Assimilation of Precipitation Information Using Column Model Physics as a Weak Constraint

ARTHUR Y. HOU AND SARA Q. ZHANG*

NASA Goddard Space Flight Center, Greenbelt, Maryland

(Manuscript received 23 January 2006, in final form 9 June 2006)

ABSTRACT

Currently, operational weather forecasting systems use observations to optimize the initial state of a forecast without considering possible model deficiencies. For precipitation assimilation, this could be an issue since precipitation observations, unlike conventional data, do not directly provide information on the atmospheric state but are related to the state variables through parameterized moist physics with simplifying assumptions. Precipitation observation operators are comparatively less accurate than those for conventional data or observables in clear-sky regions, which can limit data usage not because of issues with observations, but with the model. The challenge lies in exploring new ways to make effective use of precipitation data in the presence of model errors.

This study continues the investigation of variational algorithms for precipitation assimilation using column model physics as a weak constraint. The strategy is to develop techniques to make online estimation and correction of model errors to improve the precipitation observation operator during the assimilation cycle. Earlier studies have shown that variational continuous assimilation (VCA) of tropical rainfall using moisture tendency correction can improve Goddard Earth Observing System 3 (GEOS-3) global analyses and forecasts. Here results are presented from a 4-yr GEOS-3 reanalysis assimilating Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) and Special Sensor Microwave Imager (SSM/I) tropical rainfall using the VCA scheme. Comparisons with NCEP operational analysis and the 40-yr ECMWF Re-Analysis (ERA-40) show that the GEOS-3 reanalysis is significantly better at replicating the intensity and variability of tropical precipitation systems ranging from a few days to interannual time scales. As a further refinement of rainfall assimilation using the VCA scheme, a variational algorithm for assimilating TMI latent heating retrievals using semiempirical parameters in the model moist physics as control variables is described and initial test results are presented.

1. Introduction

Observations containing information on precipitation processes have become increasingly available from spaceborne microwave sensors in the past decade, and more is expected with the Global Precipitation Measurement (GPM) mission now in formulation (National Aeronautics and Space Administration 2006). These measurements include radar reflectivity from TRMM and GPM, brightness temperatures from microwave radiometers (e.g., TMI, SSM/I, AMSR-E, SSMIS, MADRAS, GMI, CMIS) and sounders (e.g., AMSU, ATMS, MHS) (see list of acronyms in the appendix), as well as precipitation rates and latent heating profiles derived from these measurements (Simpson et al. 2000). In recent years, significant progress has been made in using these observations in data assimilation to improve atmospheric analyses and forecasts. Numerical weather prediction centers such as the NCEP, JMA, and ECMWF have begun using precipitation data or rain-affected microwave brightness temperatures in operational forecasts (Treadon et al. 2002; Aonashi et al. 2004; Marecal and Mahfouf 2003; Bauer et al. 2006). Currently, precipitation information (either retrievals or rain-affected radiances) is assimilated in NWP systems much the same way as any other data to optimize the initial state for a better forecast. To this end, the system requires an "observation operator" capable of

* Additional affiliation: Science Applications International Corporation, Beltsville, Maryland.

Corresponding author address: Dr. Arthur Y. Hou, Code 610.1, NASA Goddard Space Flight Center, Greenbelt, MD 20771.
E-mail: arthur.y.hou@nasa.gov

DOI: 10.1175/2006JAS2028.1

© 2007 American Meteorological Society

relating the observable to the initial state with reasonable accuracy. In this regard, precipitation assimilation poses a special challenge.

Unlike conventional data, precipitation observations do not directly provide information on the atmospheric state in terms of temperature, wind, and moisture but are related indirectly to these variables through parameterized moist physics with simplifying assumptions. As a result, precipitation observation operators are inherently less accurate than those for conventional data or observables in clear-sky regions. In variational data assimilation, moist physics schemes are often further simplified and linearized to facilitate the construction of tangent linear and the associated adjoint models. Accuracy of precipitation observation operators is therefore a key issue in using precipitation information in data assimilation.

Precipitation observation operator errors and a portion of forecast model errors arise from the same moist physics parameterizations, which influence both model-generated rain and the model trajectory. Within the framework of traditional analysis schemes, which use the forecast model as a strong constraint, model errors cannot be mitigated in the assimilation procedure. Errors in the rain observation operator can only be statistically accounted for as a part of the total observation error covariance but not corrected. In such systems precipitation is assimilated only at locations where the observation operator based on the model physics is sufficiently accurate, while in practice, model errors can restrict data usage. For instance, in the assimilation of rain-affected microwave radiances at ECMWF, channels that are more sensitive to scattering by model-generated solid precipitation are not used (Moreau et al. 2004). Precipitation assimilation using the model as a strong constraint can also produce moisture fields in conflict with other types of observation such as total column water vapor (Lopez et al. 2006). Yet, the ability to use precipitation information to improve analysis products is important since the representation of the global hydrological cycle remains a serious problem, even in state-of-the-art NWP analysis systems (Andersson et al. 2005).

In seeking ways to use the available precipitation data more effectively, one strategy is to develop assimilation algorithms using the forecast model as a weak constraint to improve the precipitation observation operator within an analysis cycle. For example, model errors of a prescribed temporal form can be estimated along with other increments of state variables within a four-dimensional variational data assimilation (4DVAR) precipitation assimilation scheme (Zupanski 1997; Zupanski et al. 2002). While applying weak constraints to a full analysis system is computationally demanding, for precipitation assimilation one can exploit the close relationship between precipitation and moist physics to use column model physics as a weak constraint. Hou et al. (2000, 2001, 2004) developed a 1D variational continuous assimilation (VCA) procedure for precipitation assimilation by assuming that forecast errors in rain arise primarily from model deficiencies rather than the initial condition and explored the benefits of relaxing the perfect model assumption. In a series of experiments, they showed that rainfall assimilation using the VCA scheme is effective in improving global analyses and forecasts, providing a strong incentive for pursuing the weak constraint approach for assimilating precipitation-related information such as clouds, rain, and latent heating, either in the measurement space or as geophysical retrievals.

Building on the work of Hou et al. (2000, 2001, 2004), this paper further investigates assimilation of precipitation-related observations using the model as a weak constraint. In section 2, we discuss a prototype problem illustrating the issues with using the model as a strong constraint in assimilating rainfall data in the presence of known model physics deficiencies. Section 3 describes the general variational assimilation methodology using column model physics as a weak constraint. Section 4 compares a 4-yr Goddard Earth Observing System 3 (GEOS-3) global reanalysis assimilating tropical rainfall data using the VCA scheme with the operational NCEP/GDAS analysis and ERA-40 reanalysis. Section 5 discusses a strategy for further improvement through assimilation of TRMM-derived latent heating profiles using semiempirical parameters in the moist physics as control variables. Section 6 concludes with a discussion of future research directions and how column model weak constraints may be incorporated into a traditional 3DVAR or 4DVAR data assimilation system.

2. Model error issues in precipitation assimilation

Conventional data assimilation algorithms are not designed to address errors arising from model deficiencies. Under the "perfect model" assumption, the forecast model is used as a strong constraint, with model forecast errors attributed to uncertainties in the initial state. However, in global forecast systems the model-predicted precipitation is diagnosed from changes in the time tendency of moisture, which are strongly influenced by moist physics parameterizations. If discrepancies between the predicted and observed rain arise

