing term δR^* in order to produce the adjoint control variable $\delta \mathbf{x}^*$ which is equal to the gradient of *R* with respect to the input variable **x.**

The computer code for the ADJ-RTM is developed by finding the complex conjugate and the transpose of the TGL-RTM. To do this, the output variable of radiance becomes the input variable and the sequence of code operations is reversed for the adjoint variables; in other words, the last calculation occurs first and vice versa. However, the basic state (which is needed by the ADJ-RTM) must be calculated as in the TGL-RTM and in the same sequence. Once the correctness of the adjoint code has been verified, the model can be used for numerous operations such as 4D-Var assimilation and adjoint sensitivity experiments.

4.2 *Preliminary Results from the Adjoint Sensitivity Analysis*

It is vitally important to ascertain the relative sensitivity of the AIRS-RTA response to the model input parameters before conducting any 4D-Var experiments. This is because a sensitivity analysis is an efficient channel selection tool. With AIRS data consisting of 2378 spectral channels, many of which are redundant, it is important to par-down the number of sensitive channels to be included in data assimilation. Adjoint sensitivity provides an excellent means of checking if the numerical results produced by the AIRS-RTA are physically realistic (Amerault and Zou, 2003).

The most widely used method of sensitivity analysis consist of running a particular numerical model once, save the output as a control run, perturb one input parameter, run the model again, then compare the two model solutions. If the model solution changed significantly compared to the control run, then the response is said to be sensitive to that particular input parameter. In the case of a radiative transfer model, such as the AIRS-RTA, one may be interested in the effects that mixing ratio may have on radiance calculation. Using the method just described, however, is quite inefficient when considering that the AIRS-RTA has several input parameters and over 2000 spectral channels. Fortunately, the ADJ-RTM model provides an excellent tool to conduct a far more efficient sensitivity study.

The ADJ-RTM model is used to calculate the sensitivity of the model-simulated response to each input parameter (atmospheric temperature, perturbation pressure, mixing ratio, and ground temperature) with only one integration of the adjoint model. This clearly saves time and resources over the previously described traditional method. A detailed mathematical description of relative sensitivity calculation using the ADJ-RTM model is provided below.

a. Formulation

The response function is defined as

$$J_\alpha = J_\alpha(\mathbf{x}) = R(\alpha) \qquad (6)$$

where **x** is the vector which contains the values for surface and atmospheric parameters and $R(\alpha)$ is the radiance value of the α^{th} channel. The sensitivity of the response function J_α, with respect to the vector **x** is defined as

$$J_\alpha^{sens} = \left(\nabla J_\alpha\right)^T \delta\mathbf{x} = \left(\hat{\mathbf{x}}\right)^T \delta\mathbf{x} \qquad (7)$$

where $\hat{\mathbf{x}}$ is the result of applying the adjoint RTM onto a vector $\frac{\partial J_\alpha}{\partial \alpha}$ which consists of a unit value for one channel and zero for all other channels. If there is a variation only in the l^{th} component of **x**, then $\delta\mathbf{x}^l$ represents the vector of variation such that

$$\delta\mathbf{x}^l = \left(0,\ldots,\delta x^l,\ldots,0\right)^T \qquad (8)$$

and the sensitivity can be written as $J_\alpha^{sens-l} = \left(\hat{\mathbf{x}}\right)^T \delta\mathbf{x}^l$. Zou, et. al. (1993) defined the non-dimensional relative sensitivity as

$$S_\alpha^l = \frac{J_\alpha^{sens-l}}{J_\alpha}\left(\frac{\delta x^l}{x^l}\right) = \frac{\hat{x}^l x^l}{J_\alpha} \qquad (9)$$

where $\hat{x}^l$ is the gradient of the cost function J_α with respect to the l^{th} parameter of *x*.

