Data Assimilation of Cloud-Affected Radiances in a Cloud-Resolving Model

ROSANNE POLKINGHORNE
University of Colorado, Boulder, Colorado

TOMISLAVA VUKICEVIC
NOAA/Atlantic Oceanographic and Meteorological Laboratory, Miami, Florida

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ABSTRACT

Assimilation of cloud-affected infrared radiances from the Geostationary Operational Environmental Satellite-8 (GOES-8) is performed using a four-dimensional variational data assimilation (4DVAR) system designated as the Regional Atmospheric Modeling Data Assimilation System (RAMDAS). A cloud mask is introduced in order to limit the assimilation to points that have the same type of cloud in the model and observations, increasing the linearity of the minimization problem. A series of experiments is performed to determine the sensitivity of the assimilation to factors such as the maximum-allowed residual in the assimilation, the magnitude of the background error decorrelation length for water variables, the length of the assimilation window, and the inclusion of other data such as ground-based data including data from the Atmospheric Emitted Radiance Interferometer (AERI), a microwave radiometer, radiosonde, and cloud radar. In addition, visible and near-infrared satellite data are included in a separate experiment. The assimilation results are validated using independent ground-based data. The introduction of the cloud mask where large residuals are allowed has the greatest positive impact on the assimilation. Extending the length of the assimilation window in conjunction with the use of the cloud mask results in a better-conditioned minimization, as well as a smoother response of the model state to the assimilation.

1. Introduction

Information regarding clouds and their role in the atmospheric system is important on a wide spectrum of scales from regional weather to global climate. Quantitative observations of clouds are typically obtained by indirect remote sensing methods (Kidder and Vonder Haar 1995). Although considerable progress has been made in remotely sensing and retrieving bulk cloud properties, complex 3D cloud structure and its connection to thermodynamic fields and atmospheric motions on small spatial scales is not well specified from observations alone (Stephens and Kummerow 2007). Cloud-resolving models (CRMs) are used to study the spatial and temporal variability patterns of clouds and their environments (Khairoutdinov and Randall 2003).

The cloud fields produced by CRMs in a given case cannot be easily compared with observed cloud fields because the initial and boundary conditions are not available on cloud-resolving scales. This leads to a modeled state that, while physically realistic, is not consistent with the observed clouds from the specified case. To improve the modeled representation, observations should be combined with the model results such that the observations optimally constrain the model solution in an approach known as data assimilation (Kalnay 2003; Lewis et al. 2006; Evensen 2006).

Relatively few studies have been carried out on the assimilation of cloud and precipitation data. At this point, much more effort has been given to the assimilation of precipitation observations because more quantitative precipitation data are available from surface networks and satellite retrieval algorithms. Several works have been undertaken to investigate the impacts of assimilating microwave brightness temperatures versus rainfall (Moreau et al. 2004) as well as to examine the sensitivity of the precipitation to the initial conditions (Mahfouf and Bilodeau 2007). A few studies have been carried out to define the error covariances of clouds and precipitation (e.g., Moreau et al. 2003; Amerault and
Zou 2006; Sun and Zhang 2008). At a few operational centers, including the U.S. Centers for Environmental Prediction, the Japan Meteorological Agency, and the European Centre for Medium-Range Weather Forecasts, precipitation data are assimilated within an operational context (Errico et al. 2007a).

A recent study by Polkinghorne et al. (2010), in which a large set of cloud-resolving model simulations was evaluated using the GOES and ground-based remote sensing observations, estimated a background error decorrelation length for use in cloud data assimilation, as well as parameters for the quality control in radiance space that includes a cloud classification and the expected difference in brightness temperatures between the model radiation to be seen in conjunction with the radiation from the cloud. Additionally, the model used to retrieve the desired information from the remotely sensed quantity is subject to assumptions and errors, leading to further biases in the retrieved quantity.

Another difficulty lies in the nonlinearity of moist processes. This can lead to a multimodal cost function (Errico et al. 2000). The minimum of the cost function found by the minimization scheme is therefore likely to be a local minimum depending on where the iterative solution begins (Errico et al. 2007a). Finding the global minimum of the cost function is then very computationally expensive due to the large number of iterations required to explore the global structure of the cost function. Additionally, this nonlinearity can lead to spurious noise in the adjoint of the forecast model, leading to numerical instability. There is also no adjoint sensitivity where clouds do not exist in the model, resulting in an inability to create cloud that exists in the observations but not the model. This is a serious drawback in cloud-affected data assimilation because it limits the ability to correct model location errors.

