Mesoscale Cloud State Estimation from Visible and Infrared Satellite Radiances

T. VUKICEVIC, T. GREENWALD, M. ZUPANSKI, D. ZUPANSKI, T. VONDER HAAR, AND A. S. JONES

Cooperative Institute for Research in the Atmosphere, Colorado State University, Fort Collins, Colorado

(Manuscript received 22 May 2003, in final form 10 February 2004)

ABSTRACT

This study focuses on cloudy atmosphere state estimation from high-resolution visible and infrared satellite remote sensing measurements and a mesoscale model with explicit cloud prediction. The cloud state is defined as 3D spatially distributed hydrometeors characterized with microphysical properties: mixing ratio, number concentration, and size distribution. The Geostationary Operational Environmental Satellite-9 (GOES-9) imager visible and infrared measurements were used in a new four-dimensional variational data assimilation (4DVAR) mesoscale algorithm for a warm continental stratus cloud system case to test the impact of these observations on the cloud simulation. The new data assimilation algorithm includes the Regional Atmospheric Modeling System (RAMS) with explicit cloud state prediction, the associated adjoint system, and an observational operator for forward and adjoint integrations of the GOES radiances. The results show positive impact of GOES imager measurements on the 3D cloud short-term simulation during and after the assimilation. The impact was achieved through sensitivity of the radiances to the cloud droplet mixing ratio at observation time and a 4D correlation between the cloud and atmospheric thermal and dynamical environment in the forecast model. The dynamical response to the radiance observations was through enhanced large mesoscale vertical mixing while horizontal advection was weak in the case of stable continental stratus evolution.

Although the current experiments show measurable positive impact of the cloudy radiance measurements on the stratus cloud simulation, they clearly suggest the need to further address the problem of negative cloud cover forecast errors. These errors were only weakly corrected in the current study because of the small sensitivity of the visible and infrared window radiances to the cloud-free atmosphere.

1. Introduction

The need for improving observational estimates of the 3D distribution of cloud properties on mesoscales is relevant to a wide range of topics including weather forecasting (Bayler et al. 2000; Wetzel et al. 2001; Chevallier and Kelly 2002), land–atmosphere feedbacks (Freedman et al. 2001), aerosol–cloud interactions (Han et al. 2002), and global climate (Rossow et al. 2002; Weare 2000). Considering the complexity of 3D cloud structure and its close connection to thermodynamic fields and atmospheric motions, it is clear that the challenge of characterizing clouds by observations alone is considerable (Stephens 2002).

Quantitative observations of clouds as well as precipitation are typically obtained by indirect, remote sensing methods (Kidder and Vonder Haar 1995). Although considerable progress has been made in remotely sensing bulk cloud properties (Rossow and Schiffer 1999; Kummerow et al. 1996; Guyot et al. 2000), estimation of the 3D mesoscale state from these observations is just beginning to be addressed (Sun and Crook 1998; B. Wu et al. 2000; Benedetti et al. 2003). Benefits of 3D explicit cloud analysis are potentially large because most cloud properties desired in a wide range of applications could be derived more accurately and more straightforwardly. Examples of these applications are explicit initialization of clouds in NWP, analysis of the vertical distribution of hydrometeors for aerosol–cloud interaction studies, and analysis of the radiative effects of clouds in energy budget computations.

Previous studies on mesoscale cloud estimation from remote sensing have focused on radar measurements (Sun and Crook 1998; Wu et al. 2000; Benedetti et al. 2003). In this study we explore the utilization of visible (VIS) and infrared (IR) satellite radiance measurements. These measurements have the appealing properties of wide spatial coverage, relatively high horizontal resolution, and strong sensitivity to clouds (Chevallier and Kelly 2002; Rossow and Garder 1993). In this approach it is crucial that the cloud state be modeled explicitly as spatially distributed and time-evolving hydrometeors. This cloud state representation is equivalent to a discrete sampling from the true continuous cloud state that nec-
and conclusions are presented in section 6. The results are discussed in sections 4 and 5. The summary is presented in section 3. Data assimilation experiments and sensitivity to the assimilation of Geostationary Operational Environmental Satellite (GOES) imager observations in the case of a warm continental stratus system.

