

Exploitation des dimensions spatio-temporelles en télédétection-phenotypage

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Les 6 dimensions disponibles pour caractériser les traits

$$\textit{Trait} = f[M(x, y, z, \lambda, \Omega, t)]$$

Measurement

Scanner

Imagerie

3D imagerie

Longueur d'onde

Direction

Temps

Echantillonnage du champ de rayonnement réfléchi / émis par les couverts végétaux

Les différents systèmes d'observation

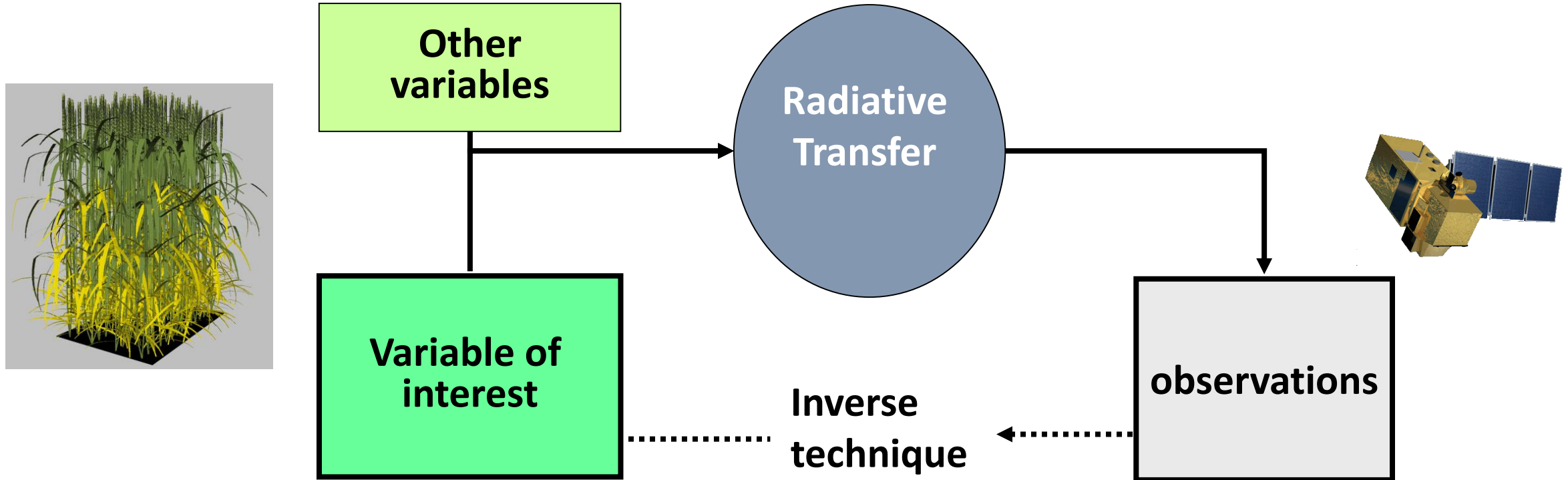


	Fixe	Porté	Tracteur	Phenomobile	Portique	Drone	Satellite
Résolution spatiale	1mm	0.2mm	0.5mm	0.5mm	0.5mm	0.5mm – 5cm	0.5m-10m
Couverture spatiale	<100m ²	<1 ha	<5 ha	<5ha	<0.3ha	<15ha	>500km ²
Temps de revisite	1h-1j	3j-30j	3j-30j	3j-30j	3h-30j	3h-30j	1j-10j
Directionnalité	0° 45°	0° & 45°	0°	0° & 45°	0° & 45°	0° (45°)	≈ 0°
Richesse Spectrale	RGB	RGB	RGB+Multi	RGB+Multi	RGB+Multi	RGB+Multi+IRT	Multi
3D	Non	Photo	Photo, LiDAR	Photo, LiDAR	Photo, LiDAR	Photo (LiDAR)	Non

Tous les systèmes échantillonnent l'espace et le temps à des résolutions variables. Typiquement :

- **Temps: 1h -> 1 mois**
- **Espace: 1/10 mm -> km**

Trait estimation is an inverse problem



The inverse problem in remote sensing / phenotyping is generally ill-posed: several solutions may provide about the same radiometric response

Using constraints to regularize the inverse problem

□ Prior information on the distribution of the input variables

- Introduced using:
 - ✓ Cost function with Bayesian term
 - LUT, iterative optimization
 - ✓ Machine learning trained over datasets generated using on the prior knowledge of the distributions
 - NNT, SVM, VIs ...
- With limitations due to:
 - ✓ Knowledge of prior distribution
 - ✓ Uncertainties in the model / measurements

