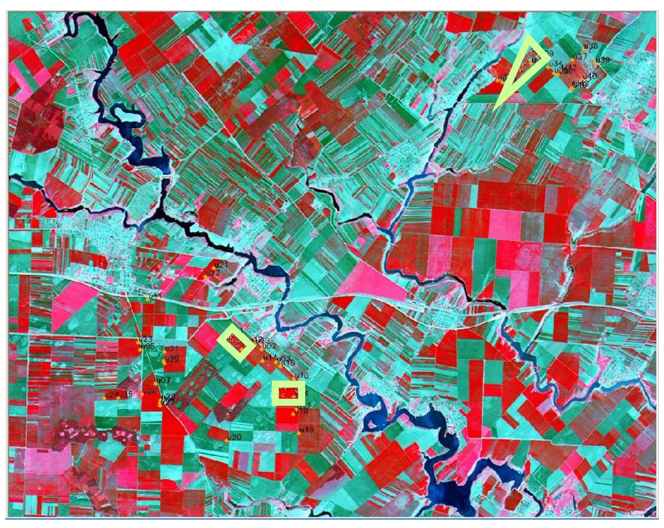
Using spatial constraints into a variationnal data assimilation scheme of remote sensing images. Example on the simple crop model Bonsaï

Claire Lauvernet, Frédéric Baret, F.X. Le Dimet



Fundulea site from ADAM project, Romania

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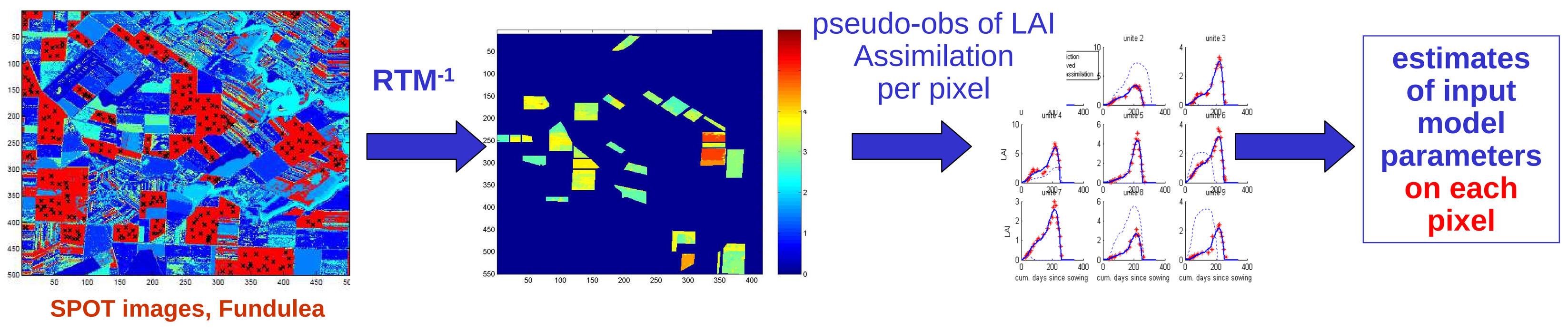
Introduction

Assimilation of remote sensing data into crop models is generally applied pixel by pixel, while the whole image data is available :



1. classical method (on single pixel) ignores possible spatial structures
2. spatial properties of time series of images = additional source of information
3. inverse problem is generally ill-posed when applied at the pixel level
4. repeating the same action a great number of times is not computer efficient

Objectives

- to exploit some spatial structures of the parameters to reduce the size of the problem and make its inversion manageable.
- to process concurrently a large set of pixels using variationnal assimilation

➧ Application on a simple model of plant growth, the BONSAÏ model

BONSAÏ model

BONSAÏ (Baret, 1986; Lauvernet 2005) is a semi-mecanistic model that simulates LAI in function of cumulated day-degrees :

$$LAI_t = L_{max}\cdot\left(\frac{1}{(1+e^{-A(ST_t-t_0-Ti)})^C} - e^{B(ST_t-t_0-(\Delta Ts+Ti))}\right)$$

$$A = \frac{1}{Ti}\cdot log\left(\left(e^{\frac{B}{C}\cdot(\Delta Ts+Ti)}\right)-1\right)$$

t0 = the growing date
Lmax = max value of LAI
B = additional parameter
Ti ,DTs = temperature thresholds
C = generalized logistic
(A = growing speed, calibrated)

