Evaluation of the Optimum Interpolation and Nudging Techniques for Soil Moisture Analysis Using FIFE Data

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ABSTRACT

Initialization of land surface prognostic variables is a crucial issue for short- and medium-range forecasting as well as at seasonal timescales. In this study, two sequential soil moisture analysis schemes are tested, both based on the comparison between observed and predicted 2-m parameters: the nudging technique used operationally at the European Centre for Medium-Range Weather Forecasts (ECMWF) and the optimum interpolation technique proposed by J. F. Mahfouf and used operationally at Météo-France. Both techniques compute the soil moisture increments as a linear function of analysis increments of 2-m parameters (specific humidity at ECMWF, temperature and relative humidity at Météo-France). Following the preliminary study by Y. Hu et al., the optimum interpolation technique has been adapted to the four soil-level ECMWF land surface scheme. Both methods are tested in the ECMWF single column model, which has been run for 4 months in 1987 at a grid point close to the location of the First International Satellite Land-Surface Climatology Project Field Experiment. The upper-air variables are updated every 6 h using the ECMWF reanalysis. The surface downward radiation and precipitation fluxes are prescribed at each time step according to in situ observations. The soil moisture analysis is performed every 6 h, using either the nudging or the optimum interpolation. The nudging is shown to be very sensitive to model biases and sometimes produces unrealistic results. The optimum interpolation technique is more robust and reliable, due to the use of two screen-level parameters and a careful selection of the meteorological situations for which the atmosphere is expected to be informative about soil moisture. It leads to improved evaporation and soil moisture and is able to compensate for biases in both the land surface scheme and the precipitation forcing.

1. Introduction

Since the early developments of general circulation models (GCMs) at the end of the 1960s, the major role played by the land surface boundary conditions has been widely recognized. The influence of soil moisture has been particularly emphasized. Various climate sensitivity studies have suggested that soil moisture anomalies can persist long enough to modify the atmospheric circulation over seasonal to interannual timescales (Shukla and Mintz 1982; Yeh et al. 1984; Delworth and Manabe 1988; Serafini 1990). As a consequence, climate simulations commonly start with an extended ''spinup'' period, in order to avoid any drift of the model due to the poorly specified initial soil moisture.

Soil moisture also has a strong impact on short- and medium-range forecasts in numerical weather prediction (NWP) models. Miyakoda et al. (1979) demonstrated that the use of realistic initial soil moisture conditions could lead to improved forecasts of precipitation and evaporation over a 2-week summer period. Rowntree and Bolton (1983) showed that the atmospheric anomalies induced by an inaccurate specification of soil moisture could persist for several days, due to the relatively slow evolution of deep soil wetness. More recently, Yang et al. (1994) performed 10-day integrations with the Center for Ocean–Land–Atmosphere Studies (COLA) GCM in order to investigate the importance of initial soil wetness (ISW) for medium-range weather forecasts. They found that the impact of an accurate initialization was strongly positive at the surface, but mainly confined to the low atmospheric levels, and showed the potential interest of a continuous update of ISW for medium-range forecasting. Beljaars et al. (1996) also emphasized the relevance of soil moisture initialization in the ECMWF (European Centre for Medium-Range Weather Forecasts) NWP. Two ensembles of 30-day integrations with contrasted initial soil moistures were performed for July 1993, during the extreme rainfall events that occurred in the United States. The integrations with moist soil produced a much more realistic pattern than the dry ones. The results also suggested that there is some predictive skill, not only in

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the short but also in the monthly range, related to the status and the size of the soil moisture reservoir.

Various strategies have been proposed in order to initialize soil moisture in NWP models, as reviewed by Mahfouf and Viterbo (1998). A precipitation and meteorological analysis can be used to drive an offline simulation of the land surface scheme, thereby providing a more realistic field of ISW than the online simulation (Mitchell 1994; Smith et al. 1994; Jones and MacPherson 1995; MacPherson 1996). Such method is however restricted to limited-area models where a dense observational network can provide reliable estimates of precipitation and surface radiation. Remote sensing can also provide some information about the surface soil moisture (Jin et al. 1997; van den Hurk et al. 1997; Calvet et al. 1998). They rely on radiance measurements that need to be converted to either temperature or to soil moisture (in relation to emissivity), but there are still large uncertainties in defining inversion techniques on the global scale, and substantial scientific and technical issues must be resolved before implementing such a strategy in operational NWP systems.

An alternative approach suitable for global data assimilation systems has been proposed by Mahfouf (1991). Short-range forecast errors of temperature and humidity at 2 m derived from surface observations (SYNOP reports) can be used to infer corrections of soil moisture. A one-dimensional variational assimilation was first developed that accounts easily for the nonlinearities between soil moisture and near-surface parameters and for the temporal distribution of observations. An optimal soil moisture content minimizes a cost-function measuring the mismatch between model forecasts and corresponding observations over a 24-h period. Using data from the HAPEX-MOBILHY field experiment, results showed that the variational method converges efficiently toward realistic values of soil moisture. The variational technique was also tested in a 5-day experiment by Rhodin et al. (1999) at the German Weather Service. The quality of the forecasts was improved but the analyzed soil moisture was consistently very low and likely to be unrealistic for the selected springtime period. This was partly due to the crude land surface parameterization scheme used (Blondin 1991). Soil moisture was merely considered as a parameter to be tuned to compensate for various model biases thereby providing better lower boundary conditions for the atmosphere.

A sequential assimilation was also proposed by Mahfouf (1991) where static soil moisture corrections applied every 6-h are linearly related to short-range forecast errors of near-surface parameters. This method is more empirical than the variational method, principally in the specification of regression coefficients and is based on a linear assumption. However it is much cheaper and easier to implement in operational data assimilation systems, and results presented by Mahfouf (1991) showed that the soil moisture retrievals produced by the sequential assimilation were reasonable enough to further investigate this approach.

Sequential assimilation techniques have been implemented operationally both at the European Centre for Medium-Range Weather Forecasts (ECMWF) and Météo-France. At ECMWF, the soil moisture increments are computed from the specific humidity increments at the lowest model level using a single empirical regression coefficient [here referred to as soil moisture ‘‘nudging,’’ see Viterbo (1996)]. At Météo-France, the routine is closer to the initial proposal of Mahfouf (1991), since the corrections are computed following an optimal interpolation (OI) technique from the 2-m increments of temperature and relative humidity (Giard and Bazile 2000). The regression coefficients are such that they minimize the variance of analysis error from the knowledge of observation and forecast error statistics. Whereas observation errors are generally well known, statistics of forecast errors are frequently empirically modeled (Rabier et al. 1998) but could in theory be provided by a Kalman filter.

The soil moisture nudging technique, as in operational use at ECMWF, is certainly efficient in preventing the model from drifting, but it is less clear whether the resulting soil moisture is realistic. Verification studies based on ERA-15 (the ECMWF reanalysis project using a frozen analysis/forecasting system over a period of 15 yr) clearly show some deficiencies of the nudging scheme. Comparison of ERA products with data from the First International Satellite Land-Surface Climatology Project (ISLSCP) Field Experiment (FIFE; Sellers et al. 1988; Betts et al. 1998a) and from the Arkansas Red basin (Betts et al. 1998b) show not only noisy and compensating soil moisture increments, but also a systematic damping of the diurnal cycle and a systematic damping of the annual cycle. The reason is that the nudging scheme is compensating for model biases, and responds to these biases too rapidly. This is the main motivation for developing a better soil moisture analysis scheme.

The OI scheme proposed by Mahfouf (1991) is in principle optimal as it takes into account observation and forecast error statistics in an objective way. Making use of two sources of information, namely observations of temperature as well as humidity rather than humidity only, is already a step forward because significant increments will occur only when the two pieces of information support each other. However, forecast errors of temperature and humidity do not always contain information about soil moisture. For instance, during rain, at nighttime, and with low solar insolation, it is not desirable to apply any soil moisture increments, because in these circumstances, the forecast errors are not linked to soil moisture errors. This has been demonstrated in sensitivity studies by Bouttier et al. (1993a). Giard and Bazile (2000) have proposed such a conditional use of the OI technique and their suggestions are incorporated in the version of the OI scheme presented in this paper.

Recently Hu et al. (1999) have studied the OI technique in the context of the ECMWF land surface and boundary layer schemes and made preliminary comparisons with FIFE data. Observation errors and conditional use of the technique were not considered in that paper.

This paper proposes an OI configuration for operational use based on existing research, and experience about forecast errors. The emphasis is on an evaluation of the new OI scheme in comparison with the old nudging scheme and using FIFE data. The full seasonal cycle of May–October 1987 will be used in single column mode. The FIFE data includes soil moisture data, so it provides the unique possibility to verify whether the scheme has skill in providing soil moisture information on the basis of atmospheric observations. Furthermore, perturbation experiments will be performed in which biases in radiation and precipitation are introduced to see how the soil moisture analysis scheme corrects for such perturbations.

In the following section, the main features of the ECMWF land surface will be summarized and a description of the nudging as well as the OI technique will be given. The FIFE data and the experimental design are described in section 3. Section 4 shows the results of the single column analysis experiments with nudging and OI. Results of the perturbation experiments are presented in section 5.

2. Land surface scheme and soil moisture analysis

a. The ECMWF land surface scheme

Soil moisture analysis based on atmospheric observations is indirect and relies heavily on the underlying model. Therefore a brief summary of the main features of the land surface scheme in the operational ECMWF model is given. For full details and comparison with observations we refer to Viterbo and Beljaars (1995). The scheme has four prognostic soil layers for moisture and temperature, with a free drainage and a zero heat flux condition at the bottom of the deepest layer. It also includes a precipitation interception layer and a skin temperature level. From the surface to the bottom, the layer thicknesses are, respectively, 0.07, 0.21, 0.72, and 1.89 m. The three top layers correspond to the root zone with a total depth of 1 m. The root density decreases exponentially with depth. The surface evaporation has a bare soil part controlled by soil moisture in the top layer and a vegetation part. The role of the vegetation is represented explicitly, through a transpiration term and an interception loss term corresponding to the evaporation of dew and intercepted rain at the potential rate. The transpiration is controlled by the leaf area index (LAI) and the stomatal conductance, which is regulated by the water availability in the root zone (top three layers) and the photosynthetically active solar radiation.

The current implementation of the scheme uses global constants for leaf area index (LAI = 4), dominant vegetation type (grass land), and minimum stomatal resistance ($R_{smin} = 240$ s m^{-1}, leading to a canopy resistance of 60 s m^{-1}) and soil type (loam), with a volumetric soil water content of 0.171, 0.323, and 0.472 m^3 m^{-3}, at wilting point, field capacity, and saturation, respectively. The vegetation fraction, C_v, is prescribed according to the Wilson and Henderson-Sellers (1985) vegetation classification. The FIFE location has a vegetation fraction of 87% according to this data source. Improvements to the global distribution of vegetation characteristics are in preparation and will be implemented in the ECMWF model in the near future.

Since the model field capacity is underestimated compared to observations for FIFE, the field capacity has been increased by 0.03 m^3 m^{-3} in the single column model (SCM) simulations of the current study. The wilting point has been increased by the same amount in order to keep the 15.2 cm of maximum available water in the 1-m root zone of the model (water above field capacity is not considered as storage because it drains off very quickly).

b. The ECMWF soil moisture nudging scheme

Data assimilation systems rely heavily on a forecast model in order to propagate the state of the atmosphere (and of the land surface) from one analysis time to the next. At ECMWF the analysis is done at 6-h intervals by modifying the 6-h forecast (first-guess) from the previous analysis on the basis of observations. However, soil moisture observations are not available on a global scale, and therefore without special precautions the first-guess soil moisture would be kept, and the long-term evolution of soil moisture would be the result of successive 6-h model forecasts. Because free running soil moisture turns out to drift, Viterbo (1996) introduced a soil moisture nudging scheme in the ECMWF model in which the 6-h atmospheric analysis increments of specific humidity at the lowest model level are used to correct soil moisture. The idea is that a too dry (or too wet) soil will lead to a too dry (or too wet) boundary layer in the first-guess forecast compared to the atmospheric analysis (which includes information from the humidity observations). The nudging can be written in the following way:

$$\theta_i^a = \theta_i^f + C_v D \Delta t (q^a - q^f), \qquad (1)$$

where θ_i^a and θ_i^f are the analyzed and first-guess values of the volumetric soil water contents of soil layer i with $i = 1, 2,$ or 3; q^a and q^f are the analyzed and first-guess values of the lowest model level specific humidity, respectively ($q^a - q^f$ is the atmospheric analysis increment); C_v is the fraction of vegetation cover; $\Delta t = 6$ h; and D [units m^3 m^{-3}/(kg kg^{-1} 6 h)] is an empirically determined constant that is applied globally. In the operational model $D = 2.77$, which is also used in the present study (ERA used the smaller value of 1.04 because with the introduction of a new cloud scheme it was believed that there was less danger of drift). The scaling factor C_v was introduced to prevent the scheme from being active in bare soil areas. This method was shown to be efficient in preventing the soil moisture to drift on a seasonal timescale.