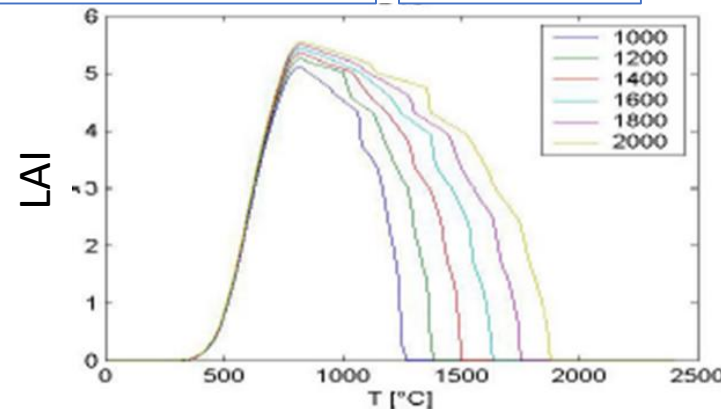
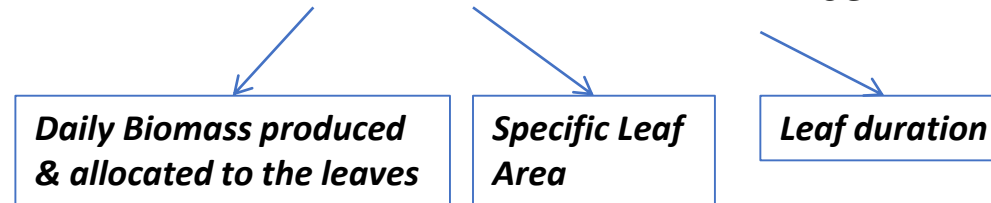
□ Temporal and spatial constraints

- Based on the assumption of a continuum of canopy characteristics in the spatio-temporal domain.

The spatio-temporal continuum: the temporal dimension (1/2)

- Vegetation structure (LAI) results from incremental processes

$$\text{LAI}(t) = \text{LAI}(t-1) + \Delta \text{DM.SLA} - \Delta \text{LAI}_{\text{sen}}$$

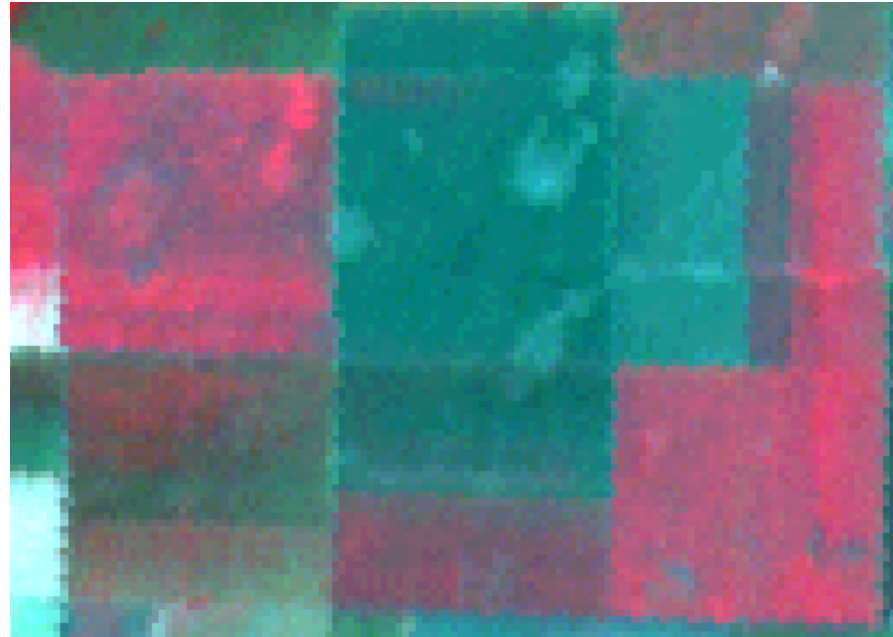


smooth dynamics

- Other structural characteristics varying slowly (LAD ...)
- Leaf properties varying also through incremental processes: smooth dynamics

The spatio-temporal continuum: the spatial dimension (2/2)

- Within a vegetation patch (few pixels in the same object), pixels in a neighborhood are generally showing a local gradient due to:
 - the PSF of the instrument/reprojection
 - Factors of local variability mainly linked to soil properties and crop implantation