Variationnal data assimilation theory

State Variables LAI,biomass,... — model — Parameters Variables — Initial Conditions

model

$$\begin{cases} \frac{dX}{dt} = F(X,K) \\ X(0) = u \end{cases}$$

cost fonction

$$J(K) = \frac{1}{2}\|C.X(K) - X_{obs}\|^2_{X_{obs}} + \frac{1}{2}\|K-K_0\|^2_K$$

adjoint model

$$\begin{cases} \frac{dP}{dt} + \left[\frac{\partial F}{\partial X}\right]^T P = C^t(CX - X_{obs}) \\ P(T) = 0 \end{cases}$$

optimality condition

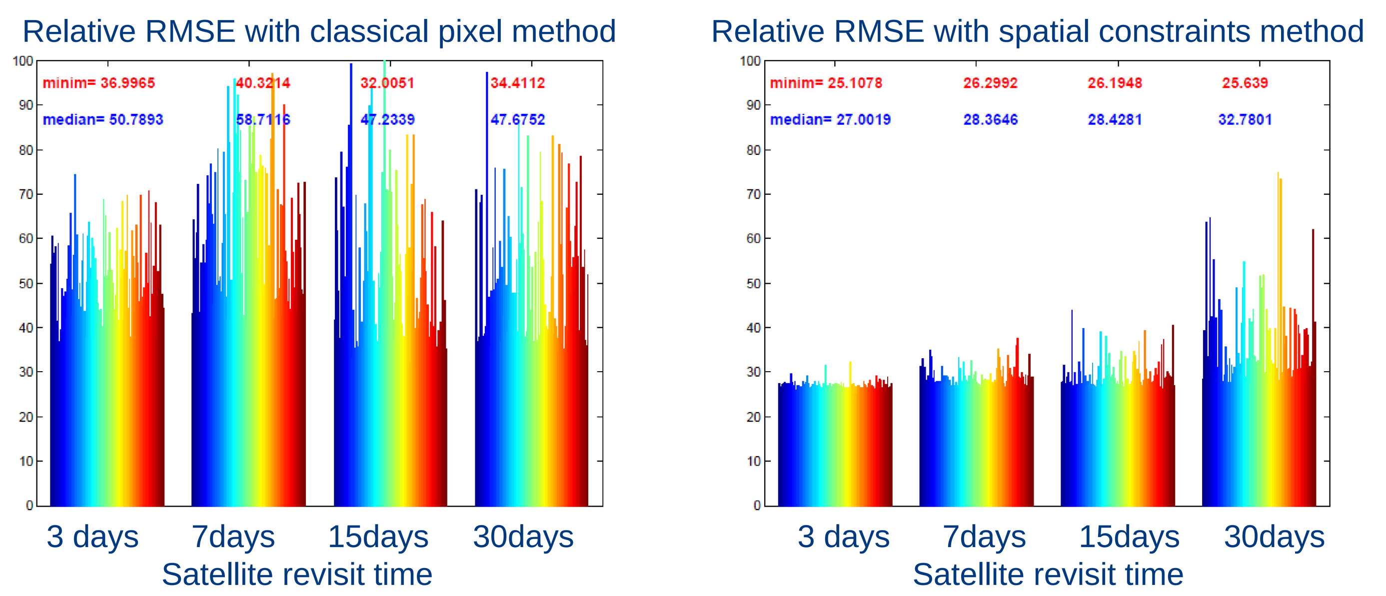
$$\nabla_K J = -\left[\frac{\partial F}{\partial K}\right]^t P + K - K_0$$

Optimality System contains ALL available information : *observations, model, statistics, prior information…*

Adjoint model is performed with TAPENADE DA tool.