However, recent comparisons of ERA (Gibson et al. 1997) with observations from the FIFE experiment (Betts et al. 1998a) and the Arkansas Red River basin (Betts et al. 1998b) suggest that the resulting soil moisture is not always realistic. The simulated diurnal and seasonal cycles are both reasonable in a qualitative sense, but they show systematic biases introduced by the nudging mainly as the result of model deficiencies. The low-level specific humidity in the model shows systematic biases that depend on time of day with a too strong midmorning peak and a too low late afternoon minimum, leading successively to negative and positive soil moisture increments. Over the Arkansas Red River basin, the nudging exhibits a strong seasonal cycle resulting in an unrealistic damping of the seasonal soil moisture cycle.

Looking more generally at the global geographical distribution of the ECMWF operational increments for various months in 1996 and 1997, a recent study by Douville et al. (1998a) led to similar conclusions. The diurnal and seasonal behavior of the soil moisture analysis identified by Betts et al. (1998a,b) are found not only over the United States but also over most continental areas, and are probably due to systematic biases in the model's near-surface specific humidity. The monthly mean increments can be of the same order of magnitude as the monthly mean precipitation and are likely to jeopardize the realism of the analyzed annual cycle of soil moisture at least in the mid and high latitudes. The nudging contributes to some significant improvements in the predicted precipitation between the first guess and the forecast, but the improvement could be larger if the scheme did not have to compensate for model biases. All data assimilation algorithms are primarily designed for bias-free models and observations, and they do not give optimal results in the presence of model biases.

It is clear that there is a need for an improved soil moisture analysis in the ECMWF model, even if the current routine has shown the ability to avoid a drift. As suggested by previous studies (Mahfouf 1991; Bouttier et al. 1993a,b; Giard and Bazile 2000), soil moisture increments should be applied only when the low-level atmosphere is really informative about soil moisture. The use of two predictors (temperature and relative humidity) instead of one (specific humidity) should have a positive impact because the two parameters have to support each other to have the full effect on soil moisture increments and therefore there is less chance of model bias–related increments. The original nudging scheme was based on humidity increments at the lowest model level (about 30 m above the surface) because that was the only atmospheric analysis available at the time. Recently a 2-m temperature and relative humidity analysis has been developed that avoids the need for vertical spreading of surface station data (SYNOP) to the nearest model level. Finally, the soil analysis should benefit from an explicit use of forecast and observation error statistics.

c. *The OI soil moisture analysis*

The OI soil moisture analysis scheme also uses analysis increments of near-surface atmospheric parameters, but uses temperature as well as relative humidity and combines the different pieces of information in an optimal way with help of observation error and forecast error statistics.

The OI soil moisture analysis proposed by Mahfouf (1991) is based on the analysis increments of 2-m temperature and relative humidity. Every 6 h, corrections applied in each soil layer (analysis increments) are linear combinations of atmospheric increments of 2-m temperature and relative humidity. Relative humidity has been selected as a variable rather than specific humidity because the observation and model error statistics for relative humidity depend less on temperature than the error statistics for specific humidity. Like for the nudging, only the three top soil layers are considered by the analysis since the deep soil layer does not contain roots and does not influence directly the surface evapotranspiration. The analysis increment for soil moisture at layer i is defined by

$$\Delta\theta_i = \theta_i^a - \theta_i^f = \alpha_i(T^a - T^f) + \beta_i(\mathrm{RH}^a - \mathrm{RH}^f). \tag{2}$$

Superscript a stands for analyzed values, superscript f for forecasted values, and subscript i identifies the soil layer. The coefficients α_i and β_i determine the weight that is given to the increments of temperature $(T^a - T^f)$ and relative humidity $(\mathrm{RH}^a - \mathrm{RH}^f)$ with respect to the first guess of soil moisture θ_i^f. The coefficients are such that they minimize the variance of resulting analysis error:

$$\alpha_i = \frac{\sigma_{\theta_i}^f}{\Phi\sigma_T^f}\left\{\left[1 + \left(\frac{\sigma_{\mathrm{RH}}^a}{\sigma_{\mathrm{RH}}^f}\right)^2\right]\rho_{T,\theta_i} - \rho_{T,\mathrm{RH}}\rho_{\mathrm{RH},\theta_i}\right\}F_1F_2, \tag{3}$$

$$\beta_i = \frac{\sigma_{\theta_i}^f}{\Phi\sigma_{\mathrm{RH}}^f}\left\{\left[1 + \left(\frac{\sigma_T^a}{\sigma_T^f}\right)^2\right]\rho_{\mathrm{RH},\theta_i} - \rho_{T,\mathrm{RH}}\rho_{T,\theta_i}\right\}F_1F_2, \tag{4}$$

with

$$\Phi = \left[1 + \left(\frac{\sigma_T^a}{\sigma_T^f}\right)^2\right]\left[1 + \left(\frac{\sigma_{\mathrm{RH}}^a}{\sigma_{\mathrm{RH}}^f}\right)^2\right] - \rho_{T,\mathrm{RH}}^2, \tag{5}$$

where $\rho_{x,y}$ represents the correlation of forecast errors between parameters x and y, σ^f and σ^a are the standard deviations of forecast and analysis errors. Empirical functions F_1 and F_2, to be defined later, reduce the coefficients when the coupling between the soil and the lower boundary layer is weaker and the atmospheric forecast errors contain less information about soil moisture.

In the full three-dimensional model T^a and RH^a are analyzed atmospheric fields of temperature and relative humidity at screen level; that is, they have gone through an analysis procedure to put the surface observations (SYNOP) on a regular model grid. In the framework of the SCM simulations using observed data, we think of T^a and RH^a as observations and the specified analysis errors, σ^a, are observation errors. However, when applied in the ECMWF 3D forecast system, the analysis errors will be the sum of representativeness and measurement errors. For the SCM simulations presented here, the standard deviations of the observation errors have been set to $\sigma_T^a = \sigma_T^o = 2$ K and $\sigma_{\mathrm{RH}}^a = \sigma_{\mathrm{RH}}^o = 10\%$.

The statistics of forecast errors have been obtained through a Monte Carlo method, following Mahfouf (1991). An ensemble of one hundred SCM simulations was performed in which the initial soil moisture content is varied randomly between zero and the saturation value θ_{sat}. Several ensembles have been obtained with different values of the vegetation cover in order to determine the dependence of the statistics on C_v. A clear-sky situation with maximum insolation has been selected to determine the error statistics; the effects of reduced radiation are described in the empirical functions F_1 and F_2. A fundamental assumption of the Monte Carlo method is that forecast errors of temperature and relative humidity are the result of errors in soil moisture, and therefore the standard deviations of the errors of these three parameters are related, and the errors are also correlated.

The nonlinear response of the low-level atmosphere to variations in soil moisture, as discussed in many sensitivity studies, implies that the linear assumption of optimal interpolation is not strictly compatible with the soil moisture analysis problem. Therefore, any attempt to derive optimal coefficients will present drawbacks, since they should depend upon soil moisture itself. For example, less sensitivity of 2-m temperature and humidity to soil moisture variations is found when the soil is close to field capacity since evaporation takes place at potential rate. In theory, the size of soil moisture perturbations in the Monte Carlo method should reflect the one of typical forecast errors. However, such an approach would require sampling the whole range of soil moisture conditions around which the perturbations are performed. To limit the number of perturbed one-column integrations, larger initial perturbations were chosen to explore the full phase space of the system (i.e., outside the range of validity of the tangent-linear regime). Mean statistics of the correlations of forecast errors between the atmosphere and the underlying surface are thus produced. These correlations provide a statistical description of the physical interactions between the land surface and the surface boundary layer. Once these correlations are computed from the Monte Carlo method, standard deviations of forecast errors for soil moisture are scaled to the typical size of such errors, which we set to 0.01 m^3 m^{-3}. This volumetric content corresponds to 10 mm of water since the root zone is 1 m deep. Such a value is not far from the precipitation minus evaporation minus runoff ($P - E - R$) errors that can be seen in summer over Kansas in the ECMWF NWP model from the difference between day 1 and day 2 forecasts (see, e.g., Rabier et al. 1998). However, maps of these estimated forecast errors show large variability in both space and time. In arid areas, the errors are close to zero while they exceed 10 mm in rainy regions. The definition of the standard deviations of the forecast errors on the global scale will therefore require more work in the future.

The statistics thus derived from the Monte Carlo method are appropriate for ''ideal'' conditions with strong insolation. Formulations for the dependence of α_i and β_i on environmental conditions like solar radiation and cloudiness, precipitation, snow, wind, and temperature, follow Giard and Bazile (2000). The two empirical functions F_1 and F_2, are used to reduce the optimum coefficients when the coupling between the soil and the lower boundary layer is weak. To obtain negligible soil moisture corrections during the night and in winter, F_1 is a function of the cosine of the mean solar zenith angle, μ_M, averaged over the 6 h prior to the analysis time:

$$F_1 = \frac{1}{2}\{1 + \tanh[\lambda(\mu_M - 0.5)]\}; \qquad \lambda = 7. \tag{6}$$

The OI coefficients are also reduced when the radiative forcing is weak in cloudy situations. For this purpose, the atmospheric transmittance, T_r, is computed from the mean surface downward solar radiation forecasted during the previous 6 h, $\overline{R}_g$, as

$$T_r = \left(\frac{\overline{R}_g}{S_0\mu_M}\right)^{\mu_M}, \tag{7}$$

where S_0 is the solar constant, and the empirical function F_2 is expressed as

$$F_2 = \left(\frac{T_r - T_{\mathrm{rmin}}}{T_{\mathrm{rmax}} - T_{\mathrm{rmin}}}\right), \tag{8}$$

with $T_{\mathrm{rmin}} = 0.2$ and $T_{\mathrm{rmax}} = 0.9$.

Furthermore, soil moisture increments are not applied if one or more of the following conditions is fulfilled: (i) if the last 6-h precipitation exceeds 0.6 mm, (ii) if the instantaneous wind exceeds 10 m s^{-1}, (iii) if the air temperatures is below freezing, or (iv) if there is snow on the ground.

The dependence of standard deviations and correlation coefficients on vegetation cover is derived empirically from the model and represented by a quadratic interpolation between their minimum and maximum values for $C_v = 0$ and $C_v = 1$, respectively:

TABLE 1. Statistics used in the simulations presented in this paper. Units correspond to the use of $m^3\ m^{-3}$ for θ_i, K for T, and (0–1) for RH.

$\sigma^f_{\theta_i}$	0.01
σ^O_T	2
σ^O_{RH}	0.1
$(\sigma_T)_{\min}$	1.25
$(\sigma_T)_{\max}$	0.87
$(\sigma_{RH})_{\min}$	0.095
$(\sigma_{RH})_{\max}$	0.090
$\rho_{T,\,RH}$	−0.99
$(\rho_{T,}\theta_i)_{\min}$, $i = 1, 2, 3$	(−0.90, −0.91, −0.86)
$(\rho_{T,}\ \theta_i)_{\max}$, $i = 1, 2, 3$	(−0.82, −0.92, −0.90)
$(\rho_{RH,}\ \theta_i)_{\min}$, $i = 1, 2, 3$	(0.93, 0.90, 0.83)
$(\rho_{RH,}\ \theta_i)_{\max}$, $i = 1, 2, 3$	(0.83, 0.93, 0.91)

$$\rho_{RH,\theta_i} = (\rho_{RH,\theta_i})_{\min} + C_v^2[(\rho_{RH,\theta_i})_{\max} - (\rho_{RH,\theta_i})_{\min}], \tag{9}$$

$$\rho_{T,\theta_i} = (\rho_{T,\theta_i})_{\min} + C_v^2[(\rho_{T,\theta_i})_{\max} - (\rho_{T,\theta_i})_{\min}], \tag{10}$$

$$\sigma^f_{RH} = (\sigma_{RH})_{\min} + C_v^2[(\sigma_{RH})_{\max} - (\sigma_{RH})_{\min}], \tag{11}$$

$$\sigma^f_T = (\sigma_T)_{\min} + C_v^2[(\sigma_T)_{\max} - (\sigma_T)_{\min}]. \tag{12}$$

This empirical dependency fits reasonably well the variation of these coefficients with the vegetation cover as computed by the Monte Carlo method. The numerical values used in Eqs. (9) to (12) are given in Table 1.