2. 4DVAR algorithm

The RAMDAS algorithm consists of four major components: 1) nonlinear forecast model, 2) observational operators, 3) adjoint of the forecast model, and 4) minimization algorithm.

a. Forecast model

The RAMS is a well-known and well-tested nonhydrostatic, cloud-resolving research model (Cotton et al. 2003). Of greatest interest to this work are the cloud microphysical and turbulent mixing parameterizations, which are briefly described below. Other characteristics of the RAMS can be found in the review paper by Cotton et al. (2003) and the references therein. Clouds and precipitation in RAMS are explicitly predicted via a microphysics parameterization that features a one-moment scheme (mixing ratio) for cloud liquid water (Walko et al. 1995) and a two-moment scheme (mixing ratio and number concentration) for six other hydrometeor types, including pristine ice, aggregates, snow, graupel, hail, and rain (Meyers et al. 1997). The hydrometeor size distribution is approximated by a gamma distribution with a prescribed width. Although a more sophisticated bin microphysics parameterization is also available within RAMS (Feingold et al. 1996) this study utilized the bulk cloud microphysics scheme. Longwave and shortwave radiative fluxes are parameterized using a two-stream model that allows radiative heating to influence the growth of water droplets and ice particle vapor deposition (Harrington et al. 2000; T. Wu et al. 2000). The turbulence parameterization option used in this study is the level 2.5 scheme by Mellor and Yamada (1974).

b. Adjoint model

The adjoint model in RAMDAS is an adjoint of the true tangent linear of the numerical RAMS. The linearization was performed with respect to full model solution at every time step. This means that the reference state for the adjoint integration is saved every time step in the forward forecast model integration. This feature requires large amounts of data storage but ensures highest accuracy of the adjoint solution (Errico et al. 1993). The adjoint in RAMDAS includes all physical parameterizations as in RAMS with the exception of the atmospheric radiation and convective parameterizations. Atmospheric radiation is thought to be of secondary importance for the short-term cloud forecast in the data assimilation. The convective parameterization was not considered because it is typically not used in high-resolution cloud prediction cases.

The accuracy of the adjoint model solution was tested in the standard way by comparing it to the tangent linear model solution. The latter was compared, for a limited number of cases, to the RAMS nonlinear perturbation...
solution. Of importance to the cloudy radiance data assimilation is that the cloud microphysical parameterization performed quasi linearly in short-term forecasts except at a small number of local critical points of regime transition associated with small hydrometeor mixing ratios. This result is similar to Vukicevic and Bao (1998) where a convective parameterization linearization was investigated but in different regional forecast model. The ultimate test of appropriateness of the adjoint model solution in data assimilation is its performance in the nonlinear 4DVAR algorithm. Current results show that the RAMS adjoint provided appropriate information about the cost function gradient. The cost function used in RAMDAS is defined in section 4.

c. Observational operators

Although only GOES imager observations are used by RAMDAS in this study, VISIROO is capable of computing radiances for a wide range of narrowband satellite sensors. A description of VISIROO and its capabilities is given in more detail by Greenwald et al. (2002, 2004). Only a short summary of its principal features is presented here. RAMDAS also includes an observational operator for conventional NWP observations. This observational operator, as well as the corresponding adjoint operator, was adopted from Weather and Research Forecast (WRF) model 3DVAR algorithm (Wu et al. 2001). The conventional NWP data were used in ZVEV.

The VISIROO is a system for forward computing of visible and infrared radiances in both clear and cloudy plane-parallel conditions and for adjoint computations of the sensitivity of these radiances to the input parameters from the forecast model. A schematic of the VISIROO depicting the forward and adjoint models is presented in Fig. 1. The forward part of the operator features two different radiative transfer (RT) models, both of which handle multiple scattering. The first computes radiances at solar wavelengths, called the spherical harmonic discrete ordinate method (SHDOM; Evans 1998), while the other computes infrared radiances using a delta-Eddington approach (e.g., Deeter and Evans 1998). The operator also makes use of anomalous diffraction theory (ADT) to estimate cloud single-scattering (i.e., optical) properties for all types of particles, including nonspherical ones. The clear advantage of ADT is that it makes exploiting various kinds of satellite measurements and accounting for different hydrometeor types predicted by the forecast model easier and more straightforward, as opposed to ad hoc lookup table methods based on more exact but time-consuming calculations. Extinction by gases is computed from the Optical Path Transmittance (OPTRAN) method (McMillin et al. 1995). The VISIROO has been verified against GOES imager data for a forecasted continental stratus system in Greenwald et al. (2002).

