2.5 ASSIMILATION OF MODIS TEMPERATURE AND WATER VAPOR PROFILES INTO A MESOSCALE ANALYSIS SYSTEM

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1. INTRODUCTION

The Melbourne, Florida NWS is currently running, real-time, the Advanced Regional Prediction System (ARPS, Xue 2002) with its analysis component the ARPS Data Analysis System (ADAS, Brewster 1986) over most of the Florida peninsula at 4-km resolution (Fig. 1). ADAS uses the Bratseth (1986) successive correction method to blend observations with a background (first-guess) field. The Bratseth scheme is computationally efficient and quite flexible in that it can discriminate between background and observation errors. ADAS ingests the following observational types: single-level (e.g. surface), multi-level (e.g. upper air, profiler), WSR Level II radial winds and reflectivity, and single-Doppler retrieved winds. The Melbourne NWSFO ADAS configuration includes the high density network of observations at the Kennedy Space Center (surface, profiler, and tower data), the Florida Automated Weather Network (FAWN), Automatic Position Reporting System (APRS), Aircraft Communications Addressing and Reporting System (ACARS), METAR surface observations, GOES-8 visible (1-km) and infrared (4-km) satellite imagery, NASA Doppler wind profilers, and buoy observations (Case et al. 2002). The analysis is run every 15 minutes. Sashegyi et al. (1993) have used the Bratseth scheme to improve geostrophic wind modeling in Atlantic Lows and Lazarus et al. (2002) have used the ADAS/Bratseth scheme to produce near-real-time analyses in the complex terrain of the intermountain west.

Of the many forecasting challenges in Florida, none is more important than the sea breeze. In order to better represent the sea breeze, it is important to know the temperature and moisture distribution in the lower troposphere—especially upstream (to the east) of the Florida peninsula. Unfortunately, both surface and upper air data is sparse in this region. For example, on Florida's east coast, there are only three moored buoys and seven Coastal-Marine Automated Network (C-MAN) stations (one in St. Augustine, FL, five scattered from Lake Worth, FL to Sand Key, FL and one on the western shore of Grand Bahama Island) that provide atmospheric conditions near the ocean surface. The buoys and automated stations measure air temperature, barometric pressure, wind speed and direction but do not measure dew point or relative humidity. This is problematic in that the analysis is dominated by a coarse background field (currently the RUC-2 40 km) in what is often the upstream region of the Florida domain.

Herein, we present some preliminary results whereby we ingest satellite retrieved temperature and water vapor profiles in an attempt to enhance the ADAS analysis in regions of otherwise sparse data. Satellite data can be used to fill in gaps between observations (Lipton and Vonder Haar, 1990). Previous work by Gal-Chen et al. (1986), Doyle and Warner (1988), Lipton and Vonder Haar (1990), Lipton et al. (1995), and Ruggiero et al. (1999) each have assimilated satellite sounder data into numerical prediction models. We have configured ADAS to ingest MODerate resolution Imaging Spectrometer (MODIS) Atmospheric Profile Level 2 products retrieved from instruments aboard the Terra and Aqua satellites. Because the MODIS data are relatively new (Terra launched on 18 December 1999 and Aqua launched on 4 May 2002, Seemann et al. 2003), applications remain somewhat limited. MODIS temperature and moisture products can be used together in numerical weather prediction models when conventional meteorological observations are sparse (Seemann et al. 2003). In particular, we attempt to assess the impact of assimilating the temperature and water vapor profiles into ADAS. In doing so, we have begun to investigate the nature of the geospatial statistics relating the background field (20 km RUC-2, Benjamin et al. 2002) to the retrieved profiles (see Section 3).

2. DATA SET DESCRIPTION AND RELATED ISSUES

There are a number of relevant issues related to the conversion of satellite observed radiances into atmospheric profiles of temperature and moisture foremost of which include solution non-uniqueness (Ruggiero et al. 1999) and collocation of the satellite radiances with radiosonde data. The MODIS profiles used herein are retrieved from a set of regression coefficients determined solely from a training data set of approximately 8400 global soundings and pseudo-radiances generated by a transmittance model (Seemann et al. 2003). Note that we are attempting to use the retrieved profiles directly rather than the radiances as operational constraints are such that large volume radiative transfer calculations for the high-resolution analyses are currently impractical. While the radiative transfer problem