The magnitude of the relative sensitivity signifies the importance of each input parameter for each spectral channel. Plotting the relative sensitivities provides a way to judge which variable (and at which spectral channel) the radiance values are most sensitive for a given response function.

b. Numerical Results

The sensitivity study was conducted for radiances at all channels at two separate grid points from the input MM5 data run. Figure 6 displays the brightness temperatures for channel 1740 (1513.83 cm^{-1}) at 18:00 UTC 11 July, 2003 as produced by the RTM. Point A and point B indicate the grid point locations where the two sensitivity analyses were conducted.

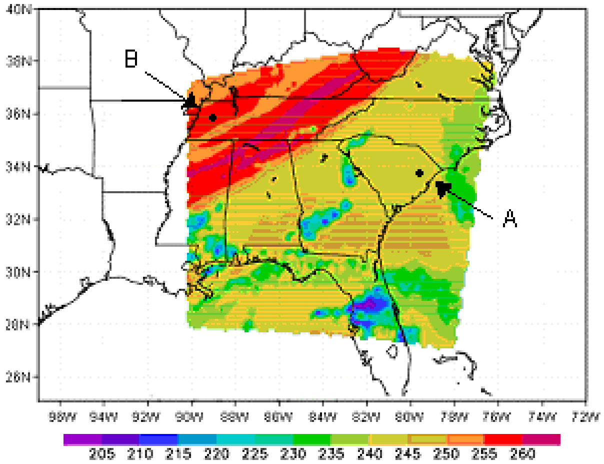

Figure 6--AIRS observations for channel 1740 over MM5 domain region. Points A and B indicate grid points where sensitivity experiments were conducted.

Two sensitivity experiments were done to ensure that the sensitivity values do not change much from one grid point to the next. Both grid points are in cloud-free environments (as defined by the MM5 cloud-water data field). A discussion of the results from the sensitivity experiment conducted at point A is presented in this section.

The sign of the relative sensitivities are important and must be discussed briefly. There are four input parameters to the AIRS-RTA that have been tested here. These are atmospheric temperature, perturbation pressure, mixing ratio, and ground temperature. Both the atmospheric temperature and ground temperature plots have mainly positive relative sensitivities. This indicates that as the temperature increases, the radiance value will increase as well (as is expected). It is still unclear why there are some areas of negative relative sensitivity in the atmospheric temperature results. For the mixing ratio and perturbation pressure plots, the largest sensitivities tend to be negative, indicating an increase of perturbation pressure or mixing ratio (water content) would decrease the radiance value in those regions. For mixing ratio, this result is straightforward. An increase in the mid-level water content would likely result in a radiance value decrease since the emission would primarily be from the mid-levels with less surface contribution. However, the results corresponding to perturbation pressure may not be as straightforward.

Perturbation pressure is the term given to the combination of *dynamic* pressure and *buoyancy* pressure. Dynamic pressure is associated with gradients in the wind field whereas buoyancy pressure is associated with the vertical derivative of buoyancy. This term does not have a significant impact on the radiance values calculated by the AIRS-RTA as the perturbation pressure term is used primarily to calculate the model pressure levels for input to the RTM; however, perturbation pressure is used as one of the adjoint model's control variables and is therefore included in this study for completeness. The largest magnitude in sensitivities are in the temperature fields, most notably in the ground temperature results (some values as high as 12.0). This is consistent with the current understanding of radiative transfer (Strow and Hannon, 2002; Liou, 1992), and this result suggests that the RTM is doing an adequate job in simulating the atmospheric radiance values at each spectral channel.

Figures 7 through 9 display three examples from the relative sensitivity study for the RTM input parameters at grid point A; the first plot displays a range used in atmospheric temperature soundings; the second plot displays a range used for water vapor soundings; and the third plot displays the sensitivity of radiance to surface parameters. The relative sensitivities in the first two plots are represented by the color contours; the x-axis represents the spectral channel wave numbers; the y-axis is the vertical level in millibars. At the bottom of each figure is a line graph of the brightness temperature (average of four surrounding grid points) provided for additional insight in deciphering the sensitivity data.