3. Data and experiment design

a. The FIFE dataset

The FIFE field campaign took place in 1987 in the Konza prairie, Kansas. The observations were made on a 15 km × 15 km site. Betts and Ball (1998) averaged the surface meteorological and flux data to give a single time series representative of the FIFE site for the period May–October. During that period, the conditions over the FIFE grassland site are considered relatively homogeneous, so that simple averaging of the data gave a representative mean.

The present study focuses on a 130-day period between 1 June and 9 October 1987. Figure 1a shows the 6-hourly evolution of the observed precipitation. June was a rainy month, while the second half of July showed a prolonged dry spell. Some strong precipitation events were also observed in August and at the beginning of September. The end of the period was fairly dry.

Figure 1b shows the downward shortwave and longwave radiation during the 130-day period. The maximum solar flux is around 700 W m^{-2} in June and slowly decreases at the end of the summer season. There are periods of low solar radiation due to the presence of clouds related to the rainy spells. The longwave downward radiation varies generally around 400 W m^{-2} but is slightly reduced at the end of the period, due to the cooling associated with the decreased insolation.

Besides the radiative and meteorological observations, the FIFE dataset also includes measurements of soil moisture and temperature. Gravimetric and neutron probe techniques have been used to estimate soil moisture profiles down to 200 cm. The mean soil moisture for each layer of the ECMWF land surface scheme has been calculated from the site-averaged data. The observations of soil moisture during FIFE were taken at variable time intervals. Between the intensive campaigns the soil moisture observation frequency was reduced to once a week, which makes the observed soil moisture evolution look smoother than the simulation.

b. Experiment strategy

The purpose of the single column experimentation for the FIFE location is to test the OI soil analysis scheme and to compare it with the nudging scheme. This is a fast and cheap alternative to long experiments with the full global data assimilation systems. Such experiments are possible, but are very expensive particularly when the seasonal timescale needs to be explored as in the case of soil moisture analysis.

The single column version of the ECMWF model is used exactly the same way as the three-dimensional model during data assimilation. The atmospheric profiles of wind, temperature, and specific humidity are specified from the nearest grid point of the ERA analysis to the FIFE location and the single column model is integrated over a 6-h interval as a first guess for the next analysis time (6-h cycling). The difference of this first guess and the ERA analysis verifying at the same time provides the analysis increments for the upper-air fields. In the case of relative humidity and temperature at 2 m, the observation minus first guess is used as an analysis increment. The single column model also needs geostrophic wind profiles and advection terms that are estimated from the ERA analysis, and specified as an interpolation between two analyses at 6-h intervals.

Before starting experimentation in single column mode it was verified that the 6-h forecasts of wind, temperature, and specific humidity reproduce the ERA first guesses. This is indeed the case to an acceptable level of accuracy although the match cannot be exact because the forcing as derived from the ERA analysis is not exactly the same as the time-dependent forcing the 3D model computes during a full three-dimensional integration. For technical reasons, the single column model version is also not exactly the same as the ERA model. The main difference relevant for this study is in the parameterization of the stable boundary layer. The diffusion of heat is stronger in the single column model than in the ERA model [see Viterbo et al. (1999) for a discussion].

All experiments start at local midnight (0600 UTC) on 1 June 1987. The SCM is integrated following a 6-h cycling for a 130-day period up to 9 October 1987. The initial atmospheric conditions are provided from the ERA analysis and the initial soil conditions are either derived from in situ observations (for most experiments) or set up with perturbed values in order to test the ro-

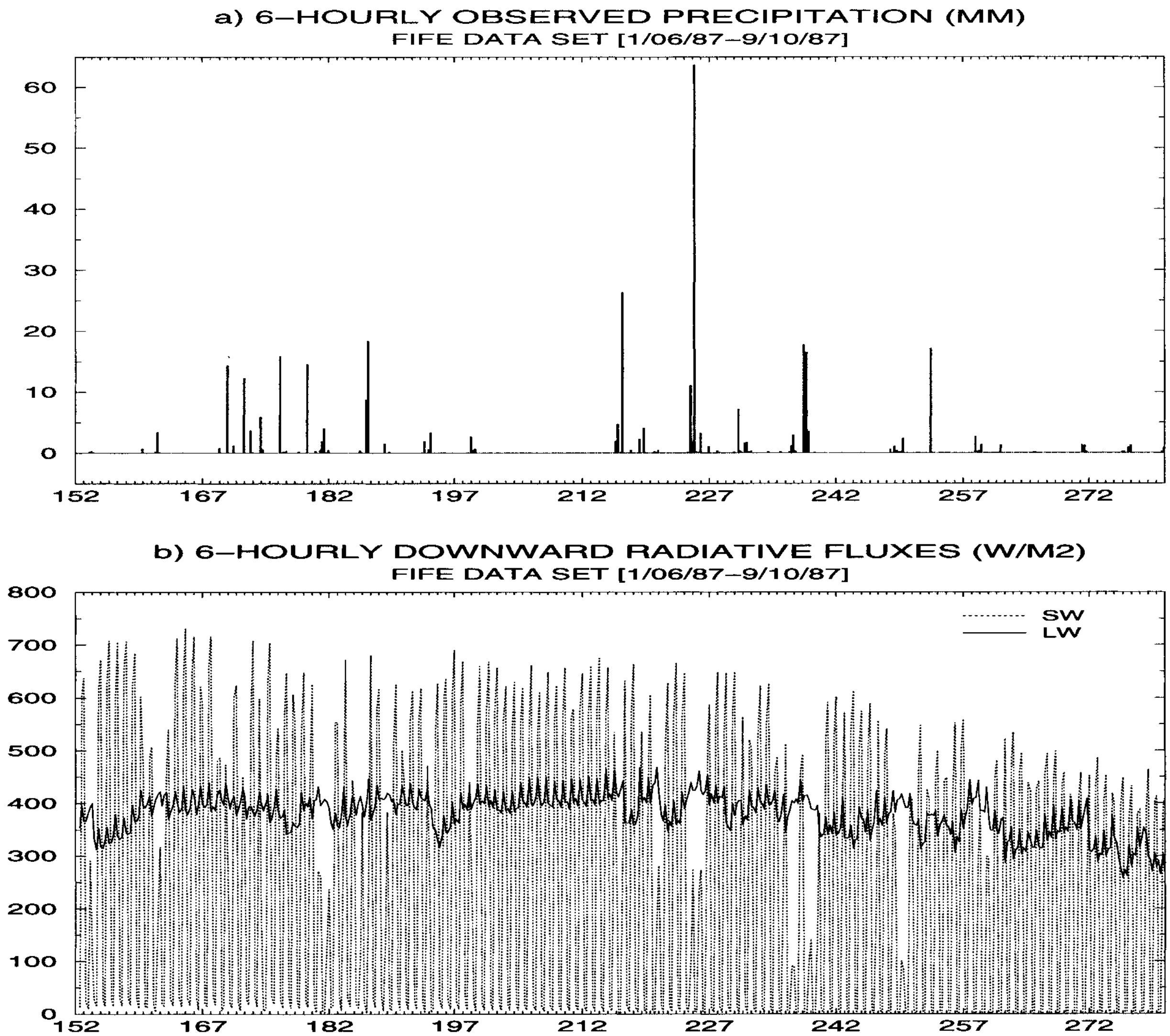

FIG. 1. Area-mean precipitation and radiative fluxes observed during the FIFE field experiment from 1 Jun to 9 Oct 1987: (a) 6-hourly accumulated precipitation in mm, (b) 6-hourly averaged downward solar and infrared radiation in W m^{-2}.

bustness of the soil analysis scheme. The SCM runs with the full physics package [including the radiative scheme described in Morcrette (1990, 1991), the convection scheme of Tiedtke (1989), and a prognostic cloud scheme described in Tiedtke (1993) and Jakob (1995)], geostrophic wind forcing, and advection terms from ERA.

The radiative fluxes at the surface and the precipitation need special attention because they provide the main forcing to the land surface scheme. The physics package of the SCM computes these fluxes, but in order to get a bias-free forcing of the land surface scheme, the model precipitation, the downward longwave radiative flux, and the shortwave radiative flux are replaced by observed values every time step. Additional experiments are performed to investigate the impact of possible model biases in these fluxes.

To test and compare the performance of the nudging and the OI soil analyses, three configurations are compared in all the following numerical experiments:

1) *Control experiment with free running soil moisture (CTL).* In these experiments, the soil moisture evolution is determined by the land surface scheme with atmospheric forcing during successive first-guess forecasts, using observed precipitation and downward solar/thermal radiation.
2) *Nudging soil moisture analysis (NUD).* The configuration is the same as in (1) except that soil moisture increments are applied with nudging equation (1) every 6 h.
3) *OI soil moisture analysis (OI).* The configuration is the same as in (1) but now the OI technique according to Eqs. (2)–(8) is applied to compute soil moisture increments every 6 h.

These three configurations are compared to assess the added value of a soil moisture analysis scheme and to assess the relative merit of both schemes. To test the robustness of the soil analysis schemes, these configurations are used with different forcings and initial conditions:

1) *Unperturbed with idealized forcing.* To create optimal input to the land surface scheme, observations of precipitation and downward radiation are used as input to the land surface scheme. Initial conditions for soil moisture on 1 June are taken from observations. In the unperturbed mode, the CTL experiment should provide a reasonable soil moisture evolution and not too much impact can be expected from the soil moisture analysis schemes.
2) *Perturbed initial condition.* In this set of experiments the soil moisture is initialized at an unrealistic value. The purpose is to see how the analysis schemes help to recover the soil moisture from the wrong initial condition.
3) *Perturbed vegetation field.* The version of the ECMWF model used in this study does not have any seasonality in the vegetation cover field, which may affect the performance of the nudging or OI analysis schemes. The purpose of the perturbed vegetation experiment is to investigate the sensitivity of the analysis schemes to uncertainties in the vegetation cover.
4) *Perturbed precipitation and radiation experiments.* The purpose of these sets of experiments is to see how the analysis schemes handle biases in the forcing from precipitation and radiation. The initial experience at ECMWF with free running soil moisture was that the soil had the tendency to run dry in summer (Viterbo 1996). It was hypothesized that the radiation was biased and that subsequently the precipitation and evaporation would drop as the result of a positive feedback between evaporation and precipitation. A soil moisture analysis scheme must have the capability of preventing such a drift to occur.

4. Unperturbed simulations with idealized forcing

In this section, three simulations, forced with observed precipitation and radiative fluxes are compared. Soil moisture at the four levels is initialized with observed values. The control experiment, CTL, is a reference simulation without any soil moisture analysis (i.e., free running soil moisture). Two analysis experiments are also performed, using the nudging and the OI techniques, respectively.

a. Behavior of the NUD and OI techniques

To understand the behavior of both the nudging and the OI soil moisture analyses, it is useful to look at the diurnal cycle of the 2-m parameters. For this purpose, a 10-day period has been selected at the end of June (days 172–182). It is the first month of the integrations so that the soil moisture and the errors in the 2-m parameters are not very different between the three experiments. However, it will be shown that the nudging and the OI techniques lead to different soil moisture increments.

Figure 2 compares the evolution of the 2-m parameters for the three simulations against the observed values. In all experiments, the model 2-m temperature is too warm, especially during the night. This systematic bias was not found by Betts et al. (1998a) in ERA and is probably due to the increase of the turbulent transfer coefficients in stable conditions that has been recently introduced in the ECMWF model (Viterbo et al. 1999). The specific humidity does not show strong biases though it tends to be overestimated during the night and sometimes underestimated during the daytime. In agreement with the previous results, the relative humidity is generally underestimated during the daytime but is reasonably predicted during the night due to a compensation of errors in temperature and specific humidity.

Figure 3 shows the 6-hourly increments obtained for that 10-day period, as well as the corresponding 6-h precipitation values. The nudging is performed every 6 h, whatever the meteorological conditions, even during strong precipitation events. The same soil moisture increments are applied to the three soil layers. Due to fluctuations (mainly the diurnal cycle) of the specific humidity errors, the corrections show a succession of positive and negative increments. During the precipitation events, the increments are mainly negative, which means that the boundary layer in the model is systematically too wet in rainy conditions. This is probably due to the warm atmospheric bias, which allows the atmosphere to sustain an overestimated amount of water when the relative humidity is close to 100%.

