Assimilation of superficial soil moisture in the land surface scheme ISBA: comparison of Extended and Ensemble Kalman filters

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Outline

- Motivations
- The land surface scheme ISBA
- Extended and ensemble Kalman Filters
- Experimental set-up
- Results
- Conclusions and perspectives

Motivations

- Soil moisture initialization is important for NWP
- Recent availability of soil moisture satellite missions (SMOS-2009, SMAP-2014)
- Evolution of soil analysis schemes in NWP models from OI to KFs (ECMWF-SEKF and EC-EnKF)
- Few studies have compared EKF and EnKF DA schemes
- Comparative study at local scale with in-situ observations for various climatic regimes and soil properties

The land surface scheme ISBA-Ags

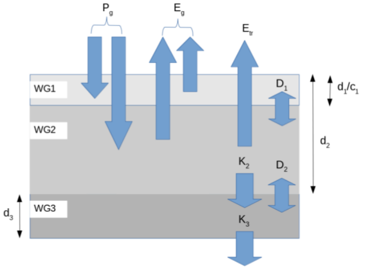

Figure 1. The soil moisture fluxes for the three-layer version of ISBA. The variables P_g, E_g and E_{tr} represent the precipitation, bare soil evaporation and transpiration respectively. The fluxes K and D represent the drainage and diffusion at the bottom of the layer.

Non linearities

- DRY SOILS ($WG < WG_{wilt}$) : no evapotranspiration
- MOIST SOILS ($WG > WG_{fc}$) : potential evapotranspiration - drainage
- OTHER REGIMES : no drainage - evaporation driven by soil moisture

Simplified Extended Kalman Filter

Background ($\mathbf{x}^b(t_i)$) is a nonlinear propagation of previous analysis:

$$\mathbf{x}^b(t_i) = \mathcal{M}(\mathbf{x}^a(t_{i-1}))$$

Observation ($\mathbf{y}^o$) assimilated at time t_i and weighted using Kalman gain ($\mathbf{K}$) :

$$\mathbf{x}^a = \mathbf{x}^b + \mathbf{K}(\mathbf{y}^o - H(\mathbf{x}^b))$$

with :

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

where **B** is a climatological and diagonal background-error covariance. The Jacobian operator **H** is obtained in finite differences by perturbing each component of the state vector **x**.

Ensemble Kalman Filter : EnSRF

Background ensemble calculated from previous analysis ensemble:

$$\mathbf{x}_j^b(t_i) = \mathcal{M}(\mathbf{x}_j^a(t_{i-1})), \qquad \textit{for} \qquad j = 1, .., m.$$

Background perturbation matrix $\mathbf{X}^b$ (of dimension $n \times m$) comes from m columns of perturbed vectors $\delta\mathbf{x}_j^b = \mathbf{x}_j^b - \overline{\mathbf{x}}^b$:

$$\mathbf{X}^b = \frac{1}{\sqrt{m-1}} \left[\delta\mathbf{x}_1^b, ..., \delta\mathbf{x}_m^b \right]$$

Ensemble background-error covariance matrix: $\mathbf{P}^b = \mathbf{X}^b(\mathbf{X}^b)^T$
The EnSRF reduces the Kalman gain in the analysis perturbation update:

$$\delta\mathbf{x}_j^a = \delta\mathbf{x}_j^b - \alpha\mathbf{KH}\delta\mathbf{x}_j^b$$

where $\alpha = 1/(1 + \sqrt{R/(HP^bH^T + R)})$

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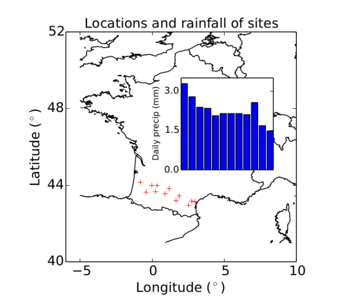
Experimental set-up

