A new land surface assimilation scheme for AAA Part 1: scientific justifications

Jean-François MAHFOUF

Météo-France/CNRM/GMME
Toulouse (France)

November 2007

Questions

- Why should we develop a new land data assimilation system for AAA ? - What are current important weaknesses that hamper future NWP applications ?
- What has been done in terms of land data assimilation methods since the OI scheme of Mahfouf (1991) ?
- What are (should be) the main ingredients of such new land data assimilation system ?

The ISBA land surface scheme (Noilhan and Mahfouf, 1996)

The ISBA-2L scheme (used in NWP models) evolves four prognostic variables (derived from the *force-restore* method of Deardorff (1977, 1978)):

$$
\begin{aligned}
\frac{\partial T_s}{\partial t} &= C_T(R_n - H - LE) - \frac{2\pi}{\tau}(T_s - T_2) \\
\frac{\partial T_2}{\partial t} &= \frac{1}{\tau}(T_s - T_2) \\
\frac{\partial w_g}{\partial t} &= \frac{C_1}{\rho_w d_1}(P_g - E_g) - \frac{C_2}{\tau}(w_g - w_{geq}) \\
\frac{\partial w_2}{\partial t} &= \frac{1}{\rho_w d_2}(P_g - E_g - E_{tr}) - \frac{C_3}{\tau} \max\left[0., (w_2 - w_{fc})\right]
\end{aligned}
$$

τ=1 day, d_1=1 cm, d_2 between 1 and 2 m

C_T, C_1, C_2, C_3 and w_{geq} depend upon soil moisture and soil texture

C_1 and C_2 coefficients

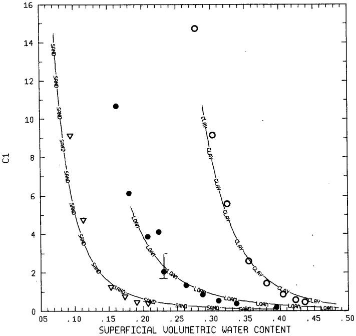


FIG. 4. As in Fig. 3 but for C_1 versus w_g given by Eq. (19).

(Noilhan and Planton, 1989)

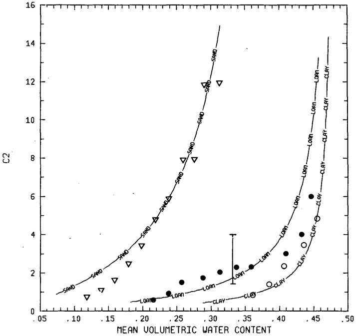


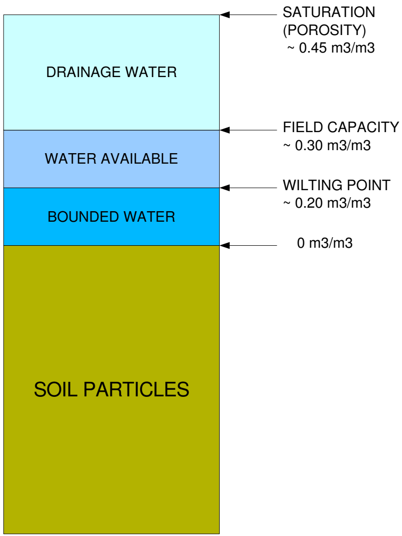
FIG. 3. Variations of the dimensionless coefficient C_2 versus w_2 given by Eq. (18), for the three main textures; the dots correspond to results given by the Reference Model (RM), in the case of sand (▽), silt loam (●) and clay (○); the error bar corresponds to different initializations of RM and is only indicative.

Soil moisture contents (1)

- volumetric water content (m3 of water /m3 soil) : w_2
- saturation water content or porosity (maximum amount of water that a given soil can hold) : w_{sat}
- water content at field capacity (value above which evaporation takes place at potentiel rate - when water excess has drained away) : w_{fc}
- water content at wilting point (value below which plants cannot extract soil water from their root system) : w_{wilt}
- SOIL WETNESS INDEX : normalized soil moisture content :

$$SWI = \frac{(w_2 - w_{wilt})}{(w_{fc} - w_{wilt})}$$

Soil moisture contents (2)



Some rough numbers for a 1 m soil depth :

- Saturation : 450 mm
- Field capacity : 300 mm
- Wilting point : 200 mm
- Water available for evapotranspiration : 100 mm

The surface energy balance

- Net radiation at the surface :

$$R_n = R_G(1-\alpha_t) + \epsilon_t(R_A - \sigma T_s^4) = H + LE + G$$

- Turbulent sensible heat flux :

$$H = \rho_a C_p \frac{(T_s - T_a - gz_a/C_p)}{R_a}$$

- Turbulent latent heat flux (bare soil evaporation + vegetation evapotranspiration) :

$$LE = LE_g + LE_v$$

$$E_g = (1-veg)\rho_a \frac{q_{sat}(T_s) - q_a}{R_{soil} + R_a} \qquad E_{tr} = veg\,\rho_a \frac{q_{sat}(T_s) - q_a}{R_s + R_a}$$

Link between soil variables and the surface boundary layer

Soil moisture and surface evapotranspiration

- For $w_2 > w_{fc}$: LE = potential evaporation
- For $w_{wilt} < w_2 < w_{fc}$: $LE = LE(w_2)$
- For $w_2 < w_{wilt}$: LE is almost negligible

Soil moisture and parameters at 2 meters

- Too low soil moisture amounts $\Rightarrow$ surface boundary layer too dry and too warm
- Too low soil moisture amounts $\Rightarrow$ surface boundary layer too moist and too cold