The OI has a smoother behavior and exhibits increments of lower magnitude. The analysis is switched off when the boundary layer is weakly influenced by the underlying soil conditions, especially during the night and during the precipitation events. The OI increments are mainly positive, due to the warm and dry bias in the 2-m temperature and relative humidity (α and β have opposite sign). They are almost the same for the three soil layers due to the choice of uniform standard deviations for the forecast errors in soil moisture.

Note also that summer relative humidity errors are correlated with the temperature errors; that is, a model positive evaporation bias will lead to a near-surface atmosphere that is too dry and too warm. The reason is that soil moisture affects the Bowen ratio, so when sensible heat flux is positively biased then moisture flux is negatively biased. Hu et al. (1999) demonstrated that this leads to an ill-posed problem with risk of instability in the idealized framework of perfect observations. With

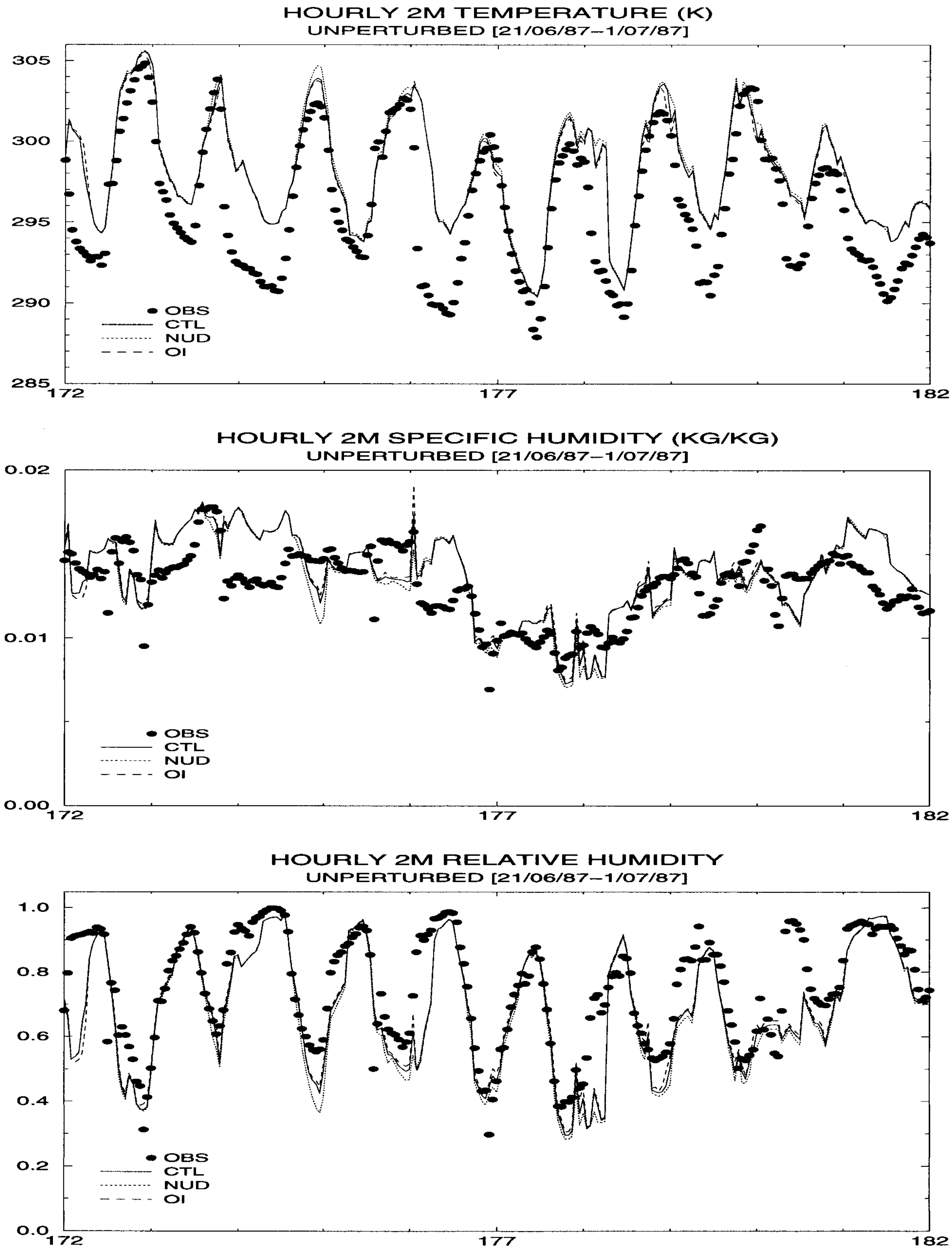

FIG. 2. Hourly evolution of the 2-m parameters for the three unperturbed experiments (control, nudging and OI) between day 172 and day 182: (top) temperature in *K*, (middle) specific humidity in kg kg^{-1}, (bottom) relative humidity.

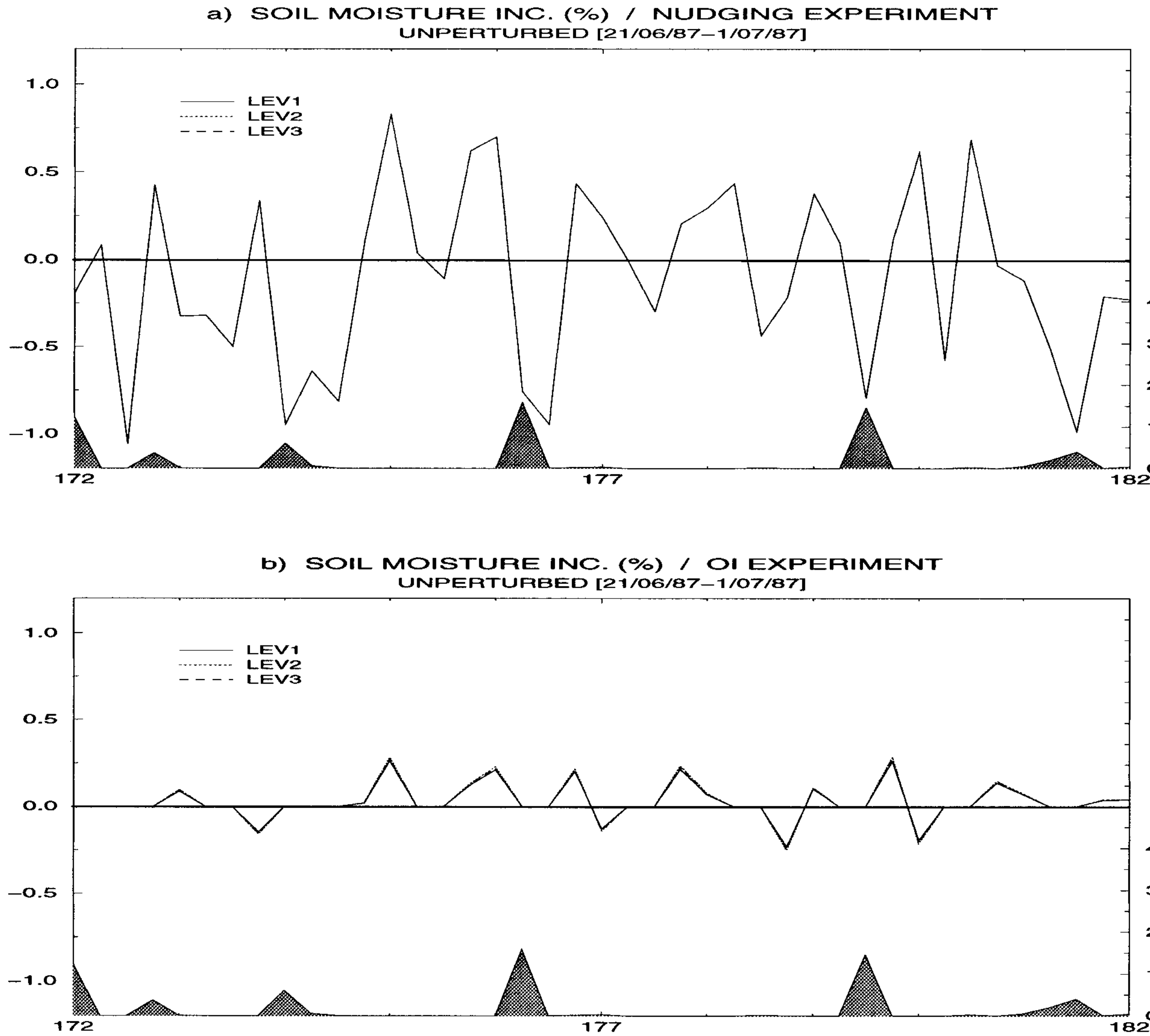

FIG. 3. Volumetric soil moisture increments (%) every 6 h produced by the unperturbed analysis experiments between day 172 and day 182 with: (a) nudging and (b) OI. Precipitation (mm) accumulated over 6-h intervals is shown by the shaded curve.

nonzero observation errors, the OI technique takes account of this correlation and remains stable.

The conclusion we draw from the diurnal cycles in Figs. 2 and 3 is that nudging and OI show very little difference in 2-m temperature and humidity, but that OI has much smaller increments than the nudging scheme. The nudging scheme has a big and unrealistic diurnal cycle in the soil moisture increments.

b. Daily mean results

Figure 4 shows the evolution of the daily mean 2-m temperature, specific humidity, and relative humidity errors. Consistent with the previous results, all simulations show a warm bias, with an average value of about 2 K and a maximum peak of 5 K. This is mainly a nighttime error although the daytime biases are also generally positive. During the dry spell in July (days 200–210), the warm bias is significantly reduced in both analysis experiments. During the second half of the integration, the warm bias is still obvious, but the OI is slightly cooler than the control experiment while the nudging is warmer. The specific humidity is generally overestimated, which is mainly due to the nighttime biases discussed in section 4a. The control experiment becomes too dry in July, whereas the specific humidity is close to the observations in the analysis experiments. From day 215 to day 281, the wet bias is slightly reduced by the nudging but slightly increased by the OI run. Opposite results are found for relative humidity, which is much better predicted by the OI run, showing the relevance of the choice of the parameters that drive the soil moisture analysis. Note that the errors in the 2-m temperature are qualitatively consistent with the results

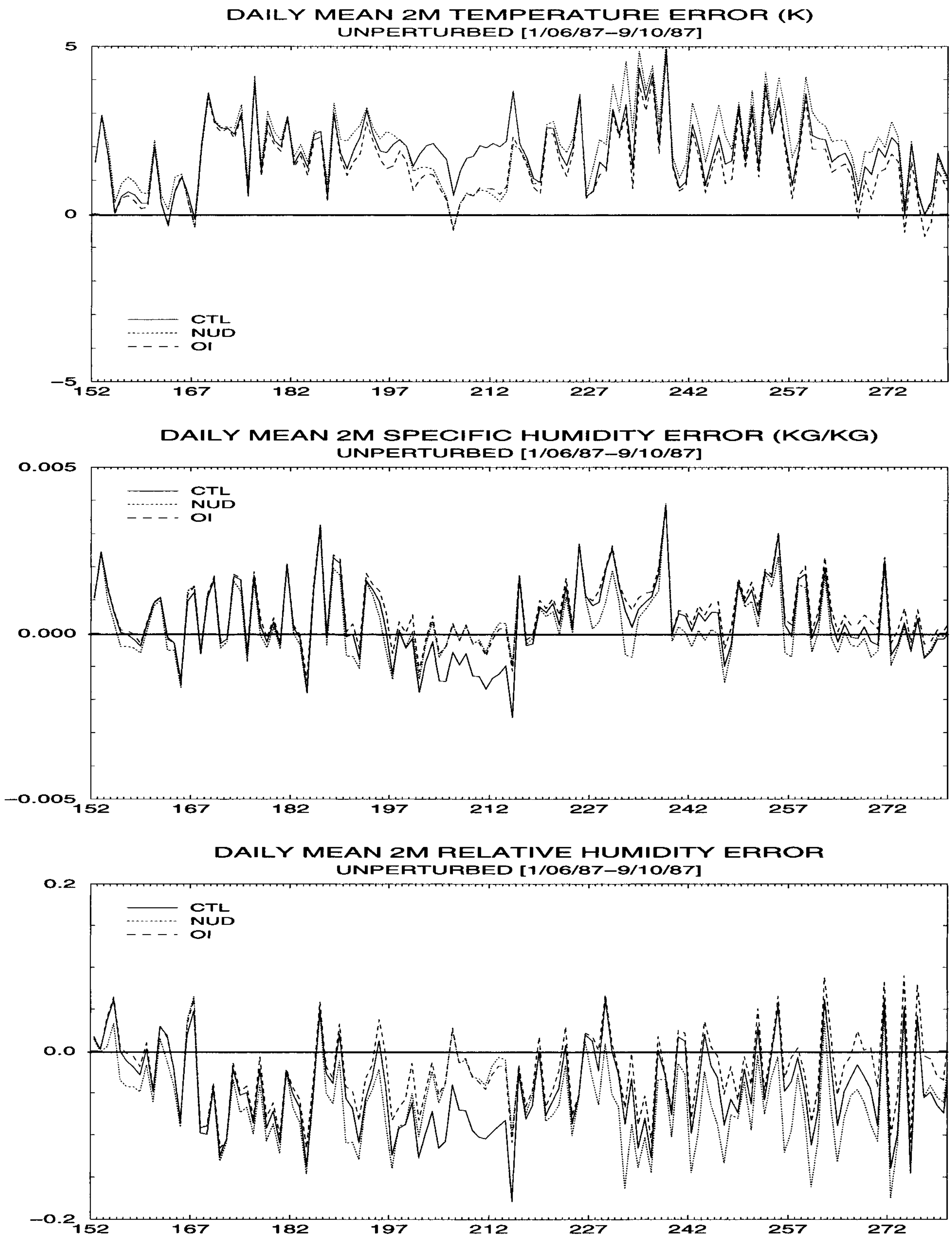

FIG. 4. Evolution of the daily mean errors in the 2-m parameters in the three unperturbed experiments (control, nudging, and OI) from 1 Jun to 9 Oct 1987: temperature in (top) K, (middle) specific humidity in kg kg^{-1}, (bottom) relative humidity.