SMOSMANIA network



- 12 grass-land sites (2007-2010)
- Daily in-situ observations of WG1 (for assim) and WG2 (for verif)
- ISBA-Ags forced with SAFRAN atmospheric analyses (8x8 km^2)
- 24-h assimilation cycle with synthetic (S) and read (R) observations
- SEKF and EnSRF parameters tuned to produce the largest analysis ACC

DA experiments with S and R

DA component	Synthetic DA experiment	Real DA experiment
Truth	Model run	Unknown
Model	Model run + Eq. (17)	Model run
Assimilated obs.	WG1: model run + obs. error	WG1: 5 cm depth in situ obs. + linear rescaling
EnSRF calibration	Eq. (17)	Eqs. (15) + (17)
SEKF calibration	Eq. (14)	Eq. (14)
Validation data	WG2: truth simulation	WG2: 30 cm depth in situ obs. + linear rescaling

$$\text{Eq (17)}: \quad Pr^* = Pr + \mathcal{N}(0, 50\% Pr)$$

$$\text{Eq (14)}: \quad \sigma_{WG}^b = \lambda^b (WG_{fc} - WG_{wilt})$$

$$\text{Eq (15)}: \quad \varepsilon_{WG} = \lambda^b (WG_{fc} - WG_{wilt})$$

EnSRF additive inflation : first order autoregressive model with $\tau = 1$ day for WG1 and $\tau = 3$ days for WG2

Impact of the ensemble size

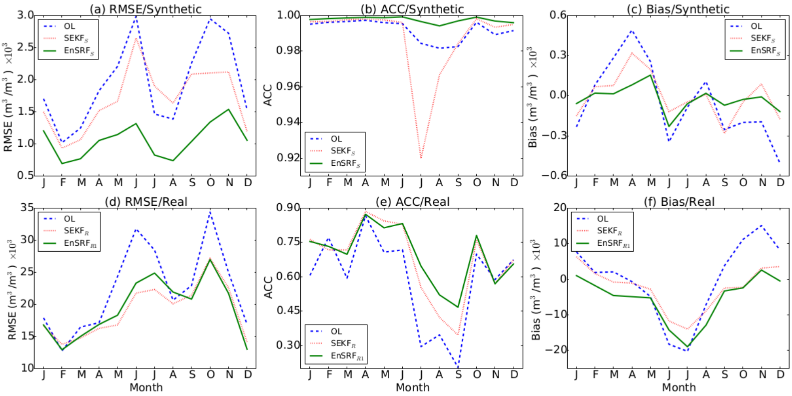
Table 4. Site-averaged and time-averaged WG2 performances for $EnSRF_S$ and $EnSRF_{R1}$ for various ensemble sizes. The calibrated EnSRF is shown in bold font.

Ens. size	$EnSRF_S$ WG2 RMSE $(m^3\,m^{-3}) \times 10^3$	$EnSRF_{R1}$ WG2 RMSE $(m^3\,m^{-3}) \times 10^3$	$EnSRF_S$ WG2 ACC	$EnSRF_{R1}$ WG2 ACC
3	1.6	24.2	1.00	0.647
6	1.4	22.5	1.00	0.687
20	**1.1**	**20.8**	**1.00**	**0.720**
50	1.1	20.9	1.00	0.719
200	1.1	20.9	1.00	0.719