d. Minimization

The minimization algorithm in RAMDAS is the limited memory quasi-Newton algorithm of Nocedal (1980), with the restart procedure of Shanno (1985) modified by Zupanski (1996). Empirical Hessian preconditioning is employed, reducing the satisfactory number of minimization iterations to about 10. The control vector is defined in terms of the potential temperature, the Exner perturbation function, vertical wind, velocity potential, streamfunction, total water mixing ratio, cloud hydrometeor mixing ratios, and number concentrations. Additional features of the minimization algorithm in RAMDAS are described in ZVEV.

3. Case study and model forecast

This work continues that of previous analyses of a warm continental stratus simulation with RAMS (Greenwald et al. 2002) and the associated VIS and IR radiance sensitivity study (Greenwald et al. 2004). The GOES-9 imager observations indicated a large low-level stratus deck in early May 1996 over the south-central United States that was persistent over several days with a minimal presence of high clouds. These conditions made the case ideal for the study of stratus from the satellite remote sensing. Figure 2 shows GOES-9 visible images of this cloud system.

In Greenwald et al. (2002, 2004) the continental stratus was simulated using a two-way nested grid configuration in RAMS with 5-km fine-spacing inner grid, 25-km coarse-spacing outer grid, 50-m vertical grid spacing in the boundary layer, and a total of 50 vertical layers up to 17 km. The vertical grid was the same for both horizontal grids. Only liquid phase of the bulk cloud microphysical parameterization in RAMS was used in the simulations, sufficient for simulating the warm stratus. Greenwald et al. (2002) demonstrated that for the inner grid the forecast model is capable of highly realistic simulation of this cloud deck including the distribution of cloud mass and its evolution over time.

A nested grid capability was not available in the RAMDAS adjoint model; neither was it possible to per-
form high-resolution simulations in the outer, large domain because of computational limitations. These constraints required that the warm stratus forecast in the data assimilation experiments be performed over only a short period of 3 h and using the coarse grid resolution in the large domain (Fig. 3). To preserve forecast skill from the high-resolution experiments in Greenwald et al. (2002), the model is first integrated in the nested grid configuration for the period 0000–1200 UTC, after which only the coarse grid was advanced for the remaining 3 h. This period (1200–1500 UTC) is then used in the data assimilation experiments. Utilization of reduced grid resolution in the data assimilation simulations relative to the desired forecast resolution is not unusual. It is used successfully in the European Centre for Medium-Range WeatherForecasts (ECMWF) 4DVAR system (Rabier et al. 2000) to lessen the computational burden while taking care that the phenomena of interest are simulated with sufficient skill within the assimilation period.

The coarse-resolution simulation during 1200–1500 UTC placed the stratus in the correct general area (framed subdomain in Fig. 3 to be compared to the equivalent in Fig. 2a), but the cloud cover is overpredicted in central and northeast Texas and underpredicted in south Texas and in Oklahoma. The mean forecast error in terms of brightness temperature corresponding to the imager’s IR window channel (channel 4) over the area with model stratus was, however, only $0.7 \text{ K}$, implying a skilled forecast in the cloud deck’s height and thermal structure of the boundary layer. Standard deviation around this mean was 3.5 K. The coarse-resolution forecast skill did not result only from the preceding high-resolution forecast, because the inner grid in Greenwald et al. (2002) included only half of the stratus cloud cover indicated in Figs. 2 and 3. Other clouds in the integration domain in Fig. 3 were not considered in the data assimilation experiments because the focus was on the observed warm stratus system. The short data assimilation period and slow advection associated with the featured stratus provided favorable conditions for this approach.