Optimum interpolation

$$
\begin{aligned}
w_g^a &= w_g^b + \alpha_1(T_{2m}^o - T_{2m}^b) + \alpha_2(HU_{2m}^o - HU_{2m}^b) \\
w_2^a &= w_2^b + \beta_1(T_{2m}^o - T_{2m}^b) + \beta_2(HU_{2m}^o - HU_{2m}^b) \\
T_g^a &= T_g^b + \mu_1(T_{2m}^o - T_{2m}^b) \\
T_2^a &= T_2^b + \mu_2(T_{2m}^o - T_{2m}^b)
\end{aligned}
$$

In practice, the screen-level observations are first interpolated on the model grid (2D CANARI OI) and then analysis increments are used as innovation vectors.

$$(T_{2m}^o - T_{2m}^b) \Rightarrow (T_{2m}^a - T_{2m}^b)$$

$$(HU_{2m}^o - HU_{2m}^b) \Rightarrow (HU_{2m}^a - HU_{2m}^b)$$

The analytical expression of the OI coefficients has been given by Giard and Bazile (2000) for the HAAA soil analysis and by Douville et al.(2000) for the ECMWF soil analysis.

ECMWF OI coefficients (Douville et al. 2000)

Monte-Carlo experiments from a column model to derive statistics of forecast errors for the root-zone (θ_1, θ_2, θ_3) of the ECMWF 4-layer soil scheme. Only two experiments for a clear sky day (low and high vegetation fractions) because of constant soil and vegetation properties but kept with TESSEL and H-TESSEL.

$$\alpha_i = \frac{\sigma^f_{\theta_i}}{\Phi \sigma^f_T}\left\{\left[1 + \left(\frac{\sigma^a_{\mathrm{RH}}}{\sigma^f_{\mathrm{RH}}}\right)^2\right]\rho_{T,\theta_i} - \rho_{T,\mathrm{RH}}\rho_{\mathrm{RH},\theta_i}\right\}F_1 F_2,$$

$$\beta_i = \frac{\sigma^f_{\theta_i}}{\Phi \sigma^f_{\mathrm{RH}}}\left\{\left[1 + \left(\frac{\sigma^a_T}{\sigma^f_T}\right)^2\right]\rho_{\mathrm{RH},\theta_i} - \rho_{T,\mathrm{RH}}\rho_{T,\theta_i}\right\}F_1 F_2,$$

with

$$\Phi = \left[1 + \left(\frac{\sigma^a_T}{\sigma^f_T}\right)^2\right]\left[1 + \left(\frac{\sigma^a_{\mathrm{RH}}}{\sigma^f_{\mathrm{RH}}}\right)^2\right] - \rho^2_{T,\mathrm{RH}},$$

F_1 and F_2 : empirical functions to account for the diurnal and seasonal cycles and for the presence of clouds

TABLE 1. Statistics used in the simulations presented in this paper. Units correspond to the use of m³ 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
$(\sigma_{\mathrm{RH}})_{\min}$	0.095
$(\sigma_{\mathrm{RH}})_{\max}$	0.090
$\rho_{T,\mathrm{RH}}$	−0.99
$(\rho_{\mathrm{T}},\theta_i)_{\min}$, i = 1, 2, 3	(−0.90, −0.91, −0.86)
$(\rho_{\mathrm{T}},\theta_i)_{\max}$, i = 1, 2, 3	(−0.82, −0.92, −0.90)
$(\rho_{\mathrm{RH}},\theta_i)_{\min}$, i = 1, 2, 3	(0.93, 0.90, 0.83)
$(\rho_{\mathrm{RH}},\theta_i)_{\max}$, i = 1, 2, 3	(0.83, 0.93, 0.91)

Weaknesses of the HAAA optimum interpolation (1)

- Variance of background error for w_2 were too large : $0.05 m^3/m^3$ (possible corrections of 200 mm/day for d_2=1 m !). It comes from the initial set-up from the Monte-Carlo experiments designed my Mahfouf (1991) in order to span the whole range of soil moisture states (from w_{wilt} to w_{fc}) (OK to get "averaged" correlations of errors between T2m, RH2m and soil moisture).
- Difficult to correct objectively since in the analytical expressions of α_i and β_i the variances and the correlations are gone ! (MF has reduced β_i by 6)

Weaknesses of the HAAA optimum interpolation (2)

- The dependence with 2m (observation) errors is not straightforward in the coefficients α_i and β_i (additional polynomial expressions from Bouttier et al. (1993)). Important since the CANARI OI can provide such errors on the analysis grid (not a constant value).
- The link between current available observations (T2m, HU2m) and soil variables is complex (non linear relation with surface evaporation fluxes, dependence with the vertical interpolation scheme and with the prognostic equations of the land surface scheme)
- Need to impose arbitrary thresholds to avoid soil analyses in conditions where the 2m errors (low radiative forcing, precipitation, snow, cold temperatures, strong winds). Mostly valid for soil moistures but not necessarily for soil temperatures.

