SURFEX LDAS

March 2012

Alina Barbu

Combined assimilation of satellite-derived soil moisture and LAI

Motivation of our work

- GEOLAND 2 project
  - Land Carbon Information Service (LCIS) on vegetation/land component of GMES.
  - Objectif : to assess the impact of weather and climate variability on terrestrial biospheric carbon and water fluxes.

- Data Assimilation in the GEOLAND 2 framework
  - Land Data Assimilation System for the carbon and water cycles is a core activity of LCIS at regional and global scale.
  - SURFEX modeling platform of Meteo-France is used in offline mode for describing the continental vegetation state, surface fluxes and soil moisture.
  - It provides an improved description of the land carbon and water fluxes by constraining SURFEX with available observations.

Collaborations

- J-F. Mahfouf (GMAP/MF)
- L. Kulmann (OMSZ)
- S. Lafont (GMME/MF)
- G. Balsamo (ECMWF)
- J-C. Calvet (GMME/MF)

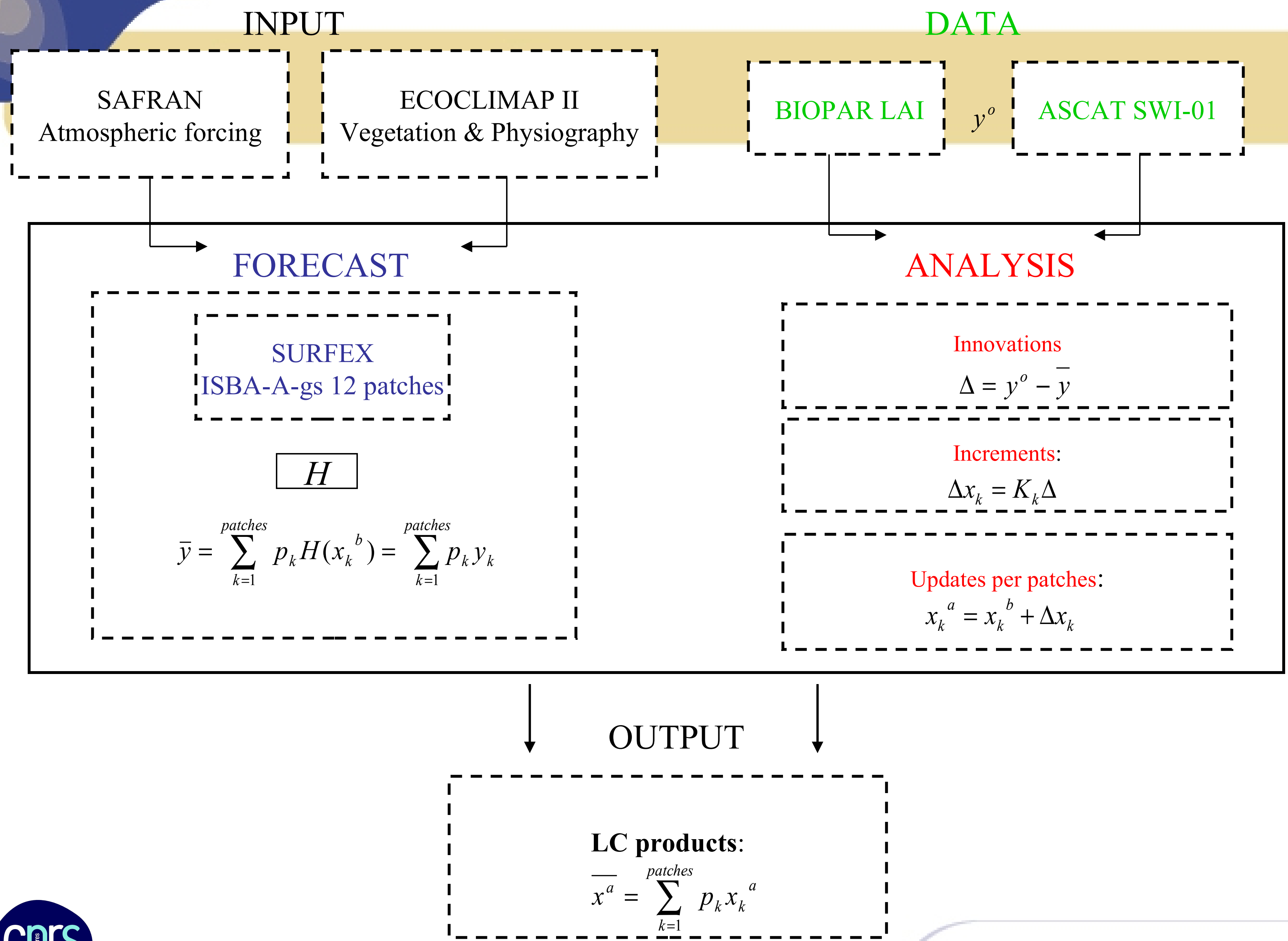
Outline

- LDAS on 12 patches.
- Comparison between different DA schemes.

- Uncertainty issues for LAI and soil moisture.
- Bias issues for LAI and soil moisture.

- SEKF assimilation of LAI and soil moisture France.
- Bias aware assimilation of LAI.

- Summary and Perspectives.


INPUT
SAFRAN
Atmospheric forcing
ECOCLIMAP II
Vegetation & Physiography
DATA
BIOPAR LAI
y^o
ASCAT SWI-01
FORECAST
SURFEX
ISBA-A-gs 12 patches
H
$\bar{y} = \sum_{k=1}^{patches} p_k H(x_k{}^b) = \sum_{k=1}^{patches} p_k y_k$
ANALYSIS
Innovations
$\Delta = y^o - \bar{y}$
Increments:
$\Delta x_k = K_k \Delta$
Updates per patches:
$x_k{}^a = x_k{}^b + \Delta x_k$
OUTPUT
LC products:
$\overline{x^a} = \sum_{k=1}^{patches} p_k x_k{}^a$

DA scheme on 12 patches

Assuming a control variable x, two patches with their fractions ($p_1 + p_2 = 1$) and one observation y.

$$\mathbf{H_1} = p_1 * \frac{\partial H(x_1)}{\partial x_1} \qquad \mathbf{H_2} = p_2 * \frac{\partial H(x_2)}{\partial x_2}$$

The increment of a patch depends
on the value of the other one
(through the innovation).

Implementation of the increment

$$\Delta x_1 = \frac{\left(\boldsymbol{\sigma}_1^b\right)^2 * \mathbf{H}_1}{\mathbf{H}_1 * \mathbf{H}_1 * \left(\boldsymbol{\sigma}_1^b\right)^2 + \mathbf{H}_2 * \mathbf{H}_2 * \left(\boldsymbol{\sigma}_2^b\right)^2 + \left(\boldsymbol{\sigma}^o\right)^2} * \Delta$$

Different DA schemes

Existing algorithms in LDAS:

SEKF

$$\mathbf{B}^{t} = \mathbf{B}^{0}$$

EKF- 2DVar

$$\Delta x^{0} = B^{0} M H^{T} \left(H M B^{0} M^{T} H^{T} + R \right)^{-1} * \Delta$$

$$\Delta \mathbf{x}^{t} = \mathbf{M} \Delta \mathbf{x}^{0} \quad \mathbf{B}^{t} = \mathbf{M} \mathbf{B}^{0} \mathbf{M}^{T} (+Q)$$

The increments are applied at the beginning of the assimilation window.