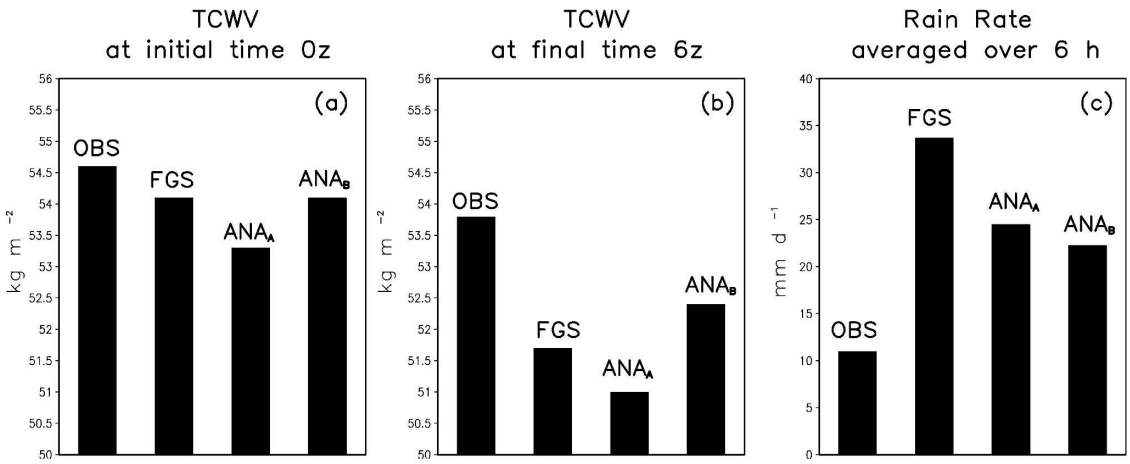

FIG. 1. An example of 1 + 1D variational assimilation of precipitation by means of initial-state adjustment (method A) vs model time-tendency correction (method B) over a 6-h analysis window at a model grid location: total column water vapor (TCWV) (a) at initial time 0000 UTC and (b) at 0600 UTC, and (c) 6-h-averaged rain rate. Shown in each panel are observations (OBS), model first guess (FGS), analysis by method A (ANA_A), and analysis by method B (ANA_B).

primarily from errors in the model physics rather than the initial state, attributing errors solely to the initial state can lead to excessive corrections on the initial state, resulting in either a degraded analysis or an outright rejection of useful observations.

The issue of model errors in precipitation assimilation can be illustrated with a simple experiment using a 1 + 1D (column and time) variational assimilation system. The model in this case consists of a column model of GEOS moist physics with dynamic forcing prescribed from a full GEOS GCM simulation. The initial moisture field is slightly drier in terms of the observed total column water vapor (TCWV). The 6-h forecast by the column model produces excessive rain compared with the TMI retrieval over the analysis window, ending with a distinctly drier state compared with the observed TCWV (Fig. 1).

We compare two variational schemes for assimilating TMI rain rates over the 6-h window. Both schemes minimize quadratic misfits between the 6-h average model rain and TMI rain, but each uses a different control variable. Method A uses the column model as a strong constraint by adjusting the initial state. In method B, the control vector is formulated in terms of incremental corrections on moisture tendency, which are applied at every time step during the 6-h model integration to better match the observed rain rate. In both cases, the error covariance statistics for the initial (background) state, moisture tendency correction, and observations are as prescribed in Hou et al. (2004).

Results show that, when model errors are present but subsumed in a prescribed observation error covariance, method A attempts to match the observed rain rate by reducing the initial moisture field, resulting in an even drier state at 0600 UTC. By relaxing the model as a strong constraint to include moisture tendency corrections to compensate for model errors, method B not only reduces the excessive rain over the 6-h window but also improves the final moisture field at 0600 UTC (Figs. 1 and 2). These results show that, in the presence of model deficiencies, rainfall assimilation using the model as a strong constraint can lead to inconsistencies between analysis variables. Specifically, a rainfall assimilation scheme that attributes errors in the model physics to errors in the initial state can improve model precipitation but at the same time degrade analyses of other variables such as moisture. Worse still, it could lead to the erroneous conclusion that precipitation observations are not useful for improving atmospheric analyses, while the problem is not with the data but how the data is used.

The above illustrations consist of two extreme examples—one attributing model forecast errors solely to initial state errors and the other to model deficiencies. In reality, both types of errors can contribute to model forecast errors, but disentangling these two sources of errors knowing only model forecast errors is a major challenge. But large biases often found in precipitation forecast-minus-observations statistics are likely indicative of the presence of significant model errors. Some form of assimilation algorithm with the model as a weak constraint will likely improve the use of precipitation observations in data assimilation. In practice, one strategy is to adopt a two-stage sequential approach by

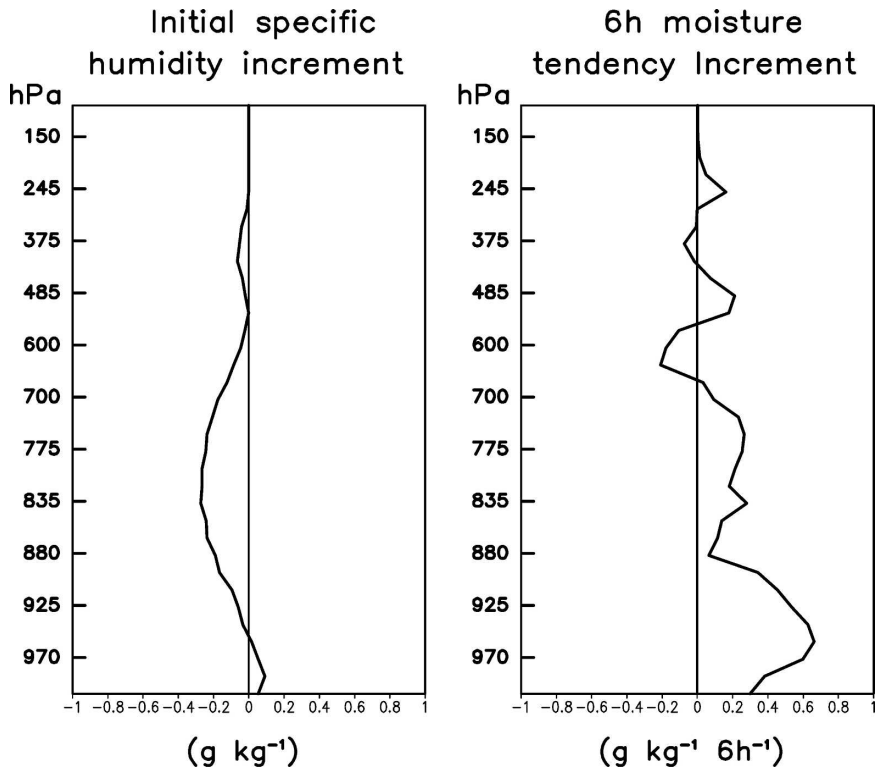

FIG. 2. Minimization solution for the case shown in Fig. 1: (left) correction to the initial moisture profile and (right) time-integrated moisture time-tendency correction over the 6-h window.

first assimilating observations of the atmospheric initial state to optimize the state variables, followed by the assimilation of rain-affected observations using the model moist physics as a weak constraint.

3. Assimilation of precipitation information using the model as a weak constraint

In a general weak-constraint variational framework, a set of chosen parameters associated with model errors is estimated along with the model state in a variational analysis. The trajectory of the model during the assimilation window is influenced not only by adjustments of the initial state, but also corrections to model time tendencies or other model parameters. The control variable can be defined as an augmented vector of the model state, $\mathbf{x}$, and model error parameters, $\mathbf{w}$, with prescribed error covariances. The goal is to use information from observations to estimate and correct not only the initial state but also model errors. This work focuses on using precipitation-related observations such as precipitation rates and latent heating profiles to estimate and correct the model deficiencies associated with moist physics. Within the framework of a traditional analysis system, precipitation-derived model corrections may be applied subsequent to initial-state corrections using other observations within the same analysis window, as in Hou et al. (2000, 2004).

We consider a variational parameter-estimation procedure, which seeks to minimize the functional,

$$J(\delta\mathbf{w}) = (\delta\mathbf{w})^{\mathrm{T}}\mathbf{Q}^{-1}(\delta\mathbf{w}) + (\mathbf{y} - \mathbf{y}^{o})^{\mathrm{T}}\mathbf{R}^{-1}(\mathbf{y} - \mathbf{y}^{o}), \quad (1)$$

where $\mathbf{y}^{o}$ is the observed rain rate or latent heating profile; $\mathbf{y} = \mathbf{H}(\mathbf{w})$, where $\mathbf{H}$ is a 1 + 1D observation operator based on a time integration of the column model physics initialized with analysis using standard observations and forced with large-scale tendencies from a corresponding GCM forecast over the analysis window. The control variable, $\delta\mathbf{w}$, which is held constant over the analysis window, consists of time tendency corrections on temperature and moisture (for precipitation assimilation), or adjustments to parameters in moist physics schemes (for latent heating assimilation). Here $\mathbf{Q}$ and $\mathbf{R}$ are error covariances for a prior estimate of $\delta\mathbf{w}$ and observations, respectively. For precipitation assimilation, the $\delta\mathbf{w}$ correction is applied to model moisture tendency to compensate for model deficiencies during the model time integration in evalu-

ating the model rain within the iteration loops for solving (1). Similarly, for latent heating assimilation, the adjustments to moist physics parameters are updated within each iteration loop. For further details, see Hou et al. (2004) for surface rain assimilation and section 5 for latent heating assimilation.