Summary of the results

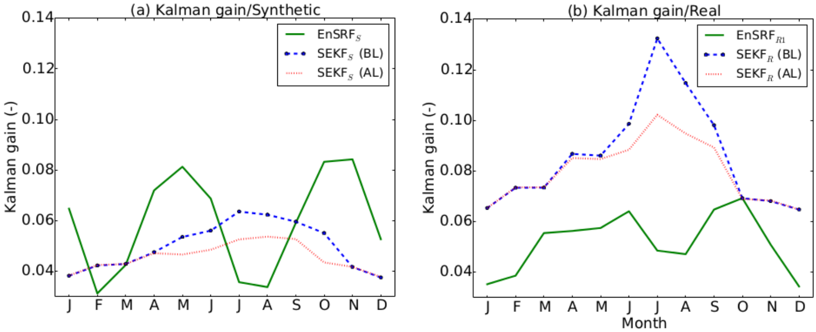
Exp.	Obs. λ^o	Calibration: WG1 λ_1^b	WG2 λ_2^b	Add. criteria	WG2 RMSE $(m^3\,m^{-3}) \times 10^3$	WG2 ACC	WG2 bias $(m^3\,m^{-3}) \times 10^3$
Ens	–	–	0.025	–	9	0.97	−4.9
Ens_{bc}	–	–	0.025	Bias correct	4	0.99	0.6
OL_S	–	–	–	$\epsilon_{Pr} = 50\,\%\,Pr$	2.2	0.995	0.0
$EnSRF_S$	0.05	–	–	$\epsilon_{Pr} = 50\,\%\,Pr$	1.1	0.999	0.02
$SEKF_S$	0.05	0.04	0.02	–	1.8	0.996	0.01
OL_R	–	–	–	–	24.7	0.607	0.03
$EnSRF_{R1}$	0.5	0.2	0.03	–	20.8	0.720	−5.32
$EnSRF_{R2}$	0.5	0.1	0.03	$\epsilon_{Pr} = 50\,\%\,Pr$	21.2	0.722	−5.82
$EnSRF_{R3}$	0.5	0.25	0.035	Bias correct	21.3	0.690	−2.79
$SEKF_R$	0.5	0.25	0.25	–	20.1	0.716	−2.21

Evaluation of deep soil moisture content WG2



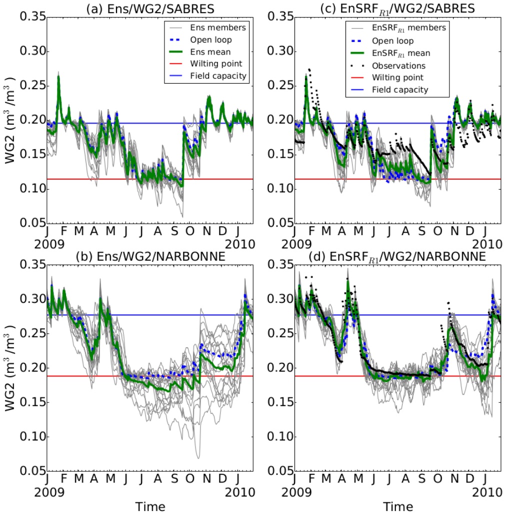
(Open loop) (EnSRF) (SEKF)

Kalman gain



(SEKF - **H not bounded**) (SEKF - **H bounded**) (EnSKF)

Ensemble forecasts + EnSRF over two contrasted sites



Conclusions (1)

- SEKF and EnSRF (20 members) have been compared at local scale over 3 years at 12 sites (SMOSMANIA network: in-situ soil moisture observations)
- Assimilation of superficial soil moisture (satellite proxy) in an optimal framework for deep soil moisture validation and error tuning
- Assimilation of synthetic observations: EnSRF superior to the SEKF
- Assimilation of real observations: no real gain of the EnSRF
- Both data assimilation schemes suffer from features of the ISBA scheme (non linear + dissipative): sub-optimal analyses
- Benefit of assimilating satellite derived superficial soil moisture for NWP and hydrology is not straightforward

Conclusions (2)

- SEKF is more robust (less parameters to specify) and cheaper but does not account for model and forcing errors
- EnSRF produces more physical seasonal variations of background errors
- Need to improve in the EnKF the precipitation forcing error representation (to account for false detection and missing events)
- Comparative study over a 2D domain with actual satellite data (e.g. L-band Tbs)

Perspectives

- Surface EnKFs should be more compatible with atmospheric EDA systems: coupling aspects
- EnKF cost will reduce when land surface schemes have more variables (multi-layer version of ISBA)
- EnKF can account for spatial (horizontal and vertical) correlations
- Improved land surface physics (multi-layer soil scheme + multi-energy budgets) should lead to more realistic Kalman gains
- Non-linearities cannot be properly adressed with KFs: variational techniques ? particle filters ?

More details in ...

Comparing the ensemble and extended Kalman filters for in situ soil moisture assimilation with contrasting conditions

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