Studies by Vukicevic et al. (2004, 2006) investigate the direct assimilation of Geostationary Operational Environmental Satellites (GOES) Imager infrared (IR) observations into a mesoscale atmospheric model with parameterized cloud microphysics. The results from these studies show that three-dimensional cloud fields consistent with the dynamical atmospheric environment and cloud observations could be obtained by assimilation of geostationary infrared satellite measurements.

However, these studies indicate that the assimilation results are sensitive to parameters in the data assimilation system that are not well known for the cloud-resolving scales. The assimilation parameters of primary interest are 1) background error decorrelation length for water variables (hydrometeors and water vapor), 2) length of the assimilation window, 3) criteria for selecting a subspace of observations that is within a range of acceptable differences from the model background, and 4) cloud-resolving model errors. The criteria for selecting the observation subspace are commonly referred to as quality control in the observation space, where the quality measure relates to the likelihood of the cloud-resolving model background information relative to the observations.
and the observations in different cloud scenarios. In the current study the impacts of these estimates on the data assimilation results are evaluated. In addition, the sensitivity to the length of the assimilation window is tested using the new quality control and background error decorrelation length. Prior assimilation experiments with the cloud-affected GOES infrared brightness temperatures in the Vukicevic et al. (2006) study showed significant degradation of the assimilation results from lengthening the assimilation window beyond 1 h, due to the negative impacts of lateral boundary conditions in the small integration domain used for the experiments. In the current study a relatively large integration domain (but still limited by computational constraints) is used to ensure a more realistic test of the impacts of a longer assimilation window while also using a more realistic data assimilation configuration with the improved quality control, background error decorrelation estimates, and higher spatial resolution in the model.

Although important, the impacts of including an explicit representation of the cloud-resolving model error in the data assimilation are not tested in the current study. The results from the Vukicevic et al. (2006) study indicate that a simple linear representation of the model error that has been used successfully in other data assimilation studies not focusing on the cloud variables is not suitable for cloud data assimilation. Design of a more suitable model error representation would require extensive experimentation that is beyond the scope of the current study and will be addressed in the future.

The goal of this study is to demonstrate the expected positive impacts of the assimilation of cloud-affected infrared radiances in a cloud-resolving model. The impacts of several parameters including a dynamic cloud mask for improving the linearity of the problem are demonstrated. We hope to identify those parameters to which the assimilation is most sensitive in order to elucidate areas that need further study for better optimization of the cloudy assimilation problem.

The outline of this paper is as follows. Section 2 describes the data assimilation system as well as the data used in the study. The case studies, background model forecasts, and data assimilation experiments are detailed in section 3, followed by an analysis of the results in section 4. A summary and conclusions are presented in section 5.

2. Data assimilation system and observations
   a. Data assimilation system

The four-dimensional variational data assimilation (4DVAR) system designated as the Regional Atmospheric Modeling Data Assimilation System (RAMDAS) is used in this study. The RAMDAS algorithm consists of four main components: the nonlinear forecast model, the observational operators, the adjoint of the forecast model, and the minimization algorithm (Zupanski et al. 2005).

The forecast model in the system is the Regional Atmospheric Modeling System (RAMS), version 4.1, which is a nonhydrostatic, cloud-resolving research model developed at Colorado State University (Cotton et al. 2003). In this model, clouds and precipitation are explicitly predicted using 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, hail, rain, snow, and graupel (Meyers et al. 1997). Since the number concentration of cloud liquid water is not computed in the model, it is set to be $1.7 \times 10^3$ kg m$^{-3}$ (depending on air density, equivalent to about $187$ cm$^{-3}$) where the cloud liquid water mixing ratio is greater than zero, as in Greenwald et al. (2002). The model initial state and boundary conditions are interpolated to the model grid from National Centers for Environmental Prediction (NCEP) final analysis (FNL) data (information online at www.ncdc.noaa.gov).

The primary observation operator is a system for computing nonpolarized radiative transfer for either collimated solar and/or thermal emission sources of radiation in both clear and cloudy plane-parallel conditions, known as the Spherical Harmonic Discrete Ordinate Method Plane Parallel for Data Assimilation (SHDOMPPDA; Evans 2007). SHDOMPPDA is similar to the Spherical Harmonic Discrete Ordinate Method (SHDOM; Evans 1998), with the main difference between the two being that SHDOM is for 3D radiative transfer, while SHDOMPPDA is 1D. This model has been well tested and has been demonstrated to be accurate (Evans 2007).