of the ECMWF reanalysis shown by Betts et al. (1998a), in the sense that the daytime temperatures are too high in the model. This is reassuring because it indicates that the single column simulations reproduce the three-dimensional model for the FIFE location. However, during the night the SCM is warmer than ERA, due to a modification of the turbulence parameterization in stable conditions (Viterbo et al. 1999). This change was introduced to reduce the excessive nighttime and winter cooling over continental areas and to reduce the too large amplitude of the diurnal temperature cycle.

Figure 5 shows the evolution of the daily mean latent heat flux (upper panel), as well as the soil moisture variations in the 1-m root zone (middle panel), and in the deep soil (level 4 of the ECMWF land surface scheme; lower panel). The control experiment underestimates surface evaporation during most of the 4-month period, and particularly during the dry spell in July. During these 2 weeks, both analysis techniques have a strong impact and the latent heat flux is even overestimated at the end of July. The analysis impact is rather weak in June and the evaporation appears to be underestimated, but the observations of turbulent fluxes might be biased during that period (A. Betts 1998, personal communication). Most of the time, the OI performs better than the nudging, which is actually worse than the control experiment. The nudging run is influenced by the nighttime wet bias and tends therefore to dry the soil, thereby reducing the evaporation. This is confirmed by the soil moisture evolution in the root zone (Fig. 5b). The nudging experiment is generally drier than the control experiment, which is itself too dry, whereas the OI is much closer to the observations. However, the nudging adds water into the soil during the dry spell in July, when the specific humidity becomes too low in the control. During that period, both the OI and nudging analyses are wetter than observations, which is consistent with the fact that the evaporation is overestimated. This could mean that the dry and warm biases found in the control run during that period are not only due to soil moisture errors, but also related to model deficiencies. The deep soil moisture is not directly modified by the analysis, which is applied only in the root zone, but it is influenced through the water exchange between the layers. A drift toward dry conditions appears in the control experiment, and the nudging run is even drier while the OI run is the only simulation in which the amount of water in the deepest soil layer is close to the observations.

c. Hydrological budget

The dry drift found in the control experiment could have several explanations, which can be understood through a comprehensive hydrological budget of the total soil depth (2.89 m in the ECMWF model). Figure 6a shows the evolution of the various components of this budget, with all quantities accumulated from the beginning of the integration. The precipitation is prescribed from the measurements. Observations of evaporation and soil moisture variations are also available to validate the model. As noted previously, the control experiment drifts toward too dry conditions and underestimates the surface evaporation. Due to the balance between soil moisture fluctuations and $P - E - R$, the observations can be used to assess the real runoff. The resulting accumulated runoff during the 130-day period is -39 mm, which means that the model's 2.89-m soil depth would have to be supplied with an upward flux from the deep water table or a horizontal flux from the surrounding areas. An alternative and possibly more plausible hypothesis is that the measured precipitation has been underestimated, which is common especially in windy conditions. The dry drift in the control simulation might also be partly explained by an overestimation of the runoff (+108 mm), but the underestimation of P seems to be confirmed by the fact that the drift appears mainly during the rainy events while the runoff (essentially deep drainage) is a low-frequency component.

Figures 6b and 6c show the hydrological budgets of the analysis experiments. The time-integrated soil moisture increments (represented by vertical shading) are an additional component of the water balance, so that the observed soil moisture variations must now be compared to $P - E - R + I$, where I stands for the increments. The accumulated total (levels 1, 2, and 3) increment produced by the nudging is mainly negative (except during the dry spell in July), so that both soil moisture and evaporation are worse than in the control at the end of the 4 months. On the contrary, the OI exhibits a smoother behavior and adds water into the soil most of the time. The largest positive increments appear after the rainy periods, which seems to confirm the hypothesis of an underestimated precipitation forcing. The OI is able to produce a reasonable evolution for both soil moisture and evaporation. On the other hand, the runoff (+159 mm in 130 days, which means more than 1 mm day^{-1}) is overestimated. This is most likely a model characteristic related to a too strong drainage, which is also seen in the control. To compensate for the dry bias, the OI adds water into the soil (+184 mm in 130 days) and thereby further increases the runoff until the evaporation (as well as the 2-m parameters) is corrected.

5. Perturbed simulations

To investigate the capability of the two analysis schemes to correct for nonideal initial conditions or atmospheric forcings, ''perturbation simulations'' are performed. In these experiments the ideal conditions from observations are perturbed and the response of the analysis scheme to this perturbation is studied.

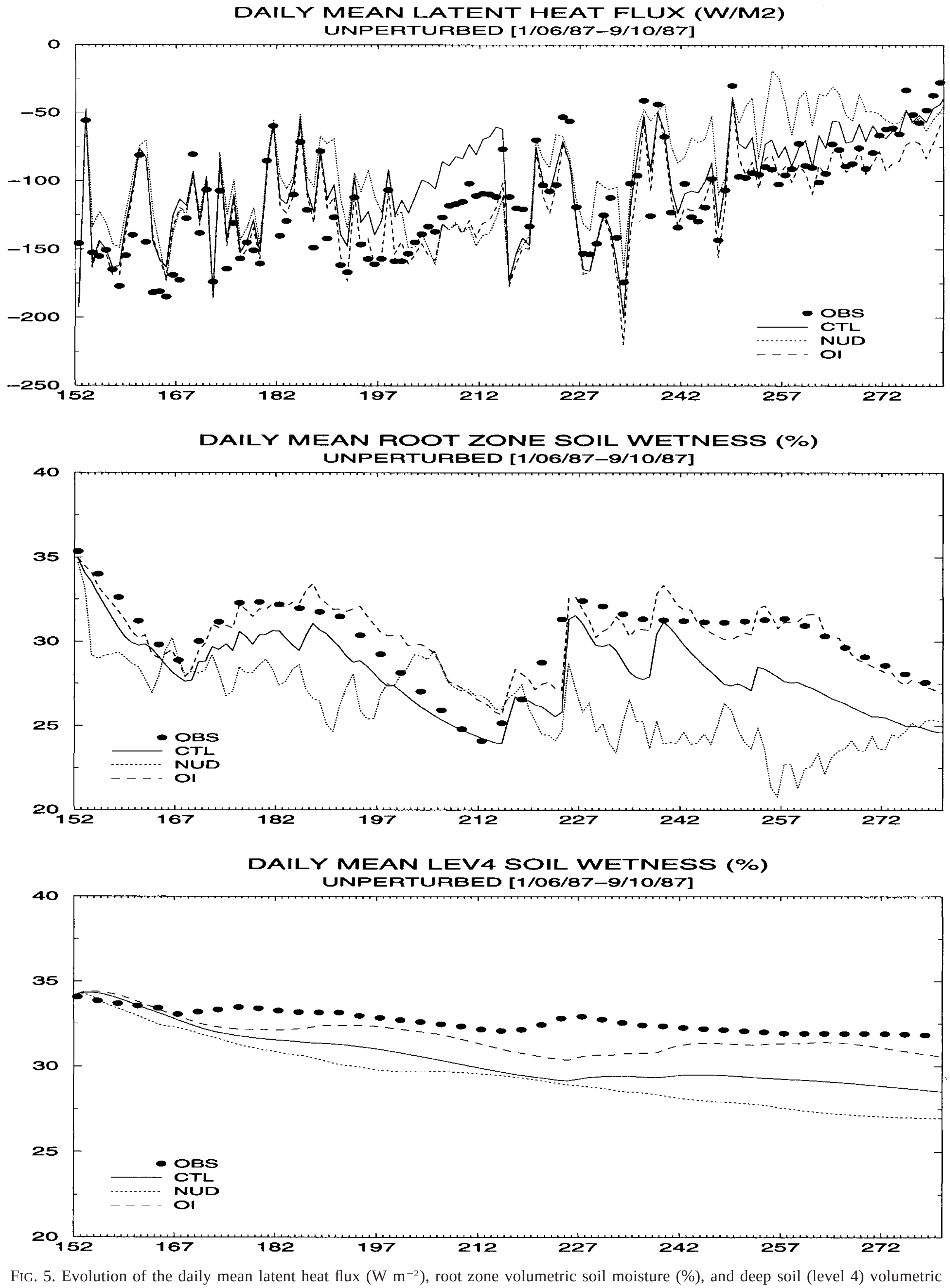

FIG. 5. Evolution of the daily mean latent heat flux (W m^{-2}), root zone volumetric soil moisture (%), and deep soil (level 4) volumetric soil moisture (%) in the three unperturbed experiments (control, nudging, and OI) from 1 Jun to 9 Oct 1987.

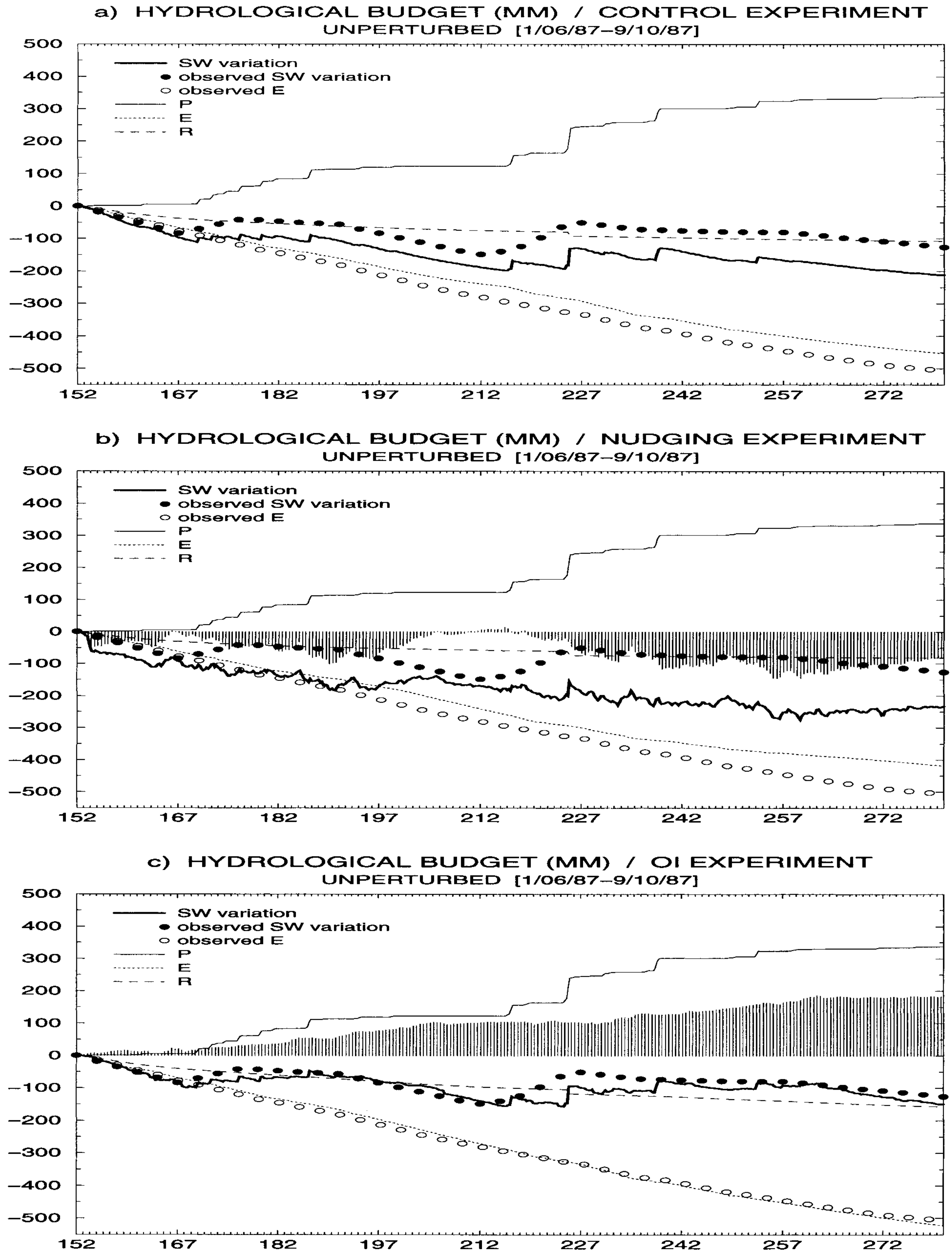

FIG. 6. Time-integrated hydrological budget simulated by the three unperturbed experiments from 1 Jun to 9 Oct 1987: (a) control, (b) nudging, (c) OI. Here, *P*, *E*, *R* and *I* stand for precipitation, evaporation, runoff, and soil moisture increments, respectively. The accumulated increments are represented by vertical shading. The observed soil moisture variation and evaporation are represented by black disks and circles, respectively.