For rainfall assimilation, several implementations of (1) as a VCA incremental moisture-tendency correction scheme have been examined in terms of their impact on different aspects of GEOS global analyses and forecasts. Hou et al. (2000, 2001) showed that assimilation of TMI and/or SSM/I rain retrievals using the VCA scheme improves not only precipitation analysis but also related climate parameters such as the upper-tropospheric moisture and top-of-the-atmosphere radiative fluxes. Hou et al. (2004) provided examples of improved hurricane track forecasts and precipitation forecast threat scores using the VCA scheme. However, these early studies were based on limited months of assimilated data. In the following section, we will use four years of the GEOS-3 "TRMM reanalysis" to examine the VCA scheme as a way for improving the representation of precipitation intensity and variability in global analysis.

4. Global reanalysis with continuous rainfall assimilation

Understanding climate variability over a wide range of space–time scales in terms of the complex interactions of the underlying physical processes requires a comprehensive description of the earth system. Global analyses produced by fixed assimilation systems (i.e., reanalyses) that combine observations from diverse sources with information from physical models—as their quality continues to improve—may be crucial for meeting this challenge. However, at the present time the utility of global reanalyses is limited by uncertainties in basic hydrological fields such as clouds, precipitation, and evaporation (World Climate Research Program 1998)—especially in the tropical precipitation, where conventional observations are relatively sparse.

Uncertainties in tropical precipitation and latent heating distributions have been a major impediment to understanding how the Tropics interact with other parts of the globe, including the remote response to tropical El Niño–Southern Oscillation (ENSO) variability on interannual time scales, and the possible global influence of the Madden–Julian oscillation (MJO) and monsoons on intraseasonal time scales. A global atmospheric analysis capable of capturing the observed tropical rainfall variability accompanied by physically consistent estimates of wind, temperature, and mass fields is the key to breaking this roadblock.

Analyses of the tropical atmosphere have long been shown to be sensitive to the treatment of cloud/precipitation processes, which remains a major source of uncertainty in the current model (e.g., Trenberth and Olson 1988). Yet, for many climate applications, it is essential that analyses can accurately depict the observed rainfall intensity and variability since what appear to be small errors in rain rate correspond to sizable uncertainties in the earth's energy balance. Roughly, an error of 1 mm day^{-1} in surface rain rate is equivalent to 30 W m^{-2} of latent heat flux in the energy budget. Currently, discrepancies in monthly mean rain rates between global analyses and Global Precipitation Climatology Project (GPCP) satellite gauge estimates can exceed 4 mm day^{-1} at the horizontal resolution of 100 km, which correspond to over 120 W m^{-2}, representing a substantial uncertainty in the surface energy balance. The aim of this study is to investigate whether spaceborne rainfall data from passive microwave sensors can be used to significantly improve the representation of precipitation in 4D global reanalyses.

a. GEOS-3 TRMM reanalysis

The TRMM reanalysis is a 1° × 1° global analysis that assimilates TMI and SSM/I surface rainfall over tropical oceans every 6 h using the VCA scheme in the GEOS-3 global data assimilation system (Hou et al. 2004). In addition to TMI and SSM/I rain rates, the system assimilates all conventional and satellite data used in the standard GEOS-3 system. The TRMM satellite, developed jointly by NASA and JAXA (formerly NASDA), was launched on 27 November 1997 (Simpson et al. 2000) and is currently operating in its ninth year. The TRMM reanalysis extends from 1 November 1997 through 31 December 2002, covering the first five years in orbit. The start date was set to 1 November prior to the TRMM launch using SSM/I rainfall data to include the peak phase of the 1997–98 El Niño. A unique feature of the GEOS-3 TRMM reanalysis is that its precipitation is not derived from a short-term forecast (as done at operational NWP centers) but given by a time-continuous model integration constrained by observations (including precipitation data) in a 6-h analysis window within the incremental analysis update (IAU) framework of the system. As a result, the wind, temperature, and mass fields can directly respond to the improved precipitation and associated latent heating patterns during the assimilation cycle, which is crucial for realizing the full benefit of precipitation assimilation.

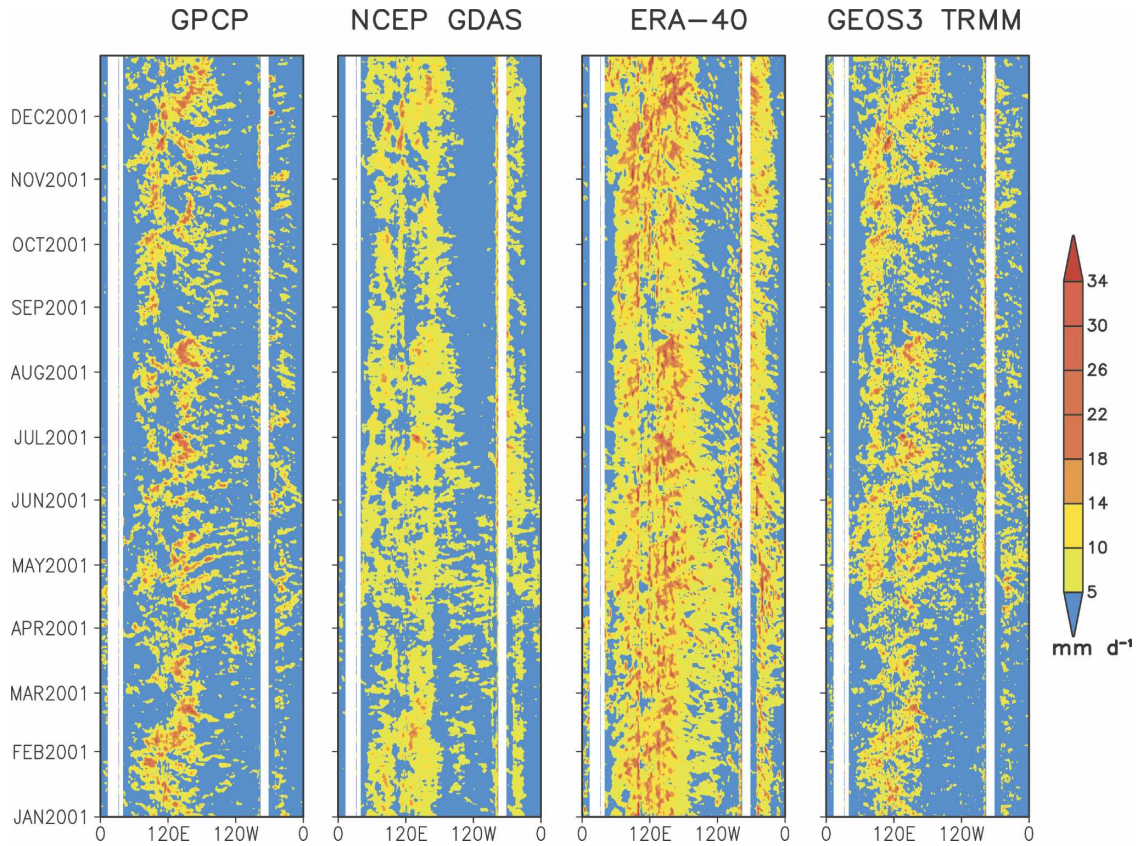

FIG. 3. Hovmöller diagrams of MJO signals in daily precipitation over oceans averaged from 10°S to 10°N for 2001. (left to right) GPCP, NCEP/GDAS, ERA-40, and GEOS-3/TRMM.