EKF

$$\Delta x^{t} = B^{t} H^{T} \left(H B^{t} H^{T} + R \right)^{-1} * \Delta$$

$$\mathbf{B}^{t} = \mathbf{M} \mathbf{B}^{0} \mathbf{M}^{T} + Q$$

The increments are applied at the end of the assimilation window.

H includes a model propagation or projects the model state into the observation space.

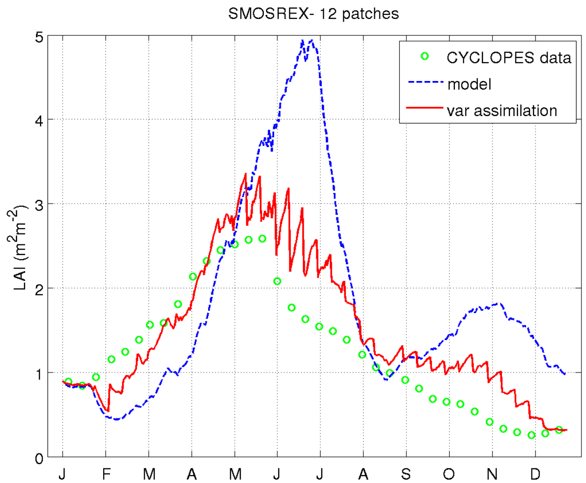
SEKF (C.Draper, L. Jarlan, A. Barbu)

EKF-2DVar (C.Draper)

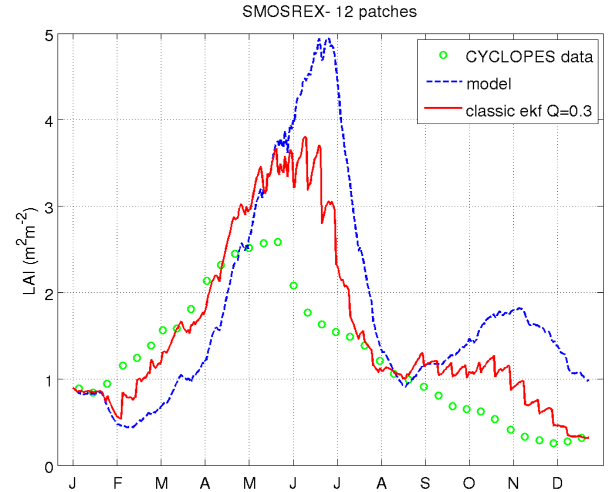
EKF (J-F. Mahfouf, A. Barbu)

Different DA schemes: a local scale example

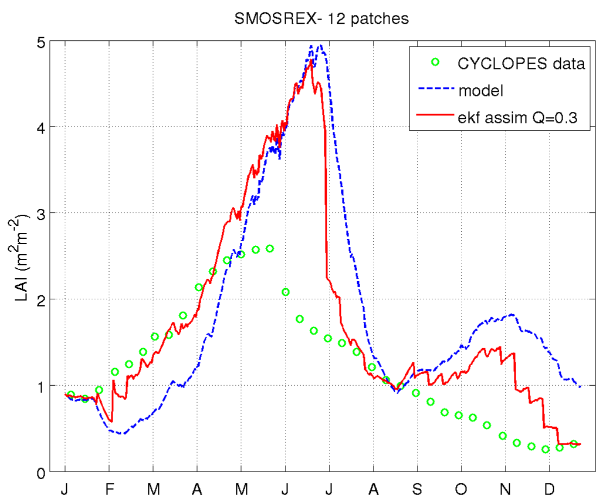
SEKF



EKF



EKF-2Dvar



EKF-2Dvar

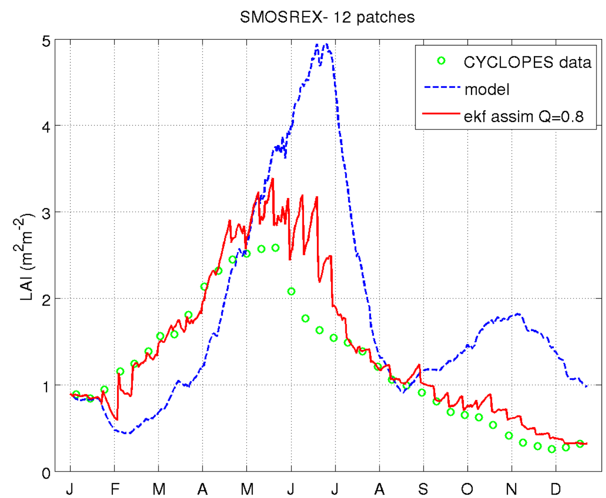


FIG 2. LAI assimilation using different DA schemes at SMOSREX site for 2007.

Bias

The term bias includes any type of error that is systematic rather than random.

DA methods are affected by biases caused by the problems:

- with observations,
- with limitation of the model,
- with the aproximation in the observation operator,
- etc...

Local scale: LAI satellite & ISBA-A-gs

Bias for the maximal values

Generally the model exhibits large values, while satellite products show a limited dynamic range of retrieved LAI.

Bias for the timing

Comparisons between simulated and retrieved LAI show discrepancies in the timing of the leaf onset/offset.

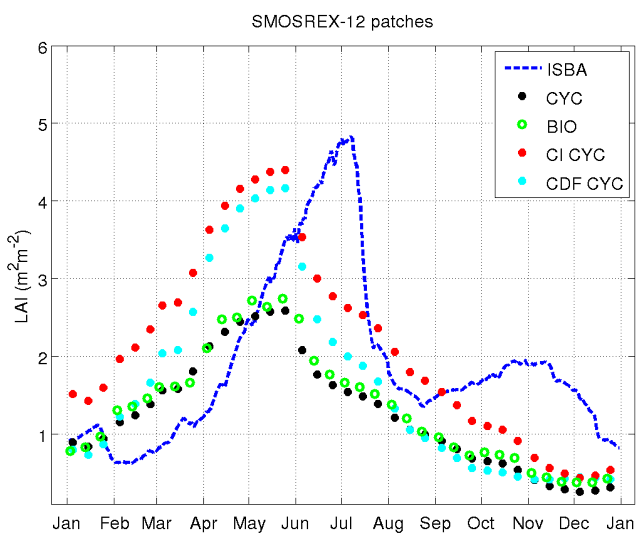


Fig. 6 – Simulated LAI, two satelite-derived LAI products and their rescaled valuesusing a CDF matching and a Clumping Index.

Clumping LAI Index CI=0.6

Local scale: assimilation experiments

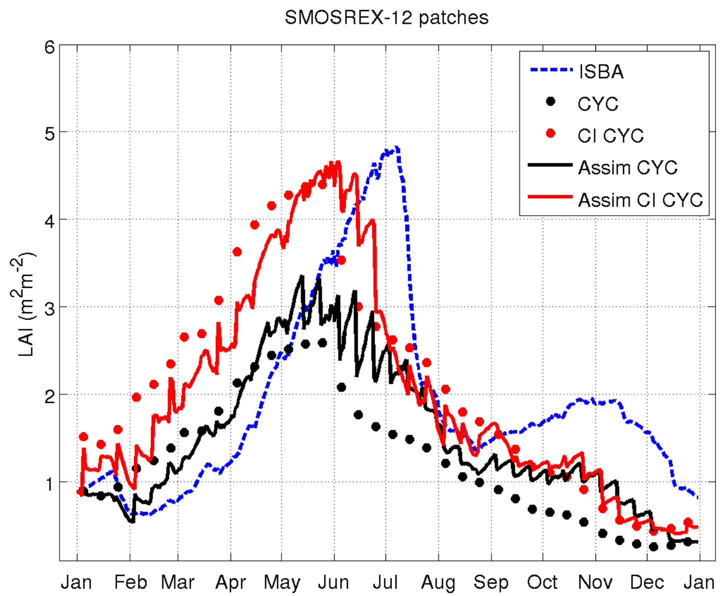


Fig. 4 – Two experiments: assimilation of CYCLOPES data (optical LAI), (in black) & assimilation of rescaled CYCLOPES data (true LAI), (in red) with an estimated Clumping Index CI.