➔ 1. directional derivatives and 2. transposition

Evaluation of both DA methods on parameter estimation

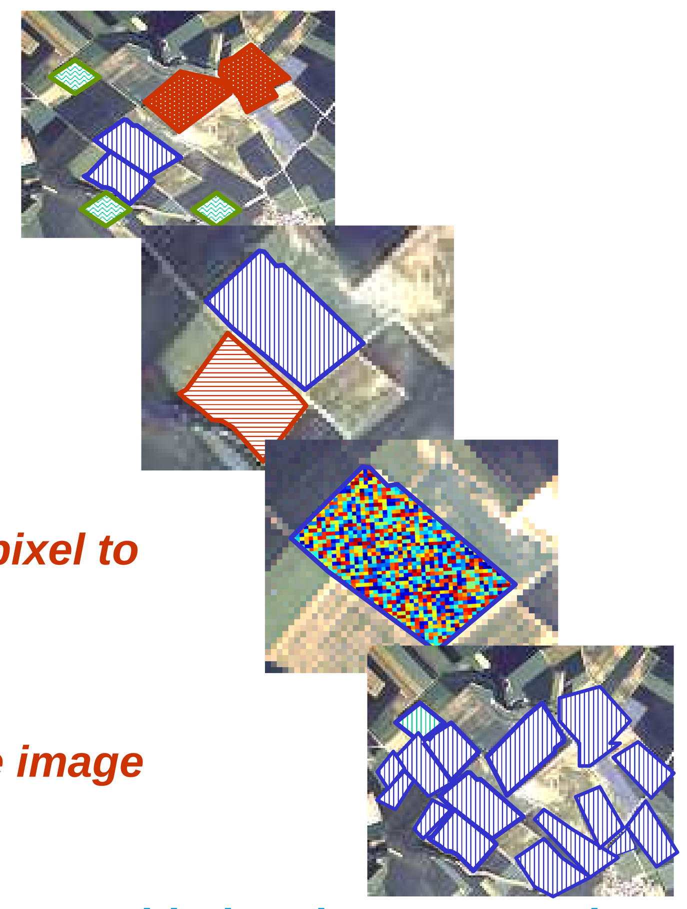


- Better global identification: 48% ➔ 28% RRMSE
- Stability considering satellite revisit time
- Reduction of the inverse problem size : 600 ➔ 314 parameters to estimate
- Better parameters estimation that are more <u>and</u> less influent (growing date)

Which spatial structures to which parameters?

The method proposed here assumes that the parameters are governed by spatial structures depending on several levels:

- **Cultivar level** phenological stages, leaves properties — ➧ *stable on all fields from same cultivar*
- **Field level** agricultural practices — ➧ *stable on all pixels from same field*
- **Pixel level** soil properties — ➧ *different from one pixel to another*
- **Non-significant and not sensitive** — ➧ *stable on the whole image*

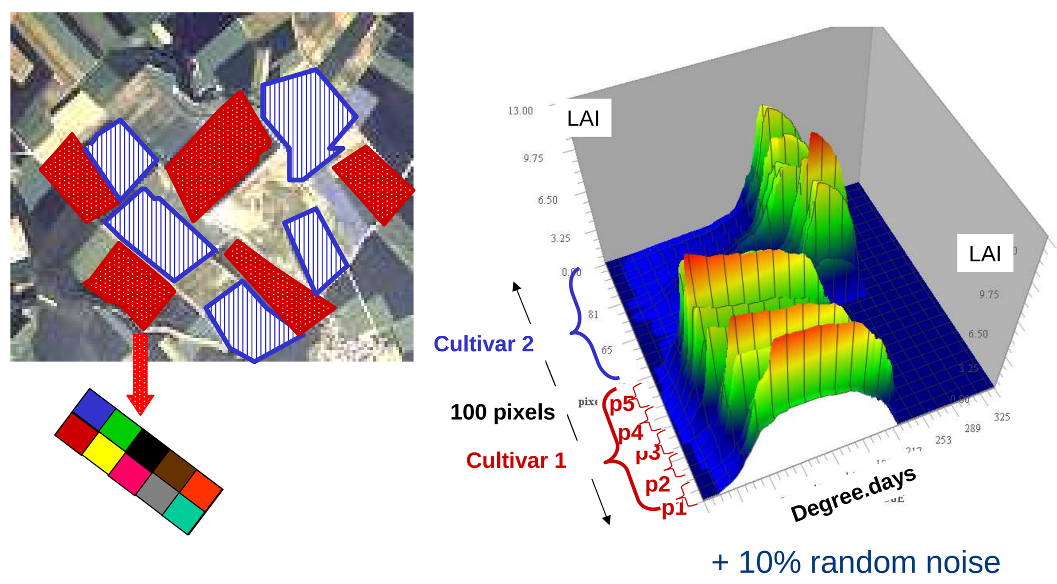


We now have to estimate all these parameters considering these constraints and dependencies

⚠ **The connectivity between neighbour pixels & correlation are not taken into account here.**

Twin experiments to test sensitivity of the spatial constraints method on the satellite revisit time

- **Generation of noisy LAI observations: 2 cultivar, 5 fields/cultivar, 10 pix/field**

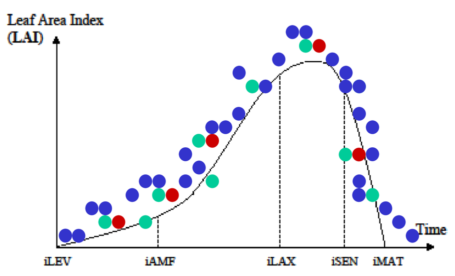


param.	spatial structures
t0	field (10)
Ti	cultivar (2)
ΔTs	cultivar (2)
B	pixel (100)
Lmax	pixel (100)
C	pixel (100)

