Four-Dimensional Variational Assimilation of Total Column Water Vapor in Rainy Areas

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ABSTRACT

This paper studies the impact of assimilating rain-derived information in the European Centre for Medium-Range Weather Forecasts (ECMWF) four-dimensional variational (4DVAR) system. The approach is based on a one-dimensional variational (1DVAR) method. First, model temperature and humidity profiles are adjusted by assimilating observed surface rain rates in 1DVAR. Second, 1DVAR total column water vapor (TCWV) estimates are assimilated in 4DVAR. Observations used are Tropical Rainfall Measuring Mission (TRMM) surface rain-rate estimates from the TRMM Microwave Imager.

Two assimilation experiments making use of 1DVAR TCWV were run for a 15-day period. The ''Rain-1'' experiment only assimilates 1DVAR retrievals where the observed rain rate is nonzero while the ''Rain-2'' experiment assimilates all 1DVAR TCWV estimates. The period selected includes Hurricane Bonnie, which was well sampled by TRMM (late August 1998).

Results show a positive impact on the humidity analysis of assimilating 1DVAR TCWV in 4DVAR. The model rain rates at the analysis time are closer to the TRMM observations showing a posteriori the consistency of the two-step approach chosen to assimilate rain-rate information in 4DVAR. The modification of the humidity analysis induces changes in the wind and pressure analysis. In particular the analysis of the track of Hurricane Bonnie is noticeably improved for the early stage of the storm development for both the Rain-1 and Rain-2 experiments. When Bonnie is in a mature stage the influence of the 1DVAR TCWV assimilation is to intensify the hurricane. Comparison with Clouds and the Earth's Radiant Energy System (CERES) measurements also show a neutral impact on the radiative fluxes at the top-of-the atmosphere when using 1DVAR TCWV estimates.

The impact on the forecasts is a slight reduction of the model precipitation spindown over tropical oceans. Objective scores for the Tropics are improved, particularly for wind and for upper-tropospheric temperature.

Analysis and forecast results are generally better for the Rain-2 experiment compared to Rain-1, implying that the 1DVAR TCWV estimates retrieved where no rain is observed provide useful information to 4DVAR.

1. Introduction

The general problem of assimilation of observations in numerical weather prediction is the definition of the best initial conditions of a forecast model, using all the available information on the atmospheric state in an optimal way. Analysis systems based on three-dimensional (3DVAR) or four-dimensional (4DVAR) variational methods are currently the most promising approaches for global initialization. Their basis is to minimize an objective function measuring the distance of a model solution to observations available over a given time period (assimilation window) and to a model short-range forecast. The 4DVAR assimilation method, which is the temporal extension of 3DVAR, uses the model dynamics to compare the observations at the appropriate time. In principle, it is possible to assimilate in 3DVAR or 4DVAR systems any type of observations when its corresponding error is known. In practice, an accurate observation operator is needed to allow the calculation of the model equivalent of the observed quantity. In a variational context, linearized versions (tangent linear and adjoint) of observation operators are also necessary. 3DVAR systems are currently operational at the National Centers for Environmental Prediction (NCEP) and at the U.K. Met Office (UKMO). A 4DVAR analysis system based on an incremental formulation (Courtier et al. 1994) has been operational at the European Centre for Medium-Range Weather Forecasts (ECMWF) since 25 November 1997, leading to an improvement of ECMWF analysis and forecast skills compared to 3DVAR (Rabier et al. 2000; Mahfouf and Rabier 2000; Klinker et al. 2000). A 4DVAR system has also been operational at Météo-France since June 2000 and developments are in progress at various meteorological centers (NCEP, UKMO, Canadian Meteorological Centre).

The major source of atmospheric observations for assimilation over oceans comes from space-borne in-

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struments, in particular in the Tropics where conventional measurements are scarce. Since November 1997, high-resolution estimates of precipitation rates in the tropical belt have been provided by the Tropical Rainfall Measuring Mission (TRMM) (Simpson et al. 1996; Kummerow et al. 1998). Because tropical large-scale rainfall patterns and their associated energy release are known to influence the global circulation, the assimilation of rainfall measurements in the Tropics is likely to improve global atmospheric analyses and forecasts.

The assimilation of satellite-derived rain rates is far from being a trivial exercise, but the emergence of variational methods appears to provide an efficient framework for such developments. Despite many feasibility studies published in the literature, rainfall observations are not currently used in global operational data assimilation systems. Zupanski and Mesinger (1995), Zou and Kuo (1996), Tsuyuki (1997), and Guo et al. (2000) presented a number of results from 4DVAR assimilation of precipitation with regional and global models. These studies demonstrated the technical feasibility of such an approach, but their conclusions are very difficult to extrapolate to an operational context because they suffer from strong limitations: absence of a background and/or gravity wave control terms in the cost function, arbitrary specification of observation errors, limited number of observations or use of analyses as observations, absence of quality control on the data, and no cycling of the analyses. A number of important issues need to be addressed before an efficient use of satellite-derived rain rates can be made for operational applications. The use of physical parameterizations (such as cumulus convection) with strong nonlinearities and thresholds is expected to lead to problems in the minimization algorithms. The nature of these problems can vary with the physical processes and the setup of the variational problem. The quantification of observation errors from retrieval algorithms has not yet been properly assessed. The underlying hypotheses of the current 4DVAR formulations need to be studied in the context of rainfall assimilation: use of Gaussian statistics for observation errors, perfect model assumption, and use of global and static background errors.

A possible way to evaluate the usefulness of any new type of observations in global operational variational analysis systems at a reasonable cost is to use a one-dimensional variational (1DVAR) approach. In this case, the assimilation is performed in two steps. The first step consists of a 1DVAR assimilation of the observed quantity in which 1DVAR seeks for adjusted model variables (e.g., temperature, sea level wind speed) that fit, in a least square sense, the observations within both model and observation errors. The second step is the assimilation of the 1DVAR retrieval products in 3DVAR or 4DVAR. Since 1DVAR products are basic thermodynamic/dynamic model variables, they can be easily introduced in a global data assimilation system without too much technical work and without substantial increase of computing cost. One weakness of this approach is to introduce in the global system correlations between the observations and the model state. However, the one-dimensional framework allows a detailed study of model adjustments related to the assimilation of one particular type of observations. A 1DVAR approach was used operationally at ECMWF for assimilation of Television Infrared Observation Satellite (TIROS) Operational Vertical Sounder (TOVS) radiances in clear air (Eyre et al. 1993) from June 1992 to May 1999 and was implemented for Special Sensor Microwave/Imager (SSM/I) brightness temperatures assimilation in nonrainy areas in June 1998 (Phalippou 1996; Gérard and Saunders 1999).

The aim of the present paper is to study the impact on analyses and forecasts of the assimilation of TRMM-derived rain rates in the ECMWF 4DVAR system. Compared to previous published papers on the 4DVAR assimilation of rainfall rates we perform an evaluation within the ECMWF operational configuration over a 15-day period with a cycling of the analyses. Such methodology allows us to assess the impact of rain-rate assimilation in a statistical sense, and not only on a selected case study. A 1DVAR approach was chosen because it allows the influence of this new type of observation to be evaluated without requiring too much technical developments and computing resources. The 1DVAR method was developed and tested by Marécal and Mahfouf (2000; hereafter MM2000). It allows the retrieval of adjusted temperature and humidity profiles that provide a model rain rate within both the model and the surface rain-rate observation errors. Their results showed that 1DVAR is generally able to modify the model temperature and humidity profiles in order to get a rainfall rate close to the observation when the model initially produces rain. In this paper, results of two 4DVAR assimilation experiments are analyzed making use of the total column water vapor (TCWV) retrieved from MM2000's 1DVAR.

A summary of the 1DVAR basis and of MM2000's main results is given in section 2. Section 3 describes the 4DVAR assimilation experiments designed to test the assimilation of surface rain rate through the 1DVAR approach. Analysis and forecast results are discussed in sections 4 and 5, respectively. Section 6 shows results of a sensitivity experiment to the rain-rate observation error. Concluding remarks are given in section 7.

