Land surface assimilation

Jean-François Mahfouf and Pedro Viterbo

European Centre for Medium Range Weather Forecasts
Shinfield Park, Reading (UK)

Abstract

This paper provides a review of techniques recently developed for initialising the prognostic variables of land surface parametrizations in numerical weather prediction models. The importance of soil moisture initialisation is emphasized since the evolution of the boundary layer is very sensitive to its specification and the associated time scales are much longer than those of medium range forecasts. The analysis of snow mass is also described, using the ECMWF method as an illustrative example. Different methods and data available for the initialisation of other slowly varying components at the surface, such as soil temperature, vegetation fraction, leaf area index and albedo, are described at the end.

1 Introduction

The importance of land surface processes has been recognised for a long time by the climate modelling community, in order to describe in a consistent way all the components of the water and energy cycle over long periods of time. As a consequence a variety of schemes have been devised ranging from the simple bucket model of Manabe (1969) to the complex soil-vegetation SiB (Simple Biosphere) model of Sellers et al. (1986).

Although a number of sensitivity studies have shown that land surface processes can also affect medium range weather forecasts (Rind 1982; Rowntree and Bolton 1983; Yeh et al. 1984; Rowell and Blondin 1990; Beljaars et al. 1996), the parametrization of the interactions between continental surfaces and the lower atmosphere is still rather crude in most numerical weather prediction models.

Recent field experiments, such as HAPEX-MOBILHY 86, FIFE 87 or BOREAS 94, have enabled the development and the validation of land surface schemes describing the most important processes governing the water, heat and momentum exchanges while remaining simple enough to be included in operational weather forecasts models (Noilhan and Planton 1989; Viterbo and Beljaars 1995). Such parametrizations can improve significantly the quality of the forecasts of weather elements (Bougeault et al. 1991; Lanzinger 1995). Initialisation of the prognostic soil variables at global scale is an important issue given the very different time scales of evolution between the atmospheric and the soil systems. Realistic schemes appear to be sensitive to the specification of initial soil temperatures and water contents (Jacquemin and Noilhan 1990; Bouttier et al. 1993a, 1993b). The increase in realism of other physical parametrizations (clouds, radiation, convection) in numerical weather prediction models has also made errors in the surface representation easier to identify. The importance of positive feedbacks between the surface and the atmosphere must be underlined : realistic mechanisms should be represented (which is not possible when surface boundary conditions are fixed), but spurious ones, resulting from systematic errors in the representation of some components of the energy and water cycles, should be removed with an appropriate initialisation procedure.

In the following, we will start in Section 2 by describing the basic features common to most surface schemes. Special features of the land surface assimilation are identified in Section 3, in terms of data availability and its relation to model variables. Section 4 reviews the problems of simple surface initialization procedures. Methods for the initialisation of soil water in numerical models using near-surface temperature and humidity observations are described in Section 5, while Section 6 explains the drawbacks of on-site surface observations of soil moisture and discusses the need for remote sensing. Finally, Section 7 reviews the initialisation of other slowly varying land surface variables, such as snow mass, deep soil temperatures and vegetation characteristics.

2 Design of land surface parametrizations

2.1 General features

The aim of land surface schemes is to compute temperature and specific humidity at the lower boundary of atmospheric models. These two variables are required in the estimation of heat, water and momentum exchanges between the continental surfaces and the lower atmosphere.

The surface temperature T_{sk} is derived as the solution of the surface energy balance written as:

$$R_n = LE + H + G \tag{1}$$

where R_n is the net radiation flux converted in latent heat flux LE, sensible heat flux H and ground heat flux G.

The ground heat flux G depends upon deep soil temperatures and soil thermal properties.

The surface specific humidity can be written formaly as :

$$q_s = A \times q_{sat}(T_{sk}) + B \times q_L \tag{2}$$

where q_L represents the value of specific humidity at the lowest model layer. The quantities A and B (described with more details in the next paragraph) depend upon soil moisture θ which is obtained by solving the surface water budget :

$$\frac{d\theta}{dt} = P - E - R \tag{3}$$

where P is the precipitation flux, E the total evaporation flux and R the surface runoff.

This brief description shows that a land surface scheme must manage at least two prognostic equations for the temperature and soil moisture in the soil. Heat and water transfers are governed by the following diffusion laws :

$$\frac{\partial T_s}{\partial t} = \frac{\partial}{\partial z}\left(D_T \frac{\partial T_s}{\partial z}\right) \tag{4}$$

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}\left(D_\theta \frac{\partial \theta}{\partial z}\right) + \frac{\partial K_\theta}{\partial z} \tag{5}$$

The diffusivity D and conductivity K coefficients are non-linear functions of soil moisture content. The diffusion equations are generally discretized over 2 to 4 layers in order to deal with time scales ranging from days to months.

2.2 Surface fluxes

The link between soil and atmospheric variables is provided through the expression of the surface fluxes, usually based on Monin-Obukhov theory; the crucial variable here is the evaporation flux because its magnitude depends explicitly upon surface properties. Recent land surface schemes represent differently the grid box fractions covered by: a) bare soil, with evaporation controlled by soil moisture in a shallow top soil layer; b) vegetation, with transpiration controlled by soil moisture in the root zone affecting the magnitude of stomatal resistance; c) snow or interception reservoir, evaporating at the potential (maximum) rate. These two last components require the existence of model prognostic equations for snow mass and interception reservoirs.

Evaporation from bare soil can be written as (see Mahfouf and Noilhan 1991 for a review) :

$$E_g = \rho \frac{h_u q_{sat}(T_{sk}) - q_L}{R_a} \tag{6}$$

The efficiency of the turbulent transfers is accounted for through the aerodynamic resistance R_a, while the control by the surface soil moisture θ_s is represented by the surface relative humidity $h_u(\theta_s)$ [$A = h_u$ and $B = 0$ in Equation (2)]. A typical variation of $h_u(\theta_s)$ is presented on the left panel of Fig 1. Evaporation take place at the potential rate above a threshold value (field capacity) θ_{fc} (defined from soil texture) up to the saturation θ_{sat}.

Transpiration from vegetation canopy writes similarly:

$$E_{tr} = \rho \frac{q_{sat}(T_{sk}) - q_L}{R_c + R_a} \tag{7}$$

The analogy with Equation (2) leads to $A = R_a/(R_a + R_c)$ and $B = R_c/(R_a + R_c)$. Water transfers from the root zone to the atmosphere depend both on biological and physical controls. Plants limit their water losses in unfavorable environmental conditions determined by soil moisture in the root zone, atmospheric water vapour deficit, solar radiation, air temperature and carbon-dioxide concentration. A typical dependency of the canopy resistance R_c with soil moisture is shown on the right panel of Fig 1. Below a threshold value often defined as the permanent wilting point θ_{pwp}, it is assumed that plants are unable to pump water from the root

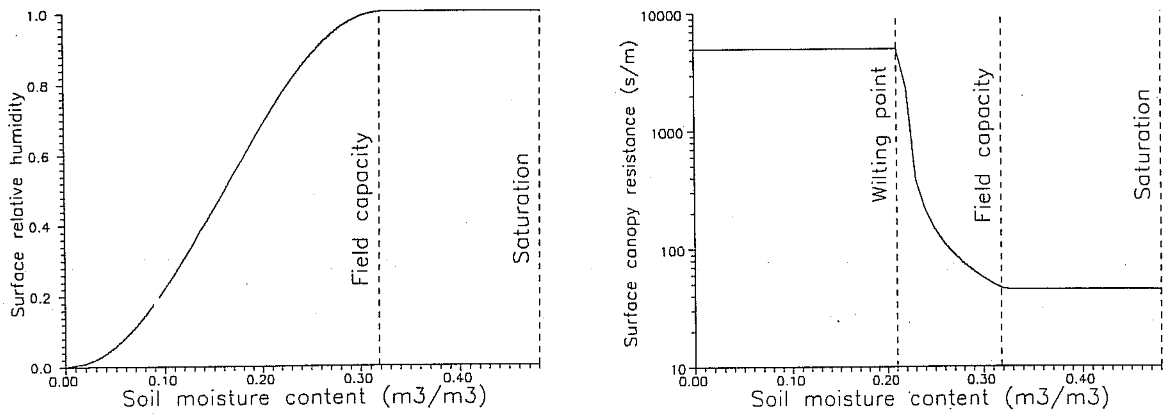


Figure 1: Surface relative humidity h_u as a function of the surface volumetric water content (left) and canopy resistance R_c as a function of the mean volumetric water content (right). (From Mahfouf 1991).

zone to the stomatal cells, corresponding to a rapid decrease of transpiration (increase in R_c). As for bare soils, it if often assumed that above the field capacity the plant transpiration is not controlled by soil moisture.

3 Introduction to land surface assimilation

The major problem of land surface assimilation is the lack of routine observations of soil moisture and soil temperature. This is specially true in the case of soil moisture, where current methods cannot provide global coverage routinely (see Section 6b for more details). Furthermore, soil moisture observations show large variability in small spatial scales (see e.g. Wetzel and Chang 1988); not all scales are of relevance for the atmosphere, and the assimilation method has to take that into account. For soil temperature the climate network exists, with a coverage similar to the SYNOP stations and with most of the stations performing observations at least daily; unfortunately, those observations are not exchanged routinely at the time of measurement, so in practice they can only be used, in delayed mode, for verification purposes.

The nature and availability of the observations imposes the use of proxy variables for soil moisture. The amount of water in the root zone impacts on the evaporative fraction, which in itself determines, for a given amount of net radiation, midday summer screen level temperature and humidity (see previous section and the review by Betts et al. 1996). On the other hand, the time evolution of soil water depends on the rainfall intensity and on its timing. Three main types of data have been used in the past to infer soil moisture: (a) Screen level atmospheric temperature and humidity; (b) Rainfall rates; and (c) Radiometric surface temperature (infrared, microwave). Note that, since those observations already represent, to a certain extent, the impact of soil moisture on the atmosphere above, they have already filtered out the smaller scales in soil water.

There are two aditional difficulties in the assimilation of land surface observations. First, these observations are non-linearly related to soil moisture and soil temperature (through the equations of the land surface scheme). Secondly, the statistics of forecast errors, used to spatially distribute the local increments in atmospheric analyses, are not known for soil variables.