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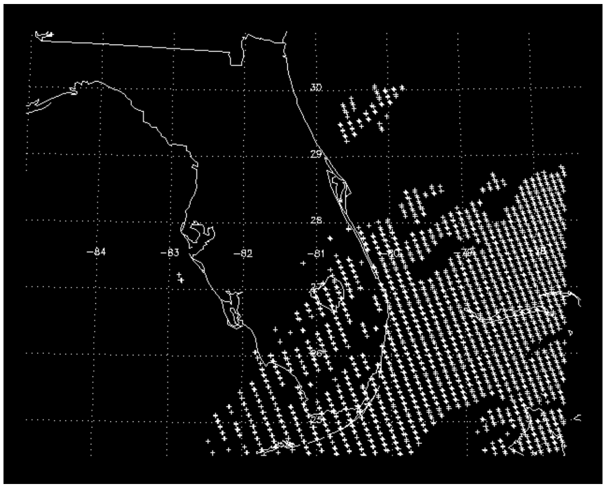

Figure 1: NWS Melbourne Florida ADAS domain. A '+' indicates the location of a MODIS Aqua sounding for the 18 UTC overpass 3 July 2003.

is both non-unique and underdetermined (fewer radiances than model levels) and the error covariance of temperature and vapor profiles can be difficult to determine (Kalnay 2003), herein we attempt to better understand their behavior over a limited domain. The advantage of using the retrieved data from a purely statistical algorithm is that it does not use a background field as a first guess—mitigating the impact of inconsistencies generated as a result of blending the retrieved profiles with a different background field in ADAS. Although the coefficients are global, the training data are subdivided into 7 brightness temperature zones based on the 11 micron BT calculated from each, and the retrievals use only the subset of the training data corresponding to the same BT as seen by MODIS band 31 (Seemann, personal communication). The only required ancillary data is NCEP-GDAS surface pressure (input to the regression).

Comparisons between the MODIS profiles and radiosonde data for temperature and water vapor by Seemann et al. (2003) indicate that the retrieved MODIS profiles capture the vertical structure of the atmosphere very well. We have begun to evaluate the MODIS temperature and vapor profiles by comparing them with proximity soundings within the ADAS domain (Fig. 2) for a trial date—3 July 2003. We are also examining the impact of the retrieved profiles on the first-guess field (i.e. RUC-2 20 km) as well as the practicality of ingesting a subset of these profiles into the real-time ADAS analyses.

The current overpass time for the MODIS temperature and water vapor profile data over the ADAS domain is approximately 1800 UTC for the Aqua platform and 0300 UTC for the Terra platform. Each retrieved sounding maps temperature and water vapor to 20 pressure levels ranging from 1000 hPa to 100 hPa. The number of available profiles (within the ADAS domain) varies, depending on clouds or other obstructions in the path of the satellite beam. In a cursory examination of a one-week period, the number of profiles in a given overpass

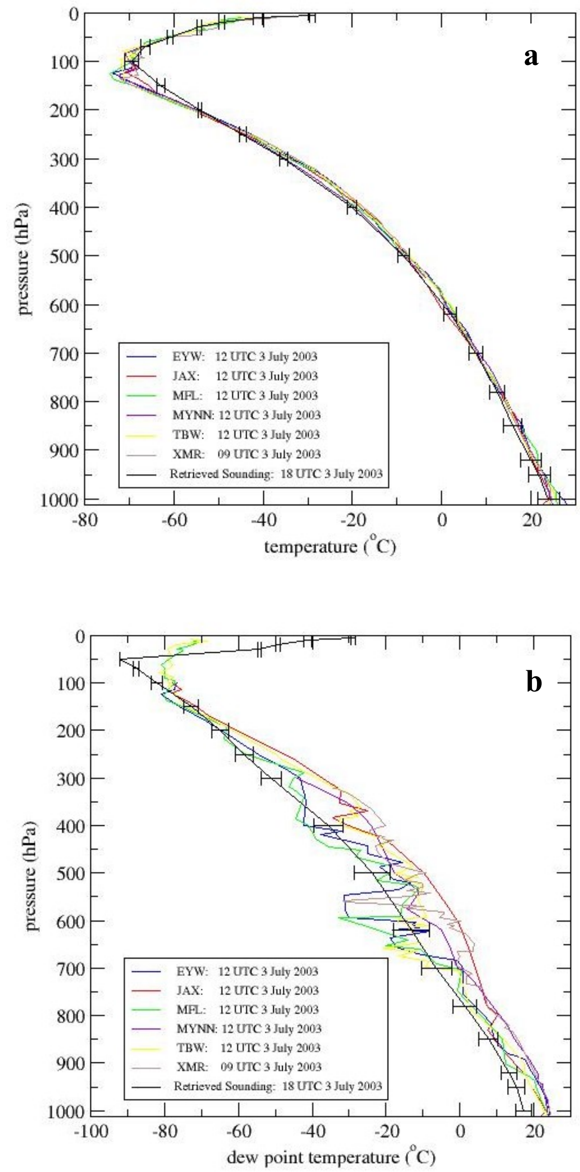

Figure 2: MODIS Aqua mean retrieved a) temperature and b) dew point temperature profiles (with accompanying error bars, 1σ) and 12 UTC proximity soundings within the Florida ADAS domain for 3 July 2003.