2. 1DVAR retrieval

a. Method

We define R_o as an observed surface rain rate and $\mathbf{x}$ as a vector representing the atmospheric state (or control variable) at the observation location. The 1DVAR retrieval seeks an optimal atmospheric state $\mathbf{x}$ that minimizes a distance between the model and the observed surface rainfall rates, knowing a background constraint provided by a short-term forecast profile $\mathbf{x}^b$. When the background and the observation errors are uncorrelated and each has a Gaussian distribution, then the maximum likelihood estimator of the state vector $\mathbf{x}$ is the minimum of the following cost function:

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x} - \mathbf{x}^b)^T\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}^b) + \frac{1}{2}\left[\frac{R(\mathbf{x}) - R_o}{\sigma_o}\right]^2, \quad (1)$$

where $\mathbf{B}$ is the background error covariance matrix from the ECMWF 4DVAR system (Rabier et al. 1998; Derber and Bouttier 1999), σ_o the standard deviation of the observation error, and $R(\mathbf{x})$ is an instantaneous surface rain rate obtained from the model atmospheric state $\mathbf{x}$. Finally, $R(\mathbf{x})$ is computed using the parameterizations of the moist convective and of the large-scale precipitation processes. The control variable vector $\mathbf{x}$ contains 63 elements: profiles of temperature T and specific humidity q on 31 model levels and surface pressure P_S. MM2000 used background fields calculated from an ECMWF model version (Cycle 18r3) with spectral truncation T_L319 (corresponding to a 60-km resolution approximately) and 31 vertical levels (up to the 10-hPa level).

b. Observations

The rainfall rates used by MM2000 came from the TRMM observations. TRMM's main objective is to measure rainfall and energy exchanges of tropical regions (Simpson et al. 1996). TRMM carries three instruments that provide independent estimates of precipitation: a radar, a microwave imaging radiometer (TMI), and a visible/infrared imaging radiometer (Kummerow et al. 1998). The TRMM satellite is in a circular orbit at an altitude of about 350 km with a 35° inclination angle resulting in a coverage of the Tropics and the subtropics only (between −40° and +40° latitude). The TRMM products used by MM2000 were the instantaneous surface rainfall rates (2A12 product level 4) provided operationally by the National Aeronautics and Space Administration (NASA). They are retrieved from the Kummerow et al. (1996) algorithm applied to TMI brightness temperatures and are provided at the highest pixel resolution (about 7×5 km^2). Because TMI-2A12 rain estimations are less accurate over land than over sea (Kummerow et al. 1996), only observations over ocean were used. To be consistent with the model rain rates, which are representative of a much larger area, the observations assimilated in 1DVAR (i.e., R_o) were obtained by averaging the TMI-2A12 rain rates at the model resolution. No estimate of the rain-rate error is provided with the 2A12 product. In agreement with the scientists in charge of the 2A12 algorithm, a simple relation was used in MM2000 for the rain-rate error σ_o as a function of the rain rate R_o:σ_o was set to 25% of R_o with a minimum threshold value of 0.01 mm h^{-1}.

c. Main results

In their study, MM2000 showed that when precipitation is present in the background field, 1DVAR generally provides adjusted profiles of temperature and specific humidity leading to a rain rate close to the observation within the observation error (for 70%–80% of the profiles). In this case, 1DVAR modifies the humidity profiles much more than the temperature profiles. For background profiles providing no precipitation, 1DVAR is not able to trigger precipitation even if observed. This weakness was also found by Treadon (1997), who performed 3DVAR assimilation of satellite-derived rain rates in the NCEP operational global spectral model.

Because there is no objective estimate of σ_o, MM2000 performed sensitivity tests on σ_o value. If σ_o is increased from 25% of R_o to 50% of R_o, this has an impact on 1DVAR results for moderate and heavy rain rates. When the observation error is increased, the 1DVAR provides smaller but nonnegligible humidity and temperature changes, meaning that an important part of the information contained in the observations is still used.

3. 4DVAR assimilation of TCWV retrievals in rainy areas

a. 1DVAR configuration

In the present study, the background state $\mathbf{x}^b$ used in 1DVAR comes from fields generated using a more recent ECMWF model version (Cy21r1) with spectral truncation T_L319 and 50 vertical levels (up to the 0.1-hPa level). However, only the 31 lowest model levels are used in the control vector since surface rainfall rate is not influenced by stratospheric levels.

The TMI products selected for the present study are the latest version of the instantaneous surface rainfall rates provided operationally by NASA (2A12 product level 5). As in MM2000, σ_o is set to 25% of R_o with a minimum threshold value of 0.01 mm h^{-1}. Since σ_o was roughly estimated, the sensitivity of 4DVAR results to the specification of σ_o is discussed in section 6.

b. Method

The operational ECMWF assimilation system is based on an incremental four-dimensional variational method (Rabier et al. 2000; Mahfouf and Rabier 2000; Klinker et al. 2000). 4DVAR seeks an optimal balance between observations and the dynamics of the atmosphere by finding a model solution that is as close as possible, in a least square sense, to the background information (model short-term forecast) and to the observations available over a given time period (6 or 12 h). The incremental formulation of 4DVAR (Courtier et al. 1994) consists of computing the background trajectory and the departures (observations minus model) using the full nonlinear model at high resolution, including a full set of physical parameterizations, and min-

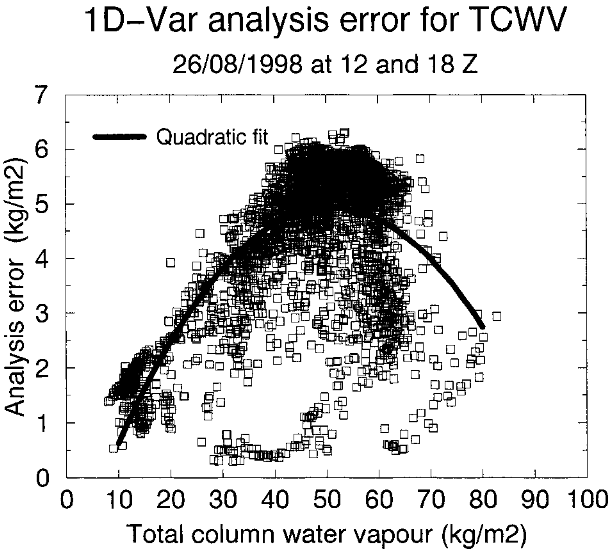

FIG. 1. Scatterplot of 1DVAR analysis error on TCWV (σ_{TCWV}) in kg m^{-2} as a function of TCWV in kg m^{-2}. The number of TCWV retrievals used is 3505. The solid line corresponds to the best fit by second-order power law. Coefficients of the quadratic fit are given in (3).

imizing the cost function in a low-resolution space for the increments at initial time using a tangent linear model and its adjoint at low resolution with a limited set of physical parameterizations (Mahfouf 1999).

Because MM2000 showed that their 1DVAR retrieval mostly modifies specific humidity to adjust the observed rain rates, a 1DVAR humidity-related quantity was chosen for assimilation in 4DVAR. The total column water vapor (i.e., the vertical integral of specific humidity) was preferred to specific humidity profiles because the assimilation of profiles would have enhanced the undesirable correlation between these observations and the model background.

The accuracy of 1DVAR TCWV is the 1DVAR analysis error in TCWV that can be estimated objectively. As shown by Rodgers (1976), the 1DVAR analysis error covariance matrix $\mathbf{A}(\mathbf{x})$ of the atmospheric state $\mathbf{x}$ can be approximated by

$$\mathbf{A}(\mathbf{x}) = \left[\mathbf{B}^{-1} + \frac{1}{\sigma_o^2}\mathbf{R}^{\mathrm{T}}(\mathbf{x})\mathbf{R}(\mathbf{x})\right]^{-1}, \qquad (2)$$

where $\mathbf{R}(\mathbf{x})$ is the Jacobian matrix of the partial derivatives of the simulated rain rate with respect to the control variable $\mathbf{x}$. The error variance of the analyzed TCWV (denoted σ^2_{TCWV}) is then obtained by applying the vertical integration operator to the specific humidity elements of the $\mathbf{A}$ matrix. The elements of the $\mathbf{A}$ matrix depend on the considered atmospheric state $\mathbf{x}$ and thus a value of σ_{TCWV} can be computed for each 1DVAR retrieval. A scatterplot of σ_{TCWV} values as a function of 1DVAR analyzed TCWVs computed using 3505 retrievals is shown in Fig. 1. There is generally a large spread of the σ_{TCWV} values for a given TCWV. Nevertheless, the global tendency for σ_{TCWV} is to increase until TCWV reaches approximately 50 kg m^{-2} and to decrease for higher TCWV values. This behavior is modeled by fitting the data with a second-order polynomial (see Fig. 1):

$$\sigma_{\mathrm{TCWV}} = -1.72 + 0.261 \times \mathrm{TCWV} - 0.00257 \times \mathrm{TCWV}^2. \qquad (3)$$

To avoid negative or unrealistic small values for σ_{TCWV}, a minimum threshold of 1 kg m^{-2} is applied to (3).

Since 1DVAR is not always successful in adjusting the observed rain rates, a quality control was applied to 1DVAR products before entering 4DVAR; only 1DVAR retrievals providing a rain rate fitting the observation within the observation error are selected (as explained more precisely in MM2000). After this quality control, about 1500 to 2000 ‘‘1DVAR TCWV observations’’ can be possibly retained per 4DVAR assimilation cycle (i.e., every 6 h).

c. *Design of the experiments*

Three experiments were designed to assess the impact of assimilating 1DVAR TCWV in rainy areas in the ECMWF 4DVAR system using a $\mathrm{T_L}$319L50 (Cy21r1) model configuration, 6-h cycling, and a T63 resolution (~200-km grid size) for the 4DVAR minimization. The three experiments were run for a 15-day period, between 1200 UTC 18 August 1998 and 1200 UTC 2 September 1998. This period was selected because it includes the whole life time of tropical cyclone Bonnie, which was well sampled by TMI. Bonnie reached the state of tropical storm on 20 August 1998 and the state of hurricane on 22 August 1998. Later, it hit the coast of North Carolina on 27 August 1998 and turned into a subtropical cyclone from 29 August 1998. For each experiment a series of 10-day forecasts was run from the 12 UTC analyses.

The first experiment is the ‘‘control,’’ which only assimilates the operational dataset of the considered model version; humidity data used are specific humidity profiles from radiosondes below 300 hPa, surface relative humidity, and SSM/I TCWV in nonrainy areas over oceans.