b. Comparison of TRMM reanalysis with NCEP GDAS analysis and ERA-40

Current global general circulation models and analyses have only limited capability to accurately reproduce the intensity and propagation of tropical precipitation systems and intraseasonal oscillation patterns (Lin et al. 2006). Shown in Fig. 3 are Hovmöller diagrams of MJO signals in precipitation over tropical oceans averaged between 10°N and 10°S from three global analyses and the GPCP satellite gauge estimate (Global Precipitation Climatology Project 2004). The three analyses consist of ERA-40 (European Centre for Medium-Range Weather Forecasts 2004), which does not assimilate precipitation data; the operational NCEP/GDAS analysis (National Center for Environmental Prediction 2004), which assimilates TMI and SSM/I rainfall rates in its 3DVAR system (from 16 October 2001); and the GEOS-3/TRMM reanalysis. Compared with GPCP estimates, the ERA-40 precipitation is overly active and more intense, while the GDAS analysis underestimates the MJO intensity and variability. By assimilating 6-h TMI and SSM/I rain rates using the VCA scheme, the GEOS-3/TRMM reanalysis is able to closely replicate the observed intensity and propagation of tropical precipitation systems. Figure 4 shows that of the three analyses, the TRMM reanalysis has smallest biases and rms errors, as well as better temporal correlations with respect to GPCP estimates.

To assess the extent to which precipitation assimilation accounts for the agreement between the TRMM reanalysis and GPCP, a GEOS-3 control assimilation without rainfall data was performed for 1 May through 31 August 1998, which corresponds to the intensive observation period (IOP) of the South China Sea Monsoon Experiment (SCSMEX). Figure 5 shows that rainfall assimilation reduces the rms errors and improves temporal correlations of the GEOS-3 precipitation analysis relative to GPCP estimates over this 4-month period. The fact that the GEOS-3 control, NCEP, and ERA-40 analyses have comparable rms errors and correlations with GPCP suggests that the better GEOS-3/TRMM rainfall analysis is due to rainfall assimilation rather than a better baseline GEOS-3 system. The im-

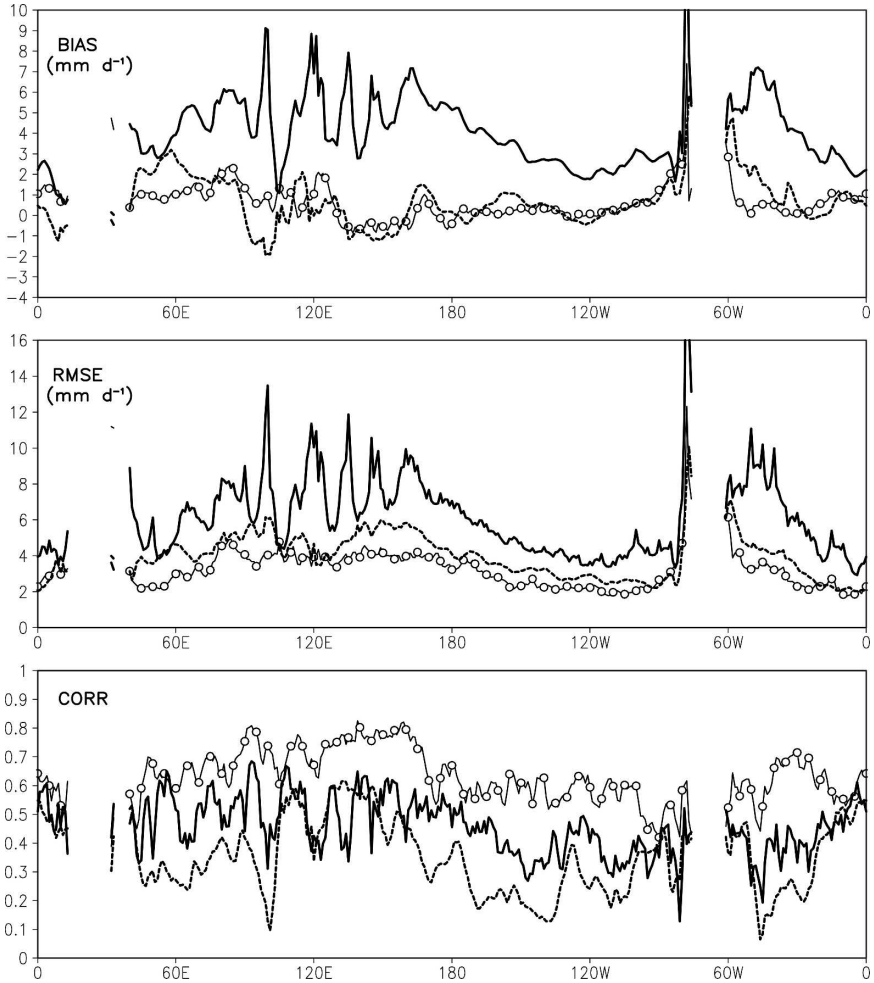

FIG. 4. (top) Biases, (middle) rms errors, and (bottom) time correlations of the three precipitation analyses shown in Fig. 3 with respect to GPCP estimates: GEOS-3/TRMM (open circle), NCEP/GDAS (dash line), and ERA-40 (solid line).

proved outgoing longwave radiation (OLR) in GEOS-3 analyses as a result of rainfall assimilation is shown in Fig. 6.

The positive impact of precipitation assimilation on tropical dynamical fields in the GEOS-3/TRMM reanalysis was examined in detail in Hou et al. (2004) in terms of synoptic features in hurricanes. Figure 7 shows that the improved precipitation in the TRMM reanalysis relative to the GEOS-3 Control directly modifies the monthly mean omega velocity at 500 hPa and the horizontal divergent wind at 200 hPa. Given the tight coupling between latent heating and vertical motions in the Tropics, the changes in the omega velocity closely correlated with the changes in the horizontal precipitation pattern are likely improvements, which cannot be directly verified with observations. The horizontal wind can also benefit from the improved precipitation pattern, but the vertical profile of latent heat must also be improved to effectively upgrade the divergent wind analysis (see section 5).

A wavelet analysis of a 4-yr (1998–2001) time series of precipitation averaged over the region 4°S–4°N, 120°–160°E (over the warm pool) has been performed. Results show that the GEOS-3/TRMM reanalysis is considerably better at capturing the observed intensity and variability of precipitation as verified against GPCP. Shown in Fig. 8 are the wavelet time correlations and rms errors as a function of the oscillation period. Compared with the GDAS analysis and ERA-40, the TRMM reanalysis has significantly higher time correlations with GPCP precipitation and smaller rms errors for all time scales longer than a few days.

As an example of the internanual variability in precipitation captured in global analyses, Fig. 9 displays changes in the January-mean tropical precipitation between the 2001 La Niña and the height of 1998 El Niño.

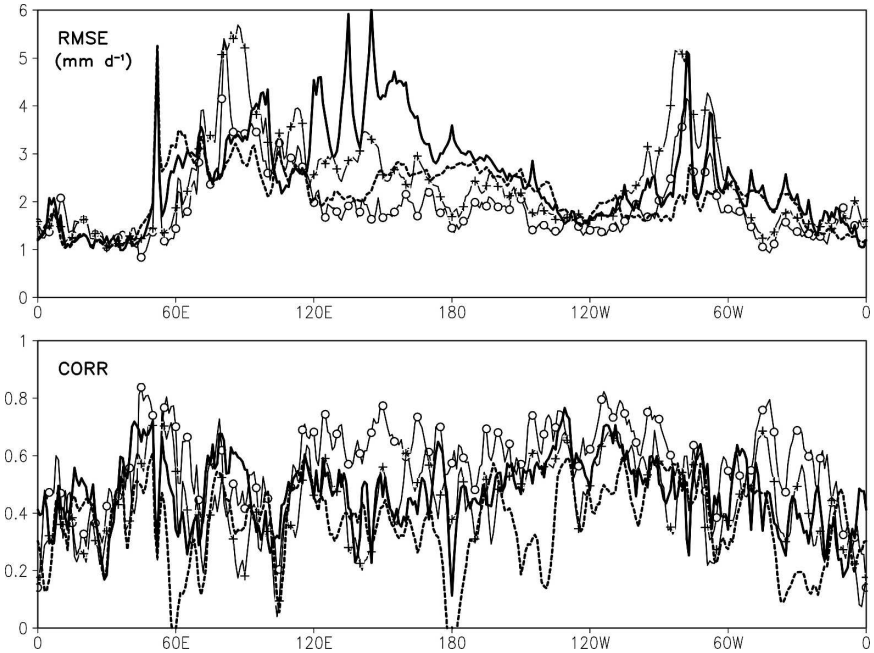

FIG. 5. Comparison of GEOS-3 analyses with (open circle) and without (cross) precipitation data assimilated for the period of 1 May to 31 August 1998. NCEP GDAS (dash line) and ERA-40 (solid line) are also shown for the same period: (top) tropical-mean rms errors verified against GPCP and (bottom) time correlations with GPCP.