The RAMS adjoint is an adjoint of the true tangent-linear model of the RAMS discrete algorithm (Zupanski et al. 2005). The linearization is performed with respect to a full model solution every 20 time steps, or every 5 min of model time with a 15-s time step. This means that the reference state for the adjoint integration is saved every 20 time steps in the forward forecast model integration. Although saving the reference state more frequently would improve the accuracy of the adjoint solution (Errico et al. 1993), doing so requires a prohibitive amount of data storage. The adjoint in RAMDAS includes all physical parameterizations as in RAMS, with the exception of the atmospheric radiation and the convective parameterizations. Atmospheric radiation is thought to be of secondary importance for the short-term cloud forecast. The convective parameterization is not considered, as it is rarely 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 (Vukicevic et al. 2004).

The minimization algorithm implemented in RAMDAS is the limited-memory quasi-Newton algorithm of Nocedal (1980), with the restart procedure of Shanno (1985) and modified by Zupanski (1996). To reduce the number of iterations necessary for convergence of the cost function, empirical Hessian preconditioning as described in Zupanski et al. (2005) is employed. The control vector used in this study is described in terms of the initial conditions for the perturbation Exner function, potential temperature, velocity potential, streamfunction, total water mixing ratio, and pristine ice mixing ratio.

b. Cost function

The cost function used in the experiments is computed as

\[
J = \frac{1}{2}(x_0 - x_h)^T B^{-1}(x_0 - x_h) + \frac{1}{2} \sum_{i=1}^{n} [H(x_i) - y_i]^T R^{-1}[H(x_i) - y_i],
\]

(1)

where \(x_0\) is the model initial condition vector, \(x_h\) is the background (i.e., the guess) initial condition vector, and \(B\) is the background error covariance matrix. In addition, \(H\) is the SHDOMPPDA forward observation operator, \(x_i\) is the model state at time \(i\), \(y_i\) is the observed radiances at time \(i\), and \(R\) is the observation error covariance matrix. Also, \(R\) is defined as a diagonal matrix, with the variances used for each instrument and channel presented in Table 1.

The background error covariance matrix is defined as described in Zupanski et al. (2005) by a variance and correlation matrix:

\[
B = B_D^{1/2} W C_C^T W^T B_D^{1/2},
\]

(2)

where \(B_D\) is the variance (e.g., diagonal), \(W\) is a linear interpolation from control variable space to model space, and \(C_C^T\) is the correlation matrix defined in the control variable space. The square-root correlation matrix \(C\) is a block-diagonal matrix, with each block representing autocorrelation of a particular control variable component. Each block of \(C\) is also a symmetric band Toeplitz matrix. The bandwidths \(d\), \(f\), and \(g\) in the \(x\), \(y\), and \(z\) directions then correspond to

\[
d = \frac{l_x}{2\Delta x}; \quad f = \frac{l_y}{2\Delta y}; \quad g = \frac{l_z}{2\Delta z},
\]

(3)

where \(l_x\), \(l_y\), and \(l_z\) denote the decorrelation lengths of the matrix \(CC^T\) in the \(x\), \(y\), and \(z\) directions, respectively, and \(\Delta x\), \(\Delta y\), and \(\Delta z\) denote the grid spacing in the \(x\), \(y\), and \(z\) directions. The horizontal decorrelation length is computed by averaging the autocorrelation of the residuals over several cases, as described in Polkinghorne et al. (2010). The vertical profile of the variances is modeled using exponential functions as described in Zupanski et al. (2005).

The second term on the right-hand side in Eq. (1) is evaluated using the quality control procedure in observation space that makes use of the cloud classification scheme and a prescribed maximum residual (described in the next section). This quality control process effectively results in a horizontal mask with values of 0 or 1 on the forecast model grid, which is then applied when computing the observation cost function.

c. Cloud classification and quality control

The GOES satellite brightness temperature and visible reflectance are used to identify the type of cloud present in the observations and the model background using a simple threshold-based cloud identification scheme. This cloud classification identifies pixels as high cloud (above 5 km), low cloud (below 5 km), or clear and is described in Polkinghorne et al. (2010). In that study the relatively simple cloud classification suitable for assimilation of cloud-affected GOES radiance data is validated against high-resolution (in time and vertical direction) ground-based cloud radar observations. The results show about a 20% error primarily caused by misclassification of the low clouds and clear conditions during nighttime periods and by the presence of thin high clouds, which are classified as low because of warm brightness temperatures. This level of error is acceptable for the purposes of this study as the error in the background forecast is significantly larger on average under all cloudy conditions.
d. Observations

Due to the high spatial and temporal resolutions (4-km horizontal resolution, approximately every 30 min) of the GOES Imager datasets available in the Atmospheric Radiation Measurement (ARM) archive, channels 1 (0.63 \textmu m), 2 (3.9 \textmu m), 4 (10.7 \textmu m), and 5 (12.0 \textmu m) are assimilated (Menzel and Purdom 1994). Data from the GOES-8 satellite are used in this study. In addition, ground-based data from four different instruments at five ARM sites are used as an independent data source with which to verify the analysis. These locations include the central facility near Lamont, Oklahoma (C1); and four boundary facilities: Hillsboro, Kansas (B1); Vici, Oklahoma (B4); Morris, Oklahoma (B5); and Purcell, Oklahoma (B6).