The second experiment (denoted the ‘‘Rain-1’’ experiment) is identical to the control except that it includes the assimilation of a reduced number of quality controled 1DVAR TCWV estimates in 4DVAR; only the 1DVAR retrievals corresponding to a nonzero rain-rate observation are selected. The reason for this sorting is that when there is no rain in the observation, 1DVAR seeks the nonrainy state that is the closest to the background state. This retrieved state may differ from the real one since there is a large number of possible atmospheric states that lead to no rain. This means that in this case the problem is ill-posed. Moreover, SSM/I TCWV estimates from brightness temperatures are already assimilated operationally in nonrainy areas, leading to a possible conflict between the two TCWV estimates.

A third experiment identical to Rain-1 but including all quality controlled 1DVAR TCWV estimates was run (denoted the ''Rain-2'' experiment). This experiment was motivated by two reasons. First, TCWV estimates from 1DVAR when no rain is observed can possibly add some useful information to 4DVAR although there is more uncertainty in 1DVAR TCWV than in SSM/I TCWV (when available) in nonrainy conditions. Second, the number of 1DVAR TCWV observations retained for the Rain-1 experiment are around 400 per assimilation cycle. This number, which is about four times smaller than for the Rain-2 experiment, might be too small to lead to a significant impact on 4DVAR analyses and forecasts.

In the three experiments, estimates of TCWV from SSM/I brightness temperature observations were used in nonrainy areas using a 1DVAR approach (Phalippou 1996; Gérard and Saunders 1999). It is important to underline that the 1DVAR used for SSM/I is different from the one developed by MM2000 for the present study. Indeed, SSM/I TCWV retrievals are based on the inversion of observed brightness temperatures through a radiative transfer model. Because SSM/I TCWV is erroneous when rain is present, a strict rejection procedure was designed to discard SSM/I brightness temperatures in rainy conditions. Rain is identified by applying a regression algorithm (Bauer and Schluessel 1993) to the observed SSM/I brightness temperatures. Note that this modification is now used in the current operational 4DVAR version. This new quality control prevents a possible and undesirable conflict between SSM/I TCWV and 1DVAR TCWV where it rains.

Since TRMM only covers the Tropics and the subtropics, results (tables and figures) of these three experiments will be given and discussed for the latitude band sampled by TMI. The term ''global'' will represent hereafter this latitude band, except in section 5c where the full globe will be considered.

4. Impact on analyses

a. Statistics of model departures from observations

Figure 2 shows the global mean statistics of the 4DVAR assimilation of 1DVAR TCWV. The background departure is the difference between the observation and the background (short-term forecast). The analysis departure is the difference between the observation and the analysis. The observations considered here are the 1DVAR TCWV estimates. To compute these statistics, the background and analysis fields are converted into TCWV. Because the Rain-1 experiment only uses TCWV estimates when rain is observed, the number of observations used in the Rain-1 experiment (~23 000) is about four times smaller than in the Rain-2 experiment (~103 000). This means that most of 1DVAR retrievals for the Rain-2 experiment correspond to grid points where no rain is observed. This is mainly due to the fact that the 1DVAR approach is unable to trigger rain when the model background rain is zero (see MM2000).

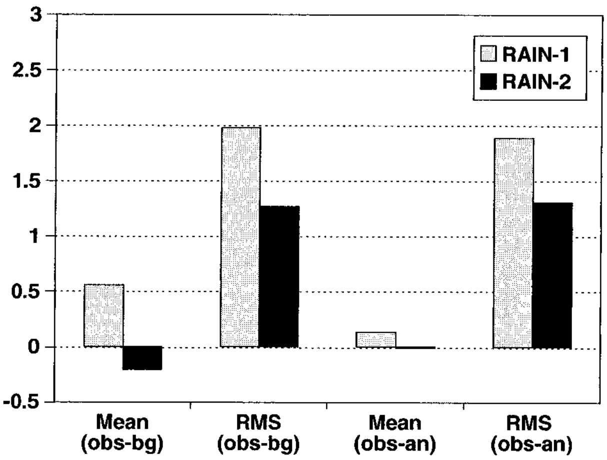

FIG. 2. Global mean statistics of the 1DVAR TCWV used in 4DVAR for the 15-day period. Units are in kg m^{-2}. The background departure (obs−bg) is the 1DVAR TCWV retrieval minus the background TCWV (6-h model forecast). The analysis departure (obs−an) is the 1DVAR TCWV retrieval minus the 4DVAR analyzed TCWV. The number of observations used to compute the statistics is 23 058 for the Rain-1 experiment and 103 097 for the Rain-2 experiment.

For the Rain-2 experiment, the mean background departure exhibits a negative bias of −0.21 kg m^{-2}. On average, 1DVAR TCWV observations tend to decrease rainfall rate. This suggests that the model initially produces rain at some of the locations corresponding to a zero rain observation. A positive bias of 0.56 kg m^{-2} is found for the Rain-1 experiment meaning that, in this case, 1DVAR TCWV observations tend to increase precipitation by increasing TCWV. For both experiments, the bias is reduced by the analysis, indicating that part of the information from 1DVAR TCWV estimates was extracted by the 4DVAR system.

The root-mean-square (rms) departure for the Rain-1 experiment is reduced by the analysis showing a better fit to observations. The slight increase of the rms of analysis departures for the Rain-2 experiment can be explained by the fact that most of the 1DVAR TCWV observations are assimilated where no precipitation is observed. In this case, a different SSM/I TCWV retrieval located close to the 1DVAR TCWV may also be used by the assimilation system. This is reflected in the SSM/I TCWV statistics, which show a small deterioration of the rms of analysis departures for the Rain-2 experiment (not shown).

Compared to SSM/I statistics of model departures, all mean and rms values for 1DVAR TCWV are smaller than for SSM/I TCWV by a factor of 2 or more. This means that the current experiments only change humidity by small amounts compared to SSM/I.

TABLE 1. Global mean values in kg m^{-2} of analyzed TCWV and rms of TCWV increments averaged over the 15-day experiment period.

Experiment	Mean analyzed TCWV	Rms of TCWV increments
Control	35.98	1.81
Rain-1	36.01	1.76
Rain-2	35.92	1.66

b. Analysis of total column water vapor

The global mean values of 4DVAR analyzed TCWV are given in Table 1. The differences between the three experiments are small (<1%) and are associated with small rms of background departures (~2 kg m^{-2}) compared to SSM/I (~4.5 kg m^{-2}) and to the low occurrence of rainy areas within TMI coverage. The Rain-1 experiment provides a slightly moister atmosphere than the control while the opposite result is found in the Rain-2 experiment. This is consistent with the model departure statistics showing that the tendencies for both experiments are, respectively, to increase and to decrease TCWV on average.

The rms of TCWV increments allows the relative quality of the humidity analysis for the three experiments to be evaluated. These increments are the departure in TCWV between the background and the analysis. A reduction of the rms in regions where humidity observations are assimilated means that short-range forecasts are closer to the observations and that smaller corrections are necessary for the assimilation. The rms of TCWV increments for the three experiments are displayed in Fig. 3 and global values are given in Table 1. Both experiments using 1DVAR TCWV provide rms increments smaller than the control experiment in many areas (e.g., in the Intertropical Convergence Zone), thereby showing a positive impact of rain-derived observations. The improvement is more important for the Rain-2 experiment (8%), indicating that the use of all 1DVAR TCWV estimates even where no rain is observed provides a better TCWV analysis. In other words, this means that the information extracted from 1DVAR TCWV estimates where no rain is observed is valuable to 4DVAR although SSM/I TCWV estimates are probably more reliable. It is also important to note that the Rain-1 experiment leads to an improved humidity analysis despite the small number of 1DVAR TCWV retrievals used in 4DVAR.

c. Impact on rainfall rates

The modifications of the humidity analysis induced by the assimilation of 1DVAR TCWV in 4DVAR aim