Weaknesses of the HAAA optimum interpolation (3)

It is difficult to consider new variables to analyse :

- The current "OI" coefficients for T_s and T_2 are taken from the previous MF analysis scheme (since Mahfouf (1991) did not perform Monte-Carlo experiments for these variables). Not good : T_s has not memory and T_2 should only be corrected during the night and in winter (stable boundary layer regimes).
- The complexity of the ISBA scheme will increase for future NWP applications. New versions of ISBA (are already available in SURFEX): ISBA-3L (3-layer scheme), ISBA-DF (multi-layer scheme solving diffusion equations), ISBA-Ags (carbon version predicting the vegetation biomass)

Weaknesses of the HAAA optimum interpolation (4)

It is difficult to consider new observations. Some observations (that are more directly informative about soil/vegetation state than screen-level parameters) are already available and other will be available soon :

- Satellite microwave radiances : AMSR-E (C-band), SMOS (L-band)
- Satellite derived soil moisture from C-band scatterometers : ERS, ASCAT on MetOp
- Satellite derived Leaf Area Index (MODIS, SPOT-VEGETATION)
- Precipitation analyses (national products from raingauges and/or radars)
- Downward radiation fluxes at the surface (LandSAF products derived from MSG)

Moving away from the OI

- Offline systems : Météo-France - SIM, NCEP - NLDAS
- 1D - coupled variational assimilations : Mahfouf (1991) (2m), Bouyssel et al. (1999) (2m), Rhodin et al. (1999) (2m)
- 3D - coupled simplified EKF : Hess (2001) (2m)
- 1D - coupled simplified EKF : Seuffert et al. (2004) (2m, Tb)
- 3D - coupled simplified 2D-Var : Balsamo et al. (2004) (2m)
- Offline simplified 2D-Var : Balsamo et al. (2006) (Tb), Balsamo et al. (2007) (2m, Tb, Ts), Munoz-Sabater et al. (2007) (wg, LAI)
- Offline EnKF : Crow et al. (2001) (Tb), Reichle et al. (2002) (Tb)

Significant contribution of Météo-France and ALADIN

The Extended Kalman Filter (1)

We consider a control vector $\mathbf{x}$ (dimension N_x) that represents the prognostic equations of the land surface scheme ISBA $\mathcal{M}$ that evolves with time as:

$$\mathbf{x}^t = \mathcal{M}(\mathbf{x}^0)$$

Therefore $N_x = 4$ and $\mathbf{x} = (w_g, w_2, T_s, T_2)$
At a given time t a vector of observation is available $\mathbf{y}_o$ (with a dimension N_y) characterized by an error covariance matrix $\mathbf{R}$.
An observation operator $\mathcal{H}$ allows to get the model counterpart of the observations :

$$\mathbf{y}^t = \mathcal{H}(\mathbf{x}^t)$$

For example, $\mathcal{H}$ can be a vertical interpolation scheme for T_{2m} and HU_{2m} or a microwave radiative transfer model for brightness temperatures (2 polarizations) T_{bV} and T_{bH}.
The forecast $\mathbf{x}$ at time t (written $\mathbf{x_f}^t$) is characterized by a background error covariance matrix $\mathbf{B}$.

The Extended Kalman Filter (2)

A new value of $\mathbf{x}$ written ${\mathbf{x_a}}^t$ (the analysis), obtained by an optimal combination the observations and the background (short-range forecast), is given by (minimum variance estimate) :

$${\mathbf{x_a}}^t = {\mathbf{x_f}}^t + \mathbf{K}(\mathbf{y}_o^t - \mathcal{H}({\mathbf{x_f}}^t))$$

where $\mathbf{K}$ is the gain matrix defined by:

$$\mathbf{K} = \mathbf{B}\mathbf{H}^T(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1}$$

The operator $\mathbf{H}$ (together with its transpose $\mathbf{H}^T$) is Jacobian matrix of $\mathcal{H}$ defined as (N_y raws and N_x columns) :

$$\mathbf{H}_{ij} = \frac{\partial \mathbf{y}_i}{\partial \mathbf{x}_j} \simeq \frac{\mathbf{y}_i(\mathbf{x} + \delta x_j) - \mathbf{y}_i(\mathbf{x})}{\delta x_j}$$

In a finite difference approach, the input vector $\mathbf{x}$ is perturbed N_x times to get for each integration a column of the matrix $\mathbf{H}$, where δx_j is a small increment value added to the j-th component of the $\mathbf{x}$ vector

The Extended Kalman Filter (3)

The analysis state in characterized by an analysis error covariance matrix:

$$\mathbf{A} = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{B} = (\mathbf{B}^{-1} + \mathbf{H}^T\mathbf{R}^{-1}\mathbf{H})^{-1}$$

The analysis is cycled by propagating in time the two quantities $\mathbf{x_a}$ et $\mathbf{A}$ up to next time where observations are available :

$$\mathbf{x_f}^{t+1} = \mathcal{M}(\mathbf{x_a}^t)$$

$$\mathbf{B}^{t+1} = \mathbf{M}\mathbf{A}^t\mathbf{M}^T + \mathbf{Q}$$

This equation requires the Jacobian matrix $\mathbf{M}$ of the model $\mathcal{M}$, that is defined as (between time t and time t_0):

$$\mathbf{M}_{ij} = \frac{\partial x_i^{t+1}}{\partial x_j^t}$$

A new matrix $\mathbf{Q}$ representing the model error covariance matrix needs to be defined.