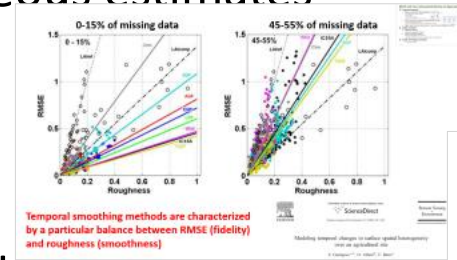
Working on local (3x3, 5x5 ...) allows reducing problems due to multi-temporal registration accuracy

(Brief and non-exhaustive) Review of Approaches

□ Temporal constraints

- Posterior processing: Filtering instantaneous estimates

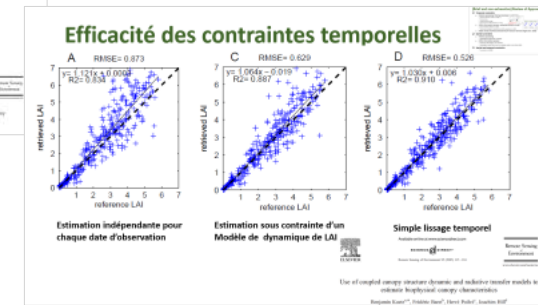
- ✓ Statistical operator (median / average ...)
- ✓ Savitsky-Golay
- ✓ Logistic/ gaussian model
- ✓ Semi-empirical model (Duveiller et al. 2011)



- Within the inversion process: embedded dynamic model

- ✓ local smoothness (Lewis et al. 2012)
- ✓ Semi-empirical dynamic model: Kötz et al. 2005, Lauvernet et al. 2008

- Steady values of surface characteristics for aerosol retrieval (Hagole et al. 2008)



□ Spatial constraints

- Posterior processing

- ✓ Spatial filtering (generally, averaging)

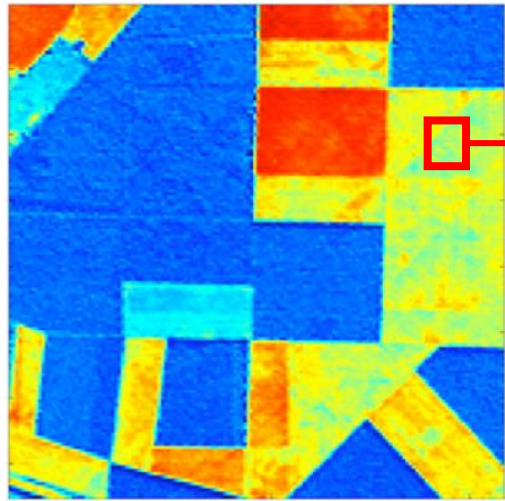
- Within the inversion process

- ✓ Atzberger 2004 (higher order statistics)
- ✓ Atzberger & Richter 2012 (common variables within a 3x3 cell and field)