ranges from 2000 to approximately 8000. Of course, quantity does not necessarily imply quality, and so we have developed some simple quality control measures in an attempt to screen the data prior to ingestion into the analyses. Here, we use the mean and standard deviation (water vapor and temperature) for each pressure level to flag potentially bad data—eliminating data that are more than two standard deviations from the mean. ADAS also performs quality control on upper air data—eliminating data based on user-prescribed threshold differences from the first-guess field. Two standard deviations appear to be a reasonable compromise between eliminating bad data while still including any natural variability. This removes approximately 5% of the overall observations.

3. ADAS DESCRIPTION

As mentioned previously, the ADAS Bratseth technique is a successive correction scheme that converges to optimum interpolation. Additionally, the Bratseth method differs from conventional successive correction techniques (e.g. Cressman 1959, Barnes 1964) in that it allows for the specification of the error covariance of the background and observations. Given sufficient iterations, the analysis converges to an optimal analysis based on some user-specified error variance. The benefit of the Bratseth technique is that it does not require the large matrix inversions of optimum interpolation. The ADAS weights take into account the observation density and the observation-to-background error variance. The spatial correlations are assumed to be Gaussian and isotropic and are given as:

$$\rho_{ij} = \exp\left(-\left|r_{ij}\right|^2 \Big/ R^2 \right) \exp\left(-\left|\Delta z_{ij}\right|^2 \Big/ {R_z}^2 \right) \qquad (1)$$

where r_{ij} and Δz_{ij} are the horizontal and vertical distances between the observations respectively (the grid point-to-observation correlations are specified similarly, Lazarus et al. 2002), and R and R_z are user specified horizontal and vertical scaling factors (Bratseth 1986). The specification of these scale factors is important. In part, they determine the degree of analysis structure that is drawn for in the presence of observations. ADAS allows the scale factors to vary from iteration to iteration and, in practice, both R and R_z are reduced to allow greater detail for successive passes. The NWS Melbourne office currently uses a single pass for each ingested data set, albeit non-optimal, it allows for the flexibility of using different scale factors for the same variable observed from different sources (ADAS does allow for different scale factors for different variables however).

Here, we focus on determining the appropriate choice for the horizontal scale factor as the characteristically smooth vertical profiles of water vapor and temperature essentially limits any applications concerning the vertical scale factor.

4. MODIS DATA EVALUATION

In an effort to determine an appropriate horizontal scale factor we have begun to examine the variance (sum of the squares) of the ‘increments’ (innovations) as a function of observation separation for all observation (profile) pairs (for a given pressure level). The total number of unique observation pairs is given by *n(n-1)/2* where n is the total number of observations. Thus, for example, 5000 profiles yields more than 10^7 observation pairs at varying separations. The initial (i.e. first pass) ADAS increments are simply the difference between the background field (20 km RUC-2) interpolated to