Variational assimilation

In the variational approach, a state $\mathbf{x}$ minimizes a cost-function measuring the departure between a background information (short-range forecast) $\mathbf{x_b}$ and available observations $\mathbf{y}_o$:

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x} - \mathbf{x_b})^T\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x_b}) + \frac{1}{2}(\mathbf{y}_o - \mathcal{H}(\mathbf{x}))^T\mathbf{R}^{-1}(\mathbf{y}_o - \mathcal{H}(\mathbf{x}))$$

The minimum of J is found by computing its gradient that is given to a descent algorithm :

$$\nabla J(\mathbf{x}) = \mathbf{B}^{-1}(\mathbf{x} - \mathbf{x_b}) + \mathbf{H}^T\mathbf{R}^{-1}(\mathbf{y}_o - \mathcal{H}(\mathbf{x}))$$

where appears the transpose (adjoint) of the observator operator $\mathbf{H}^T$

3D-Var and 4D-Var

The cost function can be applied at a given time (3D-Var), but also over a temporal interval (4D-Var) : a state $\mathbf{x}^0$ at the beginning of the assimilation window is searched so that it leads to a model state $\mathbf{x}^t$ fitting all the available observations at several times over the period. Thus, the observation operator is the combination of a first operator (forecast model) evolving the initial state $\mathbf{x}^0$ up to a time t where a vector of observations is available $\mathbf{y}_o^t$:

$$\mathbf{x}^t = \mathcal{M}(\mathbf{x}^0)$$

and a "true" observation operator (as defined in the EKF) that gives the model equivalent of the observation at the same time :

$$\mathbf{y}^t = \mathcal{H}(\mathbf{x}^t)$$

Finally, the relation between the variable to be analyzed and the available observation is :

$$\mathbf{y}^t = \mathcal{H}_1(\mathbf{x}^0) \qquad \text{with} \qquad \mathcal{H}_1 = \mathcal{H}\mathcal{M}$$

Evolved **B** matrix

This approach allows modifications of the **B** matrix over the assimilation window by the linearized versions of the forecast model: at a given time t, the effective **B** matrix is $\mathbf{MBM}^T$ (which is similar to the propagation of the **A** matrix in the Kalman filter without the error model term and without explicit matrix evolution).
The variational method is rather expensive since the linearized operator $\mathbf{H}_1$ is needed at each iteration of a minimization algorithm.

Simplified 2D-Var assimilation

The cost of the variational assimilation can be significantly reduced (i.e. no minimization), if the observation operator can be linearized as:

$$\mathcal{H}_1(\mathbf{x}^t) = \mathcal{H}\left[\mathcal{M}(\mathbf{x_f}^0)\right] + \mathbf{HM}(\mathbf{x}^0 - \mathbf{x_f}^0)$$

The analysis state at the beginning of the assimilation window can be written as:

$$\mathbf{x_a}^0 = \mathbf{x_f}^0 + \mathbf{BM}^T\mathbf{H}^T(\mathbf{HMBM}^T\mathbf{H}^T + \mathbf{R})^{-1}(\mathbf{y}_o^t - \mathcal{H}\left[\mathcal{M}(\mathbf{x_f}^0)\right])$$

This state in then propagated by the model $\mathcal{M}$ to define the initial state of the next cycle. This equation is (almost) equivalent to an EKF where the model error term $\mathbf{Q}$ is set to zero.
This approach is cheaper than a real variational assimilation and takes into account simultaneous observations at various times (implicit evolution of the $\mathbf{B}$ matrix over the assimilation window). The length of the window depends upon the linearity of the combined operator : $\mathcal{HM}$.

The Ensemble Kalman filter

The same equation as for the EKF is solved, but the matrices $\mathbf{BH}^T$ and $\mathbf{HBH}^T$ are obtained from an ensemble of predictions $(\mathbf{x_f})_i$ with i varying between 1 et N. One writes :

$$\mathbf{BH}^T \approx \overline{(\mathbf{x_f} - \overline{\mathbf{x_f}})(\mathcal{H}(\mathbf{x_f}) - \overline{\mathcal{H}(\mathbf{x_f})})^T}$$

$$\mathbf{HBH}^T \approx \overline{(\mathcal{H}(\mathbf{x_f}) - \overline{\mathcal{H}(\mathbf{x_f})})(\mathcal{H}(\mathbf{x_f}) - \overline{\mathcal{H}(\mathbf{x_f})})^T}$$

with the average operators :

$$\overline{\mathbf{x}} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{x}_i \qquad \overline{\mathbf{x}\mathbf{y}^T} = \frac{1}{N-1}\sum_{i=1}^{N}\mathbf{x}_i\mathbf{y}_i^T$$

An advantage of this approach is that there is no need to get explicitely the various matrices entering in the computation of the Kalman gain **K**.

Ensemble spread

- Each analysis $\mathbf{x}_a^i$ is given by the filter from the following equation:

$$\mathbf{x}_a^i = \mathbf{x}_f^i + \mathbf{K}[\mathbf{y}_0 - \mathcal{H}(\mathbf{x}_f^i) + \varepsilon_i]$$

  where ε_i is a random noise with gaussian distribution having a zero mean and a variance given by $\mathbf{R}$.

- The prognostic variables x can been modified to add a model error term φ defined by :

$$\varphi^{t+1} = \nu\varphi^t + \varepsilon_w\sqrt{1-\nu^2}$$

$$x^{t+1} = \mathcal{F}(x^t) + \varphi^{t+1}\Delta t$$

  with $\nu = 1/(1 + \Delta t/\tau)$.