□ Spatial and temporal constraints

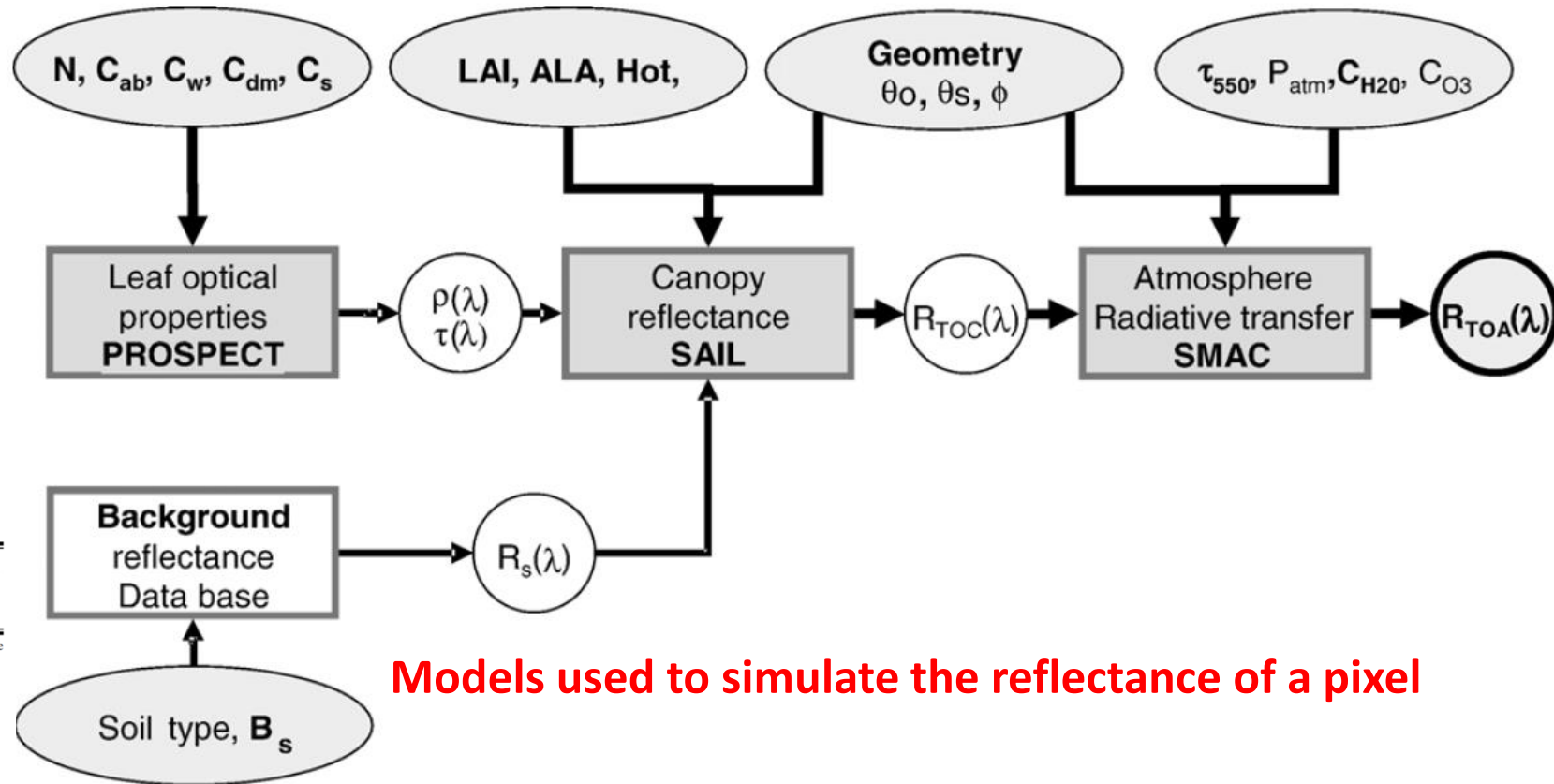
- ✓ Lauvernet et al. 2008

The proposed approach: Multitemporal-patch model inversion



For each pixel.date

$$\rho_{\text{sim}} = \text{SMAC}(\text{SAIL}(\text{PROSPECT}(N, C_{ab}, C_{dm}, C_{bp}, H) \text{LAI, ALA, } \theta_0, \theta_s, \phi), \tau_{550})$$



Models used to simulate the reflectance of a pixel



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Multitemporal-patch ensemble inversion of coupled surface–atmosphere radiative transfer models for land surface characterization

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The proposed approach: type of constraints for the input variables

□ Spatial constraints

- **Local scale ($\approx 3 \times 3$ cell depends on the heterogeneity: variogram)**

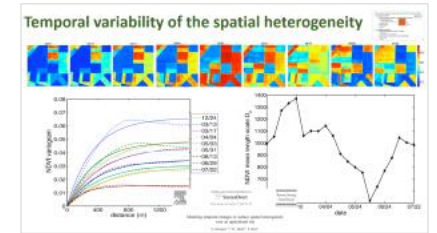
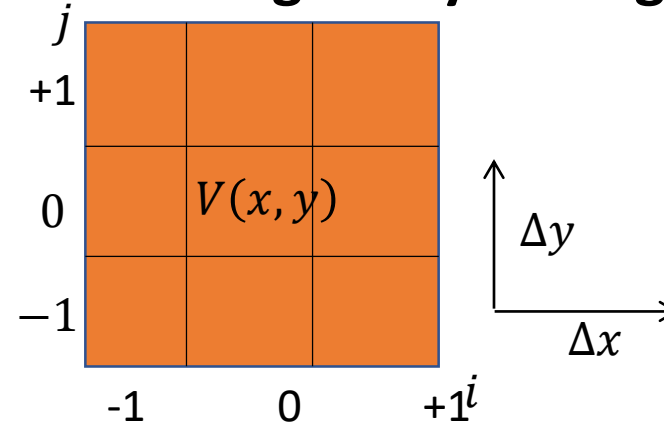
- ✓ No constraint (9 values)
- ✓ local spatial gradient (3 values)

$$V(x + i, y + j) = V(x, y) + i\Delta x + j\Delta y$$

- ✓ Equality (1 value)