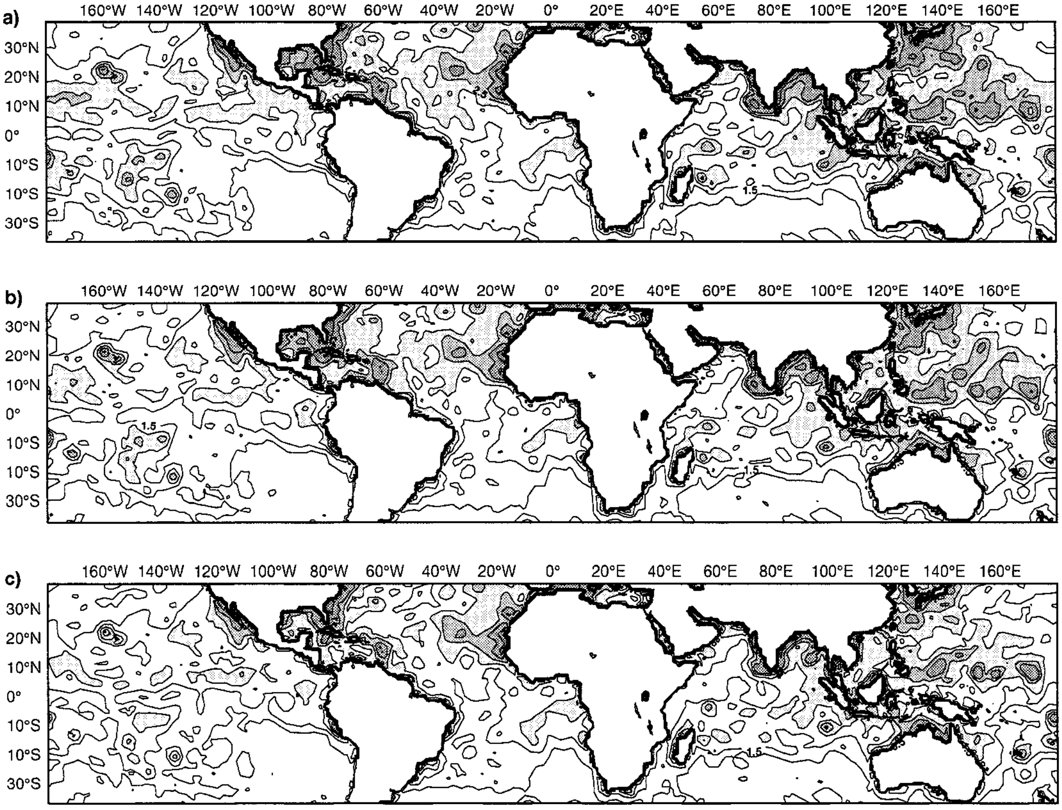

FIG. 3. Root-mean-square of TCWV increments in kg m^{-2} averaged over the 15-day period. The increment field is obtained by computing analyzed field minus background field (6-h model forecast). (a) Control experiment, (b) Rain-1 experiment, and (c) Rain-2 experiment. Contours are every 0.5 kg m^{-2} and gray shading starts at 2 kg m^{-2}.

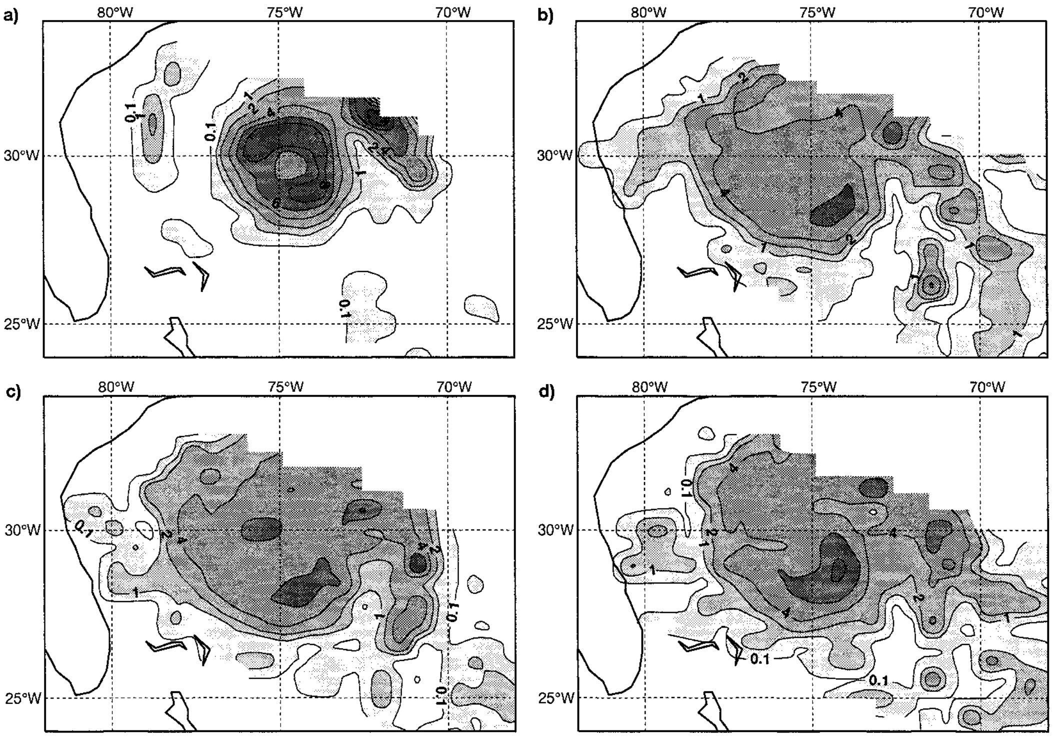

FIG. 4. Surface rainfall rate in mm h⁻¹ at 1800 UTC 25 Aug 1998. (a) From TMI 2A12 observations, (b) from the control experiment analysis, (c) from the Rain-1 experiment analysis, and (d) from the Rain-2 experiment analysis. Model results are only displayed along the TMI swath.

at producing a model surface rainfall rate at the assimilation time closer to the TMI-derived observations. Figure 4 shows the instantaneous surface rain rate at the analysis time for the three experiments together with the observed field on 25 August 1998 at 1800 UTC. This analysis time was selected because Hurricane Bonnie was well sampled by TMI during the corresponding assimilation window. The rain-rate fields for the Rain-1 and Rain-2 experiments show an improvement of both the structure and the intensity of the surface rain rate in the most active parts of the hurricane, the Rain-2 experiment giving better results. Compared to 1DVAR results (see MM2000's results), the improvement in the 4DVAR context is less important. The main explanation is that 4DVAR uses 1DVAR TCWV estimates together with many other types of observations to modify the analysis in an optimal way.

Global results averaged over the 15-day assimilation period are given in Table 2. Both rain experiments provide a surface rain rate closer to TMI observations than the control, as shown by the increase of the correlation coefficient and by a reduction of the rms differences. The Rain-2 experiment exhibits slightly better results than the Rain-1 experiment. This is consistent with the results obtained for the 4DVAR TCWV analysis.

TABLE 2. Global comparison for the 15-day period of the model instantaneous rain rate with TMI rain-rate estimates used in 1DVAR. The rms is the root-mean-square of the difference between the model values and the observation (in mm h⁻¹).

Experiment	Correlation with TMI observations	Rms (model − observations)
Control	0.27	0.69
Rain-1	0.29	0.67
Rain-2	0.30	0.64

d. Trajectory of Hurricane Bonnie

The ECMWF 4DVAR humidity analysis assumes that the background humidity errors are not correlated with other model variables such as temperature. Nevertheless, since 4DVAR takes into account the temporal evolution of any variable within the assimilation window, a modification of the analyzed humidity induces a modification of the global solution and consequently of the thermodynamic and dynamic fields. A way to evaluate the impact of 1DVAR TCWV assimilation on the analyzed pressure field is to compare the hurricane track provided by the model to the ''best track'' derived from observations (obtained from the National Hurricane Center of the National Oceanic and Atmospheric Administration). The model tracking algorithm locates the cyclone by determining the position of the minimum mean sea level pressure.

As shown in Fig. 5ab, the use of rain-derived observations in 4DVAR generally improves the location of