At each of these five locations, infrared radiances from four microwindows of the Atmospheric Emitted Radiance Interferometer (AERI) (Knuteson et al. 2004) are calculated. The wavenumber ranges of the four microwindows, 830.0–834.5, 898.5–904.7, 1095.0–1098.2, and 1231.3–1232.2 cm\(^{-1}\), are chosen from those in Turner et al. (2003). These zenith-viewing infrared radiances are mostly sensitive to cloud temperature and optical depth (for ice clouds).

Radiances from the microwave radiometer (MWR; Morris 2005) at each of the five ARM sites considered here are used at 23.8 and 31.4 GHz. Zenith-pointing cloud radar reflectivities at 35 GHz obtained from the Millimeter Cloud Radar (MMCR; Moran et al. 1998) are used at the central facility to determine cloud boundaries. The Actively Remotely Sensed Cloud Locations Process (ARSLCP) product (Clothiaux et al. 2001) is used. Radiosonde data, available from launches typically made twice a day at the central facility, provide temperature and humidity profiles.

SHDOMPPDA is used in the calculation of simulated radiances for the selected GOES Imager satellite channels. It is also used in a form modified to produce bottom of the atmosphere rather than top of the atmosphere radiances to simulate AERI brightness temperatures using four computational streams. The operator used to simulate brightness temperatures in the microwave part of the spectrum executes the radiative transfer integration for a purely absorbing atmosphere. The radiosonde profile is simulated by averaging the model temperature and relative humidity over the pressure surrounding each RAMS level. This operator also follows the sonde drift, in that it compares the RAMS grid point closest to the sonde as it ascends. The optical and scattering properties for each of the above-mentioned radiative transfer calculations are stored in precomputed tables. The closest RAMS column to each instrument is used.

3. Data assimilation experiments

a. Cases and model forecast

Two case studies are performed. In the first case study, the RAMS forecast model simulates 1100–1210 UTC 21 March 2000. The simulation is centered on the ARM central facility in Oklahoma. The simulation is initialized with FNL data at 0000 UTC 21 March 2000 and run forward in time for 11 h to ensure that the model state has spun up sufficiently to represent the cloudy atmospheric state. The GOES-8 observations indicate the presence of both stratus and cirrus clouds in the domain, as shown by the channel 4 brightness temperatures presented in Fig. 1a. The model is run on a 125 \times 125 \times 84 grid with a horizontal grid spacing of 4 km, using a 15-s time step to produce both cirrus clouds and stratus clouds, although the cirrus clouds are much thinner than observed. This is clearly seen in the much warmer brightness temperatures shown in Fig. 1b than those in Fig. 1a.

In the second case study, the RAMS forecast model simulates 2000–2110 UTC 28 March 2000 over the same domain with the same model grid and time step as in the first case study. The model state is initialized with FNL data at 1200 UTC 28 March 2000 and run forward in time for 8 h in order to ensure that model state is spun up. This case has only cirrus clouds and no stratus, as seen in the GOES channel 4 brightness temperatures presented in Fig. 2a. The forecast model simulates the presence of some of the cirrus clouds. As in the first case study, these ice clouds are again much thinner than observed, as shown by the simulated GOES channel 4 brightness temperatures in Fig. 2b. The purpose of this case study is both to verify the findings of the first case study, as well as to see the effects of adding visible and near-IR data to the assimilation.
b. Experiment design

Six main experiments are performed in addition to the control experiment for each case study as follows.

1) CONTROL EXPERIMENT

In each case study, GOES channels 4 and 5 are assimilated at three times during the assimilation window of 1 h and 10 min. In the first case study, the data are assimilated at 1109, 1139, and 1210 UTC and in the second case study they are assimilated at 2018, 2039, and 2110 UTC. A simple quality control procedure is applied excluding grid points where the difference between the model and observations is more than 50 K. In addition, the 10 grid points closest to the boundary are excluded from the assimilation to avoid generating spurious boundary effects. The background error decorrelation length for water variables is set to be 50 km, as in Vukicevic et al. (2004).