- **Field / Plot scale**

- ✓ No constraint
- ✓ Equality



□ Temporal constraints

- **Local scale (small temporal window $\approx 5-10$ days)**

- ✓ No constraints
- ✓ Smoothness (limited local variability)

- **Growth cycle scale (or part of it for real time estimation)**

- ✓ No constraints
- ✓ Equality

The proposed approach: possible constraints

Variables		Spatial Constraint		Temporal Constraint	
		3x3 cell	Field	local	cycle
Background	Ref. Spectra	gradient	-	-	Equality
	Brightness	equality	-	-	-
Canopy	LAI	gradient	-	-	Dyn. Model
	Cab	gradient	-	Smoothness	-
	Other	-	equality	-	Equality
Atmosphere	All	equality	equality	-	-

The proposed approach: the constraints actually used

Considering

- a small portion of land (<km²)
- observed at 3 dates close together

Assumptions

- Background: no constraints
- Canopy: no change with time
- Atmosphere: no change with space

		Variables		Constraints				Distribution characteristics	
				Space	Time	Mode	Standard deviation	LB	UB
Background	Bs					0.8	0.3	0.3	1.3
Leaves	N		x			1.5	1	1	4.5
	C _{ab} (μg.cm ⁻²)		x			50	30	15	100
	C _{dm} (g.cm ⁻²)		x			0.0075	0.0075	0.002	0.02
	H		x			0.8	0.05	0.65	0.90
Canopy	C _{bp}		x			0.01	0.6	0	1.5
	LAI		x			1.5	1.5	0	8.5
	ALA (°)		x			60	20	30	85
	Hot		x			0.1	0.3	0.001	1
Atmosphere	τ ₅₅₀	x				0.20; 0.35; 0.50			
	C _{H2O} (cm)	x				5.9; 2.0; 2.9			
	C _{O3} (db)	x				0.35; 0.50; 0.20			
	P _{atm} (mbar)	x				996 ; 936; 1057			
Geometry	φ (°)	x				58; 42; 41			
	θs (°)	x				46; 47; 45			
	θv (°)	x				15; 33; 2			