4 Simple land surface initialisation methods

Due to the difficulties presented above, soil variables are initialised empirically in most operational forecasts models.

A first method for initialising soil variables is to set the analysed soil variables to climatological values without using any model information (through the first-guess). In practice, this is done by adding a relaxation to climatology to the prognostic equations of the land surface scheme (Blondin 1991). The underlying idea of this term is that simple surface schemes can only describe correctly the variables having a short time scale evolution, like the surface soil temperature, and that variables having a time scale longer than a few days must be prescribed. Problems arise from the specification of climatological soil values which are based on indirect atmospheric observations and very simplifed transfer models. These products, like the soil moisture climatology of Mintz and Serafini (1992), have a high level of uncertainty as shown by Viterbo and Beljaars (1995). Another potential problem is that with a relaxation of deep variables towards climatology, seasonal anomalies cannot be forecasted. An example of such deficiency has been shown by Beljaars et al. (1996) with two versions of the ECMWF model for the 1993 US floods.

The other approach to initialise soil variables is to set the analysed values to the first-guess. In that context, an absolute confidence is given to the land surface scheme for evolving its prognostic variables and no control exists to prevent the land surface scheme from drifting to an unrealistic state. Such drifts can occur through positive feedbacks with the atmosphere, in situations where the scheme experiences systematic errors in the atmospheric forcing (too much radiation, too much rainfall, ...) or from a misrepresentation of some land surface processes. The second point can be checked with stand-alone simulations where the atmospheric forcing is prescribed. An example of a drift of the current ECMWF land surface scheme within the data assimilation system is described in the next section.

5 Soil moisture initialisation using SYNOP observations

5.1 The ECMWF method

The land surface scheme developed by Viterbo and Beljaars (1995) was introduced operationally in August 1993 and all soil prognostic variables were initialized to first-guess values. One of the main differences with respect to the previous ECMWF land surface scheme (Blondin 1991) is

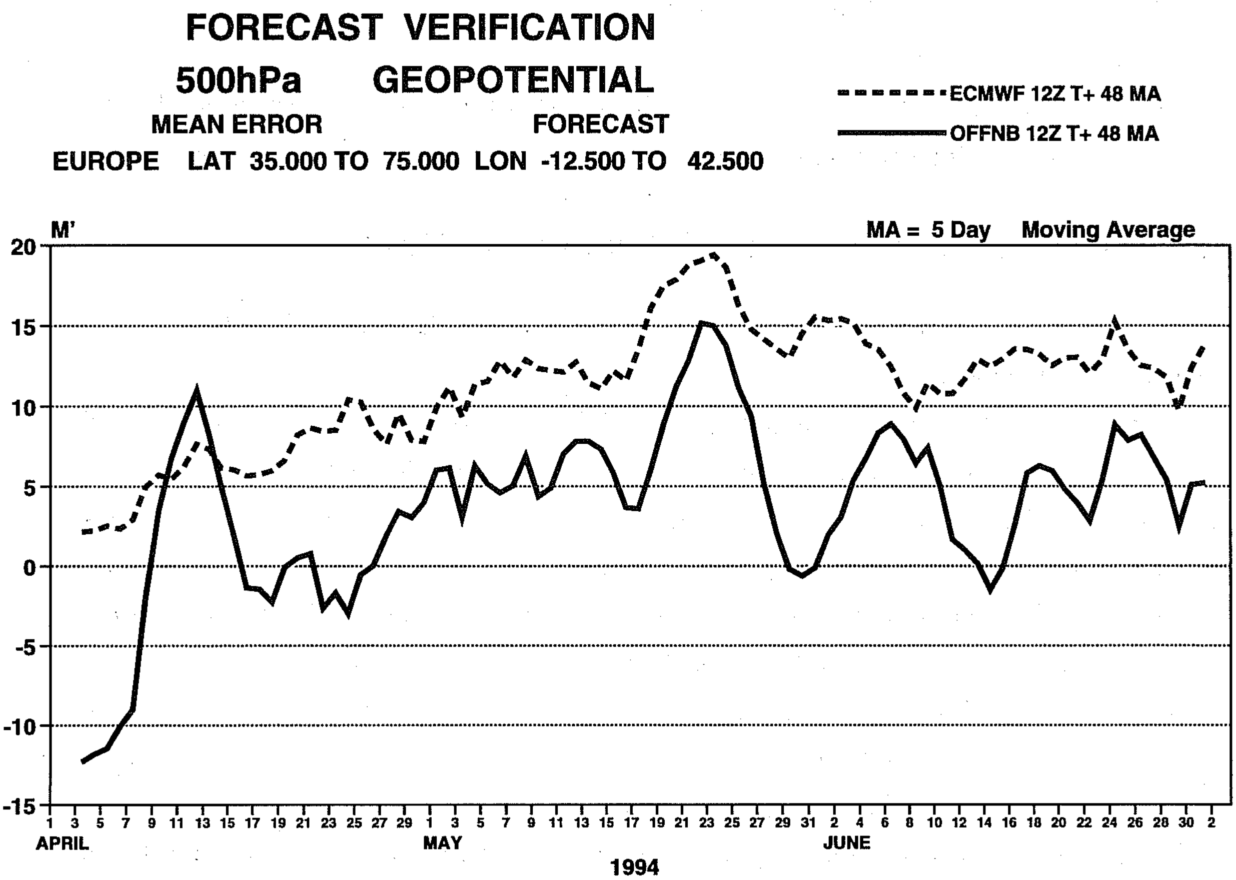
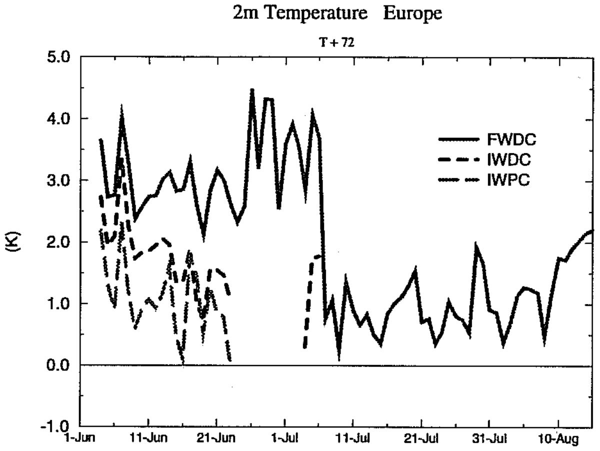


Figure 2: Bias of the 500 hPa geopotential height, averaged over Europe, for the day 2 ECMWF (dashed) and DWD (solid) forecast.

the absence of climatological relaxation for deep soil temperature and water content. During May-June 1994, the soil reservoirs were drying out, leading to surface air temperature errors increasingly positive, and in comparison with other models, such as the German Weather Service (constrained by climatological soil moisture), forecast skill was deteriorating (Viterbo and Courtier 1995). The downward drift of soil moisture appears to be linked to excess incoming solar radiation primarily caused by underprediction of clouds. Furthermore, the excessive warming at the lower troposphere affected the forecast performance, as shown in Fig 2. The 500 hPa geopotential day 2 forecast averaged over Europe is presented for April to June 1994. The ECMWF forecast (dashed line) has a positive bias from late April onwards.

Analysis increments of specific humidity at the lowest model level during May 1994 show positive values over Europe with maxima reaching 2.5 g/kg. The atmospheric analysis tries to compensate for the model bias by moistening and cooling the lower atmosphere. Therefore, the low level humidity increments can be used to identify areas where the soil is too dry. Knowing the analysis increment of specific humidity $\Delta q = q_a - q_f$, the correction of soil moisture to be



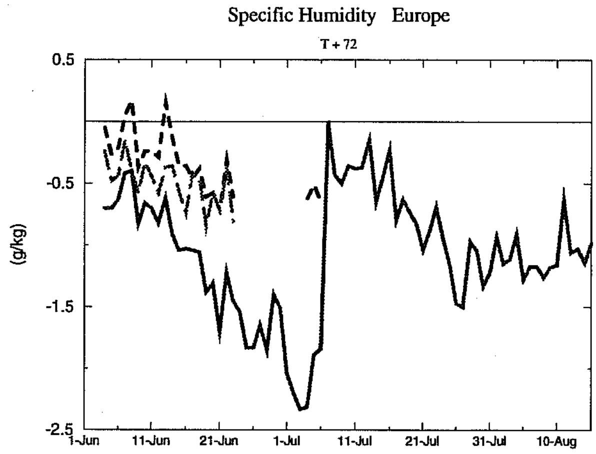
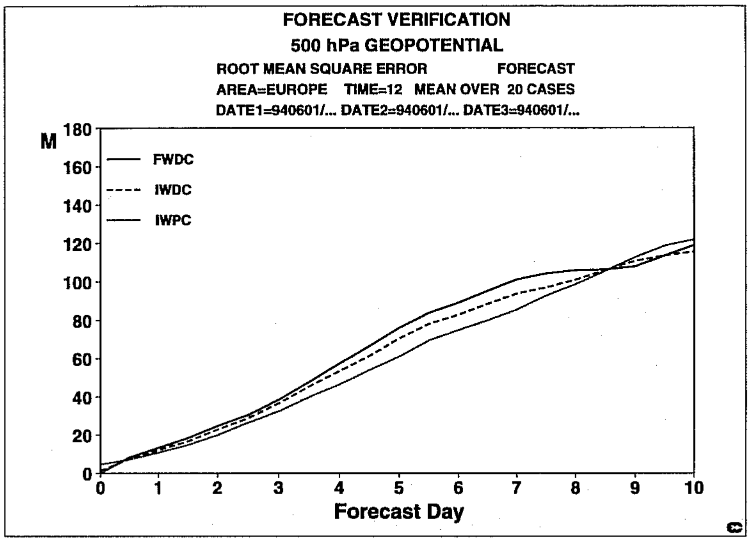


Figure 3: Averaged european bias (model minus observations) in the 2m temperature (left) and the humidity (right) for the day 3 forecast verifying at 12 UTC. FWDC: Control; IWDC: Nudging of water; IWPC: Nudging of water and prognostic cloud scheme.