The quality control process applied here is a simple method used to increase the linearity of the assimilation problem; it is assumed that the algorithm will not be able to produce changes larger than 50 K without developing a numerical instability. The threshold of 50 K is substantially larger than that used in other data assimilation systems that do not assimilate cloud-affected radiances (i.e., Kopken et al. 2004). However, it has been shown that a small change in cloud mixing ratio leads to a large change in brightness temperature (Vukicevic et al. 2006). Therefore, a threshold of 50 K has been chosen for use in this experiment.

2) EXPERIMENT ONE

The impacts of a more sophisticated quality control routine are tested. The cloud mask is applied to classify the observations as high cloud, low cloud, or clear. Only grid points that are classified as high cloud in both the model and observations or clear in both the model and observations are considered in the assimilation. The maximum-allowed residual for clear points is set to 10 K. Four experiments are performed with the first case study (EXPs 1a–1d) where the largest accepted residual for points that have high cloud in both the model and observations is varied from 20 to 50 K by intervals of 10 K. This results in approximately 97%, 87%, 70%, and 65% of the points being excluded from the assimilation, respectively. Only experiment 1d is performed in the second case study.

3) EXPERIMENT TWO

In this experiment, the impacts of smoothing the adjoint solution are examined. Experiment 1d is repeated, with the adjoint solution $G$ being smoothed according to
\[ G_{t,k} = \frac{1}{N} \sum_{n-x}^{x} \sum_{m-x}^{x} (G_{t,i,k} + G_{i+m,j+n,k}), \]  
where \( N \) is the total number of grid points in the average and \( x \) is the distance away from the point about which the average is taken. Thus, the average is taken over a region surrounding the specified grid point, the size of which is determined by \( x \). This experiment is performed with spanning lengths \( x \) of one and two grid points. The local smoothing of the adjoint solution is performed to test the effects on the analysis of decreasing the small-scale variability in the cost function gradient computation that can have significant amplitude locally in the cloud-resolving adjoint model (Vukicevic et al. 2004, 2006; Langland et al. 1996).

4) EXPERIMENT THREE

The sensitivity of the assimilation to a larger horizontal background error decorrelation length is tested. Experiment 1d is repeated with the horizontal background error decorrelation length increased to 100 km for the water-related control variables. In the study described in Polkinghorne et al. (2010), it was shown that the water variables are horizontally correlated to about 100 km.

5) EXPERIMENT FOUR

The impacts of using a longer assimilation window are studied in this experiment. In the first case study, the model simulation time is increased by running the model from 1000 to 1210 UTC on 21 March 2000 in the same domain, using the same setup as in experiment 1d. GOES channels 4 and 5 are assimilated at 1009, 1039, 1109, 1139, and 1210 UTC. In the second case study, the model run simulated the time from 2000 to 2200 UTC on 28 March 2000, with assimilation times at 2018, 2039, 2109, 2133, and 2200 UTC. This is done to test the expected positive impacts of a longer assimilation period as more observations with added unique information about the cloud evolution are allowed to influence the solution. The study described in Vukicevic et al. (2006) shows that increasing the frequency of GOES observations within a 1-h assimilation interval (from 30 to 15 min) significantly reduced the bias in the assimilation results.

This result suggests that more observations over time help to localize the maximum likelihood solution (i.e., the least squares solution) in the presence of nonmonotonic nonlinear processes in the model. This result is broadly consistent with the “long window” 4DVAR approach (Pires et al. 1996; Yang et al. 2009). Reducing the impact of the nonmonotonic nonlinearity with temporally distributed observations in the nonlinear data assimilation problem is also discussed in Vukicevic and Posselt (2008). The GOES observations with a frequency of 15 min are not used in the current study because the
ARM archive contains these data only every 30 min. Instead, the assimilation window is doubled.

6) Experiment Five

In this experiment, the impacts of assimilating spatially sparse ground-based data in addition to the satellite data are tested. Data from AERI, MWR, and radiosonde are assimilated in addition to GOES channels 4 and 5 at the five ARM sites within the model domain. In experiment 5a, the ground-based data are assimilated at the same assimilation times as the GOES data. The frequency of assimilating the ground-based observations is increased to every 5 min in experiment 5b in order to see the impacts of assimilating this sparse data more frequently. Experiment 5b is repeated with the horizontal background error decorrelation length for the water-related control variables set to 100 km in order to see the impacts of extending the range of influence of each observation point (experiment 5c).