The proposed approach: limitation of the number of unknowns

$N(p,d)$: number of pixels and dates considered

p number of pixels

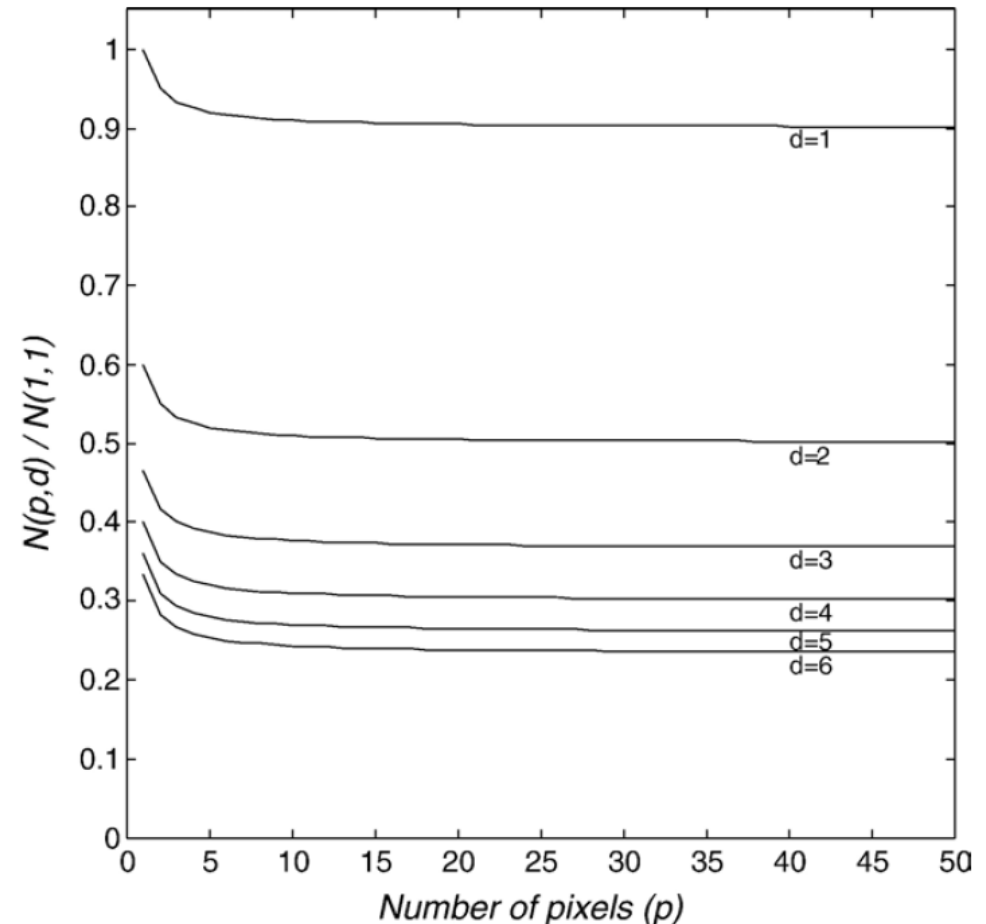
d number of dates

$$N(p,d) = d \cdot N_a + p \cdot N_c + d \cdot p \cdot N_b$$

$N_b=1$ Number of variables for the background

$N_c=8$ Number of variables for the canopy

$N_a=1$ Number of variables for the atmosphere



**The fraction of unknowns ($N(p,d)/N(1,1)$) does not vary much after 5 pixels extent and 3 observation dates
Application for $p=25$ and $n=3$**

The proposed approach: implementation

$$\rho_{\text{sim}} = \text{SMAC}(\text{SAIL}(\text{PROSPECT}(N, C_{\text{ab}}, C_{\text{dm}}, C_{\text{bp}}, H) \text{ LAI, ALA, Hot, Rs}), \tau_{550}) = M(A, C, \text{Bs})$$

Inversion (parameter estimation) using a variational approach: L-BFGS-B: quasi-newton algorithm to minimize the following cost functions:

- Single pixel and date solution:

$$J_{i,j}(A, C, \text{Bs}) = \sum_{\lambda} \frac{(\rho_{\text{mes},i,j} - \rho_{\text{sim}})^2}{\sigma_{\text{mes},i,j}^2} + \frac{(A - A_0)^2}{\sigma_A^2} + \frac{(C - C_0)^2}{\sigma_C^2} + \frac{(\text{Bs} - \text{Bs}_0)^2}{\sigma_{\text{Bs}}^2}$$

- Multitemporal-Patch inversion:

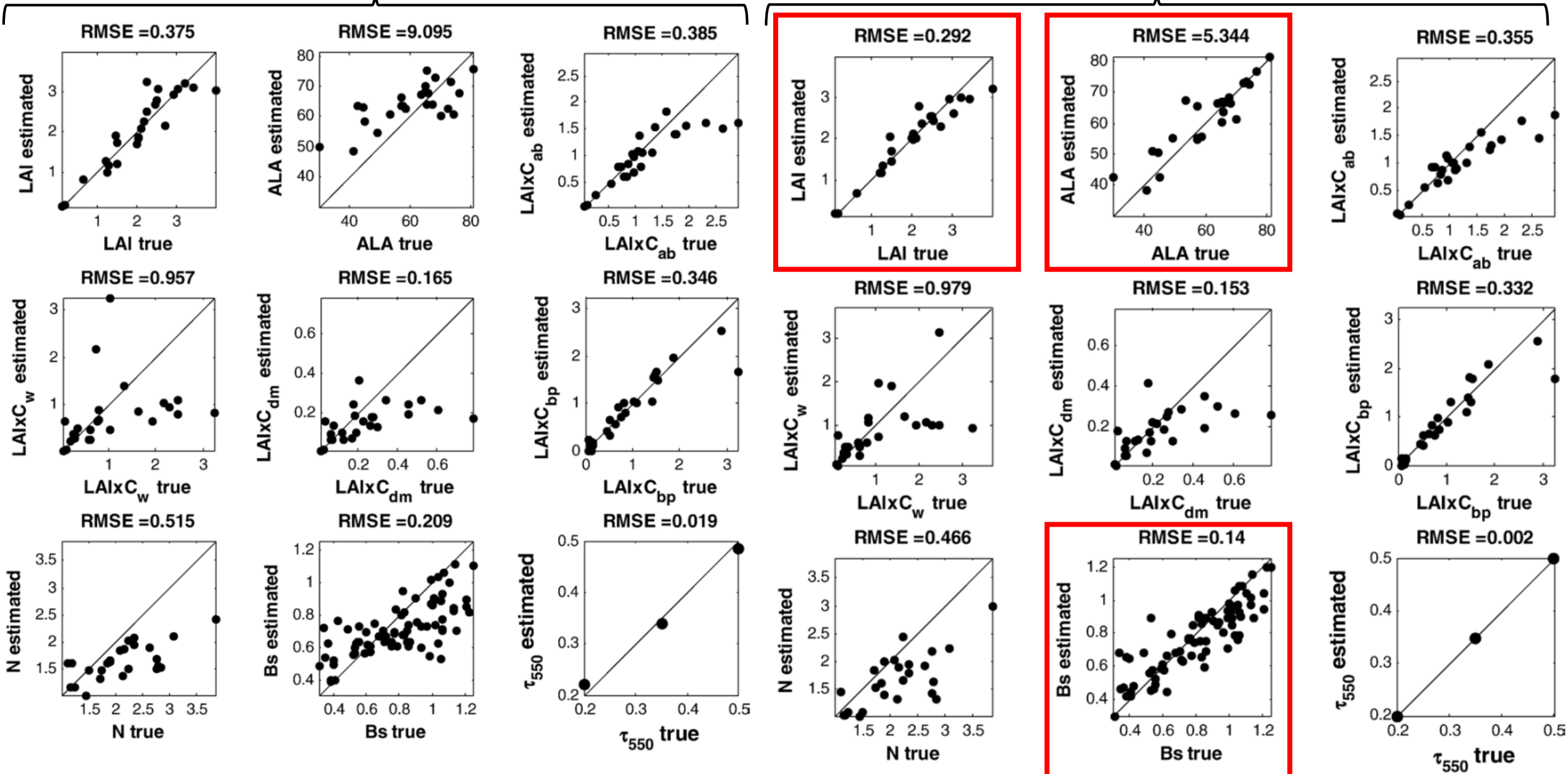
$$J(A, C, \text{Bs}) = \sum_{\text{dates}} \sum_{\text{pixels}} \sum_{\lambda} \frac{(\rho_{\text{mes}} - \rho_{\text{sim}})^2}{\sigma_{\text{mes}}^2} + \sum_{\text{dates}} \frac{(A - A_0)^2}{\sigma_A^2} + \sum_{\text{pixels}} \frac{(C - C_0)^2}{\sigma_C^2} + \sum_{\text{dates}} \sum_{\text{pixels}} \frac{(\text{Bs} - \text{Bs}_0)^2}{\sigma_{\text{Bs}}^2}$$