- To avoid an underestimation of the analysis error covariance matrix $\mathbf{A}$, after each analysis cycle an inflation factor α leads to a redefinition of the various analysed members as:

$$\mathbf{x}_a = \overline{\mathbf{x}_a} + \alpha(\mathbf{x}_a - \overline{\mathbf{x}_a})$$

Microwave radiation components

Interest of the microwave part of the electromagnetic spectrum (0.3 to 300 Ghz) : sensitive to water (soil, vegetation, water vapour, clouds and precipitation)

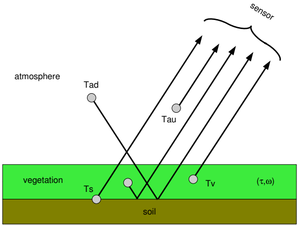
Black body emission for microwaves (Rayleigh-Jeans approximation of the Plank's law):

$$B_\lambda(T) = \frac{2kT}{\lambda^2} \Rightarrow T_B = \frac{\lambda^2}{2k} B_\lambda(T)$$

Surface emissivity :

$$\epsilon = \frac{T_B}{T}$$

Schematic description of soil/vegetation/atmosphere microwave emission



Brightness temperature for a bare soil :

$$T_{Bs} = T_{au} + e^{-\tau_{at}} T_{ad}(1-\epsilon) + e^{-\tau_{at}} \epsilon T_s$$

Brightness temperature for a vegetated surface :

$$\begin{aligned} T_{Bv} = \quad & T_{au} + e^{-\tau_{at}} T_{ad}(1-\epsilon)e^{-2\tau^*} + e^{-\tau_{at}} \epsilon T_s e^{-\tau^*} \\ + \quad & e^{-\tau_{at}} T_v(1-\omega^*)(1-e^{-\tau^*})[1+(1-\epsilon)e^{-\tau^*}] \end{aligned}$$

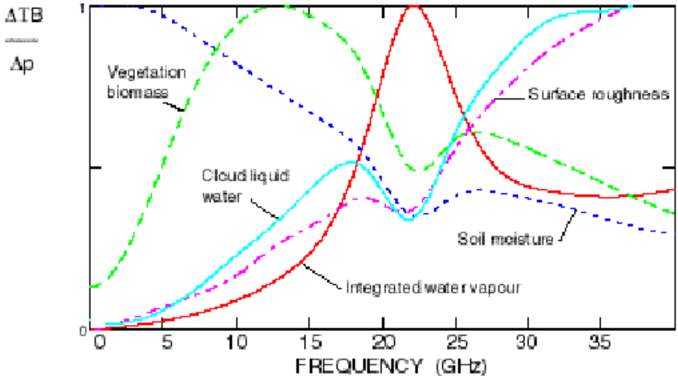
Top of the atmosphere brightness temperature :

$$T_B = (1-veg)T_{Bs} + veg T_{Bv}$$

(Kerr and Njoku,1990)

T_B sensitivity to surface and atmosphere

Interest of L-band (1.4 GHz) for soil moisture retrieval : largest sensitivity



Penetration depth vs. frequency

Interest of L-band (1.4 GHz) for soil moisture retrieval : large contribution of deeper layers

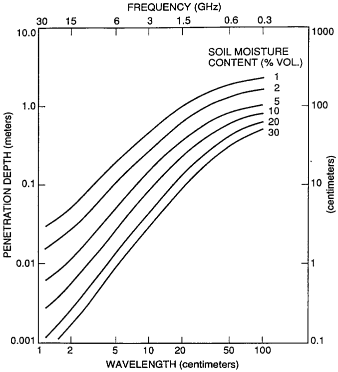


Fig. 4. Microwave soil penetration depth as a function of frequency and moisture content.

Parameters to be specified

- Surface emissivity [ϵ] = 1 - surface reflectivity [r]
- Surface reflectivity r (for a smooth surface) depends upon soil dielectric properties
- Soil dielectric constant [ε_b] is a function of soil moisture, soil texture, soil density and water salinity
- Surface reflectivity has to be corrected for surface roughness effects
- Atmospheric absorption [τ_{at}] accounts for oxygen and water vapour (at least)
- Vegetation absorption (optical depth τ^*, single scattering albedo ω^*)

Surface reflectivity

Fresnel reflection coefficients (for a smooth surface):

$$r_{sH} = \left| \frac{\cos\theta - \sqrt{\varepsilon_b - \sin^2\theta}}{\cos\theta + \sqrt{\varepsilon_b - \sin^2\theta}} \right|^2 \qquad r_{sV} = \left| \frac{\varepsilon_b \cos\theta - \sqrt{\varepsilon_b - \sin^2\theta}}{\varepsilon_b \cos\theta + \sqrt{\varepsilon_b - \sin^2\theta}} \right|^2$$

Reflection coefficients for a rough surface :

$$r_{rH} = [(1-Q)r_{sH} + Q r_{sV}]\exp(-h)$$

$$r_{rV} = [(1-Q)r_{sV} + Q r_{sH}]\exp(-h)$$

The parameters Q (for scattered part) and h (for coherent part) are related to the standard deviation of the surface height ($\simeq$ roughness length).
Remark: the polarization coupling factor can be neglected for L-band frequency.

Dielectric constants

Definition :

$$\varepsilon_b = \varepsilon' - j\varepsilon''$$

where ε' is the permittivity of the material and ε'' is the dielectric loss factor

Wet soil

$$\varepsilon_{soil}^{\alpha} = (1 - w_{sat})\varepsilon_{ss}^{\alpha} + w_{sat} - w_g + w_g^{\beta}\varepsilon_{fw}^{\alpha}$$

with:

- $\alpha = 0.65$: constant value (optimum for all soil types)
- ε_{ss} : dielectric constant of solid soil (4.7 for all soil types)
- ε_{fw} : dielectric constant of free water
- w_g : soil volumetric water content
- w_{sat} : soil porosity (water content at saturation)
- β : empirical factor function of *CLAY* and *SAND* fractions (to account for bounded water in the soil)