The success of the low-resolution short-term simulation in the current study is not to be interpreted as
suggesting that low-resolution grids for mesoscale cloud state estimation be utilized in general. It is unlikely that a horizontal grid spacing of 25 km could support successful simulations of bulk cloud microphysical processes in most cases. The current result simply shows that for the case under study the low-horizontal-resolution integration was sufficiently skillful for the purpose of initial testing of the cloudy radiance assimilation method in RAMDAS.

4. Data assimilation experiments

Greenwald et al. (2004) found that solar radiances at 0.63 and 3.92 μm corresponding to channels 1 and 2, respectively, of the GOES imager contain potentially the most information about warm stratus structure. There is also information from window IR radiances (10.7 μm; GOES imager channel 4), but it is confined to optically thinner clouds. For example, at 0.63 μm the sensitivity is greatest near cloud top where the mixing ratio is a maximum, but also extends deep within the cloud layer. Although radiances at 3.92 μm also provide important information, they are not considered in this study since they are more difficult to interpret because both scattering of solar radiation and thermal emission are included. Thus, only data from the 0.63-μm (VIS) and 10.7-μm (IR) channels of the imager were selected for the current data assimilation experiments.

a. Cost function

The cost function used in the experiments is

\[ J = \frac{1}{2}(Hx_t - y_t)^T R^{-1}(Hx_t - y_t) + \frac{1}{2}(x_0 - x_t)^T B^{-1}(x_0 - x_t) + \epsilon_t^T E^{-1} \epsilon_t + GWF, \]

where \( H \) denotes the VISIROO forward radiance operator; \( x_t \) is the model forecast vector at time \( t \) (presented in Fig. 1); \( y_t \) is observation vector at time \( t \) in units of reflectance, for the VIS wavelength or units of degrees kelvin for IR brightness temperature; \( x_0 \) is the model initial condition vector; \( x_b \) is the background (i.e., the guess) value of the initial condition; and \( \epsilon_t \) is the model error at time \( t \). The matrices \( R, B, \) and \( E \) are observation, background, and model error covariances, respectively. The term GWF represents a digital filter penalty for the high frequency waves; \((\cdot)^T\) denotes the transpose of a vector, and \((\cdot)^{-1}\) the inverse of a matrix. The definitions of \( B, E, \) and GWF are presented in ZVEV. The observation error covariance for VIS and IR was assumed diagonal with variances \( \sigma_{\text{vis}}^2 = 0.01 \) and \( \sigma_{\text{IR}}^2 = 1.0 \), respectively.

b. Assimilation of one-grid-box observations

To test the interactions between the model forecast of cloud and its environment and the satellite observations in a controlled manner, we first performed experiments with observations being available over only one grid box of the model. The GOES observations were averaged from about a 5-km footprint to the model coarse grid (25 km²). The grid box with the observations was chosen at the edge of the model cloud in central Texas at 1500 UTC where the cloud was present in the model but not in the observations (shown as a star in Fig. 3). The brightness temperature difference between the model and the observation was −2.4 K at this location. The experiments are labeled IR_lob and VIS_lob, for the IR and VIS observation, respectively.

In the 3-h assimilation window, the cost function was reduced significantly after only a few iterations in both experiments (Fig. 4). Specifically, in the VIS_lob experiment the cost function dropped to 20% of its original value after only two iterations and then remained constant. In the IR_lob experiment the cost function was reduced to 1% of the original value after only three iterations. This result is due to the efficient elimination of thin cloud in the assimilation (Fig. 5) after which the sensitivity of the cost function at the observation time to atmospheric variables at the VIS wavelength was reduced to exactly zero (Fig. 6a) and to very small values in the IR experiment (Figs. 6b and 6d). The cost function gradient in temperature is reduced to zero so rapidly in the VIS_lob experiment (Fig. 6a) because the sensitivity of water vapor absorption (which in turn is sensitive to temperature) at 0.63 μm is negligible. Water vapor absorption also occurs at 10.7 μm but the sensitivity to both temperature and water vapor is weak, as expected (Figs. 6b and 6d, respectively). This result implies that the negative cloud cover forecast errors (i.e., the cloud present in the observations but not in the forecast) cannot be readily reduced with local VIS or IR observations, at least for measurements in spectral windows.