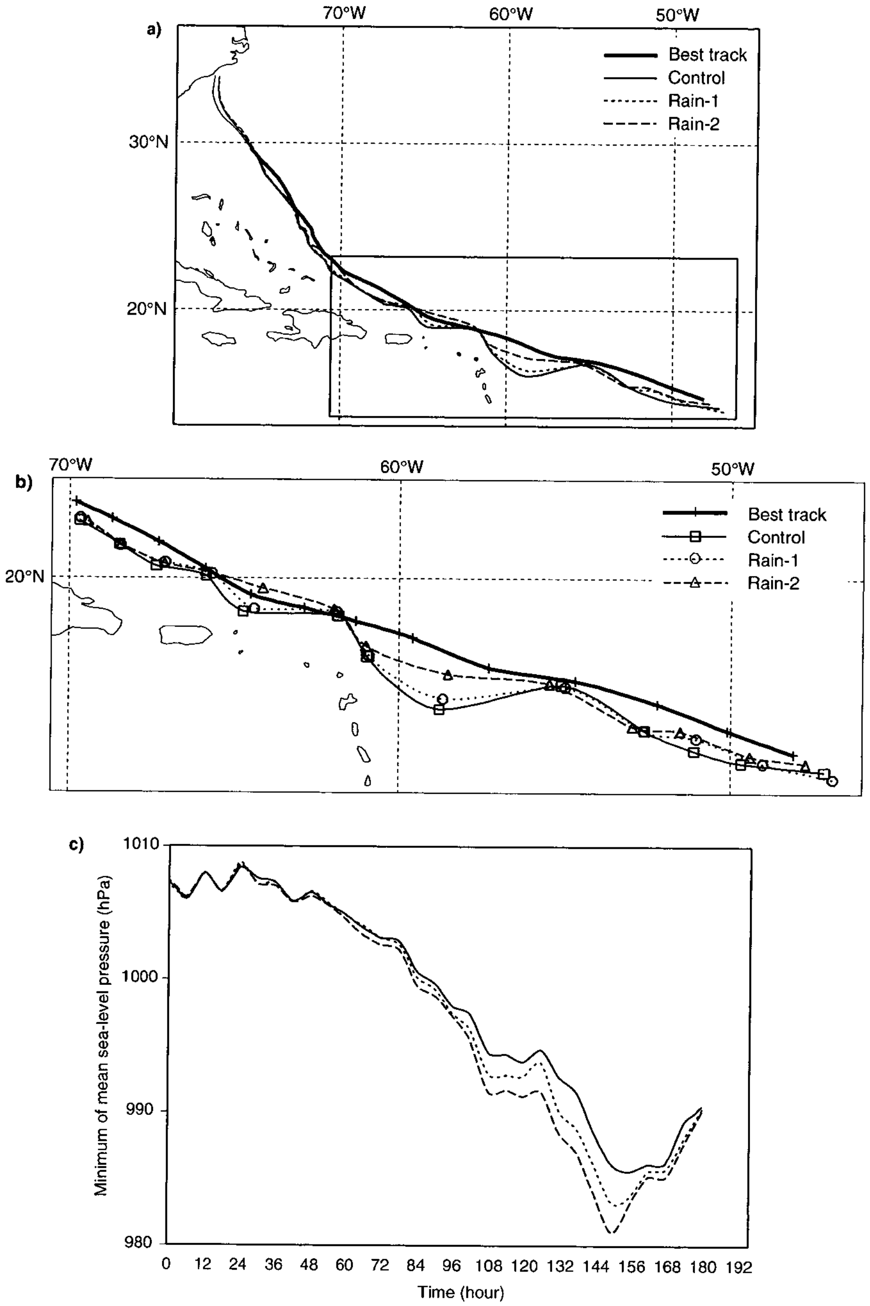

FIG. 5. Analyzed track of Hurricane Bonnie. (a) Location from 1200 UTC 19 Aug 1998 to 0000 UTC 27 Aug 1998. (b) Zoom of the location from 1200 UTC 19 Aug 1998 to 1200 UTC 22 Aug 1998. (c) Temporal evolution of the minimum of mean sea level pressure in the hurricane from 1200 UTC 19 Aug 1998 to 0000 UTC 27 Aug 1998. Symbols are every 6 h.

the track in the early stages of development of the cyclone. Here again, the Rain-2 experiment provides the best results, showing a good consistency between the humidity and the pressure analysis. It is important to note that the improvement of the cyclone track is more important for the assimilation windows that include a good sampling of Bonnie by TMI, for instance on 20 August 1998 at 1800 UTC. For this analysis time, the control, Rain-1, and Rain-2 experiments provide a pressure minimum located 256, 227, and 167 km from the best track, respectively. This shows that there is, at least locally, a real benefit on the analysis in using rain-derived information when available. When Bonnie is in a mature stage (from 23 to 27 August 1998), all three experiments provide tracks close to the best track. The small discrepancies between the model and the observed

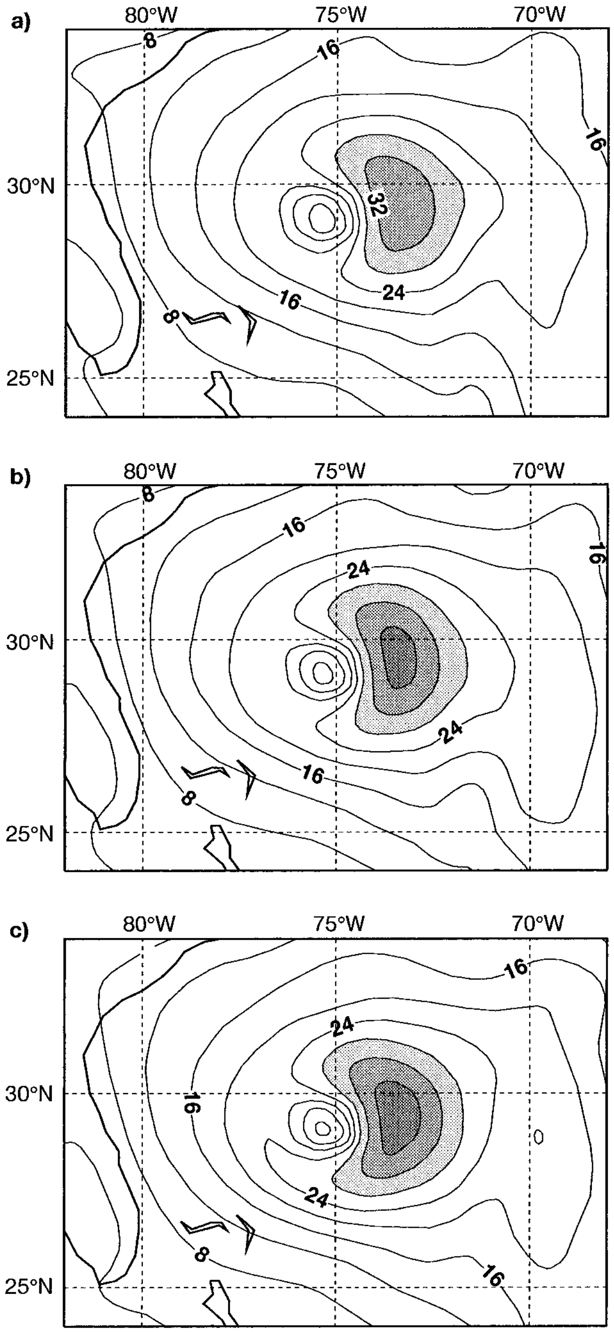

FIG. 6. Analysis of horizontal wind velocity in m s^{-1} at 700 hPa at 1800 UTC 25 Aug 1998 from (a) the control experiment, (b) the Rain-1 experiment, and (c) the Rain-2 experiment. Gray shading starts at 28 m s^{-1}.

track can be attributed to the 4DVAR minimization that is performed in a low-resolution space (~200-km grid size) and to the version of 1DVAR that assumes that TMI observations are obtained at the middle of the assimilation window (see MM2000 for complementary explanations). Figure 5c displays the minimum of mean sea level pressure in the hurricane for the three experiments. During the early stage, there are no important differences between the three experiments. During the mature stage, a much deeper cyclone is analyzed in the Rain-1 and Rain-2 experiments compared to the control experiment with a maximum difference, respectively, of 3 and 5 hPa on 25 August 1998. The minimum of mean sea level pressure in Hurricane Bonnie determined from the observations is available. It is not shown in Fig. 5 because this minimum is representative of much smaller scales than those resolved by the model. Therefore such comparison would not be meaningful.

e. Analysis of wind field

The impact on the global mean analyzed wind field (not shown) is small (<0.5%) for two reasons: the low occurrence of TMI observations in rainy areas over oceans and the use in 4DVAR of many sources of wind data.

Nevertheless, locally the wind field can be significantly modified by the assimilation of 1DVAR TCWV. This is illustrated in Figs. 6 and 7 showing the analyzed horizontal and vertical velocity fields at 700 hPa for Hurricane Bonnie on 25 August 1998 at 1800 UTC. The impact of the 1DVAR TCWV assimilation is to intensify the hurricane by increasing the maximum horizontal wind and the updraft within the hurricane. The Rain-1 experiment leads to fewer modifications compared to the control than the Rain-2 experiment, which is consistent with the results of the other analyzed fields. The impact on wind analysis in the early stage of development of the hurricane is much smaller than in the mature stage (not shown). In the early stage, the rain assimilation acts more on the location of the hurricane than on its intensity. All these results are consistent with the analysis of surface pressure discussed in the previous section.

The 1DVAR TCWV estimates induce on average small modifications to the humidity analysis compared to SSM/I, but the local impact can be quite large, as shown in Fig. 8, where the analyzed TCWV fields are compared for the three experiments. The water vapor increase in the core of the cyclone and in the spiral band located in the northeastern part of domain reaches values between 5 and 10 mm. The Rain-2 experiment produces a drier atmosphere in the cyclone compared to the Rain-1 experiment as a result of points where no rain is observed. These areas of significant differences for TCWV agree well with modifications noticed on the vertical wind field (Fig. 7). To conclude this part, it appears that the analyzed dynamics is very sensitive to modifications of the precipitation and cloud fields. This is because latent heat exchanges that take place in rainy areas have a major impact on the horizontal and vertical energy distribution and consequently on the dynamics.

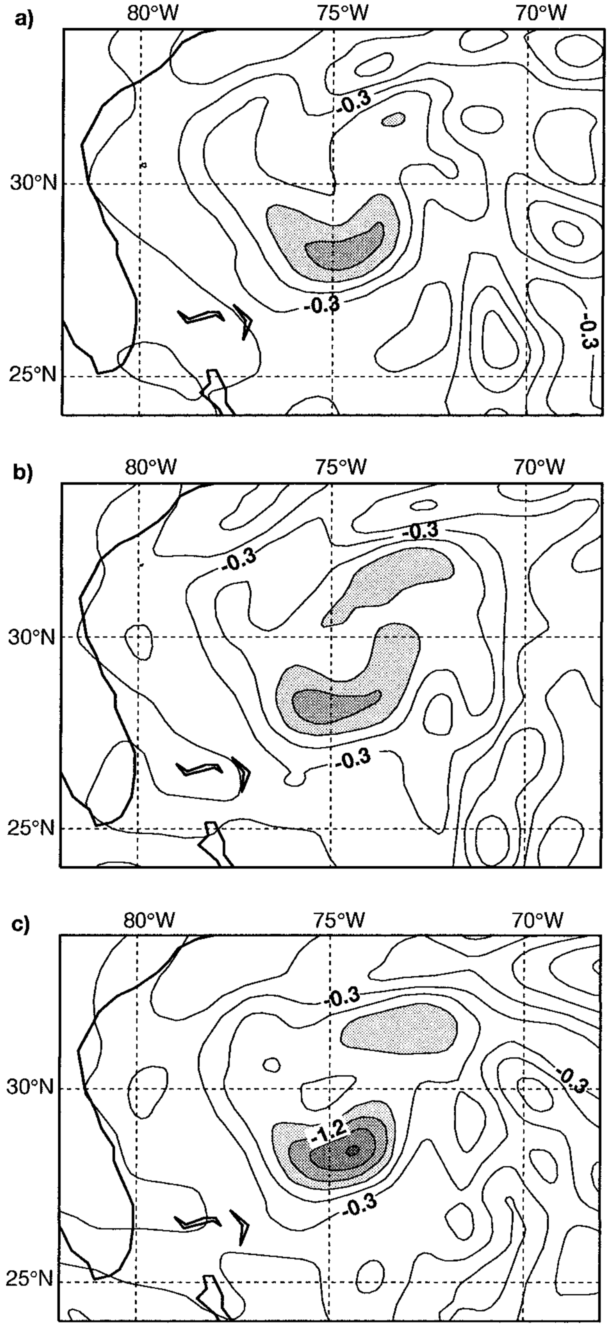

FIG. 7. Same as Fig. 6 but for vertical velocity (in Pa s^{-1}) at 700 hPa. Gray shading starts below -0.9 Pa s^{-1}.