Regional scale: LAI CDF matching?

CYCLOPES LAI is debiased by rescaling its histogram to the model simulations.

The phenology is kept and only the absolute values are adjusted.

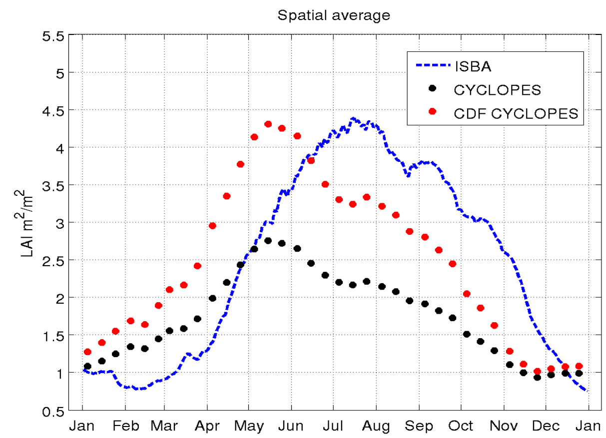
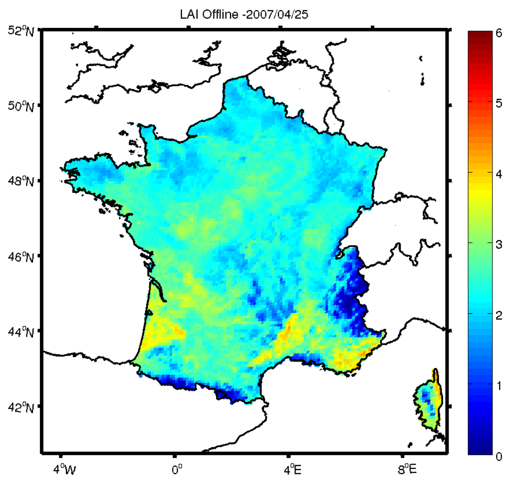
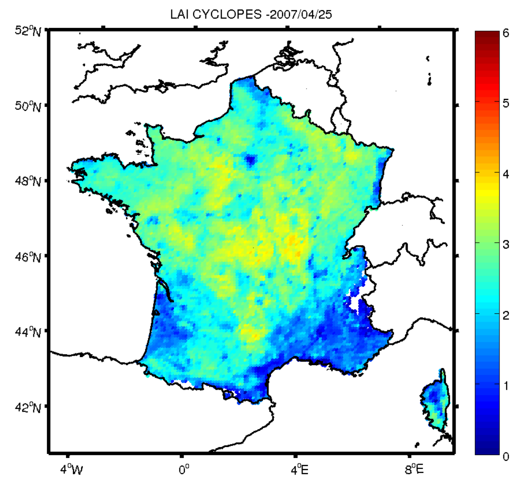
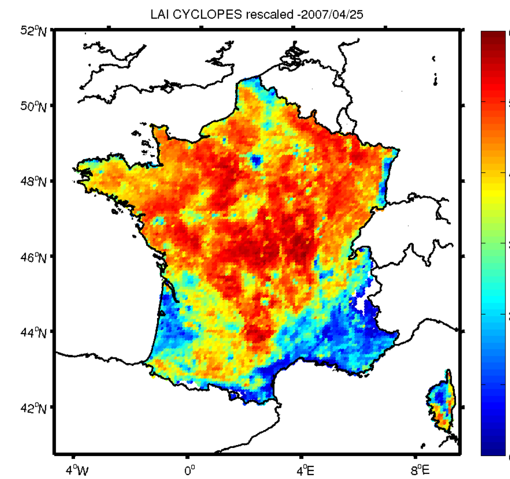


Fig. 5 – Time evolution of the simulated average LAI (in blue) of LAI CYCLOPES (in black) and its rescaled values using the CDF matching (in red).







Treatment of LAI bias (*Jarlan et al.,2008*)

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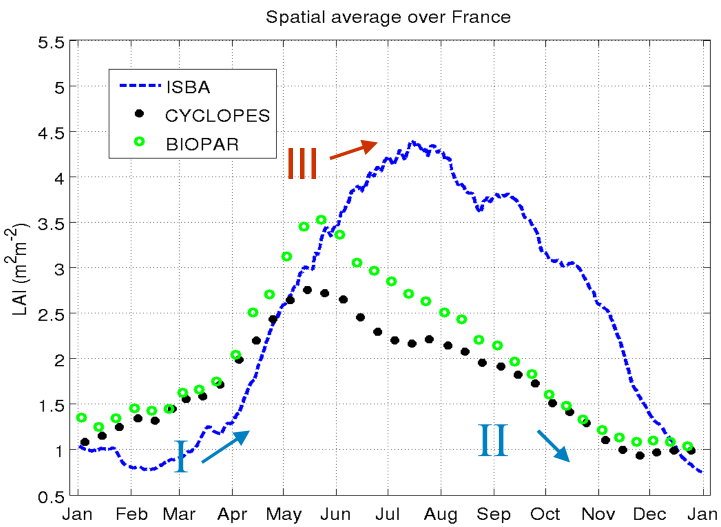
Regional scale: observation and background errors



Case I → $LAI^o > LAI^b$ $\quad \sigma^b > \sigma^o$

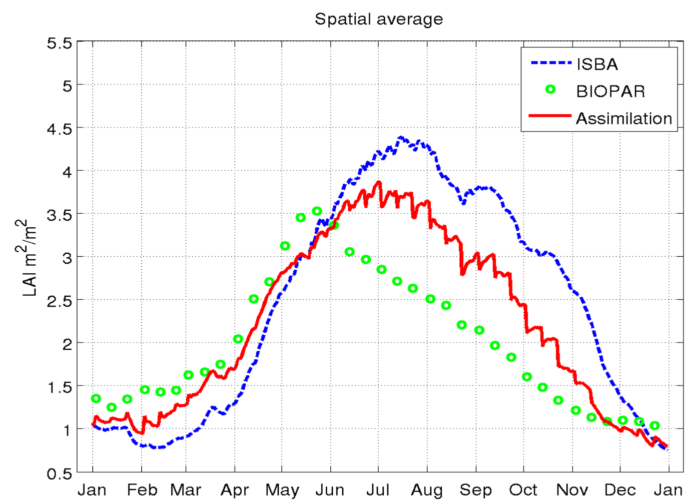
Case II → $LAI^o < LAI^b$ $\quad \sigma^b > \sigma^o$

Case III → $LAI^b > LAI^o$ $\quad \sigma^o > \sigma^b$

Then we consider:

$$\sigma^b = 0.4 m^2 m^{-2}, \sigma^o = 0.2 m^2 m^{-2} \qquad LAI \leq 2 m^2 m^{-2}$$

$$\sigma^o = 0.4 m^2 m^{-2}, \sigma^b = 0.2 m^2 m^{-2} \qquad LAI > 2 m^2 m^{-2}$$



LAI uncertainties (*Barbu et al.,2011*)

Processing the ASCAT soil moisture

The ASCAT data are provided by TU Wien on the 25 km Discrete Global Grid. The model grid is of 8 km.