applied the root zone $\Delta\theta = \theta_a - \theta_f$ is assumed to be proportional :

$$\theta_a - \theta_f = C_v D \Delta t (q_a - q_f) \tag{8}$$

with $\Delta t = 6$ hour, and the subscripts a and f refer to analysis and forecast values, repsectively. The relaxation coefficient D is constant in space and time and corresponds to a specific humidity analysis increment of 1.5 gkg^{-1} filling 150 mm of water in the soil in 9 days. The fraction of vegetation C_v in the above formula guarantees that the scheme is not active over deserts. No increments are produced in the presence of snow, and the analysed soil moisture contents θ_a are limited by the field capacity and permanent wilting point thresholds. The integrated soil water increments are distributed in each of the three soil layers following the model root extraction. This nudging scheme was implemented operationally in December 1994. It supplies soil moisture to maintain evaporation in areas of excessive radiation at the surface, caused, among other factors, by insufficient cloud cover. Fig 3 compares the day 3 forecast errors in screen level day time temperature and humidity, averaged over Europe. Three experiments are compared: Operations, FWDC, where no initialisation of soil water is applied and the diagnostic cloud scheme is used; IWDC, initial soil water method using the technique described above, diagnostic cloud scheme, and; IWPC, initial soil water method and prognostic cloud scheme. The errors in both temperature and humidity are dramatically reduced when the initialization of soil water is used, and they are reduced even further when the radiation forcing at the surface is improved by the use of the prognostic cloud scheme. Note that the soil water was reset to field capacity at 3 July, in a quick effort to correct the large systematic errors in the model; this explains the much reduced operational errors after that date. The reduction of near surface warm dry bias removes the bias at the tropospheric geopotential, impacting favourably on the root mean square (rms) of the tropospheric geopotential over land areas. Examples for the geopotential



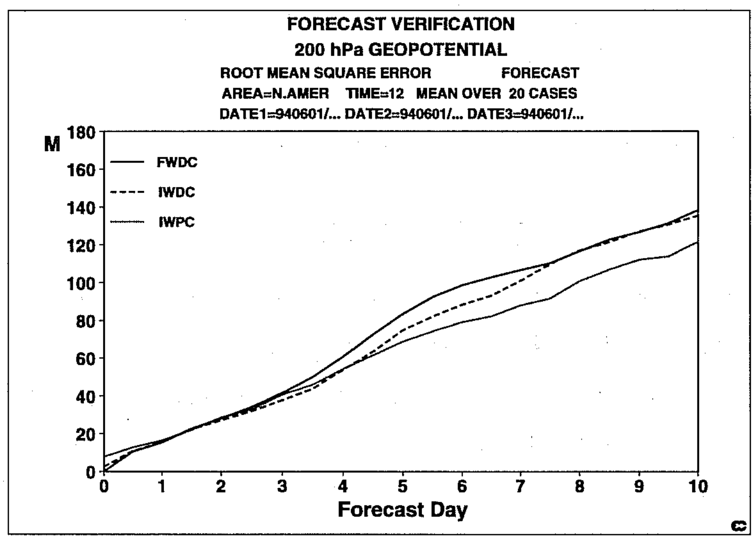


Figure 4: Averaged geopotential root mean square error for the 20 forecasts with initial dates between 940601 and 940620, for 500 hPa Europe (top) and 200 hPa North America (bottom); experiment names as in Fig 3. For all 3 experiments the root mean square is computed against the operational analysis.

rms at 500 hPa over Europe and at 200 hPa over North America are shown in Fig 4.

Similar techniques are used operationally at Météo-France (Coiffier et al. 1987) and at the Canadian Meteorological centre (Mailhot et al. 1996). Recently, Yang et al. (1994) have proposed to improve this method by using both informations of temperature and specific humidity. previous forecast errors with coefficients depending on vegetation type. Unfortunately the method proposed is biased, because a correction of soil moisture is applied even if the forecast of atmospheric low level parameters is perfect; this may lead to a long term drift.

5.2 Possible improvements

Mahfouf (1991) and Bouttier et al. (1993a, 1993b) have proposed an optimal interpolation scheme for the assimilation of soil moisture using information of both temperature and relative humidity at two metres, which can be formaly written:

$$\theta_a - \theta_f = \alpha(T_a - T_f) + \beta(RH_a - RH_f) \tag{9}$$

The optimal coefficients α and β minimise the analysis variance and are related to the forecast error statistics. They are model dependent and the success of the method depends on their accurate estimation. Mahfouf (1991) has used a Monte-Carlo technique with a one-column model, where soil moisture is perturbed randomly in a range of possible values. One conclusion of this study is that the coefficients α and β strongly depend upon the diurnal cycle (information on soil moisture from atmospheric parameters can be extracted more easily during day time in clear sky conditions) and upon the vegetation cover (over bare soil, corrections are applied to the superficial reservoir and when the vegetation cover is important soil corrections are applied over the whole root zone). Bouttier et al. (1993a) proposed a first parametrization of the optimum coefficients, recently generalized by Giard et al. (1996). In order to be used, this initialisation method requires an analysis of temperature and relative humidity at two metres (Navascues 1997); the analysis increments should be zero in those situations where parameters in the boundary layer are not informative about soil moisture, e.g. strong advection, and low radiative forcing at the surface.

Once the optimal coefficients are derived, the sequential assimilation can easily be implemented in current operational data assimilation systems; however, it assumes linear relationships between atmospheric increments and corrections to be applied in the soil which is not a good approximation for most of the physical parametrizations. Another option is the variational method, which seems a priori more suitable to the analysis of soil moisture due to the non-linearities of the problem and to the importance of the time distribution of observations (surface variables are strongly affected by the diurnal cycle). Mahfouf (1991) and more recently Callies et al. (1997) used a 1D-Var approach to estimate the initial soil moisture of a one-column model that best fit observations of temperature and relative humidity during a diurnal cycle. Therefore, the optimal soil moisture minimises the following cost-function:

$$J(\theta) = \sum_{i=1}^{N} \left[\left(\frac{T_{oi} - T_{fi}}{\sigma_T} \right)^2 + \left(\frac{RH_{oi} - RH_{fi}}{\sigma_{RH}} \right)^2 \right] \tag{10}$$

In the above formula T, RH, σ_T and σ_{RH}, represent, respectively, the screen level temperature and relative humidity, and their assumed observational errors, and the subscripts oi and fi represent the observation i and the forecast value interpolated to the point i; the summation is done over the total number of observation observation points, N. Mahfouf (1991) has validated the two methods described above with a one-column version of the Météo-France

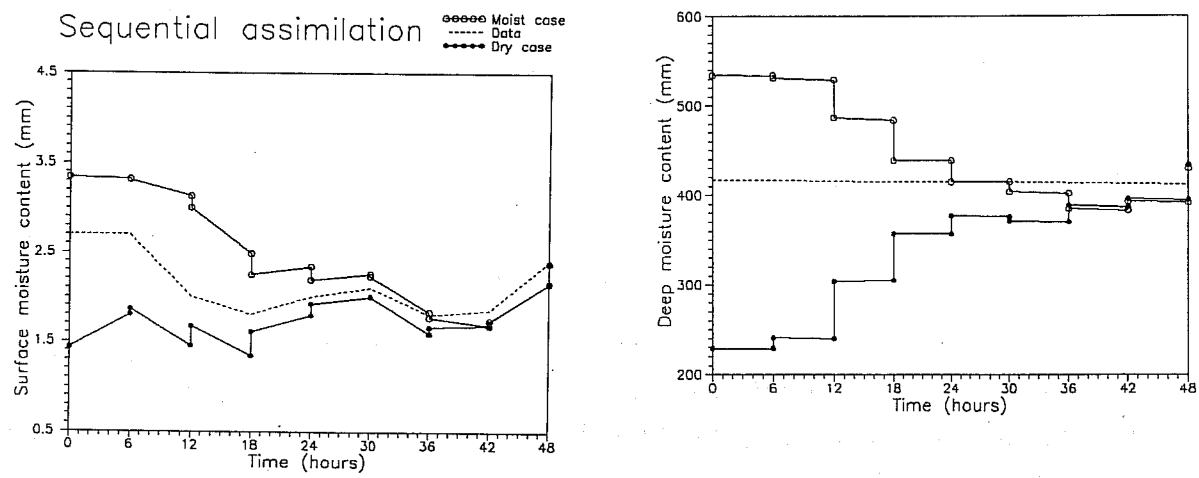


Figure 5: Evolution of the surface (left pannel) and root (right pannel) soil moisture contents during the sequential assimilation on 4-5 July 1986. Dotted curves indicate the observed values. The site is HAPEX-MOBILHY. (From Mahfouf 1991).

forecast model using data from the HAPEX-MOBILHY 1986 field experiment. Data from this campaign provided at various locations simultaneous information about soil moisture content and low-level atmospheric parameters, i.e. temperature, relative humidity, wind speed. When using observations of temperature and relative humidity, both the sequential and variational technique converge towards the neutron probe estimates of soil moisture, starting from arbitrary initial values of soil moisture (Fig 5). Mahfouf (1991) assumed that there is a priori no useful information in the first-guess which is certainly incorrect with an operational model of some skill; in realistic applications a background term should be added to the cost-function.

Results show that for clear-sky situations both methods retrieve soil moisture contents close to each other and to the observations. The variational method is more efficient but non-linearities of the problem make the efficiency of the convergence dependent on the initial start of the minimisation. When the fraction of vegetation is large, soil moisture in the root zone is retrieved more accurately than surface soil moisture. The examination of the cost-function (Fig 6) shows the existence of a secondary minimum (corresponding to ambiguity in the response, the same surface evaporation can be obtained with totally differents water contents in the soil reservoirs) as well as a plateau where surface evaporation is not sensitive to modifications in soil moisture (above field capacity, evaporation is assumed to take place at a potential rate, therefore it is no more controlled by the surface).