To improve the cloud data assimilation results over
clear and cloudy points within an area, all of the IR and VIS observations should be used. This approach has the limitation of relying on the 4DVAR algorithm to generate sufficient changes in the cloud environment to create conditions for cloud formation in places where the original cloud cover forecast error was negative. The amplitudes of the changes in the environment would depend, by definition, on the amplitudes of model forecast errors at the observation time and spatial and temporal correlations derived from a combination of background error statistics and the model-dependent 4D correlations between the cloudy and clear points. Correlations of this kind are not yet well understood. The purpose of the current study is to contribute to this area of research by first testing the potential of using a 4DVAR algorithm with cloud-sensitive satellite observations and an explicit cloud prediction model.

The negative cloud cover errors could be addressed by using other independent satellite observations that are sensitive to temperature and humidity in both clear and cloudy conditions. It is important to emphasize that VIS and IR imager data have never been used before in radiance data assimilation and it is therefore necessary to first understand their impact on cloud forecasts in isolation.

The VISIROO is also sensitive to the land surface conditions such as skin temperature and surface reflectance. Sensitivity to surface boundary conditions dominates in clear skies, as expected, but the surface parameters were intentionally not included in the set of control variables. Our approach was that the land surface
data assimilation is a challenging research area unto itself and was outside the scope of the current study. Excluding the land surface adjustment also derives from the condition that the stratus evolution is decoupled from the surface in the short-term forecast.

The dynamical response in the lower troposphere to the VIS and IR observations is of primary interest in this study because the atmospheric processes there can effectively influence the short-term forecast. Indeed, the atmospheric column warmed (Fig. 7a) and dried (Fig. 7b) in the inversion layer above the cloud in the assimilation. The process by which this happens was increasing the mesoscale mixing above the cloud top (shown in the next section). The dynamical changes caused by the introduction of the observations at the end time were actually produced by propagation of changes in the initial condition in a neighborhood of the observation point 3 h earlier. Similar results were achieved for both the IR,lob and VIS,lob experiments. In the next section we describe the assimilation of multiple GOES observations within the area of the modeled stratus cloud system.

c. Regional cloudy IR data assimilation

Similarity between the VIS,lob and IR,lob results suggested that only one of these measurements need be used for further analysis in the low-resolution liquid cloud case. The IR 10.7-μm data were chosen for the multipoint experiment because it was computationally more efficient [i.e., the adjoint of the delta-Eddington model is significantly less expensive than the adjoint of SHDOM; described in Greenwald et al. (2004)]. The GOES imager data were used only over cloudy points corresponding to the background stratus forecast at 1500 UTC (Fig. 3). The cost function was limited to these points (a total of 406 points) because the sensitivity of VISIROO to the atmosphere at clear-sky points in the model is very small, as discussed in the previous section. The cost function was computed in the exact same locations at each iteration in the 4DVAR, implying that the clear-sky points in the forecast were used after the starting iteration in locations where the cloud was cleared because of the assimilation. The multipoint experiment is labeled IR_cld.

The normalized cost function reaches a minimum after only four iterations (full curve in Fig. 4) with an amplitude of 77% of the starting value. Although this decrease in the cost function is relatively small, it is associated with a very small area mean average forecast error in the brightness temperature of only ∼0.2 K. The area for mean error computation is the same as used in the cost function, that is, over the model stratus before the assimilation. The mean error is much smaller than the assumed standard deviation for the observation error (1.0 K). The main effects of assimilation on the cloud forecast are to the cloud cover and cloud physical thickness. Cloud cover was significantly reduced in northeast Texas, slightly reduced in central Texas, and slightly enhanced in the southwest corner (Fig. 8). These changes produced cloud cover similar to the observations in Fig. 2. Cloud thickness was increased in the central portion of the cloud; however, we did not have the means of verifying this result beyond the reduction in brightness temperature and its error. Other cloudy areas in the integration domain were not changed by the assimilation, although the entire model domain was included in the data assimilation integrations. This is a consequence of local influence by the IR observations when there is weak horizontal advection over a short-term forecast.