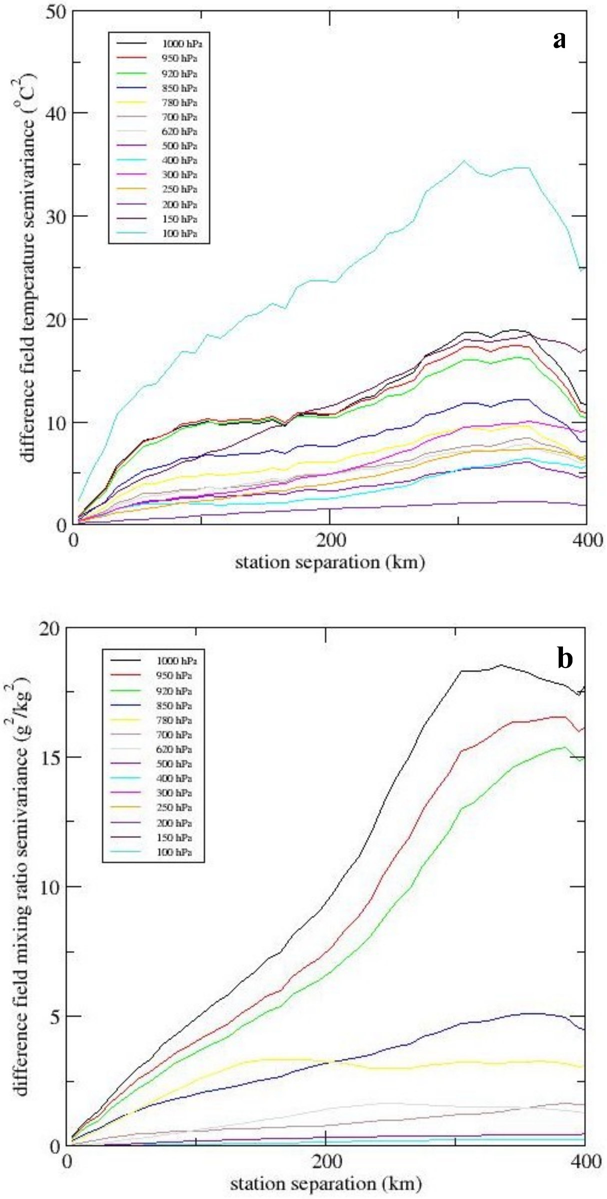

Figure 3: Averaged squared increments [i.e. observation (MODIS) minus background (20-km RUC)] for all observation pairs and pressure levels for 18 UTC Aqua overpass 3 July 2003 a) temperature, b) water vapor.

observation locations and the observations themselves. We then calculate the average variance for a given distance bin (here we use a bin width of 10 km) from 0 to 400 km (Fig. 3a and 3b). In the absence of both background and observation error, the variance should approach zero; however, this is never the case. Instead, we use this information to gain insight into the error structure inherent in the background and observations (e.g., Sen 1997). In particular, we can see that for the

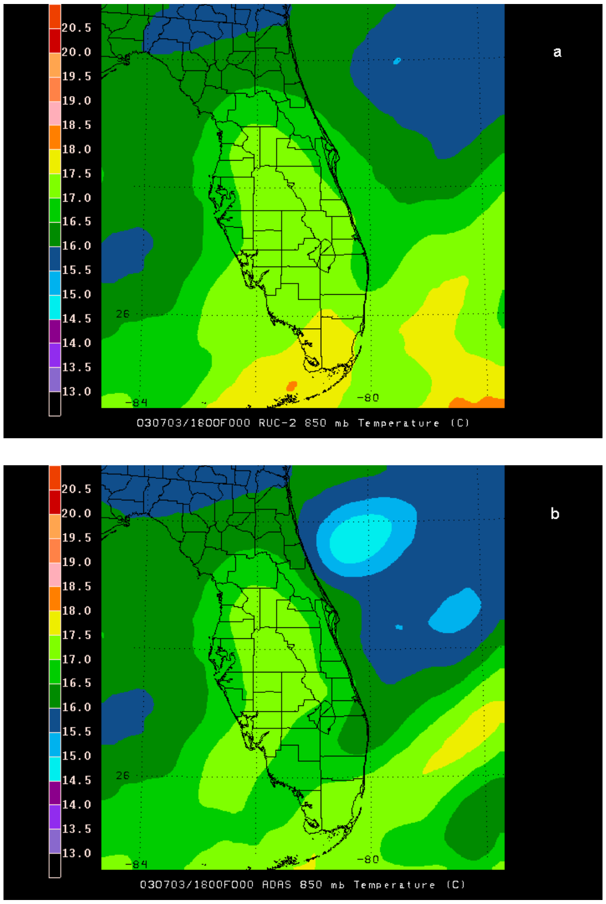

Figure 4: 850 hPa temperature (°C) for a) background (20 km RUC-2 interpolated to the 4-km ADAS grid) and b) ADAS analysis with MODIS data ingest for 18 UTC 3 July 2003.