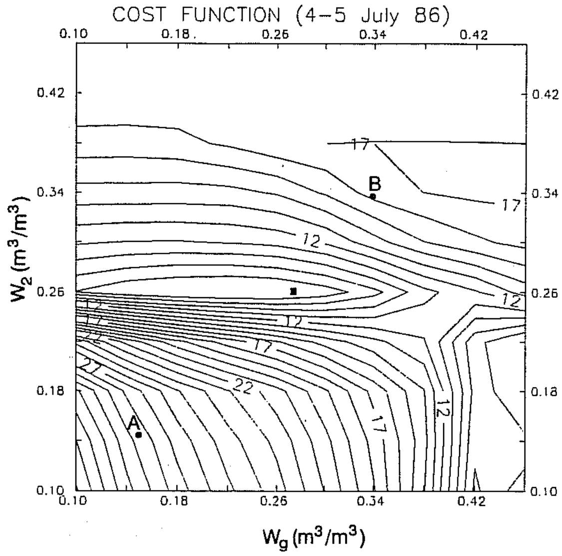


Figure 6: Variations of the cost function with soil moisture for 4-5 July 1986. (A) represents the dry guess ($\theta = 0.30\ \theta_{sat}$), (B) represents the moist guess ($\theta = 0.70\ \theta_{sat}$), and the square is the searched state (reference). (From Mahfouf 1991).

6 Other techniques to initialise soil moisture

6.1 Methods based on precipitation data

Two methods have been introduced to initialise soil moisture from precipitation data, both of them requiring the availability of measurements over large areas and an algorithm to perform a precipitation analysis beforehand. They have only been applied over areas with a good observational coverage like the US or the UK.

The first technique is an uncoupled initialisation where a land surface scheme is forced with conventional meteorological observations (temperature, humidity, wind, radiation and precipitation) to provide an estimate of soil moisture. Feasibility studies have been undertaken in various limited area models by Smith et al. (1994), Macpherson (1996) and Mitchell (1994). The improvement of the forecasts of screen level humidity when soil water is initialized with such a method, using the UK Met Office water budget scheme, is shown on Fig 7 (from MacPherson 1996) for all UK stations.

Another technique makes use of both observed precipitation rates and model first-guess. Assuming a rainfall rate increment over a 6-hour period:

$$\Delta P = \frac{P_a - P_f}{\Delta t} \tag{11}$$

This quantity is converted in soil moisture increment by using the tangent linear model of a soil moisture budget scheme:

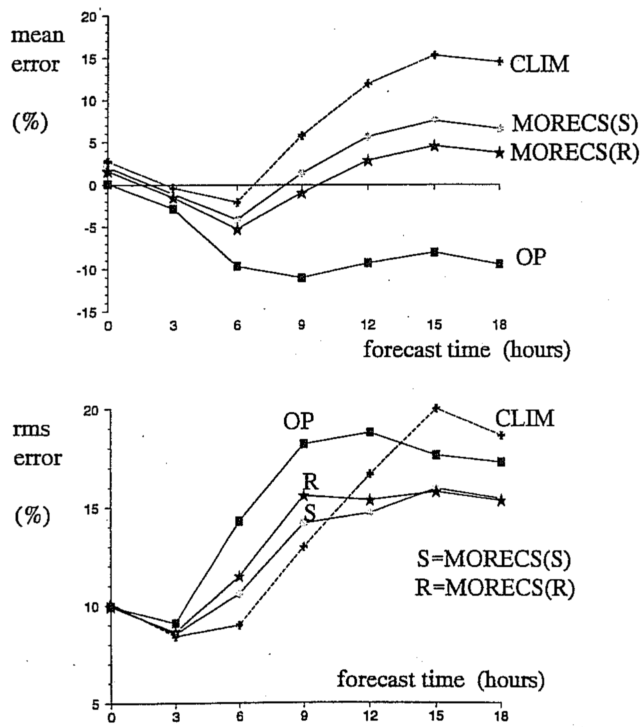


Figure 7: Screen level relative humidity verification of forecasts from 28 June 1995 00 UTC, with different initial soil moisture: Operational (OP) with free cycling moisture, climatological (CLIM); MORECS (S) and MORECS (R) refer to a smoothed and raw version, respectively, of the soil moisture initialisation using oberved precipitation. (From MacPherson 1996).

$$\frac{d\Delta\theta}{dt} = -\frac{\Delta\theta}{\theta}E + \Delta P \tag{12}$$

where E is the mean evaporation rate and θ the mean soil moisture content during the 6-hour assimilation period (trajectory). Then, the soil moisture increment $\Delta\theta$ is added to the superficial reservoir. Studies have been undertaken at ECMWF by Vasiljevic (1989, personal communication) and at UKMO by Jones and Macpherson (1995). Such a method is sensitive to the specification of surface run-off and can converge slowly when biases in the root zone are large.

6.2 On-site observations and methods based on satellite imagery

Existing techniques for ground based observations of soil moisture (see recent reviews in Schulin et al. 1992; Wei 1995) are time consuming and normally require human intervention. The representativeness error of the on-site estimates is best avoided by deploying several instruments within a relatively small area (100 m^2), increasing the cost of the measurements. In spite of its problems, on-site soil moisture data are very useful for regional esimates for climatic studies, essential to close the water budget in large-scale hydrologic experiments (Cuenca and Noilhan 1991; Goutorbe et al. 1989; Mahfouf 1990) and to calibrate remote sense retrieval techniques (Georgakakos and Baumer 1996).

There is no prospect of obtaining real-time global estimates of soil moisture based on existing technology of ground based instruments. For this reason, several algorithms have been developed to infer soil moisture from satellite observations, although none of them is currently used in an operational data assimilation system. Three types of techniques have been proposed (see reviews in Paloscia 1996; Schulin et al. 1992; Wei 1995) based on *infrared* measurements, *passive microwave* and, more recently, *active microwave* (radar) instruments.

In the infrared channels, the sensitivity of the diurnal cycle of surface temperature to soil moisture has been used to define methods based on the observed changes on the infrared skin temperature (which avoid the problem of absolute calibration of the satellite sensor). For reviews of applications see Carlson (1991), Schmugge and Becker (1991), and Schulin et al. (1992). Geostationary satellites allow for a better temporal sampling (Wetzel et al. 1984 ; McNider et al. 1994). These methods can only be applied in clear sky conditions but provide an information about soil moisture in the root zone over vegetated areas. Bastianssen (1995) developed recently a technique to estimate regional evaporation over heterogeneous terrain, based on a separate estimate of the evaporation of unstressed pixels, based on potential evaporation, and fully stressed pixels, based on the infrared diurnal cycle technique. The evaporation of the remaining cloud-free pixels can be obtained by interpolation between the wet pixels and the dry pixels. van den Hurk et al. (1997) has applied this technique to initialize the soil water of a limited area model over the Iberian peninsula. The model soil moisture is the linearized solution of a variational problem that minimizes the difference between model and satellite estimates of evaporative fraction ($H/(H + LE)$).

Microwave channels can be used to infer soil moisture due to the important variations of the dielectric constant of a soil with volumetric water content for frequencies between 1 and 5 GHz (Schmugge and Jackson 1994). *Passive microwave* techniques use the fact that soil emissivity changes with its water content. In *active microwave* sensors (radar) the signal is emitted by an artificial source and the intensity of the backscattered radiation, after reflection by the surface, is measured. The reflectivity of the soil changes with its water contents, hence the intensity of the reflected signal can be related to the soil moisture. Active microwave systems allow, for the same wavelength (same maximum penetration depth), a finer horizontal resolution, because the ground can be scanned with an angularly confined beam. One of the drawbacks of microwave retrievals is that the surface emissivity/reflectivity is also sensitive to the surface roughness and the water contents of the vegetation canopy. Nevertheless, it appears that simple estimates of surface roughness of broad vegetation classes are sufficient to correct the soil moisture estimate (Njoku and Entekhabi 1996). On the other hand, the oppacity of the vegetation layer increases with its water content, making the corrections due to vegetation increasingly unreliable for moist soils. Perhaps the major drawback of microwave estimates is the depth of penetration of the signal, limited to the top layer of the soil (2 to 10 cm, depending on the wavelength). However, for specific soil hydrological and atmospheric conditions, the soil water contents of the root layer is correlated with the top soil water. Recent studies show that it is possible to infer, in a physically consistent way, the whole profile of soil water from its values at the top layer (e.g. Njoku and Entekhabi 1996; Calvet et al. 1997).

We have shown in this section that ground-based estimates of soil moisture, although very important for calibration purposes and in intensive field efforts, cannot give a near real-time global stimate of soil moisture. Satellite estimates can achieve global coverage, but are limited to clear-sky conditions (infrared channels) or sense only the top few centimetres of soil (microwave channels). The future relies on physically based estimates of soil moisture from a combination of satellite measurements and model short-term forecasts, using a variational technique in order to find the soil water contents that fits best the satellite signal.

7 Initialisation of other land surface quantities

7.1 Snow mass

The methods used to analyse snow mass are relatively crude when compared to analysis schemes for the atmospheric variables (Lorenc 1986) and could easily be improved. In this section, the ECMWF snow analysis is described. The methodology used in other operational centres is very similar.

Every 6 hours a snow analysis is performed in three steps:

1) Snowfall analysis: From SYNOP reports of temperature and precipitation rate, a snowfall rate is estimated at the observation points, and then a spatial interpolation is done by a successive correction method.

2) Snow mass background field: A very simple snow model evolution is used to build the background S_g from the analysed snowfall P_s, the previous analysis of snow mass (persistence) S_p, a snow climatological mass S_c, and an empirical melting function M based on the 2m temperature forecast:

$$\frac{dS}{dt} = P_s - M + \frac{S_c - S}{\tau} \tag{13}$$

or in a discretized form:

$$S_g = (1 - \lambda)S_p + \lambda S_c + \Delta t(P_s - M) \tag{14}$$

3) Snow mass analysis: a sucessive correction method is applied to the snow mass increments (the difference between the background field in (2) and the observations of snow depth, suitably scaled assuming a fixed snow density of 250 kgm^{-3}).