1. Before the ASCAT data were projected onto the model grid:
-Remove data with ASCAT Estimated Soil Moisture Error >20%.
-Screen data with Surface State Flag indicating frozen surface, presence of snow.
2. After the ASCAT data were projected onto the model grid:
-Mask urban regions.
-Mask steep mountainous terrrain.
-Additional mask for frozen conditions.
3. CDF matching was performed using SDS time series for 2007.
4. Conversion of Surface Degree of Saturation (SDS) ASCAT in Surface Soil Moisture (SSM or wg) was performed using the min/max simulated SSM values.

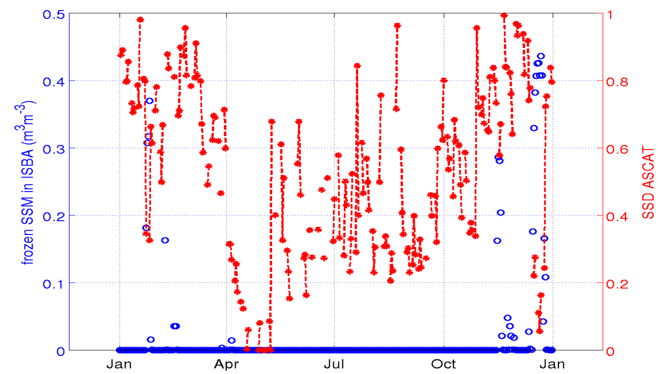


Fig. 2 – Simulated SSM solid and SDS ASCAT for one grid cell (lon=3.51, lat=50.47) for 2007.

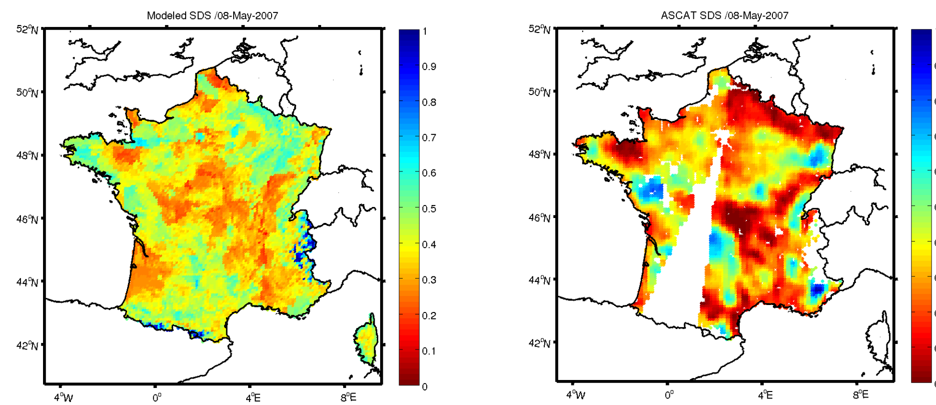


Fig. 3 – Simulated SDS (left) and ASCAT SDS (right) on May, 8.

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Bias correction of the ASCAT data

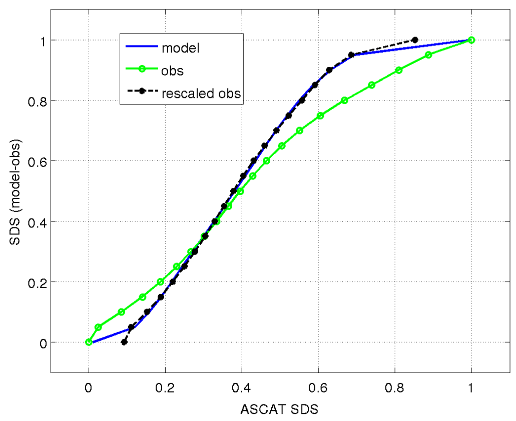


Fig 3. Calibration of the CDF of ASCAT and model SDS by a 5th-order polynomial fit.

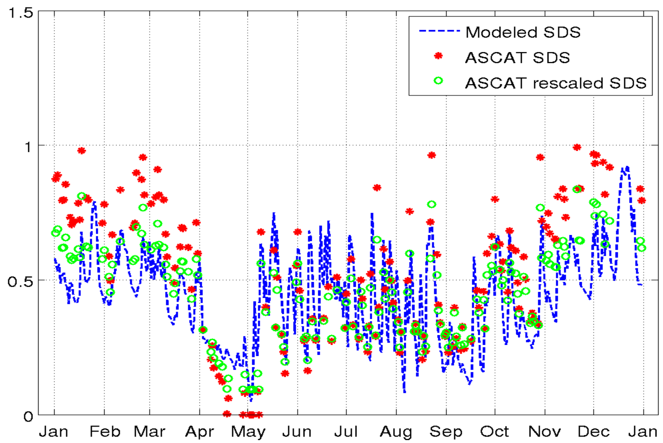
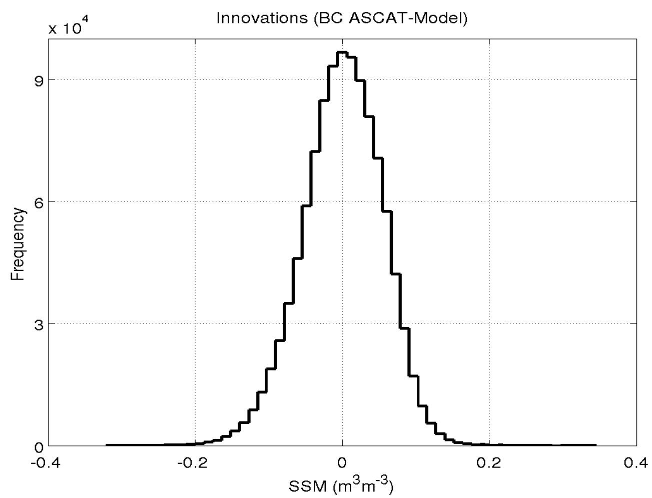


Fig 4. Time series of modeled SDS and observed ASCAT SDS before and after bias correction for one grid cell.

Error estimation for soil moisture

A priori diagnostic



$$\sigma_{innov} = 0.057 m^3 m^{-3}$$

Assuming that the errors are Gaussian and uncorrelated:

$$\left(\sigma^o\right)^2 + \left(\sigma_{wg}{}^b\right)^2 = \left(\sigma_{innov}\right)^2$$

Considering that neither the BC ASCAT nor the model is a better estimate of the true SSM (wg):

$$\sigma^o = \sigma_{wg}{}^b$$

$$\sigma^b_{wg} \cong 0.04 m^3 m^{-3}, \sigma^o \cong 0.04 m^3 m^{-3}$$

$$\sigma^b_{w2} = 0.2 \times (w_{fc} - w_{wilt}) m^3 m^{-3}$$

Estimation of observation and background error (*Mahfouf , 2009*)

Error estimation for soil moisture

A posteriori diagnostic

For diagnosis purposes the following quantities are computed:

• the differences $d_b^o = y^o - H(x^b)$

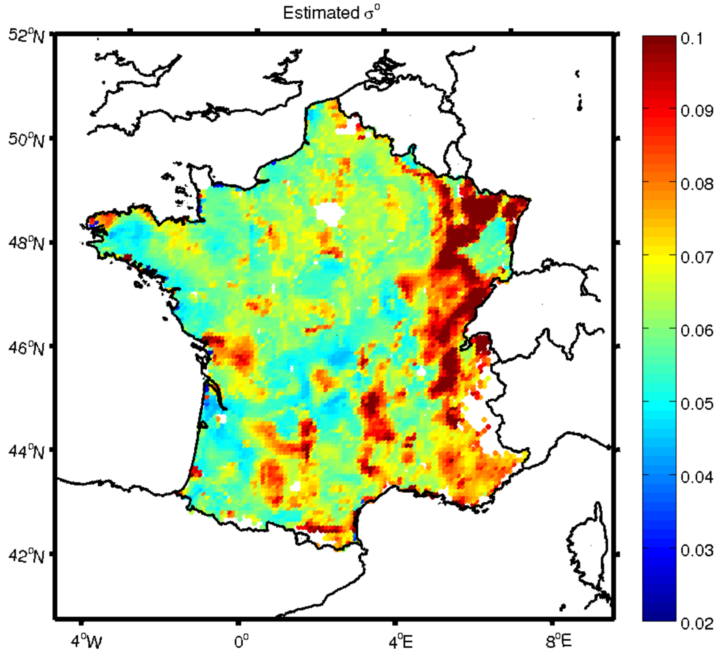
called innovations (background departures).

•the differences $d_a^o = y^o - H(x^a)$

called residuals (analysis departures).

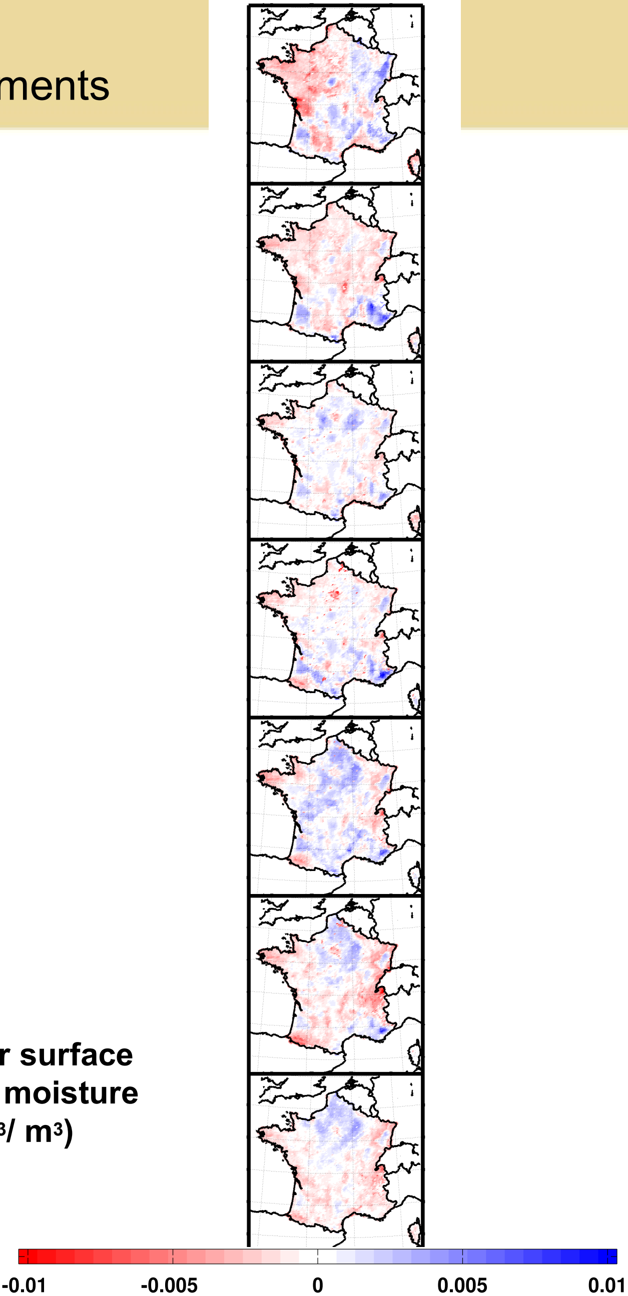
$$(\sigma^o)^2 = (d_a^o)^T (d_b^o)$$

$$(d_a^o)^T (d_b^o) = \sum_{j=1}^{nobs} (y_j^o - y_j^a)\ (y_j^o - y_j^b)$$

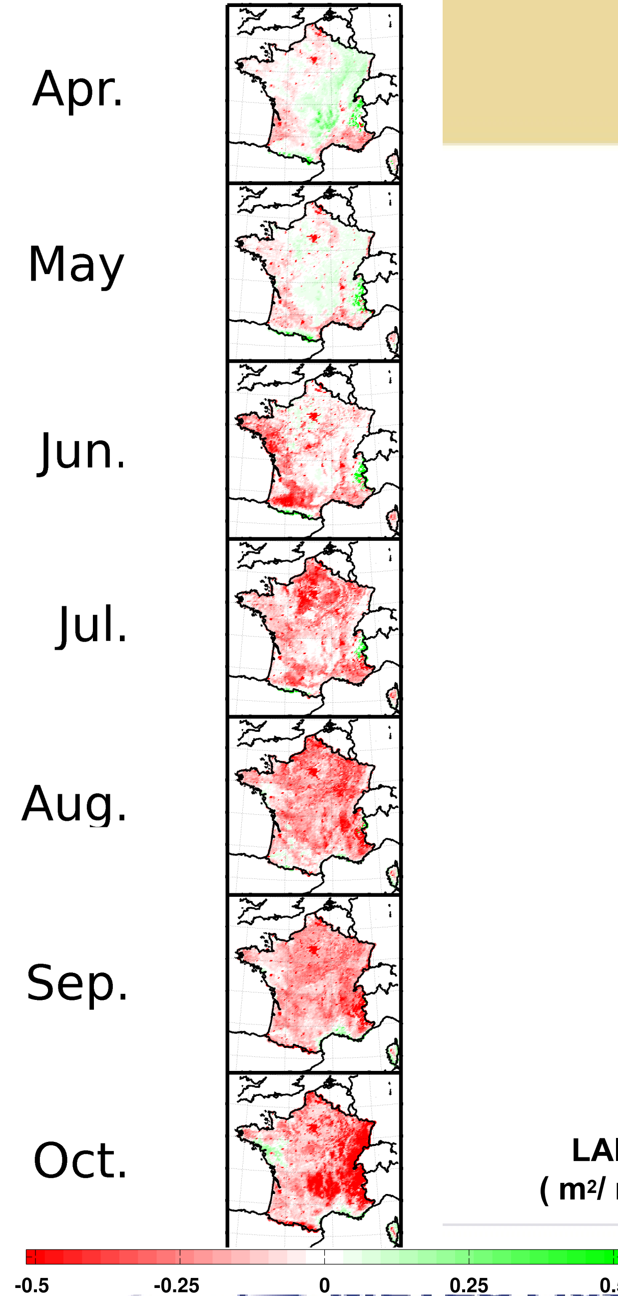


Diagnosis of observation and background error parameters (*Desroziers & Ivanov, 2001*)