Also included in these figures are identifiers indicating the channels selected by the AIRS team for their retrievals. Each identifier is color-coded to indicate which parameter (surface temperature [green], atmospheric temperature [blue], water vapor [yellow], ozone [maroon]) retrieval the specified channel is used for. This allows for a measure of consistency between the AIRS team selection and the sensitivity results provided here.

Figure 7 displays the relative sensitivity of radiance to the input parameters over the spectral range 706.99 to 767.89 cm^{-1} (channels 201 to 400). Figure 7a displays the relative sensitivity of radiance to *T*. In this range one can see that the maximum sensitivity values are now stretching closer to the model surface (also indicated by the brightness temperature plot which has the BT rising from 230 K to nearly 300 K). The AIRS team does an adequate job of channel selection through this range, the majority of which are used for *T* retrievals, except for channel 369 (757.57 cm^{-1}) which is used for ground temperature, T_g, retrievals. There are some spectral channels which exhibit interesting features in the sensitivity

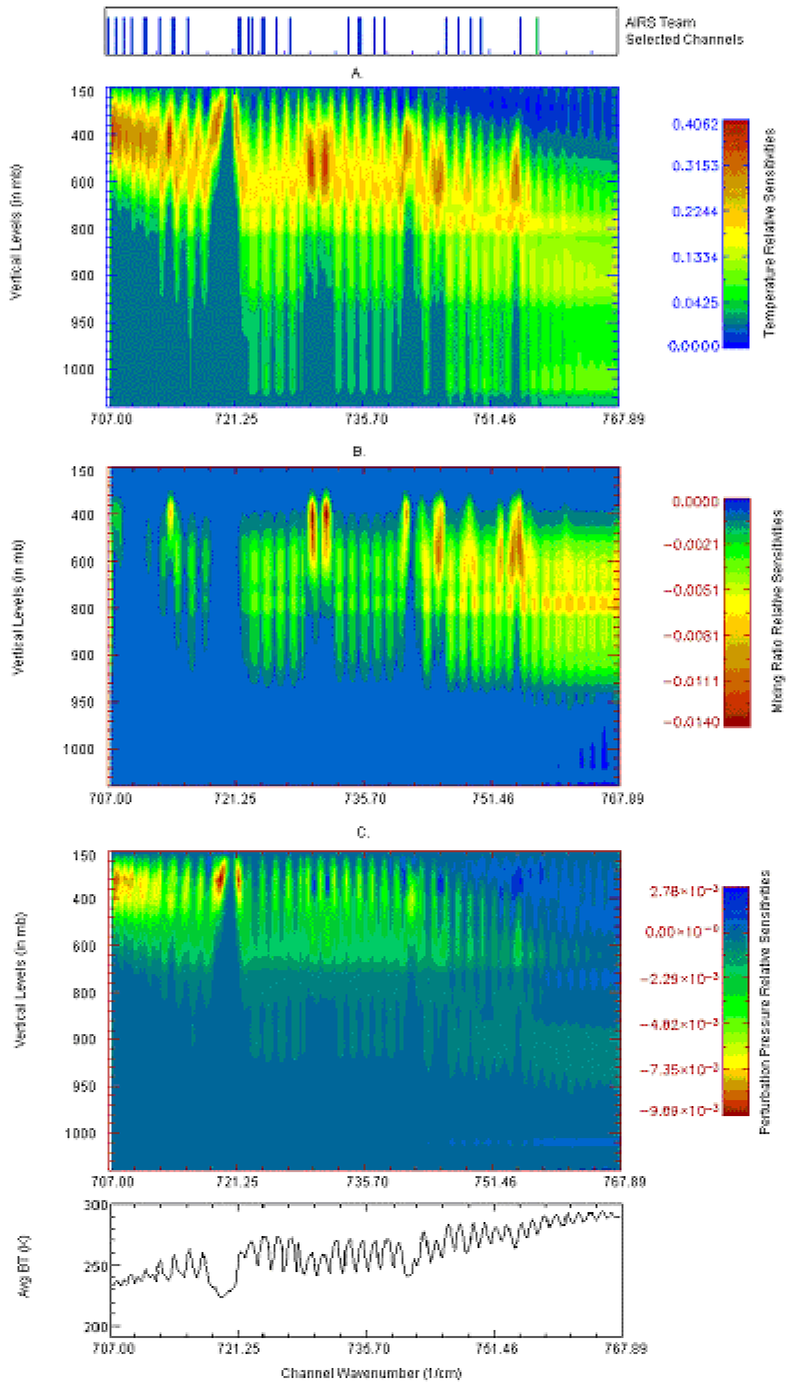

Figure 7—Sensitivity plots for spectral channels 201-400 (707.00 to 767.89 cm^{-1}). Figure 7a displays the sensitivity of radiance to atmospheric temperature (color contours); 7b for mixing ratio; 7c for perturbation pressure. Vertical levels (in mb) on y-axis; spectral range (in cm^{-1}) on x-axis. Sensitivity magnitudes indicated by color bars on right. Colored lines at top indicate AIRS-team selected channels (blue for CO_2 atmospheric temperature channels, green for surface parameters, yellow for water vapor channels, and maroon for ozone channels). Line plot at bottom indicates average BT over domain point for specified channels.