The main shortcomings are that informations from the model (first-guess) are not taken into account in the analysis process and that the snow mass climatology, towards which the analysis is relaxed and in fact the dominant term in data void regions, is rather poor. The snow climatology (Brankovic and van Maanen 1985, BvM85) has been constructed by running to equilibrium an empirical snow mass model forced by precipitation monthly climate values and adjusted for melting using a temperature climatology; notice that no snow observations were used and that the spatial resolution is rather poor (5° • 5°). Fig 8 shows BvM85 climatology for January and April, and compares its values with the 1° x 1° US Air Force (USAF) climatology (Foster and Davy 1988), the latter taking into consideration an extensive collection of regional and global surveys of ground based snow depth observations. Note that, since the USAF is a climatology of snow depth, BvM85 snow mass values have to be converted using an empirical specification of snow density: Eq (48) of Verseghy (1991), that takes into account the packing of snow under its own weight, was used. It is clear that in January, the BvM85 values extend too far south in Asia, overestimate the snow depth in south Siberia, Mongolia and eastern Europe, northwestern and eastern Canada, and underestimate the snow depth in northern Siberia, Iraq, Iran, western Europe and Central Canada. BvM85 values over Greenland are much larger than USAF, partly because the USAF represents a climatology of seasonal snow depth, while BvM85 snow mass values have been assigned the arbitrarily high value of 10 m, "to avoid unrealistic melting" (BvM85). In spring BvM85 overestimates the snow depth virtually everywhere, but for the european values (e.g. the Alps and Pyrenees), where a small underestimation is detected.

Mean monthly January and April snow depth values of the ECMWF reanalysis are shown in Fig 9, together with their difference to the USAF climatology. The overall patterns in the right panels of Fig 8 and Fig 9 are very similar, indicating that the BvM85 climate influences strongly the reanalysis values. Nevertheless, it is also clear that the information from observations in January is effectively used (values of top panel of Fig 9 are smaller than the corresponding values in Fig 8), especially for Europe and western Asia. Substantial errors in the BvM85 climatology in spring lead to large anomalies of the reanalysis mean values. As a further illustration of the reanalysis information brought by the use of observations, the monthly deviations of snow mass from the BvM85 values is shown on the left panels of Fig 10, while the right panels show the standard deviation of the monthly mean values of analysed snow mass. Since we are dealing exclusively with snow mass values, there was no need to use the density relation in this figure. The northeastern Asian values of snow in winter are similar to BvM85, and the standard deviation is small. A separate analysis (Laura Ferranti, personal communication) shows that a very large northern Asian area corresponding to the former Soviet Union has a data cover very inhomogeneous in time: the number of observations from 1979 to 1992 are 10 to 30 times smaller than in 1993. Values for the month of May (not shown) display larger differences to the climate and larger variability in northern latitudes. This is due to interannual variability in the rates of melting implicitly used in the snow analysis algorithm (see Eq 14), and controlled by the first-guess two-metre temperature.

The analysis algorithm has been further evaluated by Martin (1996), and results for snow mass are displayed in Fig 11. The values of the reanalysis (labelled ERA in the picture) are compared with those produced by an off-line integration of a detailed, physically based snow model, CROCUS (Brun et al. 1989; 1992), forced by ERA values of screen level temperature, wind speed and humidity, precipitation, and semi-empirical derived values for incoming radiation.

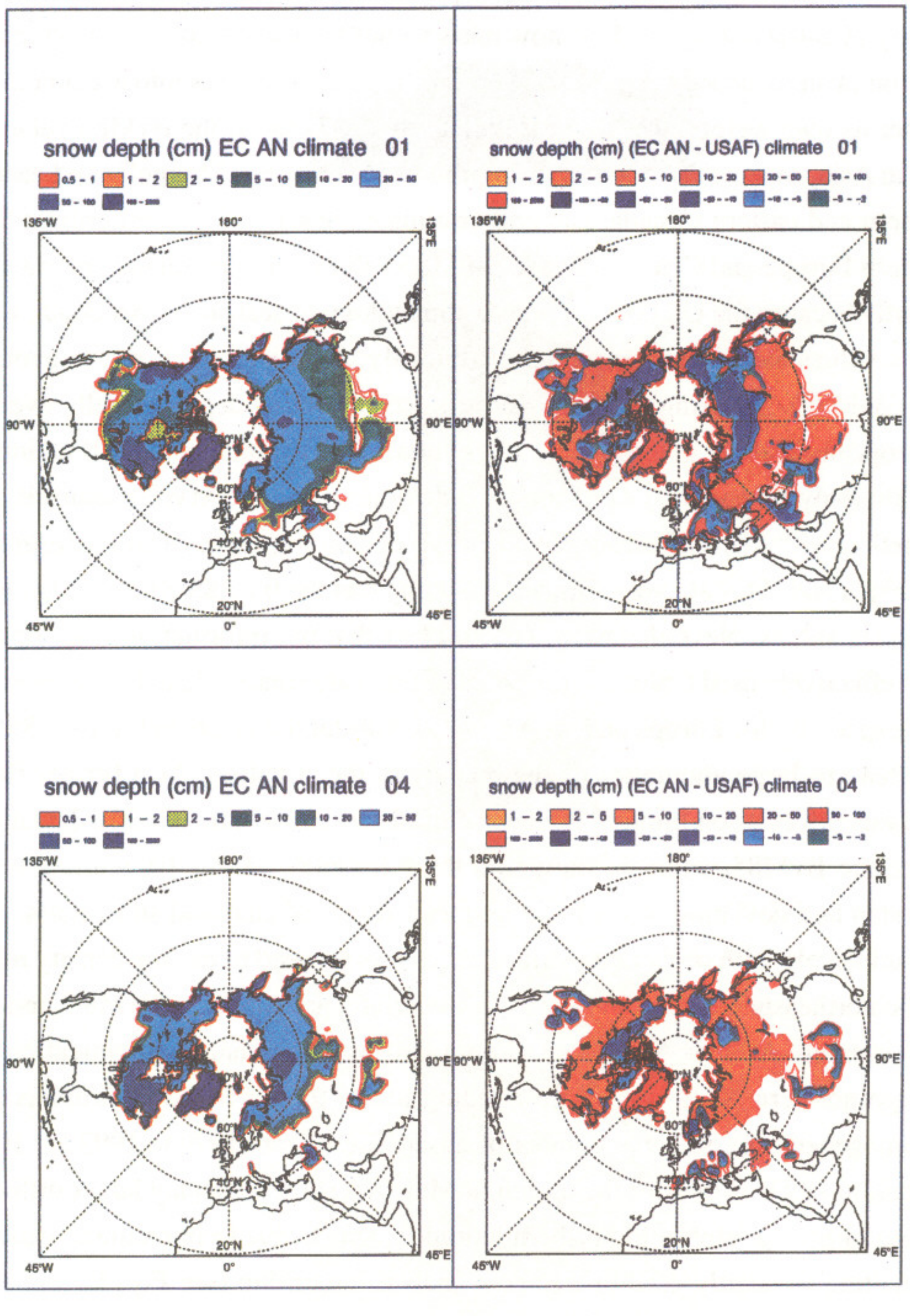


Figure 8: Snow depth (cm) for January (top) and April (bottom). The climatology used in the ECMWF analysis is shown on the left, differences to the US Air Force climatology is shown on the right. The linear snow density formula of Verseghy (1991), varying between 188 kgm^{-3} and 450 kgm^{-3}, is used to convert the snow mass values of the analysis climatology into snow depth.

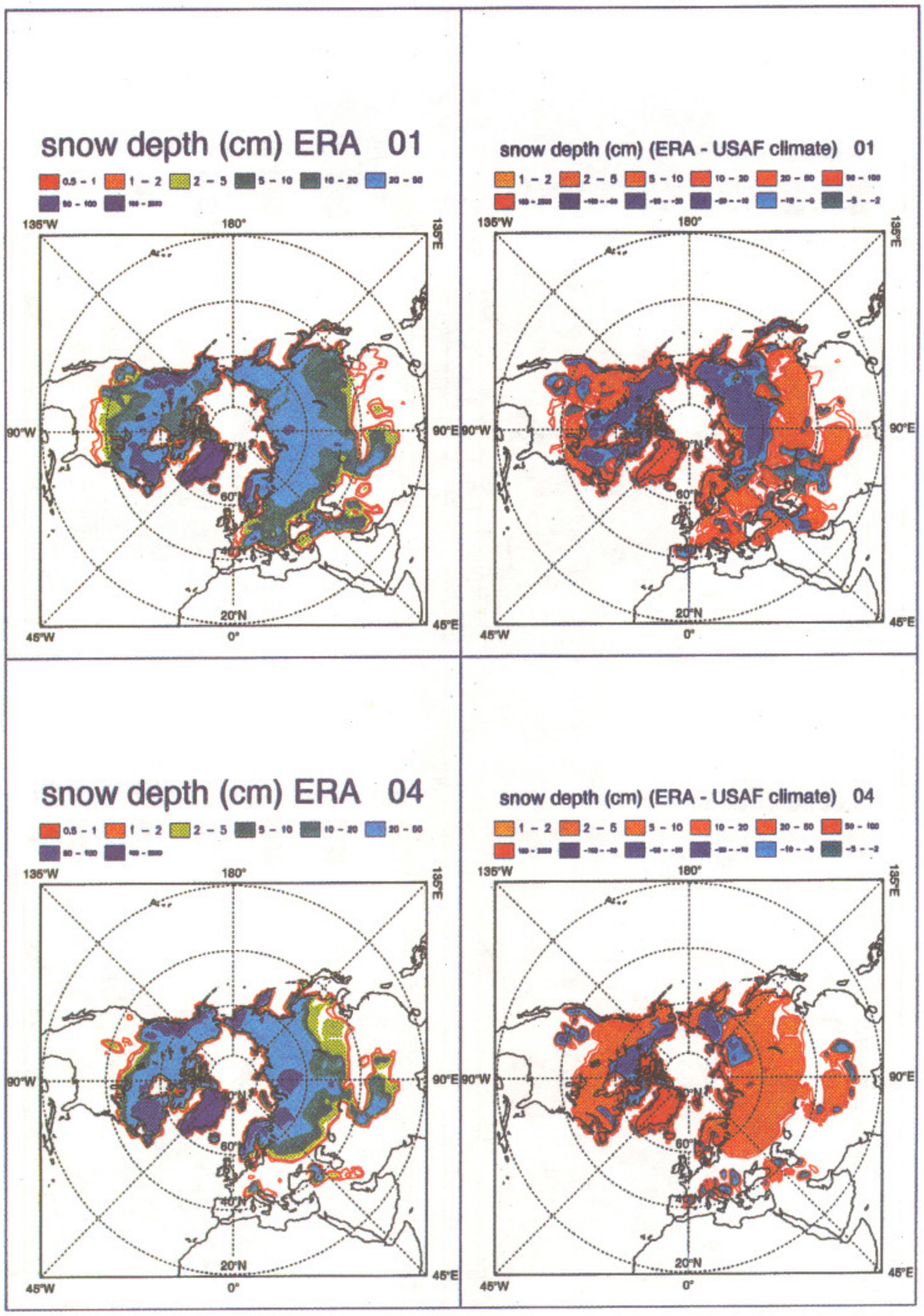


Figure 9: As in Fig 8, but for the reanalysis mean January value (top left) and the mean April value (bottom left). Right panels show the difference between these values and the US Air Force climatology.