Bare soil dielectric constant

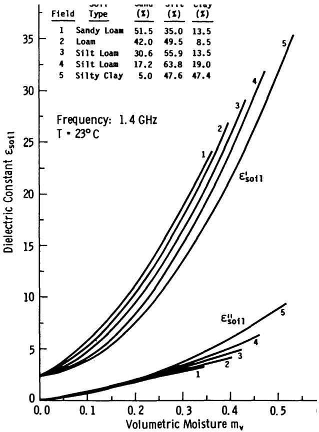
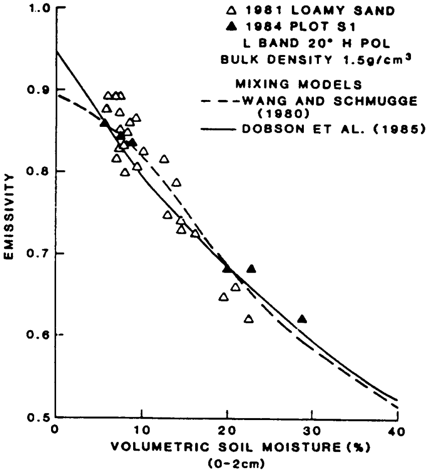


Fig. 2. Dielectric constant as a function of volumetric soil moisture for five soils at 1.4 GHz. Smooth
drawn through measured data points. (From Ulaby et al. (1986). Reproduced with permission, *Microw
Sensing: Active and Passive, Vol. III: From Theory to Applications*, by Fawwaz T. Ulaby, Richard
Adrian K. Fung. © 1986, Artech House, Inc., Norwood, MA.)

Microwave surface emissivity (H polarization)



Vegetation attenuation

$$\tau^* = \frac{b \times VWC}{\cos\theta}$$

The values b, VWC (vegetation water content) and ω^* are tabulated according to vegetation types and microwave frequency

TABLE 2. Microwave radiative transfer parameters for five vegetation-cover types: single-scattering albedo (ω_*), vegetation water content (VWC), and structure coefficient (b) for L band.

Class	ω_* (−)	VWC (kg m^{-2})	b(L − band) (m^2 kg^{-1})
Grassland	0.04	0.5LAI	0.1
Crops	0.10	0.5LAI	0.2
Coniferous	0.10	3	0.1
Broadleaf	0.10	4	0.1
Tropical	0.10	6	0.1

From Balsamo et al. (2006)

Attenuation of soil emission by a vegetation layer

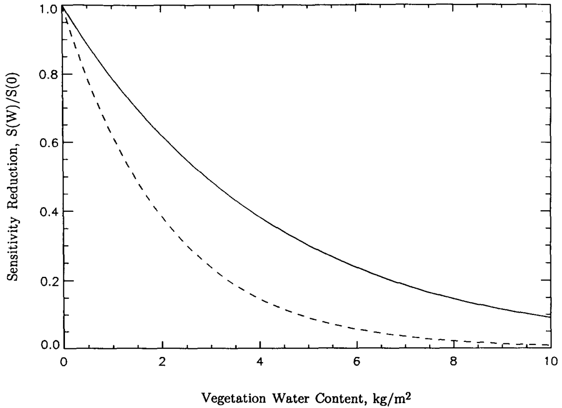


Fig. 9. Modeled reduction in sensitivity of brightness temperature to soil moisture as a function of vegetation water content, for nadir viewing. Continuous line: 1.4 GHz; dashed line: 5 GHz. (Curves display exponential factor of Eq. (11).)

Some results at local scale

- Local scale evaluations using field campaign data sets
- Availability of data for assimilation : T2m, HU2m, TbH, TbV
- Availability of independent data sets for validation : H, LE, w_g, w_2
- Single column models with imposed surface precipitation and downward fluxes from observations
- First evaluation of OI_MF using HAPEX-MOBILHY 1986 (France crops) [Mahfouf, 1991]
- First evaluation of OI_EC using FIFE 1987 (US prairie) [Douville et al., 2000]
- First comparison of OI_EC with EKF using FIFE 1987 (US prairie) [Seuffert et al., 2004]
- First assimilation of L-band Tbs with T2m/HU2m using SGP 1997(US prairie) [Seuffert et al., 2004]
  - KB = assimilation of L-band Tbs (daily or every 2-days)
  - KTR = assimilation of T2m and HU2m (9h, 12h and 15h local time)
  - KTRB = assimilation of L-band Tbs + T2m and HU2m

ECMWF soil analysis vs. Oklahoma mesonet network

Soil moisture analysis : close to the truth or a tuning quantity to compensate for land surface and forcing deficiencies ?

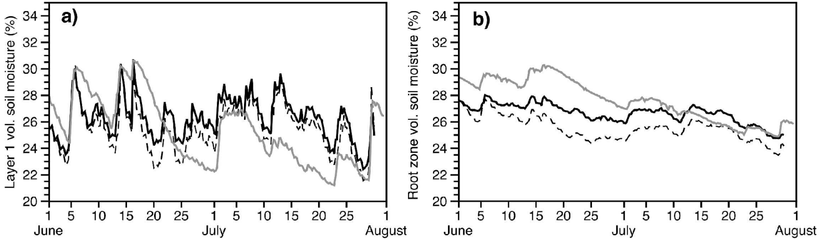
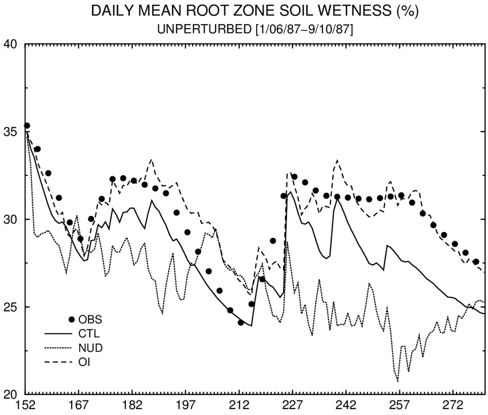


FIG. 8. Analyzed and observed (dash–dotted gray line) soil moisture (a) for the top soil layer and at 5 cm depth, respectively, and (b) for the root zone (1 m depth) for the Oklahoma area. Results from the CTRL OI and OL experiments are shown as solid and dash–dotted lines, respectively, at 6-hourly resolution.