An adjoint model is used to compute analytically the gradient of the cost function.

The proposed approach: results

Single pixel.date inversion

Multitemporal-Patch inversion



Conclusion on the proposed approach

- ❑ Efficient for few variables that are known to be sensitive to compensation effects (LAI, ALA, Bs)
- ❑ Some variables appear to be almost insensitive: the atmosphere
The atmospheric signal is very different from that of the canopy
- ❑ The proposed approach was based on model simulations. Need to be tested over actual observations
- ❑ Probably major improvement of the approach when using a model describing the dynamics of the main canopy structure variables: LAI

CONCLUSION / PERSPECTIVES

- ❑ **Temporal constraints easy to impose and very efficient**

- ❑ **Spatial constraints more difficult because of the complexity and diversity of the spatial organization**
 - Soil
 - Environment
 - Cultural practices

- ❑ **Investigation of approaches based on process models: statistical models?**

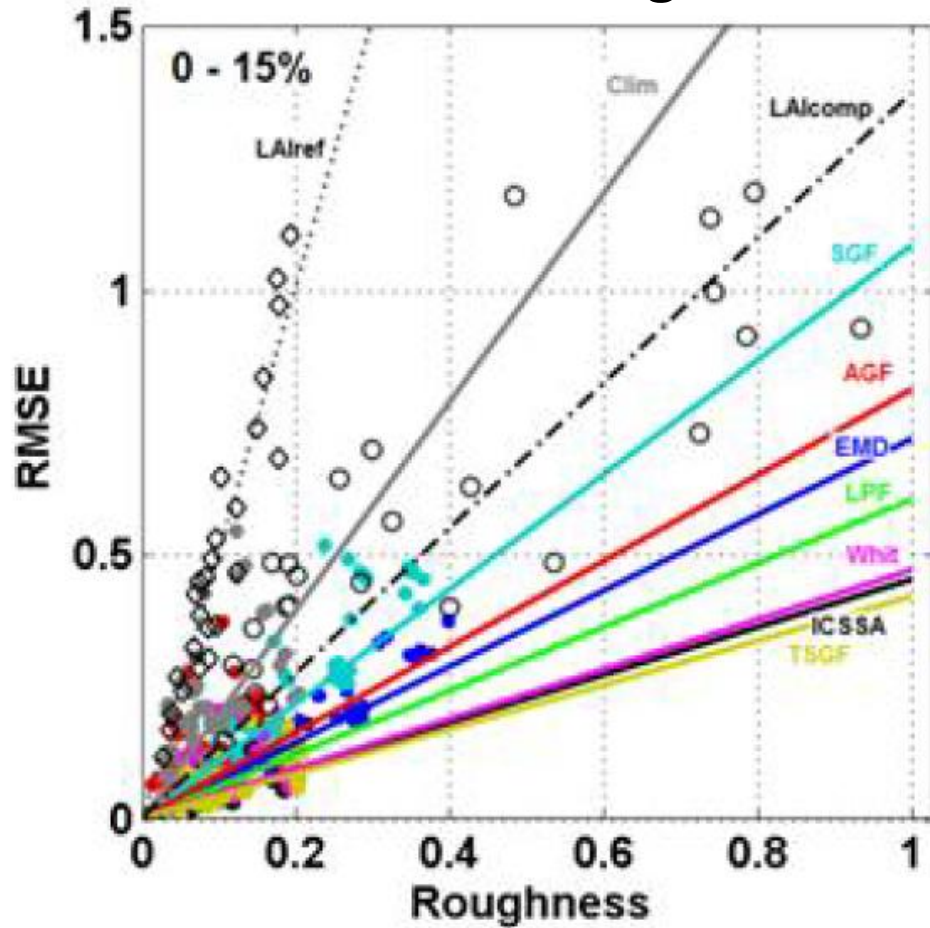
- ❑ **For phenotyping applications**
 - Tracking objects in high resolution (mm) images
 - Network of sites: assimilation in crop growth models: space= soil x environment x cultural practices