In these experiments the satellite observations in the cost function are weighted by the number of observations $N_i$ at each satellite observation time $t$:

$$J = \frac{1}{2} (x_0 - x_b)^T B^{-1} (x_0 - x_b)$$

$$+ \frac{1}{2} \sum_{m} \frac{1}{N_i} |H_i(x_i) - y_i|^2 R^{-1}_1 |H_i(x_i) - y_i|$$

$$+ \frac{1}{2} \sum_{j=1}^m |H_2(x_j) - y_j|^2 R^{-1}_2 |H_2(x_j) - y_j|,$$

where $H_1$ and $H_2$ are the forward observation operators for satellite and ground-based observations, respectively, and $R_1$ and $R_2$ are the observation error covariance matrices for the satellite and ground-based instruments, respectively. This weighting is done due to the large number of satellite observations relative to the number of ground-based observations being assimilated.

7) Experiment Six

The sensitivity of the assimilation to visible and near-IR channels in addition to the infrared channels is examined. Experiment 3 is repeated, assimilating GOES channels 1 and 2 in addition to GOES channels 4 and 5. This experiment is only done with the second case study as data from these channels are not available during the first case study. This experiment shows the impacts of the visible and near-infrared channels on the assimilation.

For each experiment where only satellite observations are assimilated, the assimilation results are verified against a set of independent, ground-based data from the ARM archive (AERI, MWR, cloud radar, and radiosonde) at their location points. These ground-based data are averaged over 400 s around the comparison time to match the RAMS grid cell advection. A root-mean-square error is computed against these observations at the satellite data assimilation times.

4. Results

a. Bulk sensitivity

To evaluate the overall impacts of varying the parameters in the data assimilation system on the assimilation results, we first look at the bulk properties of the results in terms of the cost function in Eq. (1). This is the cost function in the space of the observations that are assimilated.

Figure 3a shows the normalized cost function as a function of iteration for each experiment, while the normalized gradient norm as a function of iteration appears in Fig. 3b. The results in Fig. 3a show that the inclusion of the cloud classification and matching of the cloud type in the quality control (EXP 1) shows better convergence of the cost function in the first case study and a significantly larger total reduction of the cost function in both case studies. The results also indicate that increasing the maximum residual that implies an increase of the number of observation points in the assimilation (EXPs 1a–1d; only EXP 1d is shown) also improves the fit to the observations, as shown by a larger total cost function reduction. The smoothing applied to the adjoint solution prior to using it in the assimilation in EXP 2 has a small but positive impact on the cost function decrease. The effects of the adjoint smoothing on the final analysis in terms of the cloud fields and other model variables are discussed in the next section. EXP 3, which uses the decorrelation length that is estimated from the analysis of innovations in Polkinghorne et al. (2010), shows that the cost function is further reduced by using this more realistic and longer decorrelation length, but the impacts are small, only by a few percent.

The longer assimilation window in EXP 4 does not seem to have a positive impact because the cost function decreases less than in previous experiments. However, this cost function includes more assimilation times than the other experiments. When the cost functions are compared at the three observation times that are used in the previous experiments, the decrease is still less but closer to that seen in EXP 1d. Although the cost function relative decrease is not as large as in other experiments, the norm of the gradient is characterized with a monotonic decrease, which indicates a better-conditioned minimization. In addition, this experiment results in smoother changes to the entire state, as discussed in the next section.
EXPs 5a–c show that assimilating sparse ground-based data does not have much impact when combined with more numerous satellite data. By extending the area of impact of each observation, as in EXP 5c, the largest decrease in cost function is seen, as expected. At the five locations where these data are available in the domain, the type of cloud over the site is different in the model and observations in the first case study (i.e., where the model has low cloud, the observations have high cloud, and vice versa), contributing to the low impact of these observations. In the second case study, there are two points where the type of cloud over the site is the same in both the model and the observations, resulting in a slightly larger impact on the assimilation. EXP 6 indicates that the assimilation of visible and near-IR channels does have some positive impact on the analysis, most notably that of increasing the number of iterations and showing better convergence of the cost function to a minimum than is seen in other experiments with this case study.

Due to the highly nonlinear nature of the moist physics, the number of iterations in each assimilation experiment is limited either by the occurrence of numerical instability in the adjoint model or the occurrence of a negative step size in the algorithm. Therefore, convergence of the cost function could not be achieved in each experiment. It is presumed that the negative step size issue is due to the algorithm producing the best state it can and being unable to go further. The occurrence of numerical instability is assumed to be due to the nonlinear nature of the moist physics as no numerical instability occurs when the algorithm is tested with a noncloudy case. Additionally, this property of the adjoint in RAMDAS was not experienced in the simpler data assimilation experiments using homogeneous cloud cases in the studies by Vukicevic et al. (2004, 2006). In order for the cloud-resolving 4DVAR system to be more applicable to a wide range of cases, a more robust adjoint model would be required, as discussed in Errico et al. (2007b). This aspect of 4DVAR is beyond the scope of the current study. The experiments that do not show convergence are still useful because of the significant reduction of the cost function, which indicates that an improvement with respect to the background state is made by data assimilation.