Consistent with results of the wavelet analysis, the TRMM reanalysis is in closer agreement with GPCP than either the GDAS or ERA-40, and has notably smaller RMS errors than the GEOS-3 analysis without precipitation data. The tropical-averaged rms departures from GPCP rain rates are 2.23 mm day^{-1} for the TRMM reanalysis, 3.46 mm day^{-1} for GDAS analysis, and 4.36 mm day^{-1} for ERA-40, much larger than the

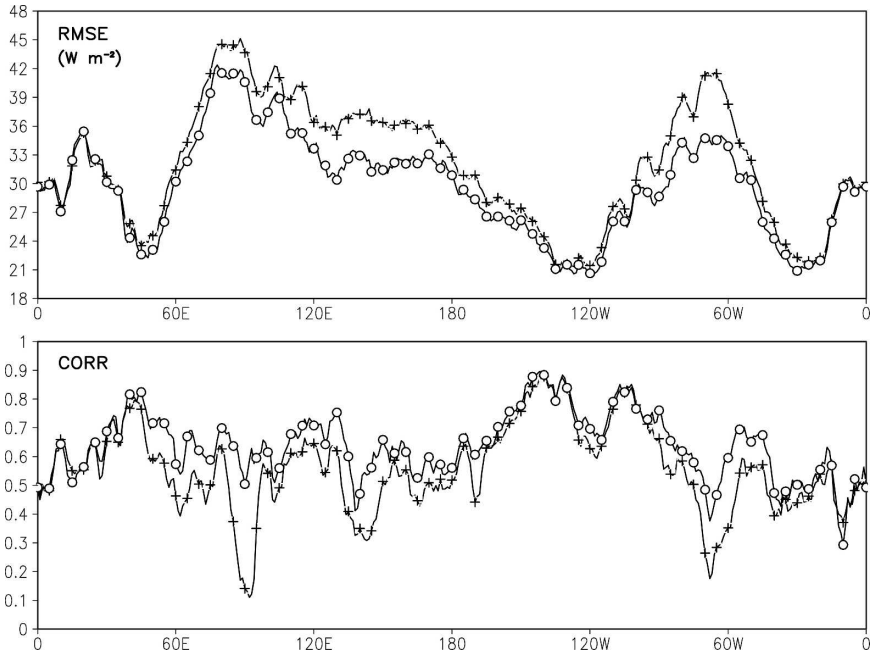

FIG. 6. As in Fig. 5 except for OLR verified against CERES measurements.

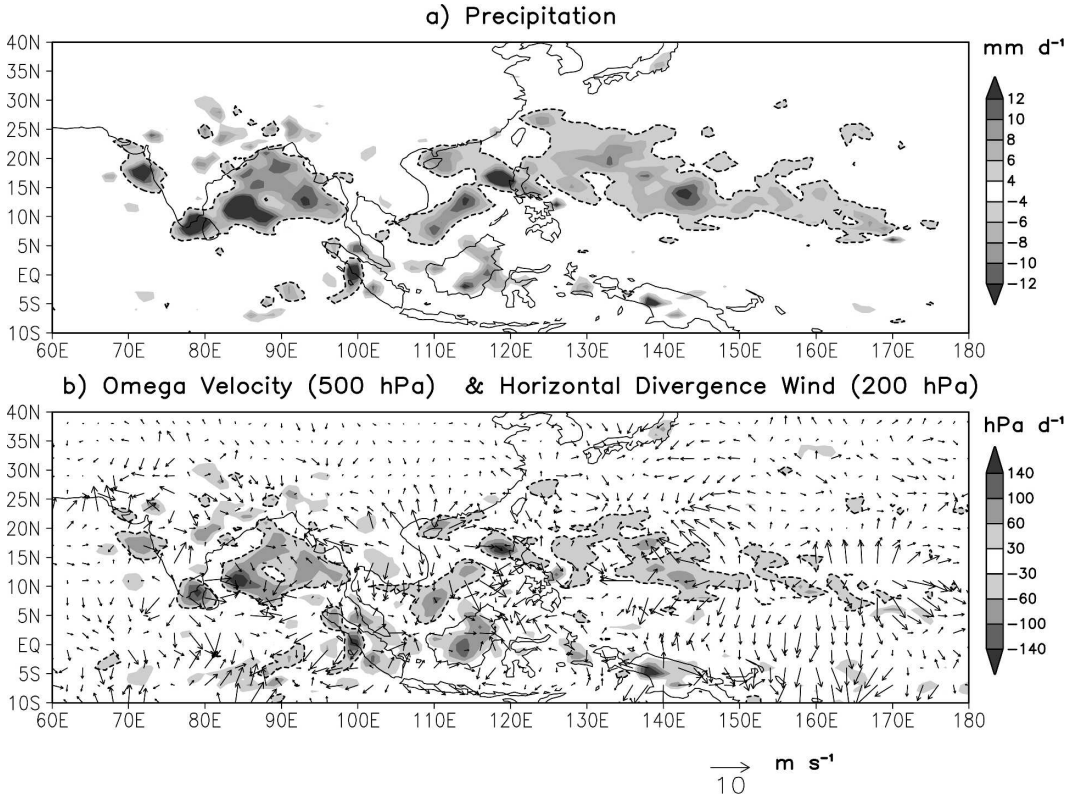

FIG. 7. Difference of GEOS-3 analyses with and without precipitation data assimilated in the western Pacific for August 1998: (a) changes in precipitation between GEOS-3/TRMM and Control (shaded areas within dashed contours indicate negative values) and (b) changes in omega velocity at 500 hPa (shaded areas within dashed contours indicate positive values) and changes in horizontal divergence wind at 200 hPa (vector). The correlation coefficient between changes in precipitation and changes in omega velocity is −0.87.

estimated uncertainty of the GPCP analysis on the order of 20%, or 0.6 mm day^{-1} (Adler et al. 2003).

5. A variational algorithm for tropical latent heating assimilation

The vertical structure of latent heat release from precipitation processes in the Tropics is strongly coupled to the vertical motion field and large-scale circulation patterns (Houze 1982). In global forecast models, latent heating profiles are determined by moist physics parameterizations derived empirically with limited observations. Typically, the parameters prescribed in moist physics schemes are static, homogeneous, and independent of the atmospheric state. Bayesian retrievals of precipitation from microwave sensors such as TMI using the simulated cloud database from a cloud-resolving model (CRM) can also provide latent heating structures that are radiatively compatible with multichannel TMI brightness temperature measurements (Tao et al. 2006). By comparison, the parameterized latent heating profiles in global forecast models, which are not subject to similar constraints, are likely to be less accurate. The possibility that assimilation of CRM-based retrievals of latent heating profiles can improve the accuracy of global analyses is attractive and remains to be explored.

In this section we examine the viability of the variational algorithm proposed in section 3 for matching model latent heating rates with TMI retrievals. The algorithm seeks adaptive corrections of a set of selected parameters to reduce misfits between the 6-h average model latent heating profiles and retrievals. The advantage of parameter estimation within the data assimilation framework is that the derived parameters are consistent with an analyzed rather than a simulated (and often biased) atmospheric state. It also offers a way to accommodate the fact that subgrid-scale convective events and microphysical properties can vary from one model grid to another and that the aggregate influence of this subgrid-scale variability cannot be captured by current parameterized schemes with global constants.