a. Dry initial conditions

In this section, the three previous experiments are repeated but they are initialized with low soil moisture (wilting point value at all levels) instead of the observed values. While this initial dry bias persists for a long time in the control, it should vanish progressively in the analysis experiments.

Figure 7 shows the evolution of the daily mean latent heat flux and of soil moisture in the 1-m root zone as well as in level 4 of the land surface scheme. As expected, the control remains much too dry during the whole integration so that the latent heat flux is strongly underestimated. On the contrary, the nudging and the OI runs add large amounts of water into the soil at the beginning of the integration and the root zone soil moisture converges toward the same solution as in the unperturbed experiments (Fig. 5). After about 2 weeks, both the OI and nudging schemes are able to restore the correct soil moisture in the root zone, thereby producing realistic latent heat fluxes. In the deep soil, the moisture deficit remains very large in the nudging runs. The OI run is much more efficient, but due to the timescale of the water transfer between levels 3 and 4, it takes more than 4 months to compensate for the strong moisture deficit prescribed in the deep soil layer (which has a depth of 1.89 m).

The conclusion from the experiments with perturbed initial soil moisture is that both analysis schemes have the capability of recovering from unrealistic soil moisture conditions. However, the OI scheme relaxes to a more realistic state and even allows for a slow recovery of layer 4.

b. Misspecification of the vegetation cover

An important source of uncertainty in the earth's surface representation in NWP and climate models is the definition of the vegetation parameters, whose distribution is sometimes poorly known on the global scale. Such uncertainties can have a double impact in NWP models since they can influence both the forecast and the soil moisture analysis. To investigate the effect of vegetation cover, the set of three experiments is repeated with the extremely low cover of 8.7% instead of 87%. As in section 4, soil moisture is set to the observed values at all levels at the beginning of the simulation.

Figure 8 compares the daily mean latent heat flux and the soil moisture simulated by the three experiments to the field measurements. In the control, the negative evaporation bias is even stronger than in the unperturbed experiment (Fig. 5) due to the large fraction of bare ground. The soil moisture is simulated reasonably well since the deficit in the unperturbed experiment is here partly compensated by the lower evaporation.

The nudging is close to the control simulation because the increments are directly proportional to the vegetation cover according to Eq. (1). The nudging is active and has a positive effect only during the dry spell in July when the increments become large despite the low value of C_v.

The OI run is the only experiment that is able to simulate a reasonable latent heat flux during most of the 4 months, though the evaporation is too low at the beginning and slightly overestimated around day 212. On the other hand, this is obtained with an overestimated soil moisture since OI has to add a lot of water into the soil in order to compensate for the low evaporative fraction induced by the low vegetation cover (bare soil tends to be less efficient in evaporating moisture than vegetation). This result demonstrates that OI cannot improve both turbulent fluxes and soil moisture if the vegetation parameters are poorly specified.

The conclusion from this perturbation experiment is that the OI is much more robust than the nudging scheme particularly with respect to latent heat flux. However the link between latent heat flux and soil moisture depends on vegetation cover so a realistic result for the soil moisture cannot be expected if the vegetation cover in the model is very unrealistic.

c. Biased precipitation forcing

The previous perturbed experiments were simple cases in which the perturbation was either in the initial condition of soil moisture or in the vegetation cover. Precipitation is an important input to the land surface scheme and a direct source in the soil water budget. However, the model precipitation has large uncertainties and therefore it is important to know how the soil analysis scheme responds to errors in precipitation. As a simple test the precipitation has been simply set to zero during the first half of the integration and multiplied by a factor 3 in the second half (from day 213 to day 281).

It is to be expected that 2-m temperature and humidity are affected by such an extreme and systematic error in precipitation. In the first half of the simulation, the warm bias of the control experiments (see Fig. 4) is indeed increased due to the lack of precipitation (Fig. 9), but the nudging and OI schemes manage to control the temperature errors between day 197 and day 213 to a large extent. Surprisingly enough the specific humidity errors are little affected, but the temperature effect is also seen as an extra dry bias in relative humidity.

From day 213 onward, with precipitation set too high by a factor of three, the specific humidity becomes too high. This wet bias is less pronounced in relative humidity due to the warm bias. During this very rainy period, the OI is close to the control experiment due to the counteracting effects of errors in temperature and relative humidity. Moreover, throughout the period the model is close to the field capacity and no soil moisture increments are applied. Beyond field capacity, surface evaporation takes place at an unstressed rate. The same rule applies for the nudging, but the nudging experiment has a lower soil moisture so that the analysis is still

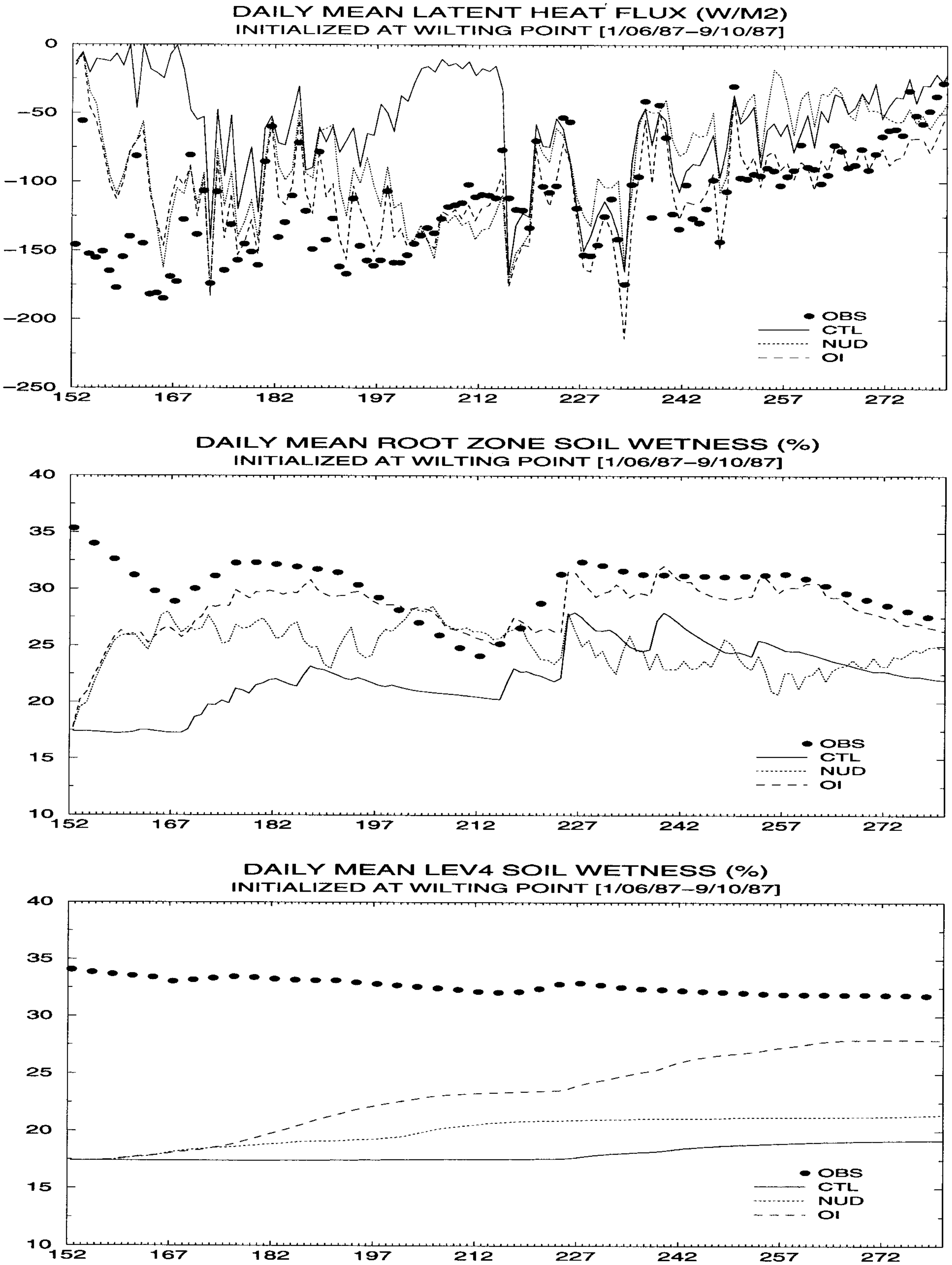

FIG. 7. As in Fig. 5 but all the experiments are initialized at the wilting point at day 152 (i.e., much drier than the observed soil moisture).

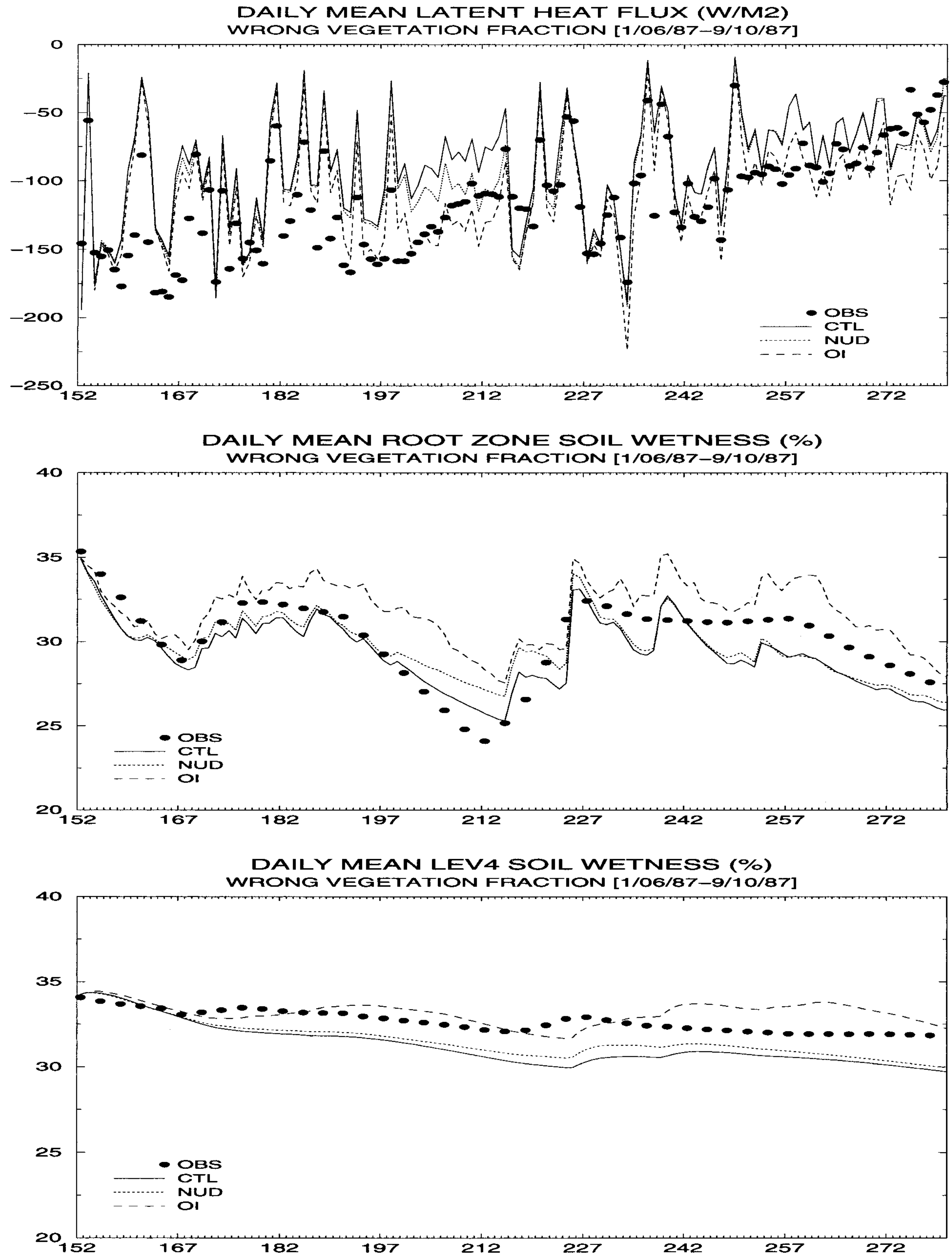

FIG. 8. As in Fig. 5 but all the experiments are performed with a misspecified vegetation cover (8.7% instead of 87%).