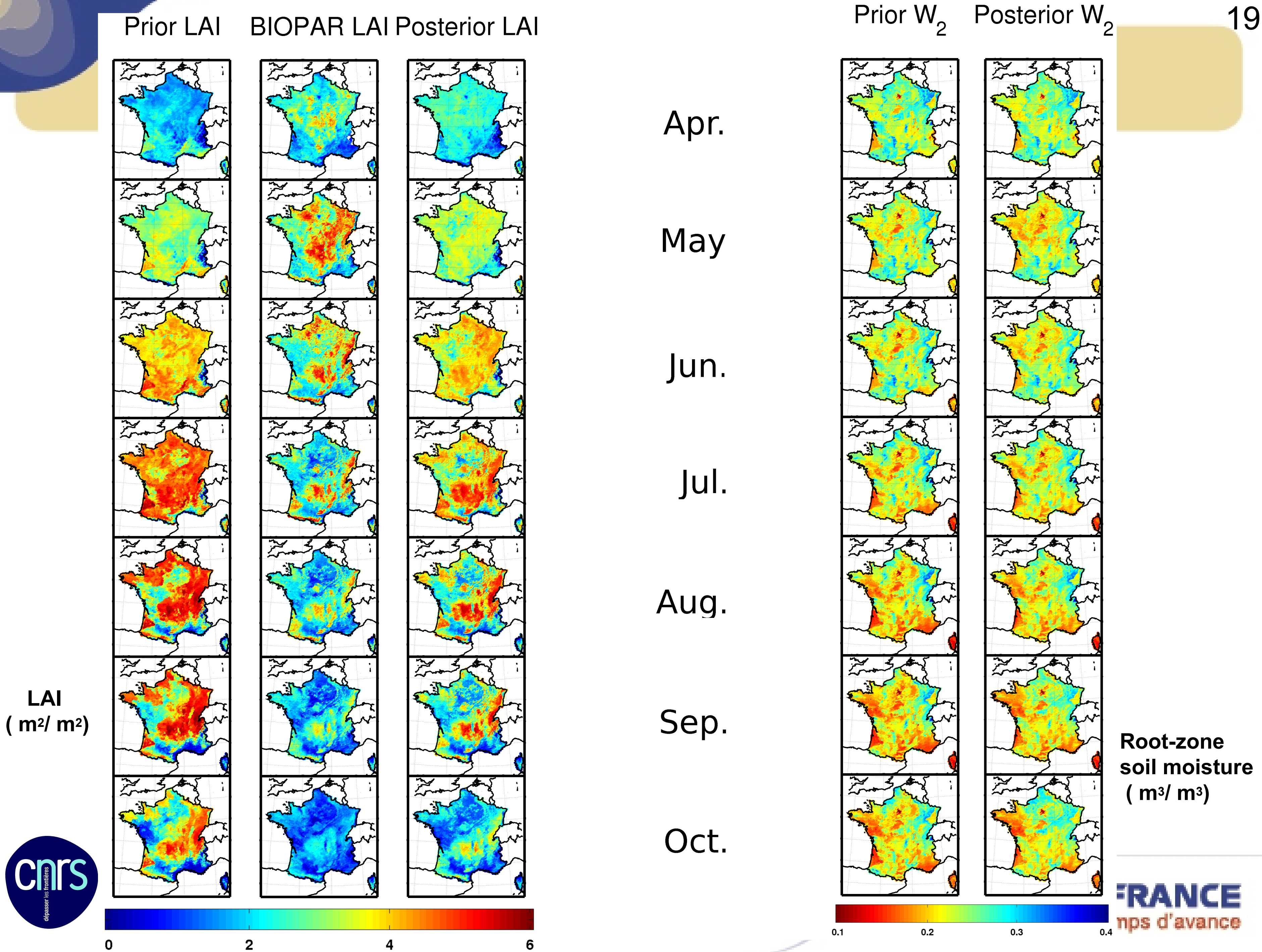
Analysis increments



Near surface soil moisture (m^3/m^3)



LAI (m^2/m^2)


Prior LAI
BIOPAR LAI
Posterior LAI
Prior W2
Posterior W2
Apr.
May
Jun.
Jul.
Aug.
Sep.
Oct.
LAI
(m2/ m2)
0
2
4
6
Root-zone
soil moisture
(m3/ m3)
0.1
0.2
0.3
0.4

Comparison with in situ data

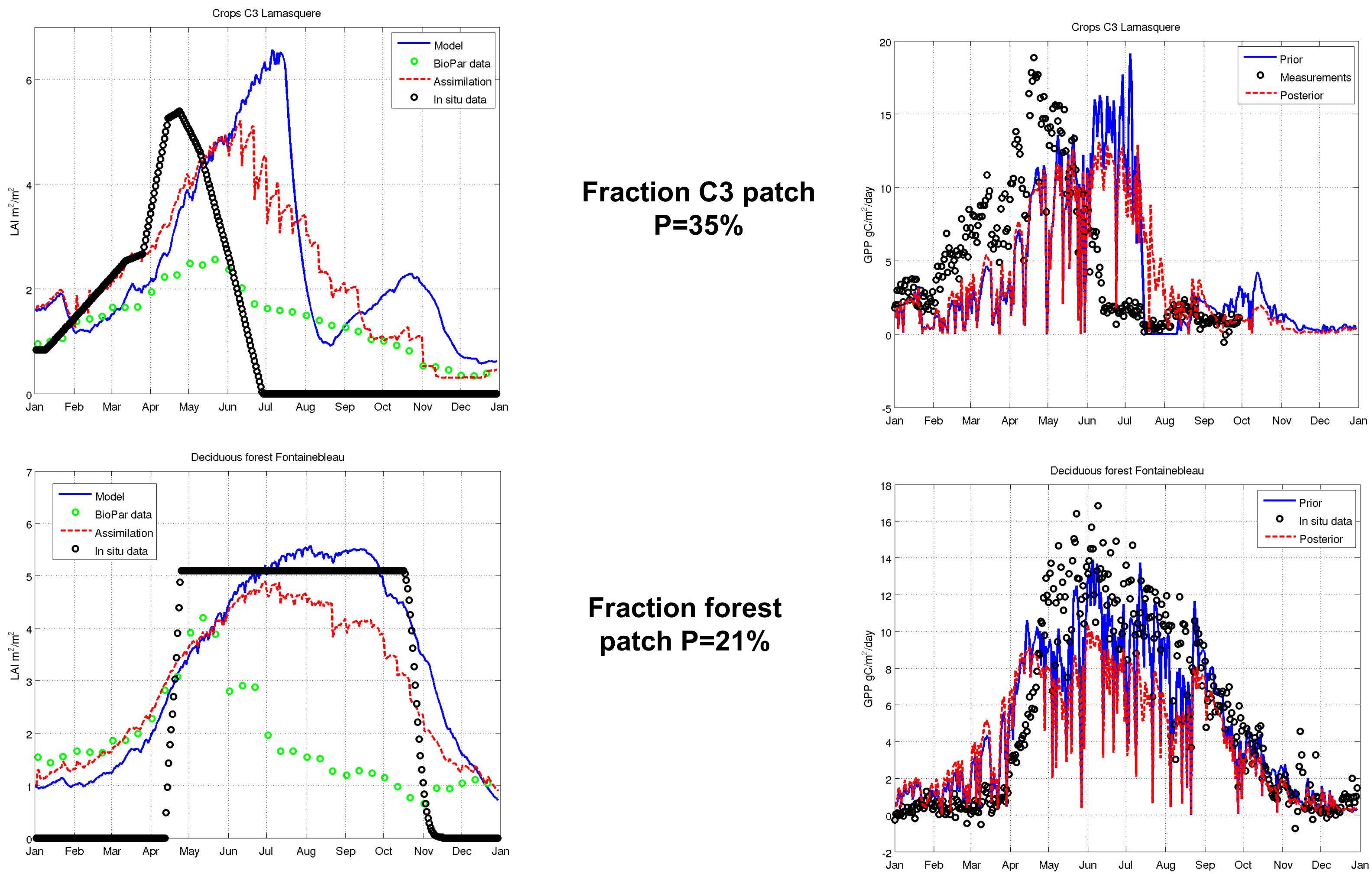


Fig. 9 – Measured (in black), simulated (in blue) and assimilated (in red) LAI (left) and GPP(right) at two FLUXNET sites.