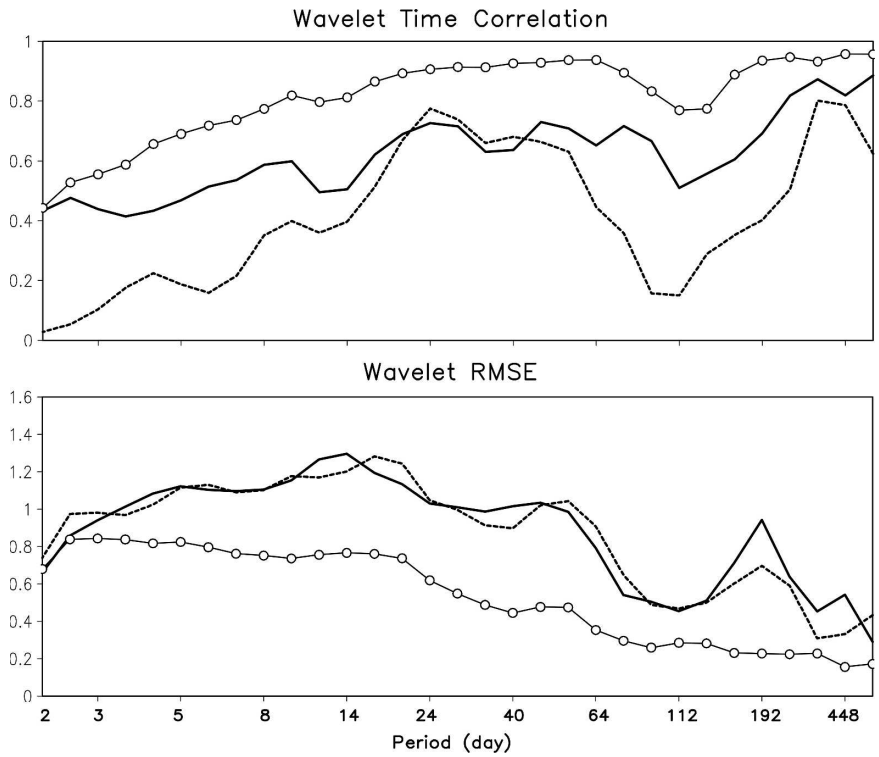

FIG. 8. Wavelet analysis of 4-year (1998–2001) time series of precipitation averaged over the warm pool (4°S–4°N, 120°–160°E): (top) time correlations with GPCP data as a function of oscillation period for GEOS-3/TRMM (open circle), NCEP/GDAS (dash line), and ERA-40 (solid line); and (bottom) wavelet rms errors, 120°–160°E, with respect to GPCP.

The challenge in this approach lies in matching the modeled and observed latent heating profiles of many degrees of freedom with a limited set of parameters to which the heating rates are responsive. For a given heating profile, the degrees of freedom correspond to the number of model levels over the heating depth, which typically exceeds 15 in this example. Moreover, matching the net latent heating rates can lead to unrealistic structures of convective and stratiform heating since they represent different processes: convective and stratiform heating profiles must be matched individually with observations, effectively doubling the number of degrees of freedom.

The selection of model physics parameters as a control variable is based on a series of sensitivity experiments using the column model of GEOS-3 moist physics (Hou et al. 2004). The experimental design is similar to what is often used in model physics development but focuses only on precipitation events. Empirical parameters in moist physics schemes were perturbed individually to determine their impact on the model heating profile. Four empirical parameters that emerged as having the largest impact on the vertical distribution of latent heating were selected as the control vector: 1) the convective adjustment time (which controls the convective mass flux), 2) the minimum critical relative humidity at the cloud top, 3) the fraction of cloud liquid that evaporates into the large-scale environment at the cloud top, and 4) the ratio of water/ice in stratiform precipitation. The error standard deviations of these parameters are prescribed to ensure that they are physically meaningful and that the heating rates are within bounds of observed values. The assigned error standard deviation is 50% for the convective adjustment time and 20% for the remaining three parameters. Since this algorithm is not designed to turn off model heating where there is no observed heating, the algorithm is applicable only where latent heating is present in both the model and the observation. In practice, latent heating assimilation can be implemented with the VCA of surface rain to improve the convective and stratiform latent heating structures over rainy locations.

Figure 10 shows two examples of the extent to which this four-parameter algorithm can match the observed heating structures. In case A, the model first guess has excessive convective heating aloft, with a maximum difference of $\sim$30 K day^{-1} at 400 hPa, while the discrepancies in startiform heating/cooling is even more pro-

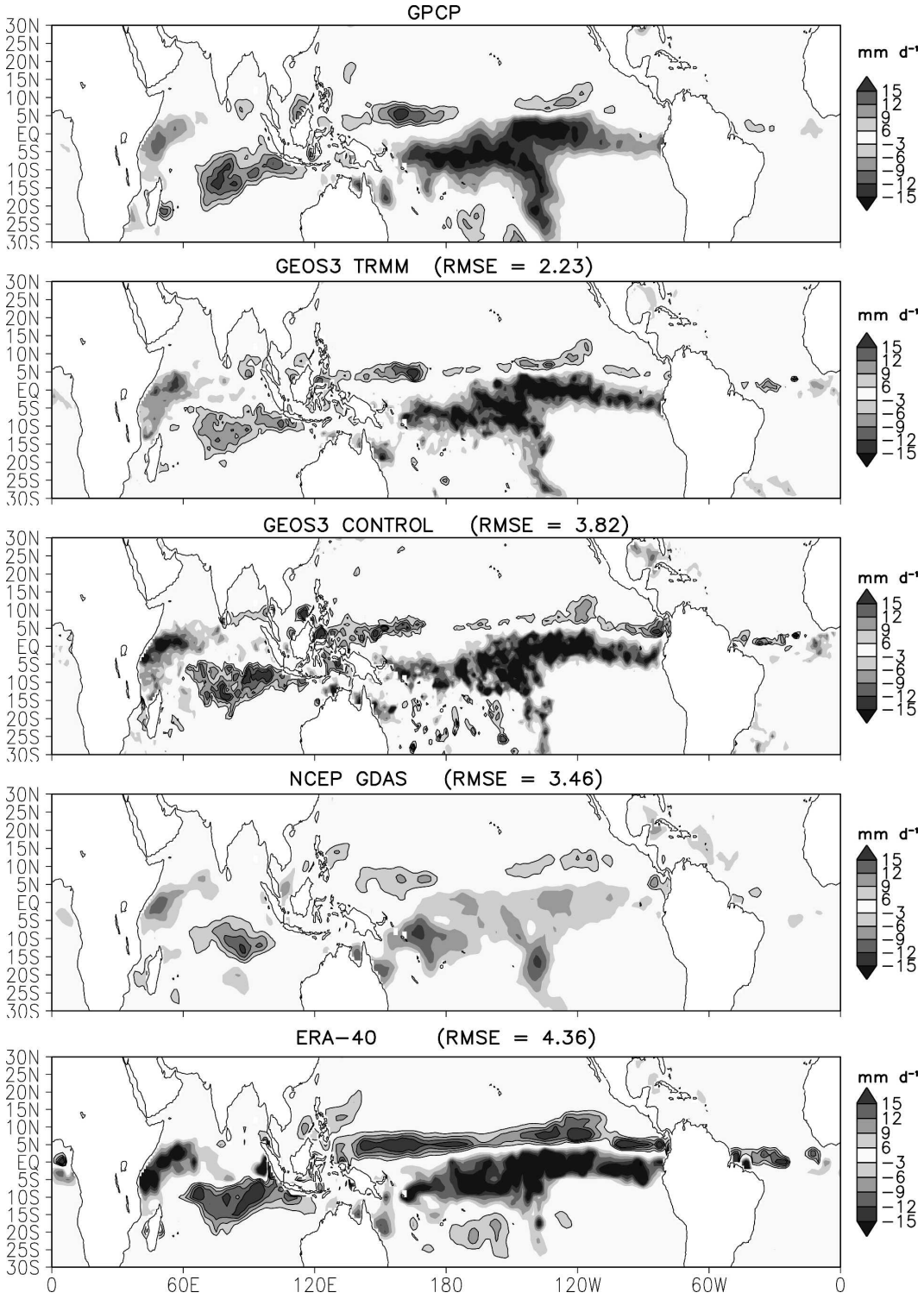

FIG. 9. Changes in tropical precipitation between January 2001 (La Niña) and January 1998 (El Niño): (top to bottom) GPCP, GEOS-3/TRMM, GEOS-3/Control, NCEP/GDAS, and ERA-40. Contours indicate positive values.