Changes in the forecasted temperature and total water mixing ratio were warming and drying, respectively, where the cloud was reduced and cooling and moistening where it was enhanced. Examples of these changes are presented in Fig. 9 for the model level corresponding to the top of the modeled stratus (990 m above ground). The amount of local warming and cooling was equivalent to the strength of the temperature inversion in the model planetary boundary layer (PBL), which was about 5 K at maximum. An example of the change
in the potential temperature vertical profile in the assimilation is shown in Fig. 10a for a point where warming and cloud removal occurred in the assimilation. The temperature change in the vertical agrees with the dynamical response mechanism in the model during the assimilation (Fig. 11). In the warming areas, mixing increases in the lower troposphere across the inversion layer with subsidence causing a dissipation of the cloud (Figs. 11c and 11d). In the cooling areas, on the other hand, an increase in lifting of moist air from the cloud base (cf. Figs. 11a and 11b) causes the temperature to decrease and results in a local moistening of the atmosphere above to produce cloud enhancement.

It is interesting to note that the local atmospheric temperature adjustment in Fig. 10a where the cloud is removed from the forecast is of the opposite sign from the sensitivity of VISIROO to the temperature in the same local point (Fig. 10b). This shows that local sensitivity of the IR cost function to the atmospheric temperature would not only be ineffective because of the small amplitude but would imply a negative rather than positive change in temperature at the cloudy points to correct the brightness temperature to the observation. This result demonstrates the difficulty of designing an algorithm for simultaneous column retrievals of the cloud and its thermodynamic environment using only the IR or VIS GOES imager measurements and suggests that additional satellite temperature sounding data would be beneficial.

The initial condition increments that caused the change in the forecast were almost one order of magnitude smaller than the forecast increments at the final time (cf. Fig. 12 with Fig. 9). The distribution of increments in the initial time was more localized for the total water mixing ratio than for temperature because of assumed error correlation lengths in RAMDAS. Comparison of positive and negative patterns of increments between the initial and final times suggests weak to no influence of the horizontal advection in the adjustment process for this case study.

5. Forecast verification

To verify the impact of the data assimilation on the forecast, the model was integrated for a 3-h period after the assimilation (1500–1800 UTC) using the coarse-resolution grid. Cloudy GOES-9 visible reflectances and IR brightness temperature data were used for verification, as before. The new model forecast starting from
the end of assimilation period only slightly improved the cloud cover in east-central Texas and southeast Oklahoma relative to the old forecast without assimilation (Figs. 13a and 13b). The observed VIS image for 1800 UTC is shown in Fig. 2b. Both forecasts captured the dissipation of the cloud system in northeast Texas but underpredicted the dissipation in the southwest and the persistence of the cloud in the south.

Mean brightness temperature forecast errors at 1800 UTC within the region used for the cost function in the assimilation was $-4.5$ and $-4.1$ K in the old and new forecasts, respectively. These values are much larger than errors at 1500 UTC, which were only $-0.7$ and $-0.2$ K for the forecast before and after the assimilation, respectively. This was mainly the consequence of cloud overprediction in southwest Texas in both forecasts, where the observed cloud dissipated rapidly. To verify this, a conditional mean error was computed excluding all points that had larger than 10-K differences between the model and observations (i.e., cloud in the forecast but not in the observations). This conditional mean error was $-0.5$ and $+0.1$ K for the old and new forecasts,

![Diagram](image1)

**Fig. 10.** As in Fig. 7, except for the (a) IR<sub>cld</sub> experiment and (b) profile of the cost function gradient to temperature at the observation point.

![Diagram](image2)

**Fig. 11.** Streamlines in vertical cross sections, marked in Fig. 9, at 1500 UTC for the (a), (c) guess forecast and (b), (d) analysis forecast. The C–D cross section is shown in (a) and (b), and the A–B cross section is shown in (c) and (d). Arrows indicate where the cloud was enhanced [(b)] and removed [(d)] in the IR<sub>cld</sub> assimilation experiment.
Fig. 12. (a) Total water mixing ratio and (b) potential temperature differences between guess and analysis at the initial time for the model level at 900 m. Contour interval is $10^{-6}$ kg kg$^{-1}$ with maximum absolute value of $4 \times 10^{-6}$ in (a) and $10^{-2}$ K with maximum absolute amplitude of $7 \times 10^{-2}$ in (b). Dashed contours represent negative, and solid contours indicate positive values.

respectively, at 1800 UTC, indicating that the new forecast was better where the cloud cover was correct. The problem of cloud over- and underprediction in the south was associated with the persistence of the lateral boundary inflow that forced a dryline in this region too far to the west (not shown). The data assimilation could not correct the lateral boundary condition error in the forecast after the assimilation period.