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Bias-Aware Data Assimilation

Forecast

State model $x_k^{\,f} = M_{k-1} x_{k-1}^{\,a}$

Bias model $b_k^{\,f} = b_{k-1}^{\,a}$

with error covariances $\mathbf{P}^f$ (state) and $\mathbf{P}^b$ (bias)

Update

$$b_k^{\,a} = b_k^{\,f} - \mathbf{L}_k [y_k^o - \mathbf{H}_k (x_k^f - b_k^f)]$$

$$\mathbf{L} = \mathbf{P}^b \mathbf{H}^{\mathrm{T}} \left(\mathbf{H}\mathbf{P}^b \mathbf{H}^{\mathrm{T}} + \mathbf{H}\mathbf{P}^f \mathbf{H}^{\mathrm{T}} + \mathbf{R} \right)^{-1}$$

$$x_k^{\,a} = (x_k^{\,f} - b_k^{\,f}) + \mathbf{K}_k [y_k^{\,0} - \mathbf{H}_k (x_k^{\,f} - b_k^{\,a})]$$

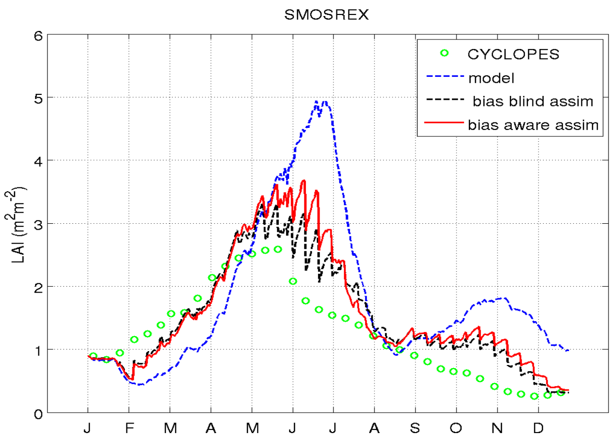
$$\mathbf{K} = \mathbf{P}^f \mathbf{H}^{\mathrm{T}} \left(\mathbf{H}\mathbf{P}^f \mathbf{H}^{\mathrm{T}} + \mathbf{R} \right)^{-1}$$

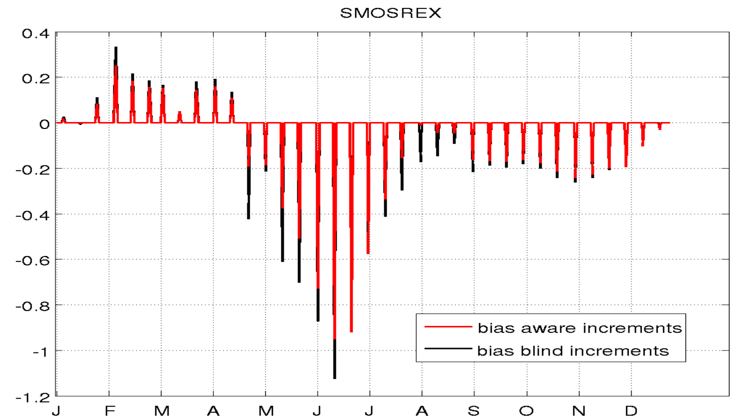
Consider $\mathbf{P}^b = \beta * \mathbf{P}^f$ with a parameter $0 < \beta < 1$ that controls the adaptivity of the bias estimates.

On-line bias estimation and correction with feedback (*Dee &Da Silva,1998*)

Local scale: LAI model bias

Bias blind assimilation vs. Bias aware assimilation

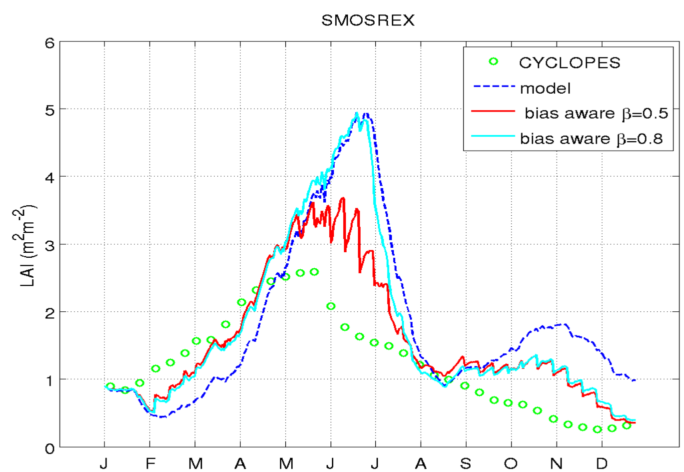




Modeled (blue), observed (green), bias-blind assimilated (black) and bias-aware assimilated (red) LAI using a parameter of 0.5 for 2007.

Sensitivity to the bias parameter

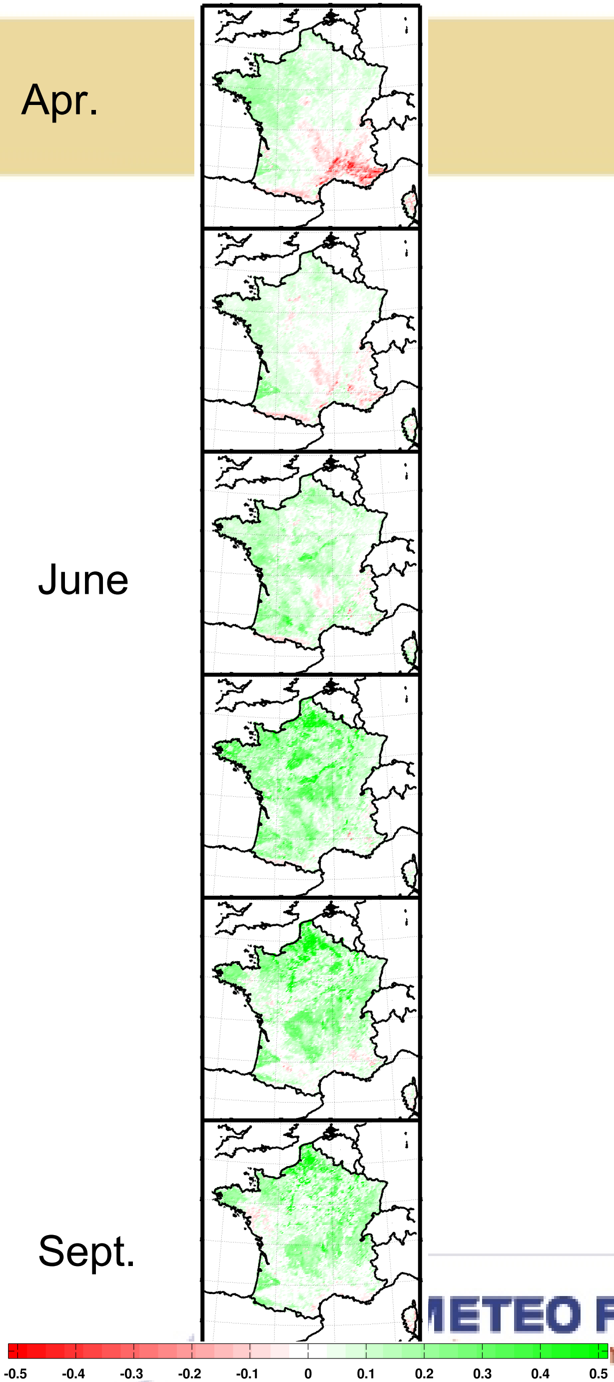
Modeled (blue), observed (green), bias-aware assimilated LAI using two different values of the bias parameter.