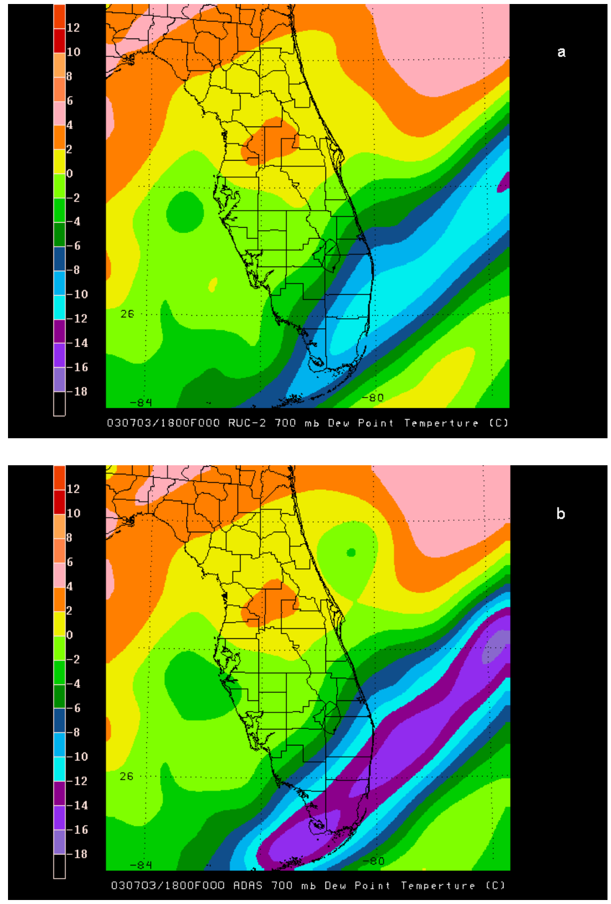

Figure 5: As in Figure 5 but for 700 hPa dew point temperature (°C) for a) background and b) ADAS analysis with MODIS data ingest.

trial date, the decorrelation length scale is somewhat ambiguous for both the temperature and vapor profiles as the variance does not necessarily asymptote to a fixed value for each of the pressure levels and for each variable. Also, the variance generally decreases with height except for the 100-hPa level where the impact of the differences between the background and MODIS tropopause levels is significant (see Fig. 2). We are currently examining the MODIS data stream and 20-km RUC-2 for an extended period to evaluate the degree to which the statistics from individual days actually reflect the long-term statistics (e.g., are the statistics stationary and without bias).

5. ADAS ANALYSIS: 3 JULY 2003

We have run ADAS for the 3 July 2003 MODIS Aqua 18 UTC overpass. Here we use all profiles (2164) and a horizontal length scale, R, of 60 km. In the absence of creating super observations or data thinning, the one-pass analysis is currently too slow for operational purposes. However, this approach establishes a benchmark for evaluating against other analysis configurations (e.g. a reduction/thinning of the number profiles). The outputs at 850 hPa for temperature and at 700 hPa for moisture are shown in Figures 4 and 5 respectively. The MODIS swath for this date is mainly concentrated across the southern portion of the ADAS domain (Fig. 1). Comparing the mean MODIS sounding with proximity soundings (12 UTC) in the ADAS domain (Fig. 2) indicate that the Aqua lower-tropospheric water vapor is significantly less than the background field for the trial date while the proximity temperature differences tend to be within the error bars (i.e.,1σ) of the MODIS data. The profiles (Fig. 2) suggest that the adjustments in the background field should be most significant for the water vapor. This is supported by Figures 4 and 5, which indicate an approximate drying of 4-6°C and a slight cooling (on the order of 0.5°C) across Southern Florida. In the absence of MODIS data (e.g. the western portion of the ADAS domain), the analysis closely resembles the background field. At this point, we are unsure as to whether or not the differences between the 20 km RUC water vapor and the retrieved Aqua profile are real or the result/combination of a model or observational bias (a question we anticipate answering as we examine longer-term statistics). However, it is possible that the cooling may be an artifact of the way the profiles are reported—setting the 1000 hPa level as sea level. This is easily correctable by using the RUC surface pressure to recalculate the 'observed' heights for each of the pressure surfaces prior to ADAS ingestion. Other issues remain, as well. For example, as indicated in Figure 1, there are a few data points scattered across the ADAS domain that do not appear to be associated with an identifiable swath. These points are responsible for the analysis 'bull's eyes' off the coast of North Central Florida and to the west off the Tampa/St. Petersburg area over the eastern Gulf of Mexico.

6. CONCLUSIONS AND FUTURE WORK

As a proof of concept, we have shown that it is possible to successfully ingest MODIS temperature and water vapor profiles into a version of ADAS that has been configured to run operationally at the NWS office in Melbourne, Florida. Preliminary results indicate that the horizontal scale factor depends on the variable being analyzed as well as the observation level. Error variances appear to decrease with respect to height and differ for temperature and water vapor. The practical implementation of the ingest in real-time will ultimately depend on a number of important factors—in particular the availability of the live broadcast data within the analysis window as well as our ability to configure an ingest procedure that appropriately reduces the number of profiles. Perhaps, the most relevant evaluation will be whether or not the ingest improves the short-term ARPS forecasts that are initialized with the ADAS analyses. Because the analyses are also used for nowcast purposes and have also been identified as an evaluation tool for the National Weather Service Graphics Forecast Editor (GFE), there is also potential to add value as a diagnostic product.

What remains to be done is a comprehensive study of the geospatial statistics for an extended period. As part of this evaluation, we hope to identify any biases in the background field and observations as well as get a handle on relevant error levels and correlation scales.

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