The results of the experiments that assimilate only satellite observations (EXPs 1–4, 6) are compared to the ground-based observations (AERI, MWR, MMCR, and sondes) as an independent verification that the
assimilation is successful. The root-mean-square error (RMSE) is computed against the independent observations. Figure 4 shows the change in RMSE normalized with respect to the RMSE of the background state for several of the experiments.

While it is impossible to draw firm conclusions using these few verification points, the data presented in Fig. 4 for the first case study suggest that the inclusion of more points in the assimilation leads to a better fit to the observations (as shown in EXPs 1a–1d), and the use of a larger, more realistic background error decorrelation length (EXP 3) results in the largest positive impact on the assimilation. The long-window experiment, for these few points, does not yield a better match to the observations when compared to the other experiments. The results for the second case study show little difference between the control experiment and the other experiments. This is most likely due to the fact that only two of the five points used in the verification lie in the region affected by the assimilation.

b. Cloud analysis and the dynamical environment

In this section the impacts of varying the conditions in the data assimilation on the final cloud analysis and the associated dynamical environment are discussed. The changes in brightness temperature after assimilation are first examined. Figure 5 shows the difference between the analysis and the background forecast run at each assimilation time for EXPs 1d, 2b, 3, 4, and 5c using the data from the first case study. Only data for GOES channel 4 are presented due to the similarity between the brightness temperatures seen in channels 4 and 5. The dark outline in Fig. 5 shows where the quality control mask is applied at each assimilation time. The area affected by the assimilation spreads beyond the points considered due to the dynamic effects of the algorithm.

In Fig. 5, it is immediately apparent that while there is significant change relative to the background state in each experiment, none of the experiments produce a spatial pattern of brightness temperatures similar to that seen in the observations. This is due to the inability of the algorithm to correct model location errors, as discussed in the introduction. The background cloud is in a different location than the observed cloud, and the adjoint model cannot put cloud where there was none in the model. However, it is still useful to examine the results presented here as they can shed light on the sensitivity of the assimilation to the various parameters tested in the experiments.

The most significant difference between the experiments is seen between the longer assimilation window (EXP 4) and the other experiments. This is expected in the first case study due to the different problems being solved in the experiments. The model run in EXP 4 begins 1 h before the model run in the other experiments; therefore, the control vector contains a different set of initial conditions. This leads to a broader, smoother pattern of cooler brightness temperatures than is seen in the other experiments.

The effects of the longer background decorrelation length used in EXPs 3 and 5c are apparent when comparing Figs. 5c and 5a, especially at the first observation time. The change in brightness temperature in Figs. 5c and 5e spreads over an area farther outside the quality control mask than is seen in Fig. 5a. This is due to increasing the length over which observations are allowed to have an impact on the assimilation. There does not seem to be any significant difference between the brightness temperatures produced in EXPs 1d and 2b.

The changes in model pristine ice mixing ratio every 30 min during the model run with the associated change in wind, humidity, and temperature are presented in Figs. 6–10. Each figure contains a horizontal cross section at a height of 8.75 km (panels a and b) and a vertical cross section of these quantities at a latitude of 37.0° (panels c and d). As before, data from EXPs 1d, 2b, 3, 4, and 5c are presented from the first case study.