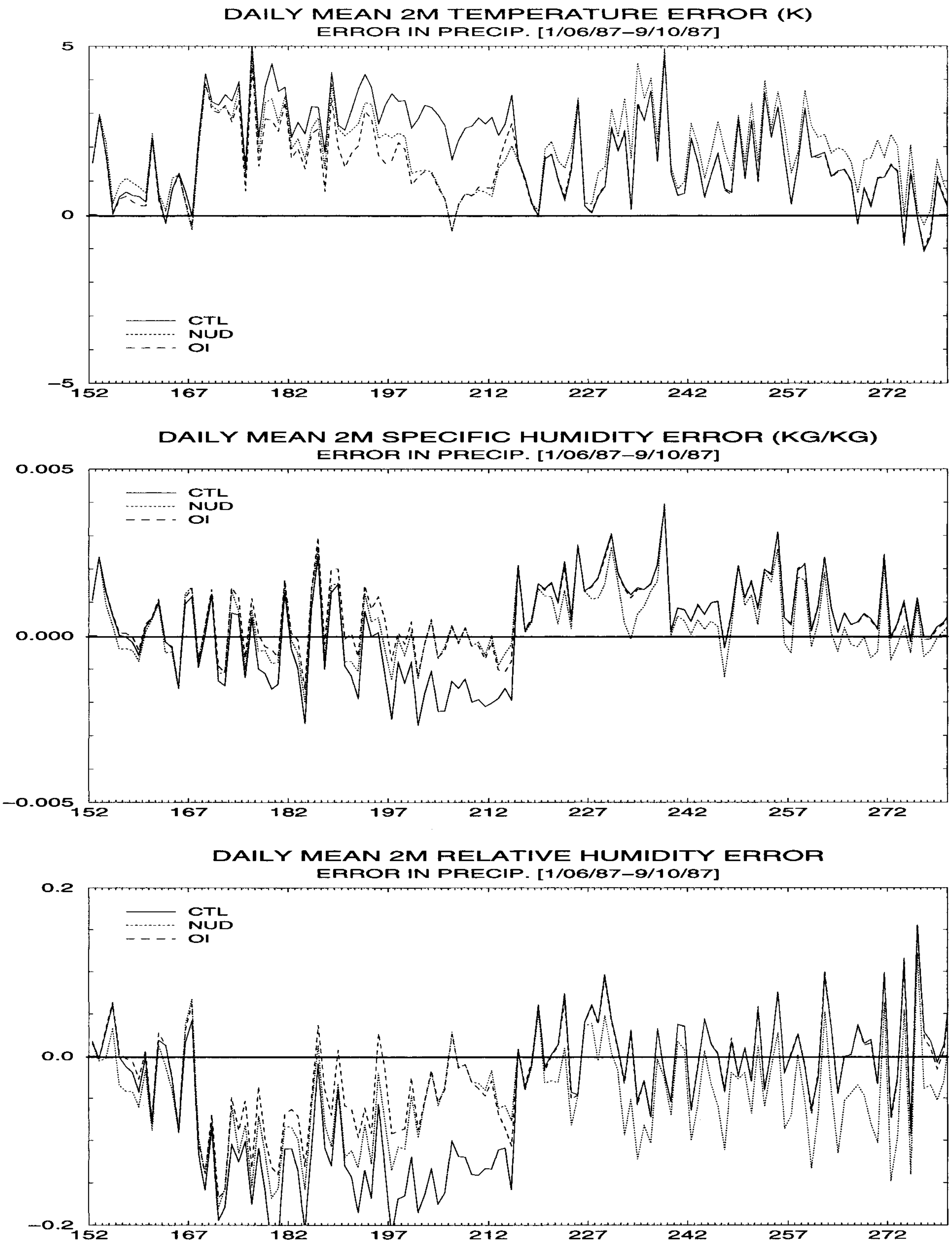

FIG. 9. As in Fig. 4 but all the experiments are forced with biased precipitation.

active. It decreases the errors in specific humidity to the detriment of the errors in temperature and relative humidity.

Figure 10 shows the hydrological budget of the three experiments. Note that soil moisture is reset to the observations on 1 August (day 213) in order to avoid a compensation between the biases prescribed before and after this date. As expected, the control experiment is much too dry during the first half of the simulation. Both analysis experiments tend to reduce this strong bias, but the results confirm that the OI performs better than the nudging for both evaporation and soil moisture. Between the beginning of June and the end of July, the variation of the total soil water content has been correctly estimated by the OI despite the prescribed zero precipitation. From day 213 onward, the control is too wet but the bias is limited by the deep drainage and by the ''internal'' dry bias of the SCM noticed in the unperturbed experiment (Fig. 6). As explained in the previous paragraph, the OI remains close to the control. The nudging experiment is too dry with too low evaporation and seems therefore to react too strongly to the errors in specific humidity. As previously discussed, these errors are probably influenced by the warm bias that allows the saturated atmosphere to hold more water than in the observations. Figure 10 confirms the spurious behavior of the nudging, especially during the second half of the integration, as well as the consistent and robust behavior of the OI, which is able to restore a reasonable soil water content in the total soil depth after a few weeks.

These results demonstrate that the OI compensates efficiently for large precipitation errors, although the underestimation of precipitation is handled better than the overestimation. In the latter case soil moisture remains too high with OI. The OI is more efficient than the nudging scheme because it uses temperature as well as relative humidity.

d. *Biased forcing by solar radiation*

Downward radiation is another uncertain parameter from the atmospheric model because it is very much influenced by clouds. As a simple test, during the first half of the integration, the downward solar radiation is increased by 25%, while for the second half it is decreased by 25%. Soil moisture is reinitialized to the observed value on 1 August (day 213) in order to avoid any compensation between the radiation biases prescribed before and after this date.

Precipitation errors affect soil moisture directly, which can be corrected rather easily by a soil moisture analysis scheme that is optimized for soil moisture. Radiation, however, influences soil moisture through evaporation, but it also affects the 2-m parameters through sensible heat flux. It is not obvious that nudging and OI are equally efficient in compensating for radiation biases as they are for precipitation errors.

The errors in the 2-m parameters are compared in Fig. 11. The warm bias of the model is increased by the radiative bias in the first half of the integration and reduced in the second half. Comparison with Fig. 4 indicates that the errors in specific humidity are not much influenced by the radiation biases, whereas the errors in relative humidity are more sensitive. As previously noticed with the biased precipitation forcing, the OI is mainly active during the first half of the simulation; after day 213 there is a balance between the 2-m temperature and relative humidity errors. The nudging improves the forecast of specific humidity to the detriment of the other 2-m parameters during the second half. Both methods perform well during the dry spell in July.

The hydrological budget is illustrated in Fig. 12. In June, the control experiment is too dry but the surface evaporation compares fairly well with the observations. This is mainly due to the 25% overestimation in the downward solar radiation, which allows the extraction of more water from the soil. Due to the increased drying of the soil, the evaporation becomes too low during the dry spell in July (which is more obvious when looking at the daily mean latent heat flux). The usual drift toward dry conditions appears during the second half of the simulation, but it remains limited since the downward solar radiation is decreased by 25%. The nudging is close to the control in June. Positive corrections appear in July, but the simulation becomes much too dry after day 213. The OI is too wet in July because it compensates for the direct impact of increased solar radiation on temperature. Due to the balance between the errors in 2-m temperature and relative humidity, the OI increments are small after day 213, and the model is slightly too dry.

On the basis of these results it is difficult to conclude that OI is better than nudging for all parameters considered. For example the evaporation during the first half of the simulation is better with nudging than it is with OI. However, soil moisture is much better with OI than with nudging.

6. Conclusions

The ECMWF single column model (SCM) was used to test soil moisture analysis schemes based on atmospheric analysis of 2-m observations of temperature and humidity. The FIFE data are used to evaluate schemes because they allow for a direct verification of fluxes and particularly of soil moisture.

The model is cycled on a 6-hourly basis during a 4-month period from 1 June to 9 October 1987. Every 6 h, the atmospheric profile is updated using ERA data and the soil moisture analysis is performed using either the nudging technique or the optimum interpolation (OI) scheme.

Before starting the study, it was verified that the single column 6-h forecasts reproduced the three-dimensional

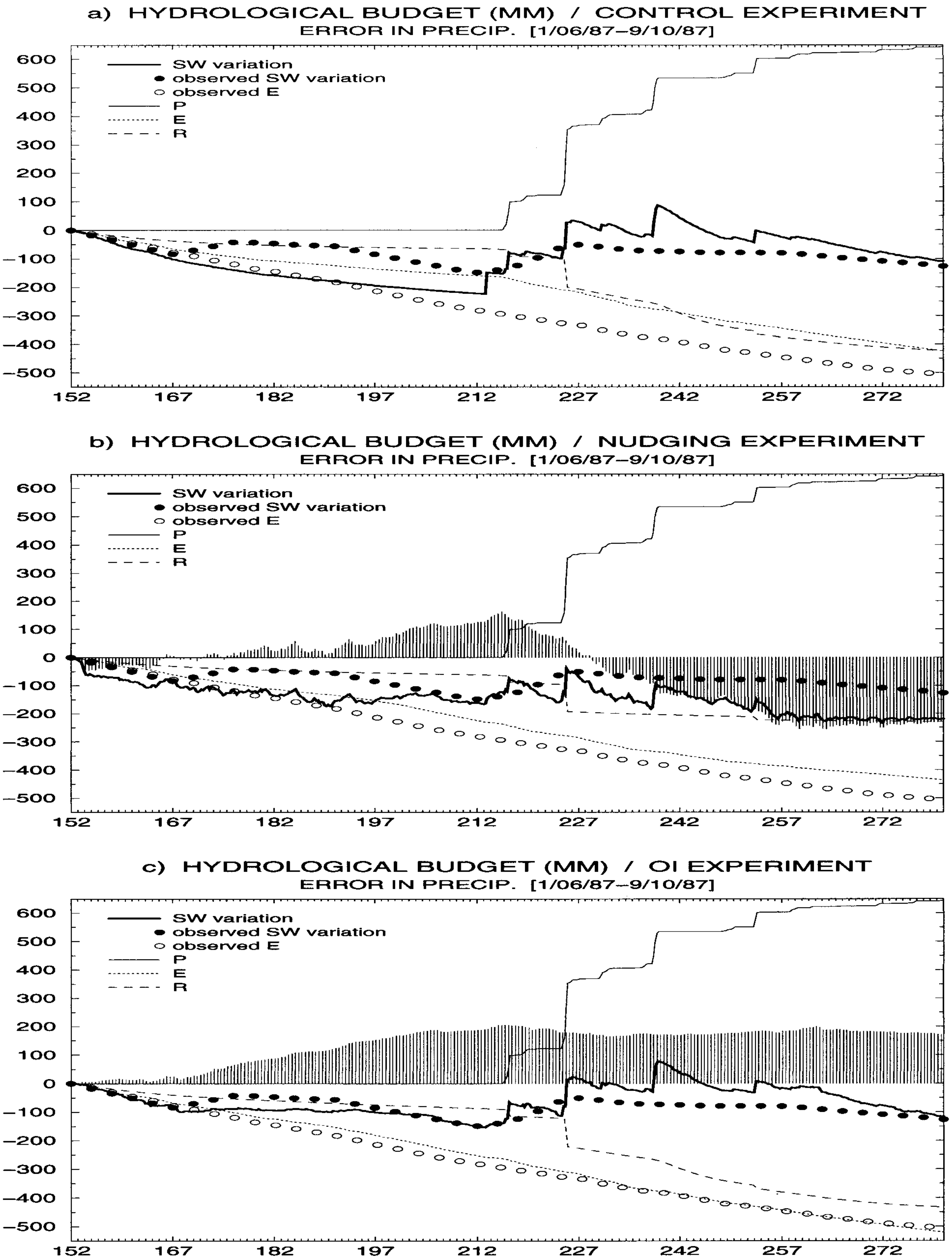

FIG. 10. As in Fig. 6 but all the experiments are forced with biased precipitation. Note that soil moisture is reinitialized to the observed value on 1 Aug (day 213) in order to avoid any compensation between the precipitation biases prescribed before and after this date.