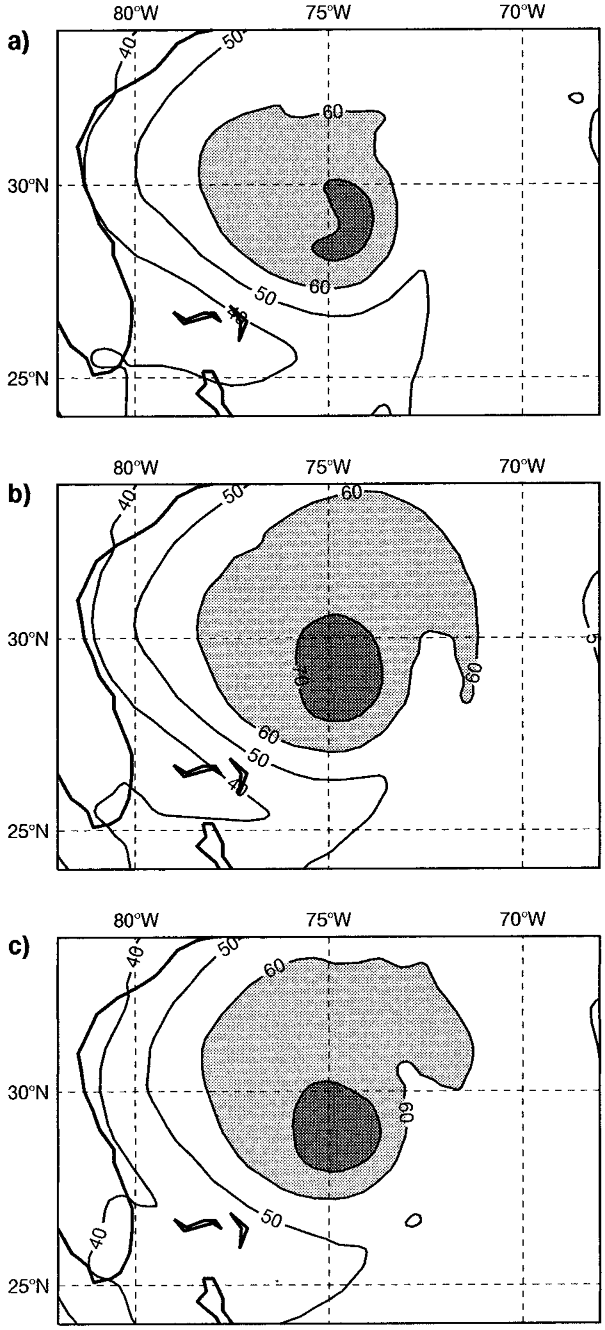

FIG. 8. Same as Fig. 6 but for total column water vapor (in kg m^{-2}). Gray shading starts above 60 kg m^{-2}.

f. Impact on radiative fluxes

Since 1DVAR TCWV assimilation modifies the water variables (water vapor, cloud, and rain), an impact on the model radiative fluxes is also expected. In order to evaluate this impact, a comparison with Cloud and Earth's Radiant Energy System (CERES) observations was done. CERES is a three-channel broadband radiometer flying onboard the TRMM platform (Weilicki et al. 1996) that gives an indirect measure of the longwave and shortwave fluxes at the top of the atmosphere. The model fluxes integrated over 6 h from the analysis time are compared to the CERES measurements averaged over the same period of time as done in Chevallier and Morcrette (2000). A global comparison of the results for the 15-day period is given in Table 3 in terms of rms differences. The global mean impact of 1DVAR TCWV assimilation is neutral for the Rain-1 experiment

TABLE 3. Global comparison for the 15-day period of the model radiative fluxes at the top of the atmosphere with CERES measurements. Values given are the rms of the difference between the model values and the observations in W m^{-2}. Model values are averaged over a 6-h period starting on the analysis time and compared with CERES measurements averaged over the same time period.

Experiment	Shortwave radiation	Longwave radiation
Control	41.1	14.3
Rain-1	41.1	14.3
Rain-2	40.8	14.0

and is slightly positive for the Rain-2 experiment but might be not significant. These results show the relatively good consistency in the model between the radiation scheme and the vertical distribution of the humidity related fields (moisture, cloud, and precipitation). Indeed, the methodology would have been incorrect if the modifications of TCWV suggested by the 1DVAR had produced a degradation of the top of the atmosphere radiative fluxes with respect to the control experiment.

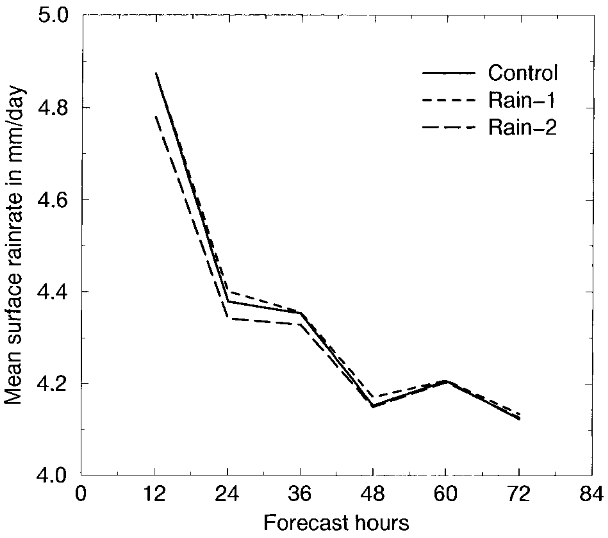

FIG. 9. Mean surface rainfall rate over tropical oceans as a function of forecast range in hours. The surface rain rate is here the accumulated rain rate between T-12 h and T, T being the forecast time.

5. Impact on forecasts

a. Hydrological cycle

The short-range forecast of precipitation is affected by the changes in the humidity analysis. Figure 9 shows the global surface rain rate over oceans accumulated over the past 12 hours as a function of the forecast range for the three experiments. The zigzag shape of the curves reflects the diurnal cycle. All the experiments give large rain rates at the beginning of the forecast that decrease rapidly with time. This behavior is known as spindown. After 48 h of forecast, the curves reach the model equilibrium for the hydrological cycle.

The Rain-1 and control experiment curves are very close. Although the Rain-1 experiment tends to increase the mean humidity, it does not increase the spindown. It retains slightly more humidity after 24 h than the control. The Rain-2 experiment reduces noticeably the spindown because, in this case, forecasts start from a slightly drier humidity analysis.

b. The trajectory of Hurricane Bonnie

In the early stage of the development of Bonnie, the analyzed track is improved by the use of rain-derived information leading to an impact on the forecasted tracks. Figures 10a and 11a show the track of the hurricane from observations (best track) and forecasted by the model starting at 1200 UTC 20 August 1998 and at 1200 UTC 21 August 1998 from the three experiment analyses. The analyzed minimum of mean sea level pressure in Bonnie is not shown because the three available analyses give significantly different evolutions, as shown in Fig. 5. Both rain experiments forecast a better track starting at 1200 UTC 20 August 1998, while the

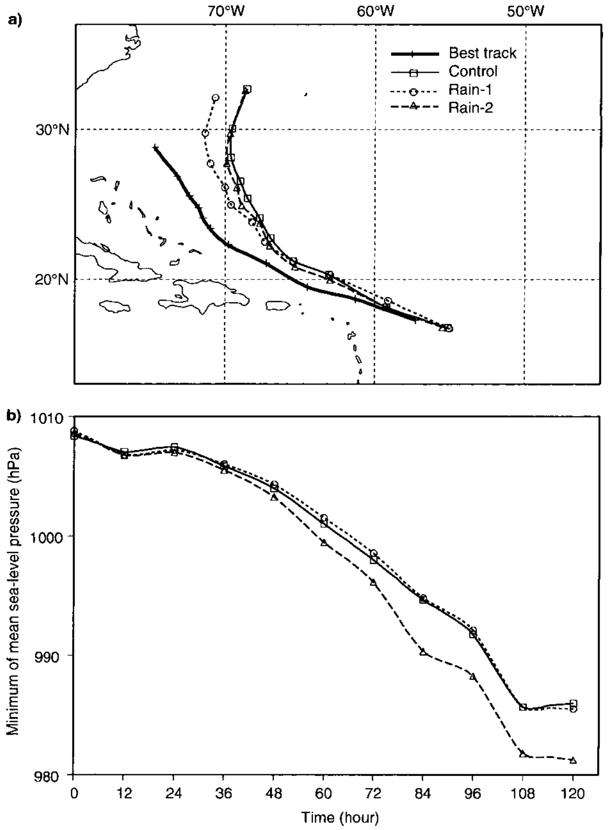

FIG. 10. Forecast tracks of Hurricane Bonnie. (a) Tracks from 5-day forecasts starting at 1200 UTC 20 Aug 1998 based on the three experiment analyses together with the best track from observations. (b) Temporal evolution of the minimum of mean sea level pressure in the hurricane (initial time corresponds to 1200 UTC 20 Aug 1998). Symbols are every 12 h.