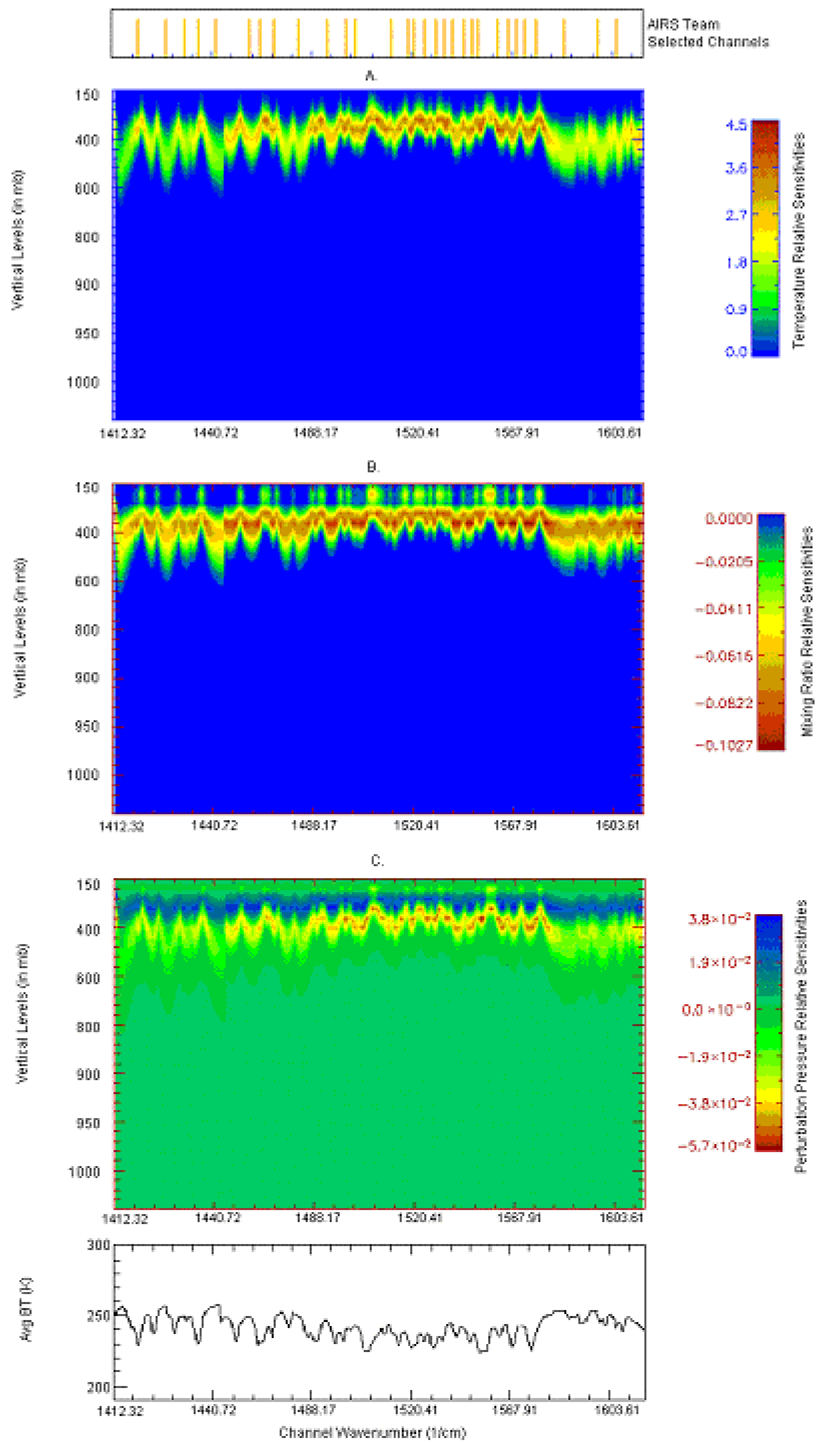

Figure 8—Sensitivity plots, as in figure 7, for spectral channels 1601-1864 (1412.32 to 1603.61 cm^{-1}).

patterns, most notably for channels from 729.58 cm^{-1} to 731.01 cm^{-1} and channels near 743.50 cm^{-1}. There appears to be distinct maximum sensitivity regions at these channels which the AIRS team decided not to use, for reasons that are as of yet unknown. The AIRS team does not select any of these channels for their moisture retrievals. This decision is consistent with figure 7b (sensitivity to *q*) that, while displaying nice patterns of relative sensitivity, shows the magnitudes of the sensitivity are relatively low (maximum value of only near -0.014).

Figure 8 shows relative sensitivity of radiance to the input parameters for the spectral range of 1412.32 cm^{-1} to 1613.89 cm^{-1} (channels 1601 to 1864). This range is primarily used by the AIRS team for water vapor retrievals; this is supported by the data in figure 8b which shows that radiance has high sensitivity to water vapor in this spectral range. The sensitivity to *T* in this range is also high, but none of these channels have been selected by the AIRS team for atmospheric temperature retrievals likely due to moisture interference. The AIRS team does a fine job in selecting channels for moisture retrievals based on the findings in this study, as many of the selected channels correspond to spikes in the sensitivity field.