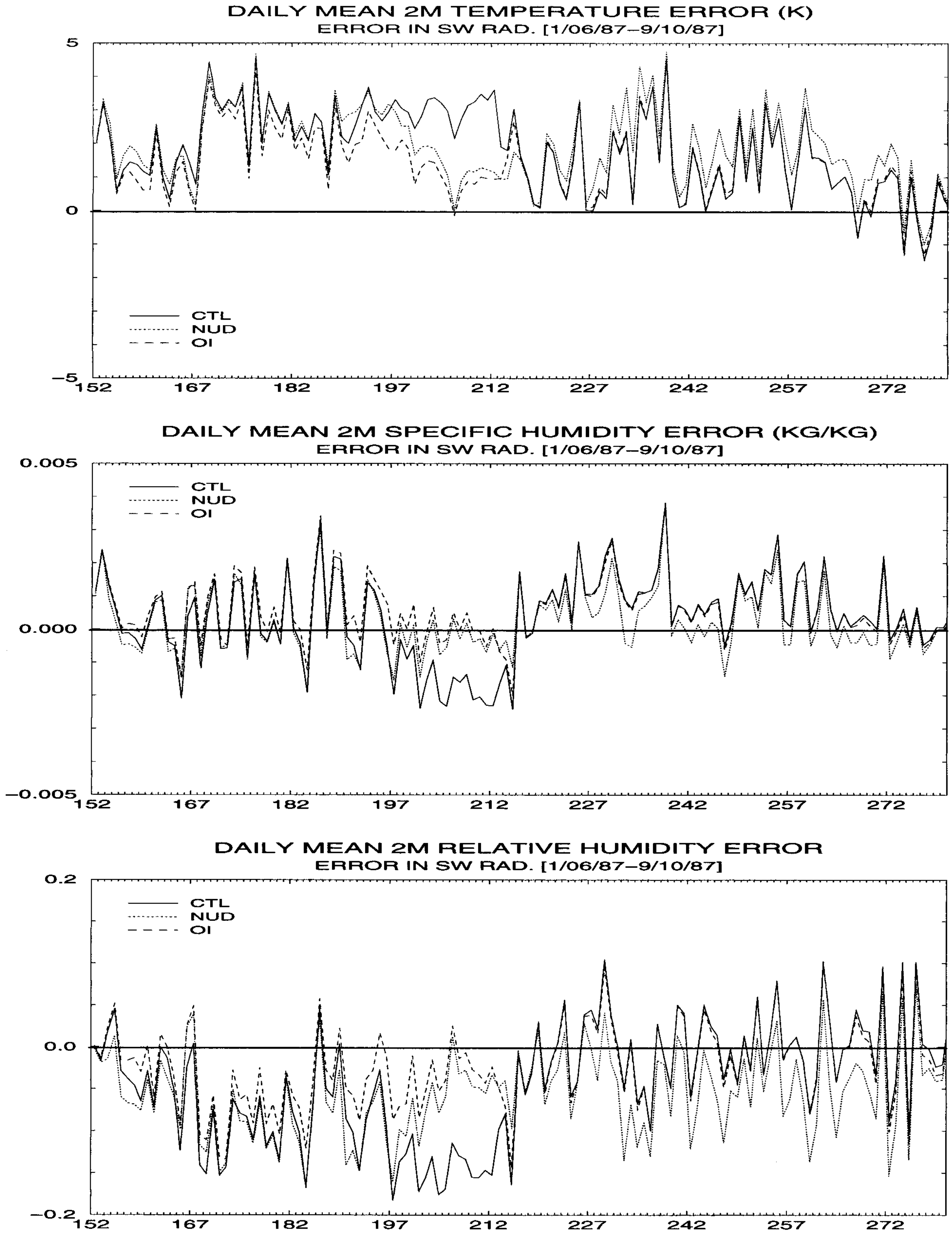

FIG. 11. As in Fig. 4 but all the experiments are forced with biased solar radiation. Note that soil moisture is reinitialized to the observed value on 1 Aug (day 213) in order to avoid any compensation between the radiation biases prescribed before and after this date.

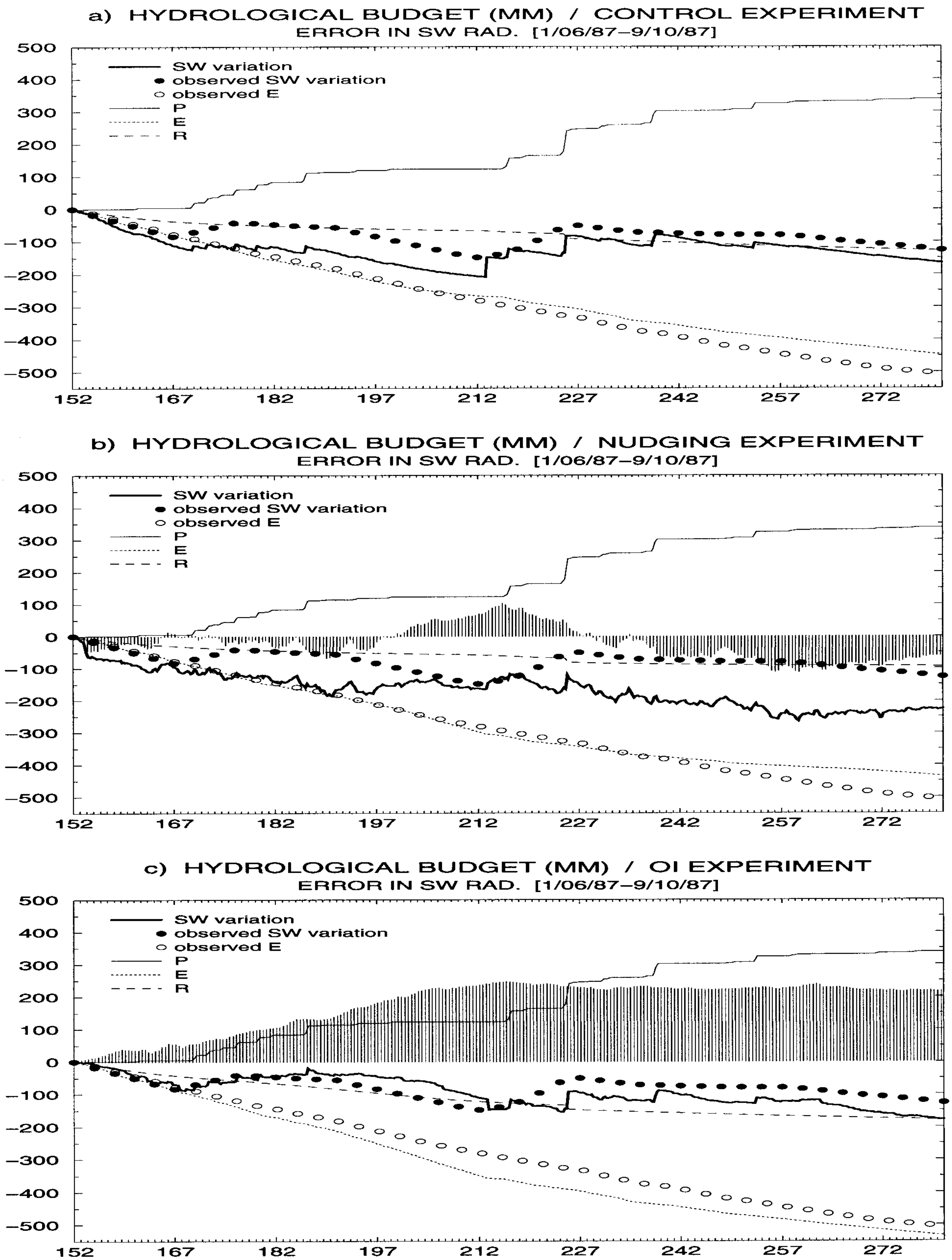

FIG. 12. As in Fig. 6 but all the experiments are forced with biased solar radiation. Note that soil moisture is reinitialized to the observed value on 1 Aug (day 213) in order to avoid any compensation between the radiation biases prescribed before and after this date.

first-guess forecasts of ERA to a reasonable degree of accuracy. These results gave confidence to the idea that the SCM is a useful tool to test soil moisture analysis schemes on the seasonal timescale. It is a cheap alternative to long data assimilation experiments with the global model.

The present study indicates that the current ECMWF nudged soil moisture analysis is able to restore the model soil water content toward realistic values during a prolonged dry spell like the one occurring in Kansas in July 1987. The nudging is therefore efficient in preventing the model to drift in summer or dry season conditions. However, since the atmospheric increments in specific humidity are used to compute the soil moisture increments, the method is very sensitive to model biases. The scheme is applied day and night and, as suggested by Betts et al. (1998a,b) and Douville et al. (1998a), the nudging is strongly influenced by model biases in the diurnal cycle of the boundary layer. For this reason, its behavior is sometimes chaotic and its performance can be poor, especially in wet or rainy conditions.

The OI technique produces smoother increments and generally performs much better than the nudging, due to the use of increments of both 2-m temperature and relative humidity and the careful selection of suitable meteorological conditions for the analysis.

The main conclusion is that nudging manages to prevent drifting and reduces errors in 2-m temperature and humidity but does not necessarily have realistic soil moisture. As such it can not be called a soil moisture analysis scheme. Optimum interpolation using 2-m temperature and relative humidity also reduces errors in 2-m parameters but produces much more realistic soil moisture.

The robustness of the the nudging scheme and the OI scheme have been tested by perturbing the forcing from precipitation and radiation. Although the accuracy of the resulting soil moisture deteriorates with perturbed forcing, the best results are obtained with the OI technique. As already pointed out by Hu et al. (1999), perturbations in precipitation are easier to handle by the analysis schemes than biases in radiation. The reason is that precipitation affects soil moisture only, whereas radiation also influences the 2-m temperature and humidity independent of soil moisture.

Although OI is superior to nudging, the OI analysis is still indirect and relies heavily on the quality of parameterizations of the model. Model biases in radiation are particularly disturbing as they have similar effects on 2-m forecasts as soil moisture errors. One way of controlling biases in radiative forcing in the future would be to implement a cloud analysis. Some control of adverse radiation effects is already present in the OI scheme through the empirical function F_2, which reduces soil moisture increments in cases of high model cloud cover. On the other hand, the OI is still active if the model predicts low cloud cover and the real atmosphere is cloudy. In this situation, the surface solar radiation may exhibit significant biases, as strong as the 25% errors introduced in the perturbation experiments. A cloud analysis based on SYNOP data would flag the poor cloud forecasts, and the soil moisture analysis could be switched off. Another way of dealing with biases in the forecast model is explored by Douville et al. (1998b). They apply a high-pass filter to the increments of the 2-m increments of temperature and relative humidity before using them for the soil analysis. In this way systematic model errors (i.e., errors that have a high correlation in time) are filtered out and do not lead to soil moisture increments. Although the initial results are encouraging, there is a risk that slow drift in soil moisture is not corrected for and therefore more experimentation is needed before firm conclusions can be drawn.

Douville et al. (1998b) also explored the possibility of soil temperature analysis based on 2-m temperature analysis increments. The idea is that near-surface temperature at night and in winter (in cases where soil moisture has less impact on atmospheric temperatures) is much affected by soil temperature. The initial results look encouraging and further experimentation will be carried out to investigate the possibility of operational use in the ECMWF model.

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