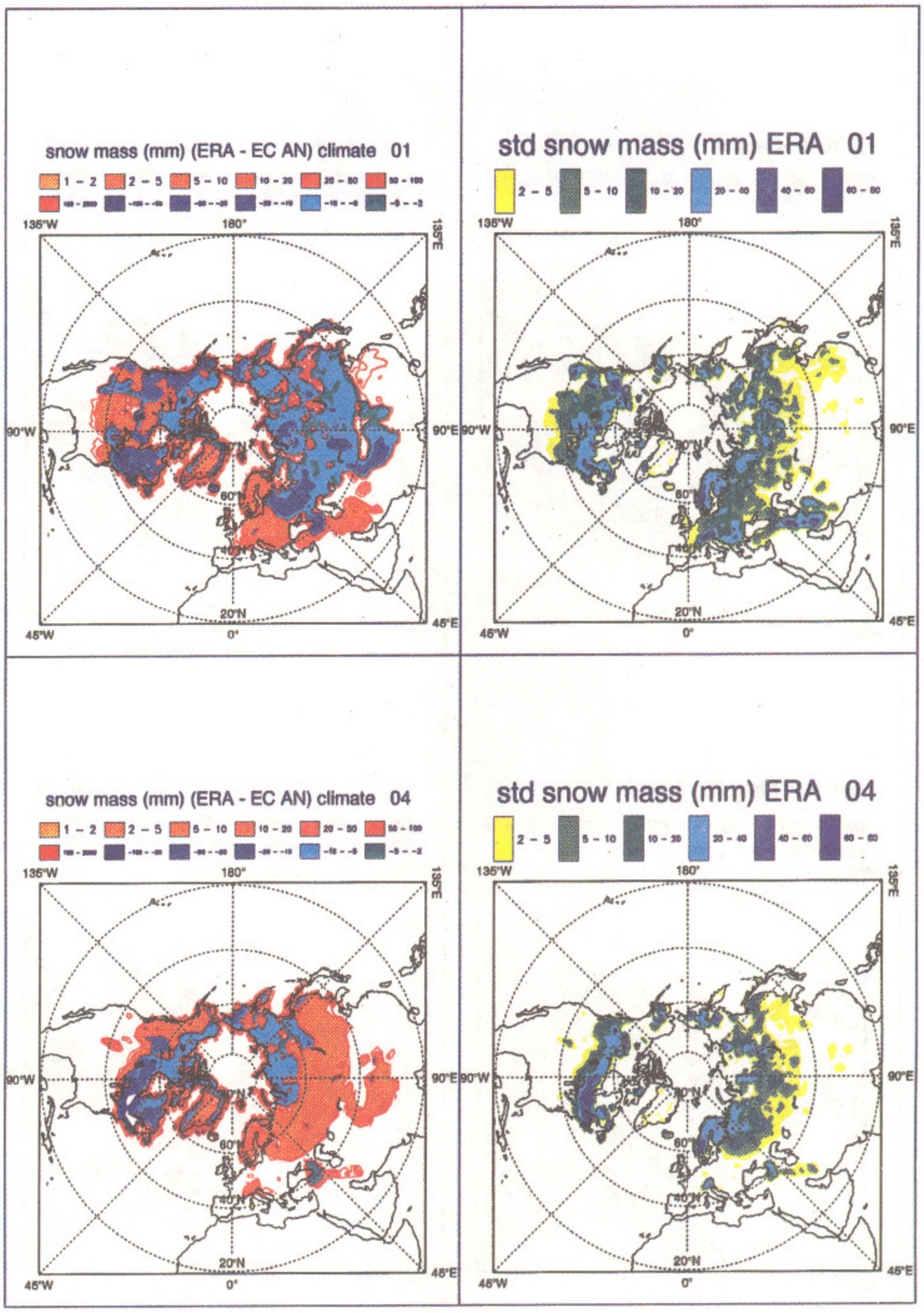


Figure 10: Snow mass (mm) difference between the reanalysis mean monthly values and the analysis climatology (left), and standard deviation of the monthly mean reanalysis values. Top row, January; Bottom row, April.

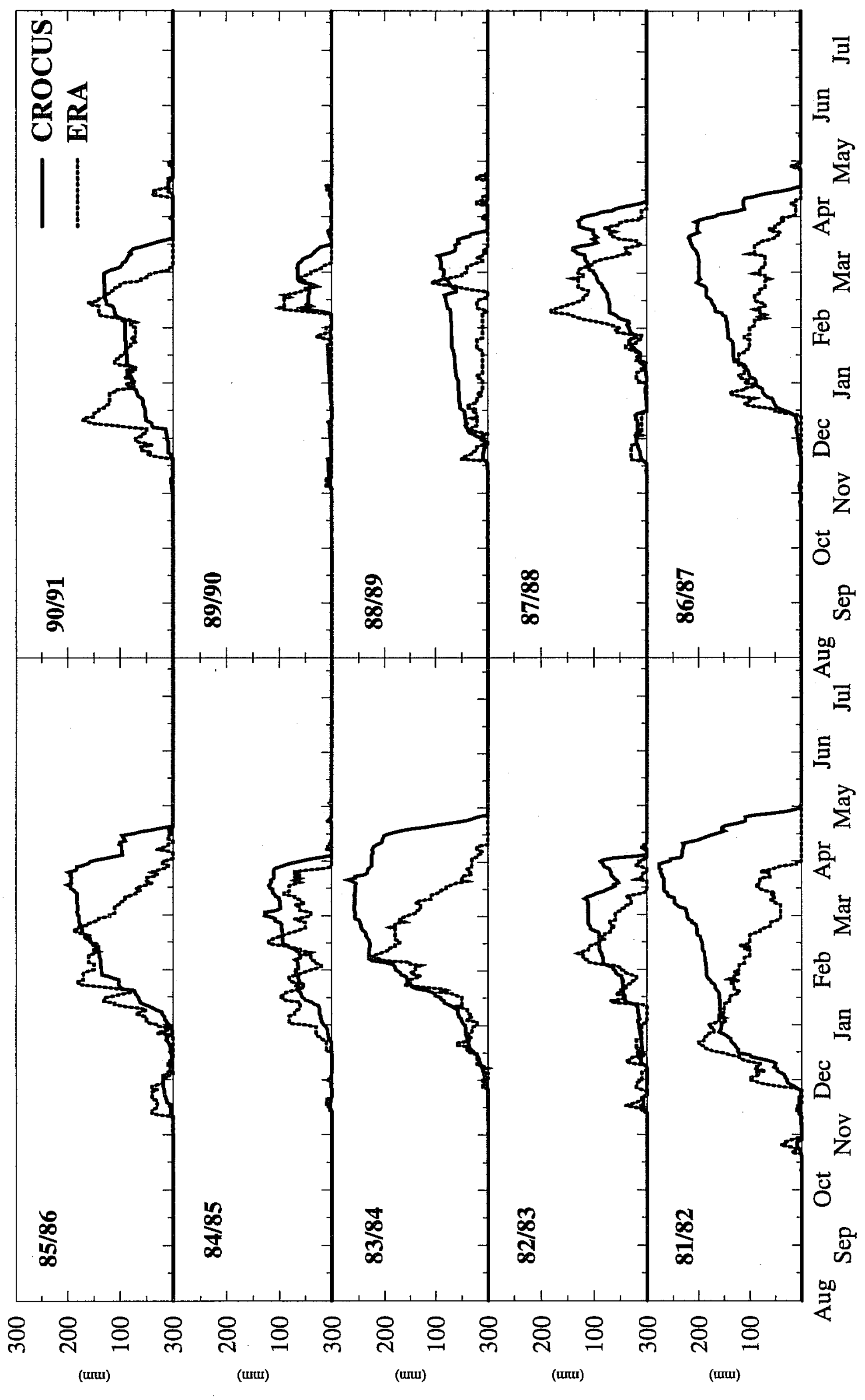


Figure 11: Daily snow mass (mm) values from 810801 to 910731 for a point over the French Alps (47 N, 6 E, altitude 1100 m). The solid line represent a proxy for the truth, estimated with Martin (1996) model (see text for more details), the dashed line shows reanalysis values.

The picture shows daily values, from 810801 to 910731, for a point in the French Alps (47 N 6 E), where the model elevation is similar to the station height (1100 m). The reanalysis snow mass values capture well the interannual variability, with maximum values for the years 81/82 and 83/84, and minima for 82/83, 88/89 and 89/90. However, the reanalysis values are systematically too high for the accumulation period, with ERA overshooting CROCUS values at times. The melting period comes too early, although the reanalysis melting rates are sometimes similar to values from CROCUS. The snow analysis (step 3 above) requires the specification of a snow density to convert the observed depth of snow in equivalent water depths (mass values) which are the quantities managed by the land surface scheme. A fixed value of 250 kgm^{-3} is assumed which appears to be too high for fresh snow, explaining the overestimation during the accumulation period. In the reanalysis values, the relaxation coefficient towards the BvM85 climatology is $\lambda = 0.02$ which corresponds to a time scale of $\tau = 12.5$ days. Poor spatial resolution over the Alps might result in lack of data and a relaxation to the underestimated climatological values (see bottom right panel of Fig 8 over the Alps).