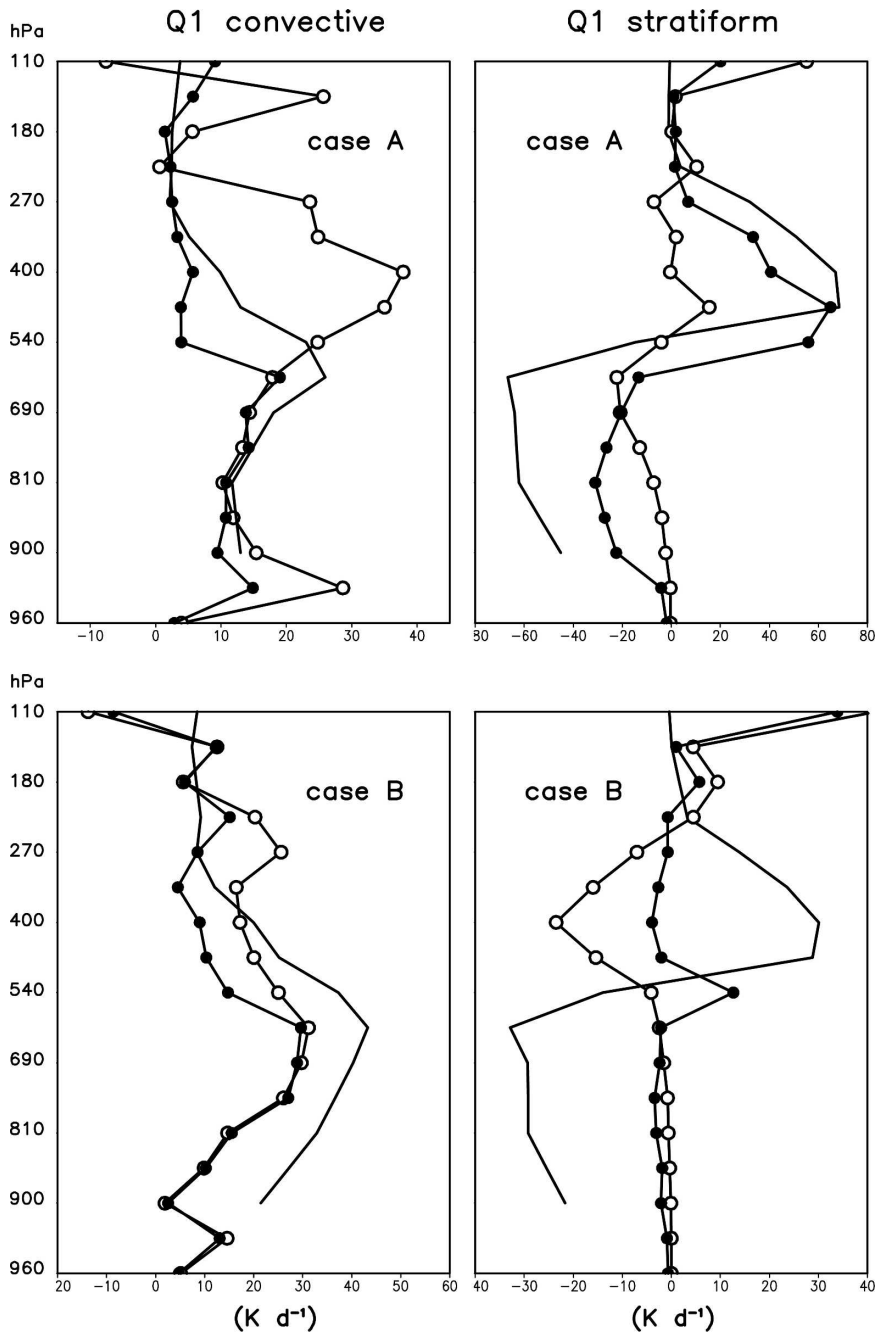

FIG. 10. (left) Convective and (right) stratiform latent heating profiles for TMI retrieval (solid), column-model first guess (open circle), and minimization solution of the latent heating assimilation algorithm (closed circle). (top) Case A is for 0000 UTC 4 Jul 2001 at 15°N, 132°E; (bottom) case B is for 0600 UTC on the same day at 4°S, 100°E.

nounced (roughly 60 K day^{-1}). Latent heating assimilation significantly improves both heating profiles, with rms error reduction of 55% and 26% for convective and stratiform heating rates, respectively.

By contrast, in case B, the quadratic misfits between the model heating profiles and the retrievals are relatively uniform with height. The minimization convergence is slow and the rms errors in latent heating structures are reduced only slightly—by 18% in stratiform heating and unchanged in convective heating. The effectiveness of the minimization procedure appears to depend upon the structure and amplitude of the model-

minus-observed departures. This is likely a result of the nonuniform sensitivity with height of the heating profiles to the selected parameters. Given the nonlinear relationships between the heating structures and the parameters, it is difficult to generalize the heating response to parametric perturbations since they are highly state dependent.

The above procedure shows promise for assimilating latent heating as a further enhancement to precipitation assimilation. In addition to improving the intensity and horizontal pattern of surface rain using the VCA scheme, the technique allows us to refine the vertical distribution of latent heating to further improve the vertical motion field. We are currently implementing this latent heating assimilation procedure in the GEOS system, together with a comprehensive quality control and data selection procedure, to perform data impact studies. Results will be presented in a follow-on paper.

6. Concluding remarks

The current generation of global analysis systems can have significant errors in basic hydrological fields such as clouds and precipitation. This paper examines the prospect of improving the quality of global analyses by assimilating precipitation-related observations using column model moist physics as a weak constraint. We generated a 4-yr GEOS-3 reanalysis that assimilates TMI and SSM/I tropical rainfall using a variational continuous assimilation scheme and compared results with the operational NCEP GDAS analysis and ERA-40. Results show that the GEOS-3 reanalysis with VCA rainfall assimilation is significantly better at replicating the intensity and variability of tropical precipitation systems ranging from a few days to interannual time scales.

In the near term, accuracy of observation operators based on parameterized physics will continue to be an issue in precipitation assimilation. Assimilation algorithms using the model as a weak constraint provide an opportunity for making online estimation and correction of model physics errors to improve precipitation observation operators within an analysis cycle. Successful implementation of this strategy in global NWP systems can lead to better use not only of available radiance measurements but also multichannel retrievals leveraging off more detailed physics of cloud-scale models.

Adding to a growing body of literature on the benefits of precipitation assimilation based on column model physics, this study offers further evidence that precipitation assimilation using the VCA scheme with a moisture tendency correction is very effective in allowing the GEOS global analysis to capture the observed intensity and variability of tropical precipitation systems on a wide range of time scales. As a strategy for further improvements, this study examines a variational algorithm within the general framework of parameter estimation to assimilate satellite-retrieved vertical latent heating structures in conjunction with rainfall assimilation. The algorithm minimizes quadratic misfits between the modeled and observed latent heating profiles using selected semiempirical parameters in the column model moist physics. The initial column-model test results are encouraging, but the full impact of this technique for latent heating assimilation in global systems has yet to be explored.

Model error corrections based on the 1 + 1D variational algorithm for precipitation and/or latent heating assimilation can be incorporated into a traditional 3DVAR or 4DVAR system following the conventional data analysis within an analysis cycle. In the GEOS-3 system, which uses IAU increments with a 3DVAR Physical-Space Statistical Analysis System, the VCA procedure for precipitation assimilation is performed after IAU tendencies due to all other observations have been computed. The rain-induced moisture tendency corrections and conventional IAU tendencies are applied together as additional forcing during a 6-h integration of the full GCM to produce the final analysis. In this case, precipitation observations over the current analysis time window are used.