Figure 9 shows the relative sensitivity of radiance to the ground temperature parameter. This plot is of the model response sensitivity to the ground temperature parameter, and is therefore displayed as a 2-D plot; relative sensitivity values on the y-axis, channel ID number on the x-axis. This parameter had the highest relative sensitivity values out of the four parameters tested, with maximum values approaching 11.0.

Examining figure 9, one can see three distinct spectral regions where the relative sensitivity to the ground temperature is highest: between channels 375 (759.58 cm^{-1}) to 1300 (1236.03 cm^{-1}), just before channel 1900 (2213.67 cm^{-1}), and again from channels 2100 to 2378 (2379.43 to 2665.28 cm^{-1}), with the last range having the highest sensitivities. Overall, the AIRS team does a good job in selecting channels from the proper ranges. Their team selected 10 channels between 375 and 1300 (759.57 cm^{-1} to 1000.11 cm^{-1}); 9 channels between 1000 and 1300 (1000.11 cm^{-1} to 1236.032 cm^{-1}); 7 channels between 1865 to 1876 (2181.49 cm^{-1} to 2191.53 cm^{-1}); and 26 channels after channel 2115 (2394.06 cm^{-1}). The decision to select the majority of surface channels from after channel 2100 is supported by this study as that spectral region contains the highest relative sensitivity values for this parameter.