The bias parameter determines the extend to which data are applied towards estimating the systematic errors.

Regional scale: LAI model bias

Monthly LAI (m^2/ m^2) differences between bias-aware assimilation and bias-blind assimilation.



Summary & Perspectives

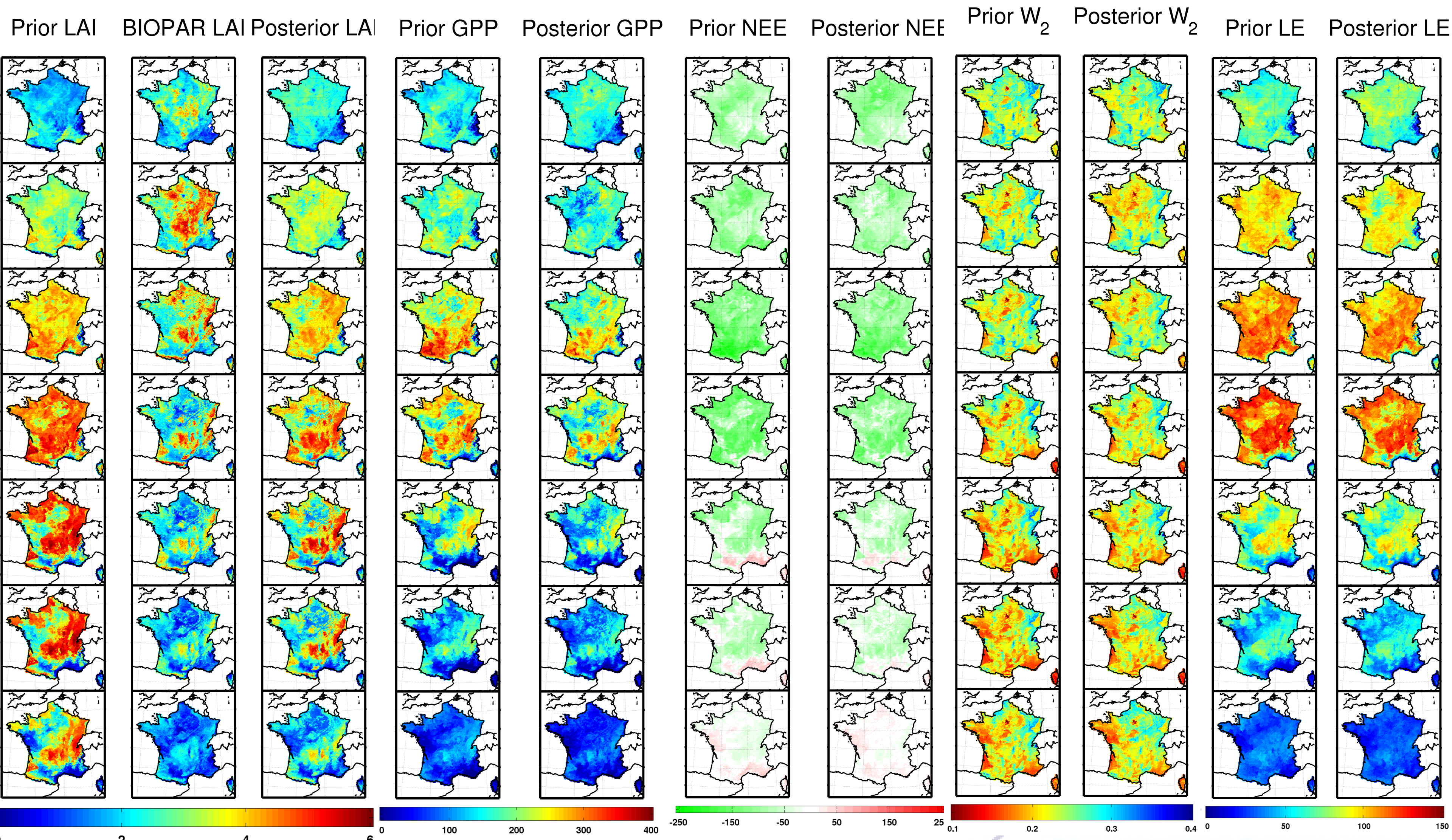
- **Summary**

  – Succesful data assimilation with multi-patches was implemented.
  – Different DA schemes were tested with 12 patches version. Choice of DA scheme depends on the application.
  – Different approaches may be envisaged to remove the bias prior to assimilation.
  – SWI and LAI were assimilated using the SEKF at regional scale.
  – Bias-aware data assimilation was implementated.

- **Perspectives**

  - A validation methodology for the assimilation results.
  - A necessary bias treatement: complex bias structure (temporal, spatial, observation and model bias).

GEOLAND products



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Diagnostic results at SMOSREX (2001-2007)

For diagnosis purposes the following quantities are computed:

• the differences $d_b^o = y^o - H(x^b)$

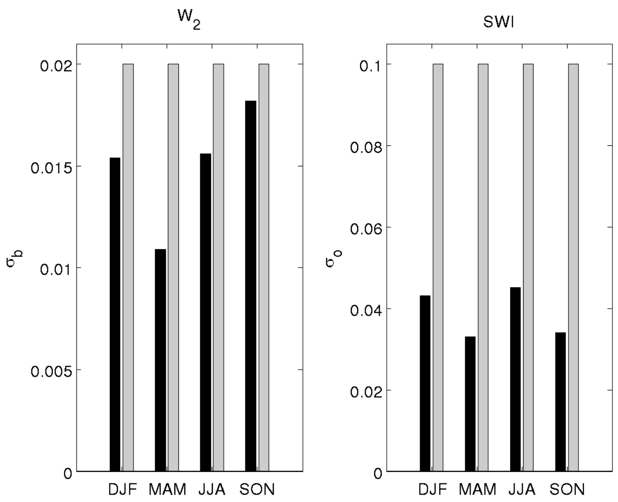
called innovations (background departures).

•the differences $d_a^o = y^o - H(x^a)$

called residuals (analysis departures).

$$(\sigma^o)^2 = \frac{1}{nobs}(d_a^o)^T(d_b^o)$$

$$(d_a^o)^T(d_b^o) = \sum_{j=1}^{nobs}(y_j^o - y_j^a)\,(y_j^o - y_j^b)$$



Seasonal soil moisture diagnostics of background (left) and observation errors (right). The diagnosed values are in black, the initial values in gray.

	Initial exp	Diagnostic exp
swi	63.8	72.3
w_2	13.4	13.4

Comparison of the LDAS performance (in %) when using the initial and diagnosed values for the root-zone soil.

Diagnosis of observation and background error parameters (*Desroziers & Ivanov, 2001*)

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