Possible improvements of this technique could be to use an updated snow mass climatology based on direct observations and available at a resolution on 1 degree compatible with the current ECMWF model resolution (Sellers et al. 1996). The land surface scheme could be improved to provide a more reliable first-guess. With the introduction of the snow density as a prognostic variable (Douville et al. 1995) it should be possible to perform an analysis in terms of snow depths, the observed ground-based variable, instead of snow water equivalent (since snowfall can easily be converted knowing density of fresh snow). Remotely sensed information should be used, since weekly, and more recently daily, snow cover charts are prepared by NOAA/NESDIS (Bruce Ramsay, personal communication, see also Sellers et al. 1996) based on a combination of visible, infrared and microwave imagery. Microwave values could be used to obtain snow mass and snow density, using the dependency of the signal on frequency and polarization (see review in Hallikainen 1996a; 1996b); the available algorithms are more accurate for dry snow, and have problems for wet snow or when there are large variations of the roughness in the field of view. The values of ECMWF analysis of snow mass should be routinely compared with the US Air Force daily analysis of snow depth, based on ground observations and satellite imagery.

7.2 Deep soil temperatures

Since deep soil temperatures evolve over time scales much longer than short and medium range forecasts, the lack of initialisation for these variables can lead to potential drifts as the one observed for soil moisture in the ECMWF model. Experience at ECMWF during the winter 95/96 has shown that this problem can occur in winter, when the atmospheric forcing over the surface is weaker, and the thermal influence form the soil deeper layers is more important. The combination of a misrepresentation of some physical processes in the land surface scheme (soil water freezing), excessive radiative cooling, and insufficient downwards heat transfer in very

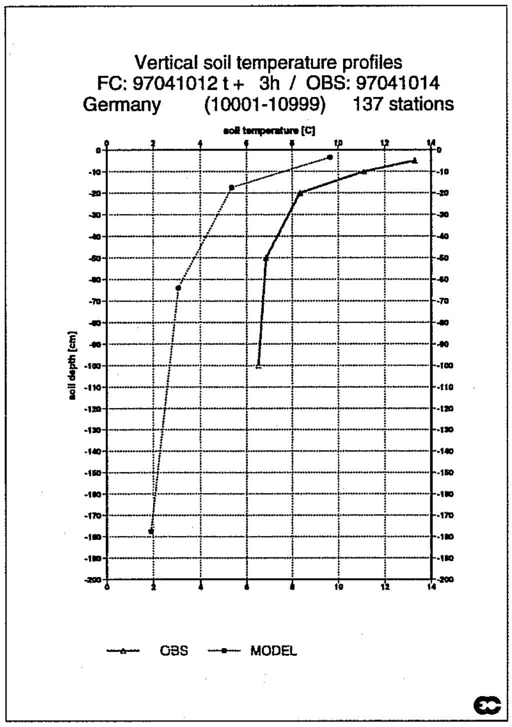


Figure 12: Soil temperature profiles averaged for a number of stations over Northern Germany, for 970410. The solid line represents the mean observed profile at 14 UTC, the dashed line represents the interpolated short term forecast values verifying at 15 UTC.

stable boundary layers led to excessive cooling of the soil, and large negative biases in screen level temperature. Nevertheless, the problem is less critical than the summer soil moisture drift since in winter the stable structure of the boundary layer decouples the atmosphere from the surface below and prevents surface errors from propagating into the mid-troposphere.

Unlike soil moisture, routine measurements of profiles of temperature in the soil are performed by most meteorological offices. Unfortunately, only very few of these measurements are transmitted in the GTS, and therefore no global or even continental coverage exists in real time. A handful of european countries sends daily values to ECMWF, and those are used regularly for validation and monitoring the model values. An example in Fig 12, where an average profile of soil temperature for stations in Northern Germany is compared with the corresponding model values, for a recent date. The model deep temperatures show a cold bias, but it is interesting to note that the model gradient is compares well with observations. This might indicate reasonably good soil thermal properties (they determine the vertical gradient), but comparatively poor atmospheric forcing in the previous weeks (determining the rate of cooling of the whole soil slab). The results are consistent with the well known systematic underestimation of longwave downward surface radiation of the ECMWF model and other models (Wild et al. 1995; Garratt and Prata 1996).

The only existing method for initialising soil temperature has been proposed by Coiffier et al. (1987) where analysed increments at 2 metres are reported directly in the soil. This sub-optimal method could be improved by an optimal interpolation following the methodology of Mahfouf (1991).

7.3 Vegetation properties

Xue et al. (1996) have recently shown that the specification of the seasonal variations of vegetation properties can have a significant impact on the simulation of monthly mean temperatures near the surface over the Northern American Continent. The sesonal evolution of the vegetation can be of importance over areas with agricultural practices (mid-latitude continents, tropical regions). Vegetation properties are currently either fixed spatially, as in the ECMWF model (Viterbo and Beljaars 1996), or can vary from month to month according to correspondence tables (Mahfouf et al. 1995). In an operational context, the use of satellite data like Global Vegetation Indexes (GVI) (see Gutman 1994) could be a better way to capture seasonallity and inter-annual variability of the vegetation. The major difficulty is to relate satellite reflectances to input parameters of the land surface scheme (leaf area index, albedo, vegetation cover,...). However, variational techniques already used for the retrieval of atmospheric vertical profiles from satellite radiances appear promising (Eyre et al. 1993).

8 Conclusions

During the last five years, the initialisation of prognostic and diagnostic surface variables has been recognised as an important issue for numerical weather prediction. Weaknesses of initialisations based either on first-guess only or climatology have been clearly identified. As a consequence, soil moisture is currently initialised in various operational weather centres using sub-optimal analysis methods and observations from SYNOP reports (ECMWF, UKMO, CMC, Météo-France, HIRLAM). These techniques could be be improved by using analysis methods already tested for atmospheric variables like optimum interpolation in the sequential framework and 4D-Var (which is rather appealing by better accounting for the non-linearities of the problem as well as the temporal distribution of observations).

The other land surface prognostic variables are still crudely initialised. Concerning snow mass analysis at ECMWF, the current scheme could be improved by using a more recent climatology and a more realistic observation operator if snow density can be computed by the land surface parametrization.

Areas not yet explored concern the initialisation of deep soil temperatures for which the time scale of evolution is also much longer than short range forecasts, and the specification of vegetation properties having a seasonal cycle (such as the albedo, the vegetation cover or the leaf area index). Remote sense data that could be useful in that context include quantities such as satellite skin temperatures or the normalized difference vegetation indices (NDVI).

Finally, the examples shown in the paper illustrate the fact that the initialization and parametrization methods have to be developed together. Realistic models are needed to support indirect measurements techniques, e.g., forecast snow density allows a better use of snow depth measurements to initialise snow mass. On the other hand, refinements in the land surface parametrization used by numerical models might be needed in order to extract from new measurement techniques its full information content.

References

Bastianssen, W.G.M. 1995 *Regionalization of surface flux densities and moisture indicators in composite terrain - A remote sensing approach under clear skies in Mediterranean climates.* Phd Thesis, Agricultural University, Wageningen, The Netherlands, 273 pp.

Beljaars, A.C.M., P. Viterbo, M.J. Miller, and A.K. Betts 1996 The anomalous sensitivity over USA during July 1993: sensitivity to land surface parameterization. *Mon. Wea. Rev.*, **124**, 362–383.

Betts, J.R., J.H. Ball, A.C.M. Beljaars, M.J. Miller and P. Viterbo 1996 The land surface-atmosphere interaction: A review based on observational and global modeling perspectives. *J. Geophys. Res.*, **101D**, 7209–7225.

Blondin, C. 1991 Parametrization of land surface processes in numerical weather prediction. *Land surface evaporation: Measurement and parametrization.*, T.J. Schmugge and J.C. André, Eds, Springer, 31–54.

Bougeault, P., B. Bret, P. Lacarrère, and J. Noilhan 1991 An experiment with an advanced surface parametrization in a meso-beta-scale. Part II: The 16 June 1986 simulation. *Mon. Wea. Rev.*, **119**, 2374–2392.

Bouttier, F., J.-F. Mahfouf, and J. Noilhan 1993a Sequential assimilation of soil moisture from atmospheric low-level parameters. Part I: Sensitivity and calibration studies. *J. Appl. Meteorol.*, **32**, 1335–1350.

Bouttier, F., J.-F. Mahfouf, and J. Noilhan 1993b Sequential assimilation of soil moisture from atmospheric low-level parameters. Part II:Implementation in a mesoscale model. *J. Appl. Meteorol.*, **32**, 1351–1364.

Brankovic, C., and J. van Maanen 1985 The ECMWF climate system. *ECMWF Tech. Mem. 109*, ECMWF, Reading, UK, 51 pp. + figs.

Brun, E., P. David, M. Sudul, and G. Brunot 1992 A numerical model to simulate snow -cover stratigraphy for operational avalanche forecasting. *J. Glaciology*, **38**, 13–22.

Brun, E., E. Martin, Y. Simon, C. Gendre, and C. Coleou 1989 An energy and mass model of snow cover suitable for operational avalanche forecast. *J. Glaciology*, **35**, 333–342.

Callies, U., A. Rhodin, and D.P. Eppel 1997 A case study on variational soil humidity analysis from atmospheric observations. *J. Hydrol.*, To appear.

Calvet, J.-C., J. Noilhan, and P. Bessemoulin 1997 Retrieving the root-zone soil moisture from surface soil moisture or temperature estimates: A feasibility study based on field measurements. *J. Appl. Meteorol.*, submitted.

Carlson, T.N. 1991 Recent advances in modeling the infrared temperature of vegetation canopies. *Land surface evaporation: Measurement and parametrization.*, T.J. Schmugge and J.C. André, Eds, Springer, 349–358.

Coiffier, J., Y. Ernie, J.-F. Geleyn, J. Clochard, J. Hoffman, and F. Dupont 1987 The operational hemispheric model at the French meteorological service. *J. Met. Soc. Japan, Special Issue on Short and Medium Range Numerical Weather Prediction,* 337–345.

Cuenca, R.H., and J. Noilhan 1991 Use of soil moisture measurements in hydrological balance studies. *Land surface evaporation: Measurement and parametrization.*, T.J. Schmugge and J.C. André, Eds, Springer, 287–299.

Douville, H., J.-F. Royer, and J.-F. Mahfouf 1995 A new snow parameterization for the Météo-France climate model. Part I: validation in stand-alone experiments. *Climate Dynamics*, **12,** 21–35.