It is not believed that any additional channels will need to be selected other than those already chosen by the AIRS team for this parameter. However, these results will be studied closely when choosing channels for the 4D-Var experiments.

5. SUMMARY AND CONCLUSIONS

As shown in this discussion, the AIRS-RTA does an adequate job of simulating the BTs over the domain for the initial test case. The model is fast and efficient making for relatively smooth integrations for the adjoint model, which is its most desirable feature. Some bias exists in the AIRS-RTA simulations, mainly a cold bias for daytime and a slight warm bias at night. The nighttime warm bias is likely due to the input data fields and the MM5's inability to correctly resolve the diurnal cycle. The daytime bias, however, appears to be the result of the MM5 over-predicting the surface moisture content. A further study of all 2378 channels will be conducted in the near future to derive correction coefficients to remove the bias before any data assimilation.

The ADJ-RTM has shown to be correct, not only from the correctness checks done previously, but also from the results of the adjoint sensitivity

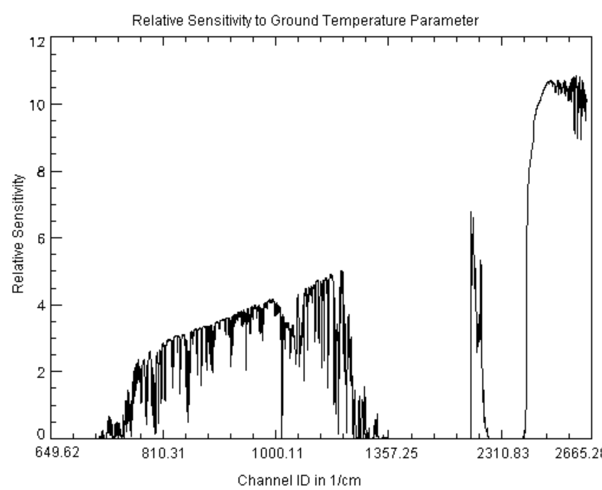

Figure 9—Radiance sensitivity to ground temperature. Sensitivity values on y-axis; channel wave number on x-axis. Note there is a spectral gap between 1613.89 and 2181.52 cm^{-1} (channels 1864 and 1865).

study. Several features of this study demonstrate the accuracy of the analysis and the success of the ADJ-RTM in analyzing the relative sensitivity values to the four parameters tested: (1) the agreement between the sensitivity plots and the brightness temperature analysis suggest that the RTM is functioning correctly and that the radiative transfer process is simulated accurately; (2) the channels selected by the AIRS team for their geophysical parameter retrievals are in good agreement with the sensitivity analysis of each parameter tested here.

If large discrepancies existed between the channels of highest sensitivity and those channels chosen by the AIRS team, one would have to assume that the sensitivity analysis is in error. It is not expected that the channels chosen by the AIRS team would agree completely with the analysis generated by the ADJ-RTM, on the contrary, a small amount of disagreement is expected. However, the overall agreement between the two methods suggests that the sensitivity analysis shown here is accurate and that the ADJ-RTM is functioning normally.

The sensitivity analysis shown in this paper can be used to select several sets of channels to be used during 4D-Var assimilation. These experiments will determine which channels perform best during each weather regime (summertime precipitation, wintertime snow, etc.), in conjunction with a future sensitivity analysis that will link the model parameters (mixing ratio, ground and air temperature) to the MM5 model response (in this case, precipitation).

Further study is required, however, before this sensitivity analysis can be considered complete. First, it must be determined which channels were excluded from the AIRS team channel selection and why (signal noise, etc.), before any channel selection can be done for this project. In addition to this, many atmospheric gas profiles (methane, ozone, etc.) are held as fixed gas amounts in the AIRS-RTA; the impact on the channel sensitivity to each input parameter must be determined when these gas amounts are changed. Doing so will aid in selecting the most useful and least troublesome spectral channels for any data assimilation experiments.

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