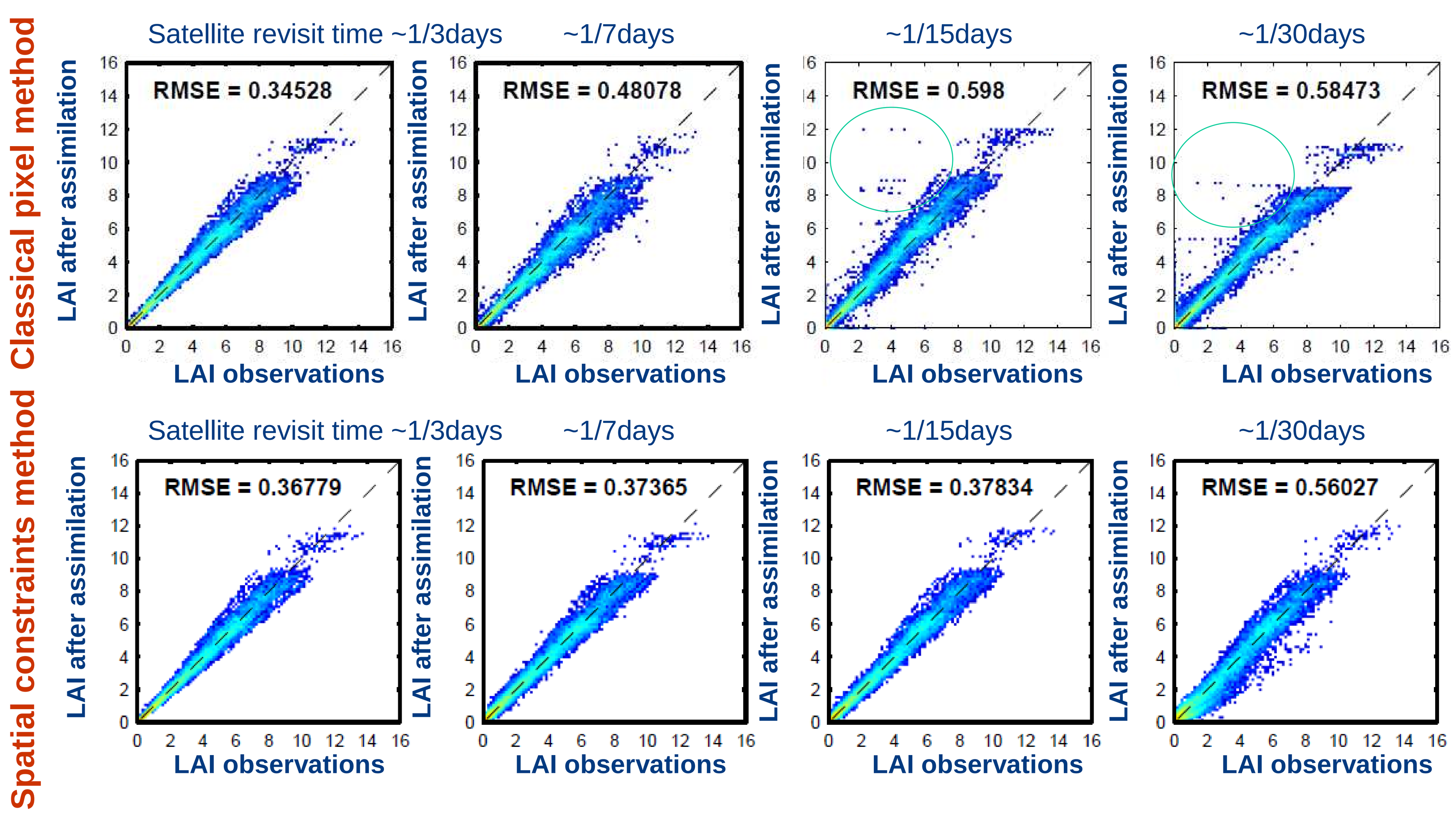
➔ 314 parameters to estimate (600 without SC)

- **4 types of satellite revisit time : every 3 days, 7 days, 15 days, 30 days**
- **on 100 cases of probability (uniform(0.5)) to be cloud masked**

➧ **58 obs. for 3 days frequency (0 - 120)**
➧ **24 obs. for 7 days (0 - 50)**
➧ **11 obs. for 15 days (0 - 22)**
➧ **6 obs. for 30 days (0 - 12)**



Evaluation of both DA methods on LAI estimation



- **As satisfying as pixel method when lot of data to assimilate**
- **The CS method is more robust if less available observations**
- **Results are more precise and stable ➔ 1/7days without ➔ 1/15days with SC**
- **Even with very poor obs. (1/30days ➔ still no local min)**
- **Convergence : 3000 ➔ 50 iterations but same CPU**

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http://kalideos.cnes.fr/spip.php?article21

www.irstea.fr

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