Eyre, J.R., G.A. Kelly, A.P. McNally, E. Anderson, and A. Persson 1993 Assimilation of TOVS radiance information through one-dimensional variational analysis. *Q. J. R. Meteorol. Soc.*, **119,** 1427–1463.

Foster, D.J., and R.D. Davy 1988 Global snow depth climatology. USAFETAC/TN-88/006, Scott Air Force Base, Illinois, 48 pp.

Garratt, J.R., and A.J. Prata 1996 Downwelling longwave fluxes at continental surfaces- A comparison of observations with GCM simulations and implications for the global land-surface radiation budget. *J. Climate*, **9,** 646–655.

Georgakakos, K.P., and O.W. Baumer 1996 Measurement and utilization of on-site moisture data. *J. Hydrol.*, **184,** 131–152.

Giard, D., E. Bazile, J. Noilhan, and H. Douville 1996 Assimilation of soil water content and temperatures in a global NWP model. 2nd Int. Sci. Conf. on the Global Energy and Water Cycle, 17-21 June 1996, Washington, DC, USA, pp. 205–206.

Goutorbe, J.-P., J. Noilhan, C. Valancogne, and R.H. Cuenca 1989 Soil moisture variations during HAPEX-MOBILHY. *Ann. Geophys.*, **7**, 415–426.

Gutman, G.G. 1994 Global data on land surface parameters from NOAA AVHRR for use in numerical climate models. *J. Climate*, **7**, 669–680.

Hallikainen, M. 1996a Physical basis for microwave remote sensing of sea ice and snow. *Radiation and water in the climate system.*, T.J.E. Raschke, Ed, Springer, 489–525.

Hallikainen, M. 1996b Retrieval of sea ice and snow parameters from microwave radiometer and radar data. *Radiation and water in the climate system.*, T.J.E. Raschke, Ed, Springer, 527–549.

Jacquemin, B., and J. Noilhan 1990 Sensitivity study and validation of a land surface parametrization using the HAPEX-MOBILHY data set. *Bound.-Lay. Meteor.*, **52**, 93–134.

Jones, C.D., and B. Macpherson 1995 A hydrology corrections scheme for the mesoscale model using observed precipitation rates. Forecasting Research Tech. Rep. 151, Meteorological Office, Bracknell, UK.

Lanzinger, A. 1995 The verification of weather parameters. *Proc. Seminar ECMWF, 5-9 September 1994*, ECMWF, Reading, UK, 373–383.

Lorenc, A. C. 1986 Analysis methods for numerical weather prediction. *Q. J. R. Meteorol. Soc.*, **112**, 1177–1194.

Macpherson, B. 1996 Initialisation of soil moisture in the operational mesoscale model. Forecasting Research Tech. Rep. 183, Meteorological Office, Bracknell, UK.

Mahfouf, J.-F. 1990 A numerical simulation of the surface water budget during HAPEX-MOBILHY. *Bound.-Lay. Meteor.*, **53**, 201–222.

Mahfouf, J.-F. 1991 Analysis of soil moisture from near-surface parameters: A feasibility study. *J. Appl. Meteorol.*, **30**, 1534–1547.

Mahfouf, J.-F., A.O. Manzi, J. Noilhan, H. Giordani, and M. Déqué 1995 The land surface scheme ISBA within the Météo-France climate model ARPEGE. Part I: Implementation and preliminary results. *J. Climate*, **8**, 2039–2057.

Mahfouf, J.-F., and J. Noilhan 1991 Comparative study of various formulations of evaporation from bare soil using in-situ data. *J. Appl. Meteorol.*, **30**, 1354–1365.

Mailhot, J., R. Sarrazin, B. Bilodeau, N. Brunet, and G. Pellerin 1996 Development of the 35-km version of the operational regional forecast system. *Atmosphere-Ocean*, submitted.

Manabe, S. 1969 Climate and the ocean circulation. I. The atmospheric circulation and the hydrology of the earth's surface. *Mon. Wea. Rev.*, **97**, 739–774.

Martin , E. 1996 Validation of the ECMWF Re-analyses. Alpine validations with the snow model CROCUS. Météo-France CNRM/CEN Internal Report, 57pp.

McNider, R.T., A.J. Song, D.M. Casey, P.J. Wetzel, W.L. Crosson, and T.N. Carlson 1995 Towards a dynamic-thermodynamic assimilation of satellite surface temperature in numerical atmospheric models. *Mon. Wea. Rev.*, **122**, 2784–2803.

Mintz, Y., and Y.V. Serafini 1992 A global monthly climatology of soil moisture and water balance. *Climate Dyn.*, **8** 13–27.

Mitchell, K.E. 1994 GCIP initiatives in operational mesoscale modeling and data assimilation at NMC. Proceedings of the Fifth Symp. on global change studies, Nashville, Tenn., Amer. Meteor. Soc., 192–198.

Navascues, B. 1997 Analysis of 2 meter temperature and relative humidity. HIRLAM Tech. rep. 28, 26 pp. Norrkoping.

Noilhan, J., and S. Planton 1989 A simple parameterization of land surface processes for meteorological models. *Mon. Wea. Rev.*, **117**, 536–549.

Njoku, E.G., and D. Entekhabi 1996 Passive microwave sensing of soil moisture. *J. Hydrol.*, **184**, 101–129.

Paloscia, S. 1996 Remote sensing of soil moisture. *Radiation and water in the climate sys-*

tem., T.J.E. Raschke, Ed, Springer, 361–400.

Rind, D. 1982 The influence of ground moisture conditions in North America on summer climate as modeled in the GISS GCM. *Mon. Wea. Rev.*, **110,** 1487–1494.

Rowell, D.P., and C. Blondin 1990 The influence of soil wetness distribution on short-range rainfall forecasting in West African Sahel. *Q. J. R. Meteorol. Soc.*, **116,** 1471–1485.

Rowntree, P.R., and J.A. Bolton 1983 Simulation of the atmospheric response to soil moisture anomalies over Europe. *Q. J. R. Meteorol. Soc.*, **109,** 501–526.

Schmugge, T.J., and F. Becker 1991 Remote sensing observations for the monitoring of land-surface fluxes and water budgets. *Land surface evaporation: Measurement and parametrization.*, T.J. Schmugge and J.C. André, Eds, Springer, 337–347.

Schmugge, T., and T.J. Jackson 1994 Mapping surface soil moisture with microwave radiometers. *Meteorol. Atmos. Phys.*, **54,** 213–223.

Schulin, R., H. Fluhler, H.M. Selim, B. Sevruk, and P.J. Wierenga 1992 Soil moisture. *Snow cover measurements and areal assessment of precipitation and soil moisture*, B. Sevruk, Ed., Op. Hydrology Rep. No. 35, WMO No. 749, Part III, 219-283.

Sellers, P.J., B.W. Meeson, J.W. Closs, J. Collatz, F.E. Corprew, D.Dazlich, F.G. Hall, Y. Kerr, R. Koster, S. Los, K. Mitchell, J.M.P. McManus, D.M. Myers, K.-J. Sun, and P. Try 1996 The ISLSCP initiative I-global data sets: Surface boundary conditions and atmopsheric forcings for land-atmosphere models. *Bull. Amer. Meteor. Soc.*, **77,** 1987–2005.

Sellers, P.J., Y. Mintz, Y.C. Sud, and A. Dalcher 1986 A Simple Biosphere (SiB) model for use whin general circulation models. *J. Atmos. Sci.*, **43,** 505–531.

Smith, C.B., M.N. Lakhtakia, W.J. Capehart, and T.N. Carlson 1994 Initialization of soil-water content in regional-scale atmospheric prediction models. *Bull. Amer. Meteor. Soc.*, **75,** 585–593.

Taconet, O., R. Bernard, and D. Vidal-Madjar 1986 Evapotranspiration over an agricultural region using a surface flux/temperature model based on NOAA-AVHRR data. *J. Climate and Applied Meteor.*, **25** 284–307.

van den Hurk, B., W. Bastiaanssen, H. Pelgrum, and E. van Meijgaard 1997 A feasibility study of the use of METEOSAT and NOAA data fro the assimilation of initial soil moisture fields. *J. Appl. Meteor.*, submitted.

Verseghy, D.L. 1991 CLASS-A Canadian land surface scheme for GCMs. I. Soil model. *Int. J.Climatol.*, **11** 111–133.

Viterbo, P., and A.C.M. Beljaars 1995 An improved land surface parametrization scheme in the ECMWF model and its validation. *J. Climate*, **8**, 2716–2748.

Viterbo, P., and P. Courtier 1995 The importance of soil water for medium-range weather forecasting. Implications for data assimilation. *Worshop on Imbalance of Slowly Varying Components of Predictable Atmospheric Motions*, W.M.O., Beijing, China, March 1995.

Wang, J.R., 1992 An overview of measurements of soil moisture and modeling of moisture flux in FIFE. *J. Geophys. Res.*, **97D**, 18955–18959.

Wei, M., Ed. 1984 Soil moisture: Report of a workshop held at Tiburon, California 25-27 January 1994. NASA Conference Publication 3319.

Wetzel, P.J., D. Atlas, and R.H. Woodward 1984 Determining soil moisture from geosynchronous satellite infrared data: A feasibility study. *J. Appl. Meteorol.*, **23**, 375–391.

Wetzel, P.J., and J.T. Chang 1988 Evapotranspiration from nonuniform surfaces: A first approach for short-term numerical weather prediction. *Mon. Wea. Rev.*, **116**, 600–621.

Wild, M., A. Ohmura, H. Gilgen, and E. Roeckner 1995 Validation of general circulation model radiative fluxes using surface observations. *J. Climate*, **8**, 1309–1324.

Xue, Y., M.J. Fennessy, and P.J. Sellers 1996 Impact of vegetation properties on U.S. summer weather prediction. *J. Geophys. Res.*, **101D**, 7419–7430.

Yang, R., M.J. Fennessy, and J. Shukla 1994 The influence of initial soil wetness on medium range surface weather forecasts. *Mon. Wea. Rev.*, **122** 471–485

Yeh, T.C., R.T. Wetherald, and S. Manabe 1984 The effect of initial soil wetness on the short-term climate and hydrology change-A numerical experiment. *Mon. Wea. Rev.*, **112** 474–490.