(Drusch and Viterbo, 2007)

Soil moisture analysis over FIFE (Summer 1987)



- CTL = open loop (no assimilation)
- NUD = first ECMWF soil moisture nudging (use of Δq with constant OI coefficient)
- OI = ECMWF optimum interpolation

Comparison of gain matrix **K** between OI_EC and EKF

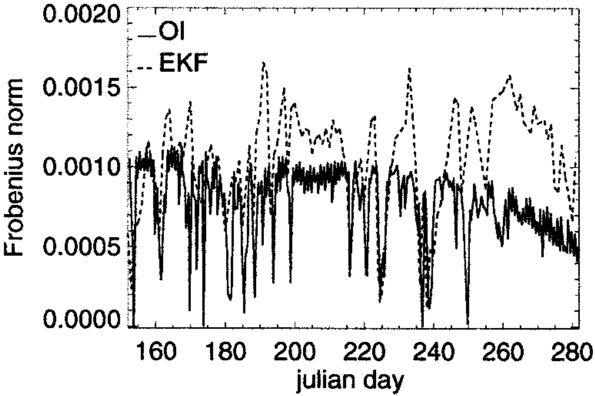


FIG. 1. Evolution of the Froebenius norm of the gain matrix for the OI and EKF analysis system (1 Jun–9 Oct 1987).

Comparison of soil moisture increments between OI_EC and EKF

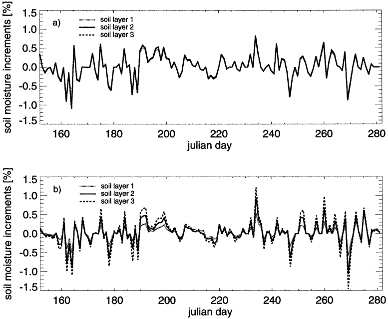


FIG. 2. Evolution of the soil moisture increments given by (a) OI and (b) the EKF analysis system from 1 Jun–9 Oct 1987 for FIFE.

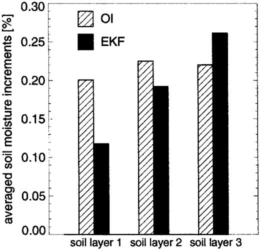


FIG. 3. Comparison of the averaged soil moisture increments over 130 days (FIFE87) for each soil layer derived by OI and EKF analysis system.

T2m and HU2m analyses

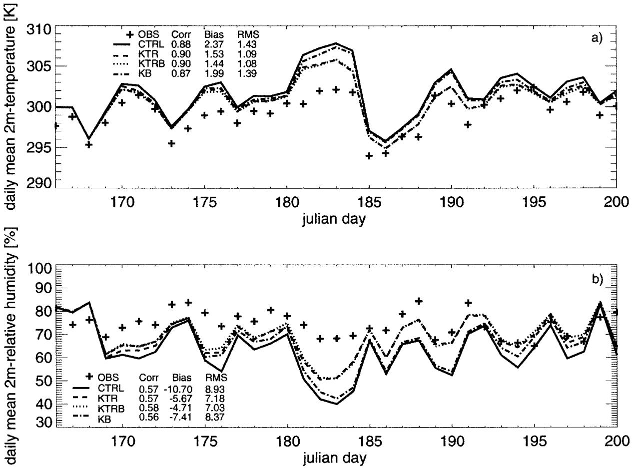


FIG. 5. Temporal evolution for 15 Jun–19 Jul 1997 of (a) 2-m temperature and (b) 2-m relative humidity simulated by the Ctrl-, KTR-, KB-, and KTRB-runs in comparison to observations from SGP97.

Brighness Tbs and surface soil moisture analyses

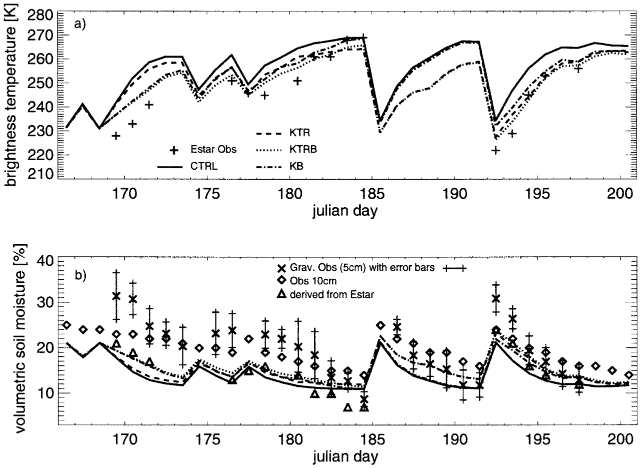


FIG. 6. The same as in Fig. 5 except for (a) 1.4-GHz microwave brightness temperature and (b) surface soil moisture.