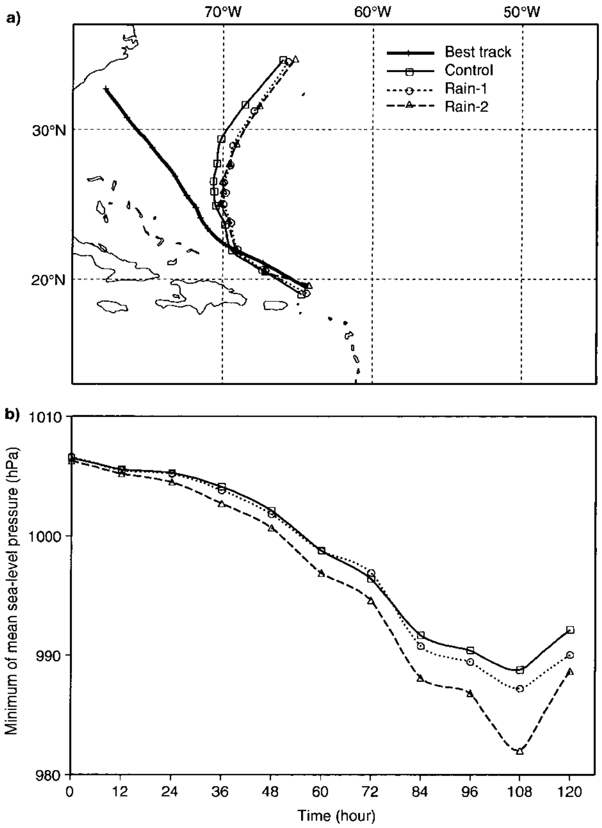

FIG. 11. Same as Fig. 10 but for the forecasts starting at 1200 UTC 21 Aug 1998.

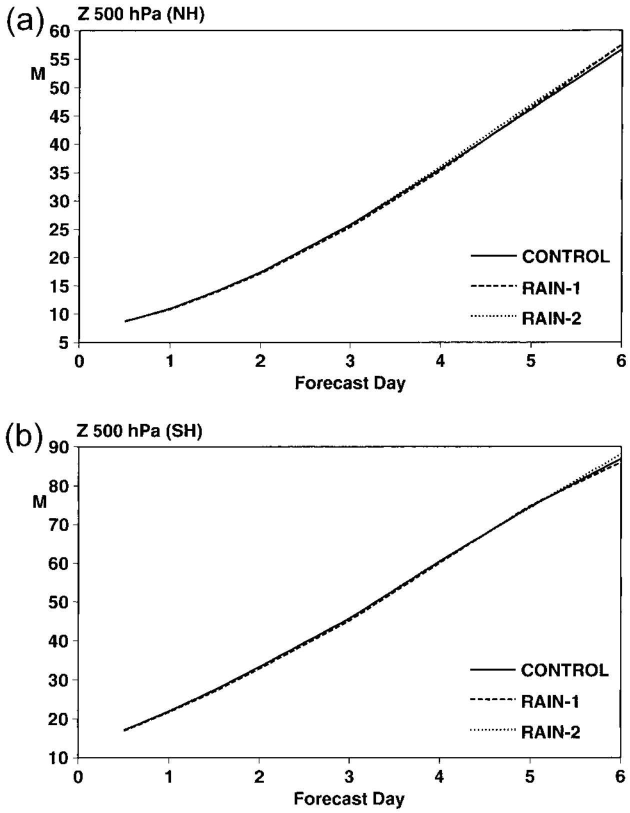

FIG. 12. Root-mean-square forecast errors of the geopotential at 500 hPa for the average over 16 cases (18 Aug–2 Sep 1998) over (a) the Northern Hemisphere and (b) the Southern Hemisphere.

opposite is found for 1200 UTC 21 August 1998. The improvement of the track is not correlated with either an increase or a decrease of the pressure minimum as illustrated by Figs. 10b and 11b. For instance, curves of the pressure minimum for the Rain-1 and control experiments are close to each other while providing different tracks. Note also that there is no direct relation between the quality of the simulated track and the analysis differences. An ensemble prediction system could be used to diagnose the sensitivity of the simulated track to different initial conditions. Puri et al. (2001) have shown that the trajectory of tropical cyclones is mostly sensitive to modifications of the initial dynamic fields. In the current experiments, the initial wind field is only slightly modified through TCWV increments.

c. *Objective scores*

In this section results are given for the full globe. To evaluate the impact of 1DVAR TCWV assimilation on forecast performances, the rms error of the geopotential at 500 hPa is calculated. Figure 12 displays the results for the Northern (between $+90°$ and $+20°$ latitude) and the Southern (between $-20°$ and $-90°$ latitude) Hemispheres. The impact of the rain assimilation is almost neutral in both hemispheres. In the Northern Hemisphere, the Rain-1 experiment provides slightly better scores than the control experiment. This result is significant to the 5% level in the short range. For the Southern Hemisphere, the Rain-1 and Rain-2 experiments provide a small improvement in the short range at a 2% and 5% significance level, respectively.

Figure 13 shows the rms errors for the tropical wind at 850 and 200 hPa up to day 4. Extending the range of the forecast verification would reduce the size of the sample since they are computed against their own analysis. A comparison versus its own analysis is necessary because tropical analyses in the three experiments differ significantly. The Rain-2 experiment performs better than the other two with a 5% level of significance. This is a consequence of the larger modifications to the initial humidity field performed in the Rain-2 experiment and of the strong dependency of tropical circulation to the diabatic heating by convection. The modification of the intensity of the hydrological cycle in the Rain-2 experiment also reduces significantly the rms errors of the upper-tropospheric temperature at 200 hPa in the Tropics (Fig. 14). The wind improvements ($\sim$0.1 m s^{-1}) have to be put in perspective with observing system experiments: by removing all satellite data in the tropical belt, rms wind errors at day 3 are increased by 0.2 m s^{-1} at 850 hPa and 0.4 m s^{-1} at 200 hPa (Bouttier

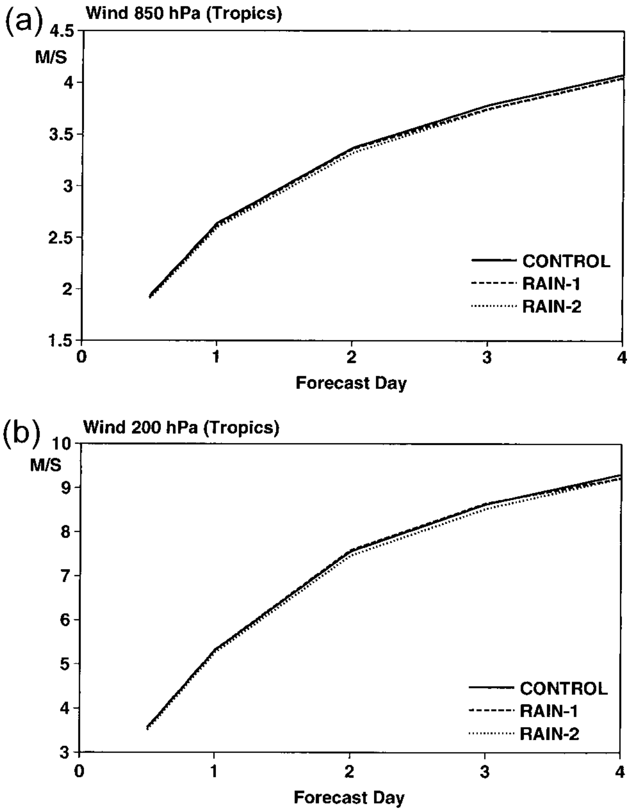

FIG. 13. Root-mean-square forecast errors for tropical winds verified against its own analysis at (a) 850 hPa and (b) 200 hPa averaged over 12 cases.

and Kelly 2001). Moreover, given the low internal variability of the tropical circulation, the significance of differences between forecast errors is higher in this region than over midlatitudes.