In a standard 3DVAR analysis system without IAU increments, the VCA procedure for precipitation assimilation can also be performed after conventional analysis. The main difference is that the precipitation data are "future" observations from the current analysis time. The VCA tendency corrections can be applied as an incremental model error correction on the forecast rainfall in the first-guess field for the next analysis cycle. In a standard 4DVAR system, the VCA precipitation assimilation can be implemented to provide an incremental model correction during the model integration within the conventional analysis window.

While model errors pose special challenges for precipitation assimilation, the close relationship between precipitation and moist physical processes also presents opportunities to quantify model deficiencies through precipitation assimilation. Extending conventional analysis systems to assimilate precipitation-related information using moist physics as a weak constraint could prove to be an effective strategy for improving not only the quality of atmospheric analyses and forecasts but also moist physics parameterizations.

Acknowledgments. We thank Derek van Pelt, Man-Li Wu, Jui-Lin Li, Xin Lin, and Siegfried Schubert of the Global Modeling and Assimilation Office at NASA Goddard for contributing to the evaluation of the TRMM reanalysis and latent heating results. It is a pleasure to acknowledge the support of NASA Precipitation Measurement Missions Research under WBS 51-621-15-45 and Interdisciplinary Science Research under WBS 51-291-01-C7.

APPENDIX

Acronyms

AMSU	Advance Microwave Sounding Unit
AMSR-E	Advanced Microwave Scanning Radiometer for Earth Observing System
ATMS	Advanced Technology Microwave Sounder
CERES	Cloud and the Earth's Radiant Energy System
CMIS	Conical Scanning Microwave Imager/Sounder
CRM	Cloud-Resolving Model
ECMWF	European Centre for Medium-Range Weather Forecasts
ENSO	El Niño–Southern Oscillation
ERA-40	40-yr ECMWF Re-Analysis
GCM	General circulation model
GDAS	Global Data Assimilation System
GEOS	Goddard Earth Observing System
GMI	GPM Microwave Imager
GPCP	Global Precipitation Climatology Project
GPM	Global Precipitation Measurement
IAU	Incremental analysis update
IOP	Intensive Observing Period
JAXA	Japan Aerospace Exploration Agency
JMA	Japan Meteorological Agency
MADRAS	Multifrequency Microwave Scanning Radiometer
MHS	Microwave Humidity Sounder
MJO	Madden–Julian oscillation
NASA	National Aeronautics and Space Administration
NASDA	National Space Development Agency of Japan
NCEP	National Centers for Environmental Prediction
NWP	Numerical weather prediction
OLR	Outgoing longwave radiation
SCSMEX	South China Sea Monsoon Experiment
SSM/I	Special Sensor Microwave Imager
SSMIS	Special Sensor Microwave Imager/Sounder
TCWV	Total column water vapor
TMI	TRMM Microwave Imager
TRMM	Tropical Rainfall Measuring Mission
VCA	Variational continuous assimilation

REFERENCES

Adler, R., and Coauthors, 2003: The Version-2 Global Precipitation Climatology Project (GPCP) Monthly Precipitation Analysis (1979–present). *J. Hydrometeor.,* **4,** 1147–1167.

Andersson, E., and Coauthors, 2005: Assimilation and modeling of the atmospheric hydrological cycle in the ECMWF forecasting system. *Bull. Amer. Meteor. Soc.,* **86,** 387–402.

Aonashi, K., N. Yamazaki, H. Kamahori, and K. Takahashi, 2004: Variational assimilation of TMI rain type and precipitation retrievals into global numerical weather prediction. *J. Meteor. Soc. Japan,* **82,** 671–693.

Bauer, P., P. Lopez, A. Benedetti, D. Salmond, and E. Moreau, 2006: Implementation of 1D+4D-var assimiliation of precipitation-affected microwave radiances at ECMWF. II: 4D-Var. *Quart. J. Roy. Meteor. Soc.,* **132,** 2307–2332.

European Centre for Medium-Range Weather Forecasts, cited 2004: ECMWF 40 year reanalysis (ERA-40) data archive. [Available online at http://www.ecmwf.int/products/data/archive/descriptions/e4/.]

Global Precipitation Climatology Project, cited 2004: GPCP merged analysis of daily precipitation. [Available online at http://precip.gsfc.nasa.gov.]

Hou, A. Y., D. V. Ledvina, A. M. da Silva, S. Q. Zhang, J. Joiner, R. M. Atlas, G. J. Huffman, and C. D. Kummerow, 2000: Assimilation of SSM/I-derived surface rainfall and total precipitable water for improving the GEOS analysis for climate studies. *Mon. Wea. Rev.,* **128,** 509–537.

——, S. Q. Zhang, A. M. da Silva, W. S. Olson, C. D. Kummerow, and J. Simpson, 2001: Improving global analysis and short-range forecast using rainfall and moisture observations derived from TRMM and SSM/I passive microwave sensors. *Bull. Amer. Meteor. Soc.,* **82,** 659–679.

——, ——, and O. Reale, 2004: Variational continuous assimilation of TMI and SSM/I rain rates: Impact on GEOS-3 hurricane analyses and forecasts. *Mon. Wea. Rev.,* **132,** 2094–2109.

Houze, R., 1982: Cloud clusters and large-scale vertical motions in the tropics. *J. Meteor. Soc. Japan,* **60,** 396–409.

Lin, J.-L., and Coauthors, 2006: Tropical intraseasonal variability in 14 IPCC AR4 climate models. Part I: Convective signals. *J. Climate,* **19,** 2665–2690.

Lopez, P., A. Benedetti, P. Bauer, M. Janiskova, and M. Kohler, 2006: Experimental 2D-var assimilation of ARM cloud and precipitation observations. *Quart. J. Roy. Meteor. Soc.,* **132,** 1325–1347.

Marecal, V., and J.-F. Mahfouf, 2003: Experiments on 4D-var assimilation of rainfall data using an incremental formulation. *Quart. J. Roy. Meteor. Soc.,* **129,** 3137–3160.

Moreau, E., P. Lopez, P. Bauer, A. M. Tompkins, M. Janiskova, and F. Cheavallier, 2004: Variational retrieval of temperature and humidity profiles using rain rates versus microwave brightness temperatures. *Quart. J. Roy. Meteor. Soc.,* **130,** 827–852.

National Aeronautics and Space Administration, cited 2006: Glo-

bal precipitation measurement. [Available online at http://gpm.gsfc.nasa.gov/index.html.]

National Centers for Environmental Prediction, cited 2004: NCEP reanalysis. [Available online at http://www.cdc.noaa.gov/cdc/data.ncep.reanalysis2.html.]

Simpson, J., and Coauthors, 2000: The Tropical Rainfall Measuring Mission (TRMM). Earth Observation and Remote Sensing Rep. 4, 71–90.

Tao, W.-K., and Coauthors, 2006: Retrieval of latent heating from TRMM measurements. *Bull. Amer. Meteor. Soc.,* **87,** 1555–1572.

Treadon, R. E., H.-L. Pan, W.-S. Wu, Y. Lin, W. Olson, and R. Kuligowski, 2002: Global and regional moisture analyses at NCEP. *Proc. ECMWF/GEWEX Workshop on Humidity Analysis,* Reading, United Kingdom, ECMWF, 33–47. [Available from European Centre for Medium-Range Weather Forecasts, Shinfield Park, Reading, RG2 9AX, United Kingdom.]

Trenberth, K. E., and J. G. Olson, 1988: An evaluation and intercomparison of global analyses from the National Meteorological Center and the European Centre for Medium-Range Weather Forecasts. *Bull. Amer. Meteor. Soc.,* **69,** 1047–1057.

World Climate Research Programme, 1998: *Proceedings First WCRP International Conference on Reanalysis.* WCRP, 461 pp.

Zupanski, D., 1997: A general weak constraint applicable to operational 4DVAR data assimilation systems. *Mon. Wea. Rev.,* **125,** 2274–2292.

Zupanski, M., D. Zupanski, D. F. Parrish, E. Rogers, and G. DiMego, 2002: Four-dimensional variational data assimilation for the blizzard of 2000. *Mon. Wea. Rev.,* **130,** 1967–1988.