6. Summary and conclusions

We present a study of visible and infrared cloudy radiance data assimilation with a cloud-resolving mesoscale model using a new 4DVAR algorithm, designated the Regional Atmospheric Modeling and Data Assimilation System (RAMDAS). The algorithm was applied to a case of warm stratus evolution. The following are the main conclusions from the numerical experiments:

- Visible (0.63-μm wavelength) and IR (10.7-μm wavelength) observations positively influenced the model cloud forecast in the assimilation but only through the sensitivity to cloudy points in the model because the cost function of these observations is only weakly sensitive to atmospheric parameters.

Fig. 13. As in Fig. 3, except for the forecast at 1800 UTC: (a) initialized without the assimilation, and (b) initialized after the assimilation in the 1200–1500 UTC period.
• Negative cloud cover error (model − observed) was weakly reduced and only when a large number of observation points was used, causing dynamical correlations between the initial conditions and the observations through a combined influence of the non-linear forecast and adjoint integration in the 4DVAR algorithm.
• The dominant mechanism responsible for correlating the observations and initial conditions for the case of warm status over the short term (3 h) was large mesoscale vertical mixing. The warming and drying of the atmosphere within the cloud was associated with increased subsidence of warm air in the inversion layer, while lifting from near the cloud base caused moistening, cooling, and cloud enhancement near the cloud top. The lifting did not penetrate as deep as the subsidence.
• The cloud forecast in the assimilation was improved in cloud cover and in IR brightness temperature when compared to the GOES-9 measurements. The area average error in the brightness temperature at the end of the assimilation was only −0.2 K.
• The 3-h cloud forecast in IR brightness temperature after assimilation was also improved where the cloud cover was correct, but this forecast had significant cloud cover errors in one portion of the domain, similar to the control forecast. This regional cloud cover error appeared to be linked to the lateral boundary condition error and could not have been improved by improved initial conditions.

In summary, the current results show that the 4DVAR assimilation of VIS and IR radiance observations with explicit prediction of bulk cloud microphysics provides a good framework for the study of cloudy atmospheric state estimation at mesoscales, because of the observation’s strong sensitivity to cloud microphysical quantities and the explicit dynamical linking between the cloud and environment. More research is needed, however, to address improving negative cloud cover forecast errors. In the current implementation this error is only weakly improved by way of model-based temporal and spatial correlations between the cloudy and clear-sky points in the forecast. This condition could potentially lead toward a bias in the cloud cover where the clouds would be adjusted to observations mostly where the cloud cover error is positive or zero.

Minimization of the negative cloud cover errors might be addressed by including other observations sensitive to local temperature and humidity to further constrain the solution and by devising means to locally correlate observed cloudy radiances with environmental variables within the observational operator when the forecast does not produce the cloud. The additional observations should come primarily from satellite remote sensing for general solution of the problem because most other observation sources are either too sparse (e.g., ground-based meteorological measurements) or limited in spatial extent (e.g., radar measurements). However, non-satellite observations should be used when and where available.

The goal of atmospheric and cloud state estimation research is to determine a sufficient set of observations for a given problem. This can be achieved only by systematic study of the information content in experimentation with data assimilation techniques. RAMDAS was developed for this purpose and will continue to be tested and implemented with other satellite observations in the future in the cloudy state estimation problem.

Acknowledgments. This study was supported by the DoD Center for Geosciences/Atmospheric Research at Colorado State University under the Cooperative Agreement DAAL01-98-2-0078 with the Army Research Laboratory and partially by the National Science Foundation Grant DEB-9977066.

REFERENCES
Harrington, J. Y., G. Feingold, and W. R. Cotton, 2000: Radiative