Root-zone soil moisture analysis with T2m, HU2m, and/or Tb

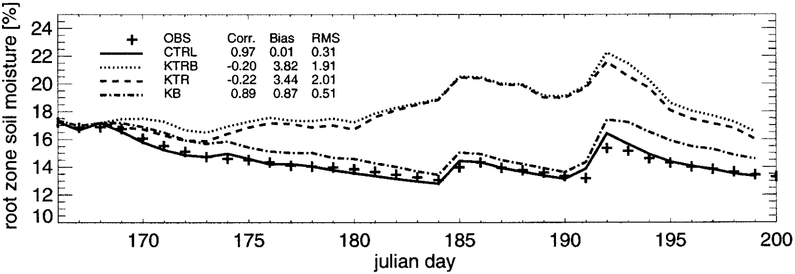


FIG. 7. The same as in Fig. 5 except for root zone soil moisture.

Surface fluxes R_n, H, LE with T2m, HU2m, and/or Tb

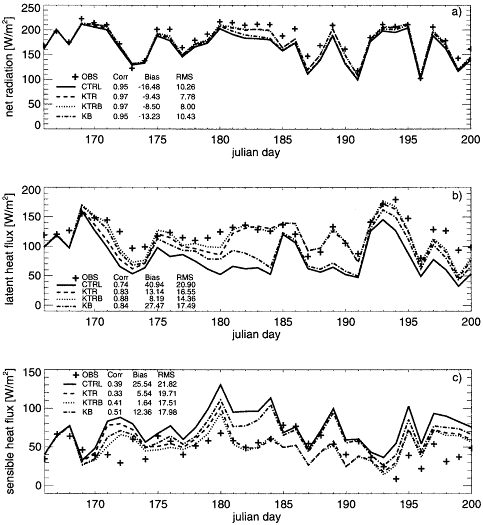
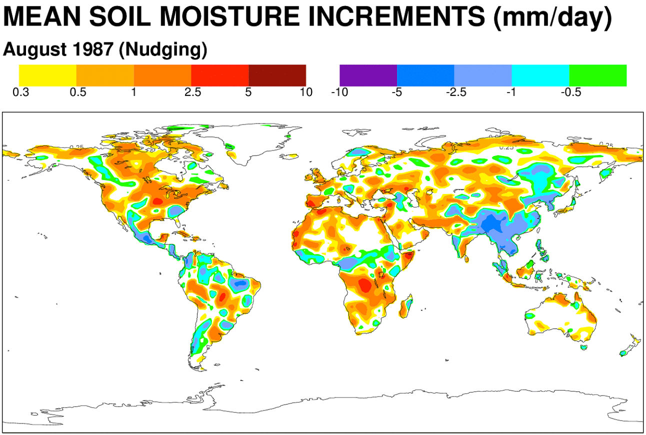
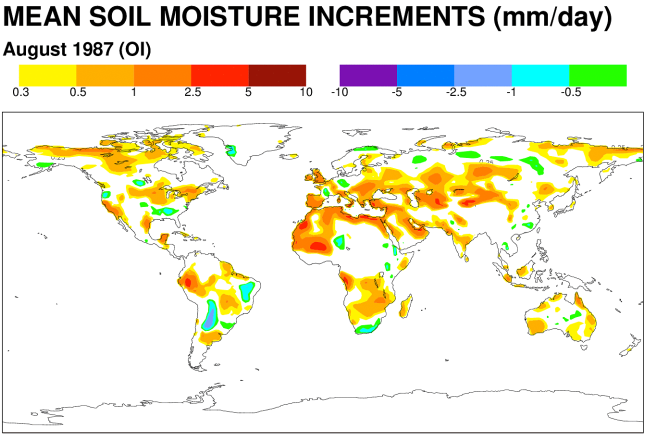


FIG. 9. The same as in Fig. 5 except for (a) net radiation, (b) latent heat flux, and (c) sensible heat flux.

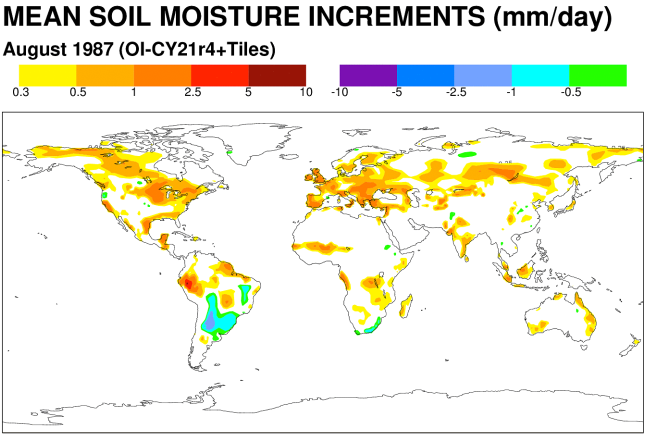
ECMWF nudging scheme



ECMWF OI scheme



ECMWF OI scheme + surface improvements



Conclusions

- Land data assimilation systems should evolve (like atmospheric systems 10 years ago) from OI to more advanced techniques (variational assimilation, Kalman filters) that can handle rather complex non-linear observation operators $\mathcal{H}$ (in particular for satellite data) and allow a more easier specification (or computation) of background $\mathbf{B}$ and observation errors $\mathbf{R}$.
- The observation operators $\mathbf{H}$ and $\mathbf{H}^T$ can be obtained efficiently (few model integrations) in finite differences as long as we treat the soil analysis problem as independent columns
- Feasibility studies have shown the potential of assimilating observations more directly linked to soil variables with advanced techniques
- In most situations the soil moisture analysis still compensate for model deficiencies (e.g. smaller increments when the land surface scheme improves)