6. Sensitivity to rainfall observation error

Because no objective estimate of σ_o (error on the observed rain rate in 1DVAR) is available, the sensitivity of the results to the choice of σ_o values was tested. MM2000 have shown that the observation term is dominant in the 1DVAR minimization because of the large background error compared to the observation error. Thus, larger σ_o values are tested in this section in order to evaluate the impact of a reduced weight of the observation term in 1DVAR. An assimilation experiment (hereafter the ''test'' experiment) using an error of 50% of R_o instead of 25% of R_o in 1DVAR was run for a period of 3 days only, starting at 1200 UTC 18 August 1998, as for the other three experiments. This increase of the observation error can also be interpreted as an indirect way to take into account errors coming from the moist physical processes. Since the Rain-2 experiment provides better results than the Rain-1 experiment, the test experiment was run using Rain-2 configuration, which includes all 1DVAR quality controled TCWV in

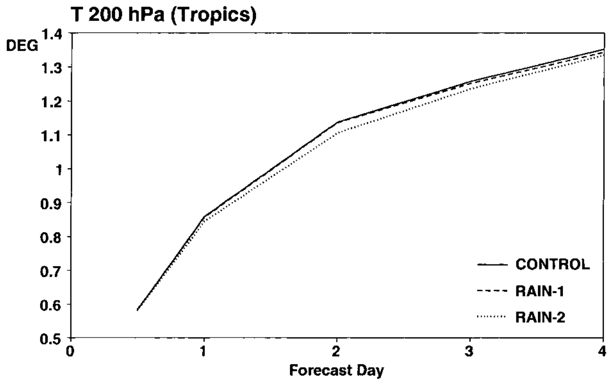

FIG. 14. Root-mean-square forecast errors for temperature at 200 hPa in the Tropics averaged over 12 cases.

4DVAR. Since σ_{TCWV} depends on σ_o [see Eq. (2)], a new relationship between σ_{TCWV} and TCWV was computed using the same samples as used to obtain relation (3). Even though σ_o was doubled, results exhibit very little difference between the new relationship and (3) (not shown). Consequently, formula (3) was also used to set σ_{TCWV} in 4DVAR for the test experiment. This means that the increase of σ_o can only modify 4DVAR analyses by changing the TCWV observations retrieved through 1DVAR.

Figure 15 displays the global mean statistics of the 4DVAR assimilation of 1DVAR TCWV for the Rain-2 and test experiments over the 3-day period. Mean background and analysis departures are similar. But the rms of background and analysis departures for the test experiment are smaller than for Rain-2. This means that 1DVAR TCWV is closer to the background for the test experiment. This is consistent with the larger σ_o values in the test experiment that lead to generally smaller modifications of humidity profiles by 1DVAR with respect to the background because of a weaker constraint. It is also important to note that about 600 more 1DVAR

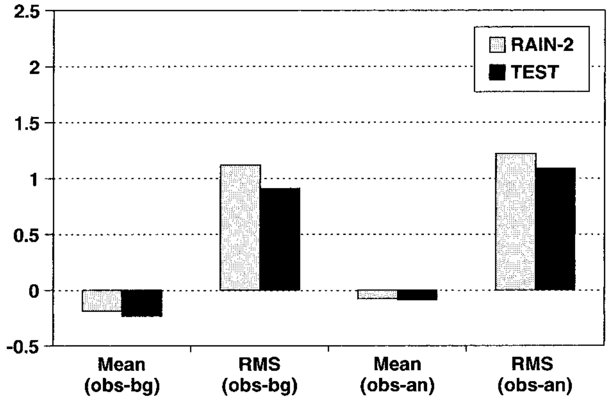

FIG. 15. As in Fig. 2 for the 3-day period (from 1200 UTC 18 Aug 1998 to 1200 UTC 21 Aug 1998) of the test experiment. The number of observations used to compute the statistics is 23 253 for the Rain-2 experiment and 23 839 for the test experiment.

TABLE 4. As in Table 1 for a 3-day period (1200 UTC 18 Aug 1998 to 1200 UTC 21 Aug 1998).

Experiment	Mean analyzed TCWV	Rms of TCWV increments
Control	36.09	1.75
Rain-2	35.96	1.58
Test	35.95	1.57

TABLE 5. As in Table 2 for a 3-day period (1200 UTC 18 Aug 1998 to 1200 UTC 21 Aug 1998).

Experiment	Correlation with TMI observations	Rms (model − observations)
Control	0.211	0.687
Rain-2	0.229	0.616
Test	0.218	0.621

TCWV observations are assimilated in 4DVAR for the test experiment. This means that more TCWV estimates passed the 1DVAR quality control and thus more information was provided to 4DVAR. This is related to the weaker constraint imposed in 1DVAR for the test experiment, which allows a larger number of successful retrievals (Marécal and Mahfouf 2000).

Global results for the TCWV analysis and for the rain-rate comparison are given in Tables 4 and 5. No major differences can be found between the Rain-2 and test experiments. They both provide a better humidity analysis as shown by the decrease of the rms of TCWV increments (see Table 4) and surface rain rates closer to observations (see Table 5). This good behavior of the test experiment compared to the Rain-2 experiment can be explained by the increase in the number of TCWV observations assimilated in 4DVAR, which counterbalances the decrease in absolute value of TCWV increments. Results for the precipitation spindown also show that the test and Rain-2 experiments provide very similar global results (not displayed).

7. Conclusions

The aim of this paper was to study the impact of the assimilation of surface rain rate in the ECMWF operational configuration of 4DVAR analysis system. Since there are still many issues associated with the direct 4DVAR problem, the approach chosen is based on 1DVAR retrievals. First, temperature and humidity profiles are retrieved using MM2000's 1DVAR method constrained by TRMM-derived rain rates. Second, 1DVAR TCWV estimates are assimilated in a 4DVAR system with a 6-h cycling. With respect to previous 4DVAR case studies (Zupanski and Mesinger 1995; Zou and Kuo 1996; Guo et al. 2000) on rain assimilation, three assimilation experiments were run for a 15-day period with a cycling of the analyses. One is the control and the other two (Rain-1 and Rain-2) assimilate 1DVAR TCWV. Rain-1 considers a limited set of 1DVAR TCWV: only quality controled 1DVAR profiles corresponding to a nonzero observed rain rate are retained to avoid a possible conflict with SSM/I TCWV assimilation in nonrainy areas. In the Rain-2 experiment all quality controled 1DVAR TCWV observations are assimilated in 4DVAR.

The global TCWV analysis is only slightly modified by the use of rain-derived data in 4DVAR. This is explained by the small humidity increments provided by 1DVAR to modify precipitation with rms values around 2 kg m^{-2}. The Rain-2 (Rain-1) experiment tends to decrease (increase) the humidity because on average a decrease (increase) of precipitation is required. Both rain experiments give a noticeable improvement of the humidity analysis as shown by the global decrease by 3% for Rain-1 and by 8% for Rain-2 of the rms of TCWV increments. The model surface rain rate at the analysis time is closer to TMI-2A12 observations. This means that the rain-rate information from observations is correctly extracted by the assimilation system even though it is done through 1DVAR retrievals. It justifies a posteriori the use of a 1DVAR approach to test the impact of rain assimilation in the ECMWF forecasting system.

The global mean wind analysis is only slightly modified by the rain assimilation. The main reason is the low occurrence of TRMM data in rainy areas within 6 h. Nevertheless, there is a noticeable local impact of assimilating rain-derived products on the wind field within and in the vicinity of rainy areas. In particular, an intensification of Hurricane Bonnie has been noticed between 23 and 27 August 1998 for the Rain-1 and Rain-2 experiments compared to control. This is consistent with the mean sea level pressure analysis, which shows a deeper minimum for both rain experiments. Before 23 August 1998 (i.e., in the early stages of the storm development), assimilating rain-derived data allows a better analysis of the track of Hurricane Bonnie. Nevertheless, this improvement does not lead to better forecasts of the track. Global comparisons with CERES radiative measurements made on board the TRMM platform show a neutral effect when rain-derived data are used in 4DVAR.

The impact on the precipitation spindown is neutral for the Rain-1 experiment even though the global mean humidity is slightly increased. The Rain-2 experiment provides a more balanced hydrological cycle, as shown by the noticeable decrease of the precipitation spindown. The global forecast performance is mainly improved for winds and upper-tropospheric temperature in the Tropics.

The sensitivity of the results to the specification of the errors on TRMM surface rain rates was tested in a 3-day experiment. Results show that by setting the rain-rate error to 50% of R_o instead of 25% of R_o, the global results are only slightly modified. The main reason is that the TCWV error is mostly unchanged when the rain-rate error is increased. Moreover, the impact of the smaller TCWV increments provided by 1DVAR in the test experiment is counterbalanced by the increased number of quality controlled 1DVAR TCWV (Marécal and Mahfouf 2000).

All these results show a positive impact on the ECMWF analyses and forecasts of using rain-derived information in the 4DVAR. The Rain-2 experiment performs generally better than the Rain-1 experiment. This indicates that the use of 1DVAR TCWV estimates where no rain is observed is useful even though these estimates are likely to be less accurate than TCWV retrievals from SSM/I brightness temperatures. The two-step approach for rain-rate assimilation gives satisfactory results. Nevertheless, it tends to filter the information contained in the rain-rate observations before entering 4DVAR and weakens the coupling with the dynamics. This limitation of the 1DVAR approach together with the positive impact found in this study motivate the ongoing development of a direct 4DVAR assimilation of surface rain rates.

Another issue concerns the number of 1DVAR observations used per assimilation cycle. Rain only occurs sparsely and TRMM provides a limited coverage of the globe within 6 h. Moreover, data are only used over oceans and where the model first guess provides nonzero rain rates leading to a reduced number of rain-derived observations that can possibly be assimilated by the 4DVAR. A way to increase this number would be to use the SSM/I on board the Defense Meteorological Satellite Program satellites, which sample larger areas than TRMM. Even if SSM/I radiometers have fewer channels than TMI, ongoing studies based on TRMM data should provide improved algorithms to compute the surface rain rate from SSM/I brightness temperatures.

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