The most significant differences between experiments are again seen between the longer assimilation window (EXP 4; Fig. 9) and the other experiments (Figs. 7, 8, and 10). Although the change in pristine ice mixing ratio occurs at approximately the same location, the magnitude is significantly less and the dynamic response of the model is much smoother in EXP 4 than in the other experiments, as seen in the smaller changes in both wind and temperature. This result indicates that the longer assimilation window leads to a more balanced 4D analysis, consistent with the better conditioning of the least squares data assimilation solution. The experiments with a longer horizontal background decorrelation length (EXPs 3 and 5c; Figs. 8 and 10) show a significantly
Fig. 5. The change in GOES channel 4 brightness temperature (analysis − background) for the first case study for EXPs (a) 1d, (b) 2b, (c) 3, (d) 4, and (e) 5c at 1109, 1139, and 1210 UTC 21 Mar 2000.
FIG. 6. The change resulting from EXP 1d in (a) pristine ice mixing ratio at 8.75 km, with the (b) associated change in humidity (filled color contours) and temperature (line contours). The corresponding change in wind is shown below each contour plot, and the change with a positive (negative) zonal component is shown in red (blue). The temperature contours have a spacing of 1 K, with the solid lines representing positive change, the dashed lines representing negative change, and the heavy line representing zero change. The X–Z cross sections in (a) and (b) are shown in (c) and (d) at 37.0° latitude.
Fig. 7. As in Fig. 6, but for EXP 2b.
FIG. 8. As in Fig. 6, but for EXP 3.
FIG. 9. As in Fig. 6, but for EXP 4.
FIG. 10. As in Fig. 6, but for EXP Sc.
increased area of pristine ice mixing ratio at the initial model time, leading to a thicker cloud throughout the model run. This causes a noisier dynamic response, which is especially notable in the changes in temperature in the upper troposphere. In looking at the time series shown, the increase in noise with time is apparent, especially in the vertical cross sections, as expected. The longer horizontal background decorrelation length causes the observations to have an effect on the assimilation at greater distances from each observation point, leading to the observed increase in the affected area. As before, there is little difference seen between EXPs 1d and 2b (Figs. 6 and 7).

Each sensitivity experiment leads to an increase in the pristine ice mixing ratio in the initial conditions, as expected. As shown above, the experiments with the increased background decorrelation length (EXPs 3 and 5c) result in the greatest increase to this quantity, although the dynamic response of the other variables is very noisy. It is interesting to note that while the areas of greatest change in temperature and pristine ice mixing ratio tend to correspond, the areas of greatest change in horizontal wind do not correspond with these variables. The experiment with a long assimilation window (EXP 4) results in a better forecast in that there is a less dramatic increase in pristine ice mixing ratio and a smoother dynamic response. A 3D time series of the simulated pristine ice mixing ratio and the associated GOES channel 4 brightness temperatures after assimilation for this long-window assimilation experiment are shown in Fig. 11. While the brightness temperatures resulting from this experiment do not match the spatial pattern of the observed brightness temperatures, they do correspond better than the other experiments.

5. Summary and conclusions

This study demonstrates the feasibility of assimilating cloud-affected radiances in a cloud-resolving model in order to improve the quality of the model cloud representation. When model clouds more closely resemble observed clouds, the actual spatial and temporal variability patterns of the clouds may be more accurately studied. A forecast run of 3 h using the improved initial conditions after assimilation shows that the impacts of the assimilation persist at least up to this time.

A series of data assimilation experiments are performed for two cloudy cases. Cloud-affected infrared satellite channels are assimilated at three times during the forecast run using a 4DVAR data assimilation system.
designated as RAMDAS. A dynamic quality control mask is implemented such that only grid points that have high clouds or are clear in both the model and the observations are considered in the assimilation. This is done in order to improve the linearity of the data assimilation problem. A very simple cloud mask is used to identify cloud type in the observations; a more sophisticated cloud mask may lead to an improved assimilation.

The experiments performed include varying the maximum-allowed residual in the quality control mask from 20 to 50 K in increments of 10 K, smoothing the adjoint solution, changing the background error decorrelation length for water variables from 50 to 100 km, increasing the assimilation window from 1 to 2 h, including spatially sparse but temporally abundant ground-based measurements in the assimilation, and adding visible and near-IR channels to the assimilation. These experiments are validated against independent ground-based data from the ARM archive. However, the spatial sparsity of the ground-based data used in the validation may bias the results.

According to both the cost functions of the experiments and the change in fit with ground-based data, the greatest impacts on the assimilation are found by increasing the number of points in the assimilation by allowing a greater difference in brightness temperature between the model and the observations. Additionally, these data show that increasing the background error decorrelation length to 100 km results in the greatest cost function decrease and greatest increase in pristine ice mixing ratio. While increasing the length of the assimilation window does not lead to a greater decrease in cost function, it does lead to a smoother dynamical response to the assimilation and a better forecast. The different responses of the algorithm to each experiment demonstrate how sensitive the algorithm is to the parameters tested in this study. In addition, the responses to the various experiments are different in each case study, showing the need for further work to elucidate the reason for this.

None of the experiments yields a dramatic improvement in the modeled state due to the inability of the algorithm to correct location errors. Preliminary attempts to validate these experiments in greater detail show the lack of cloud-sensitive data available at cloud-resolving scales. It is thus difficult to conclude which experiment results in a state closest to the observed values.

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