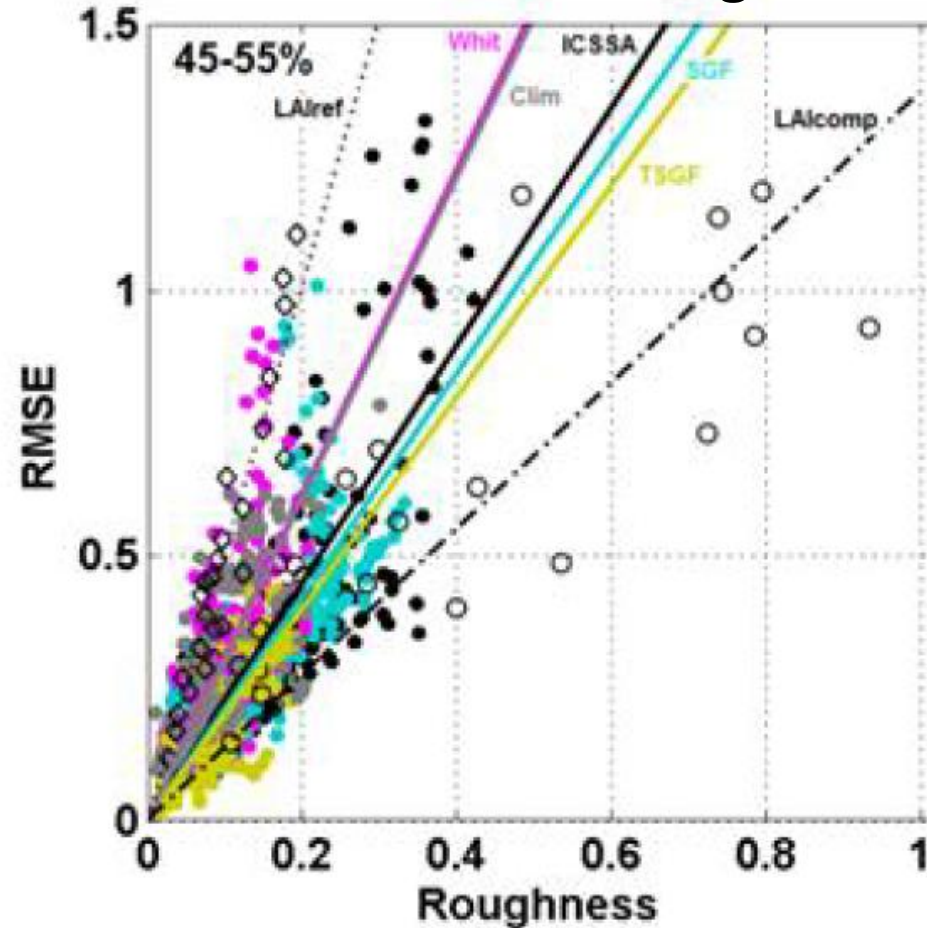
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0-15% of missing data



45-55% of missing data



Temporal smoothing methods are characterized by a particular balance between RMSE (fidelity) and roughness (smoothness)



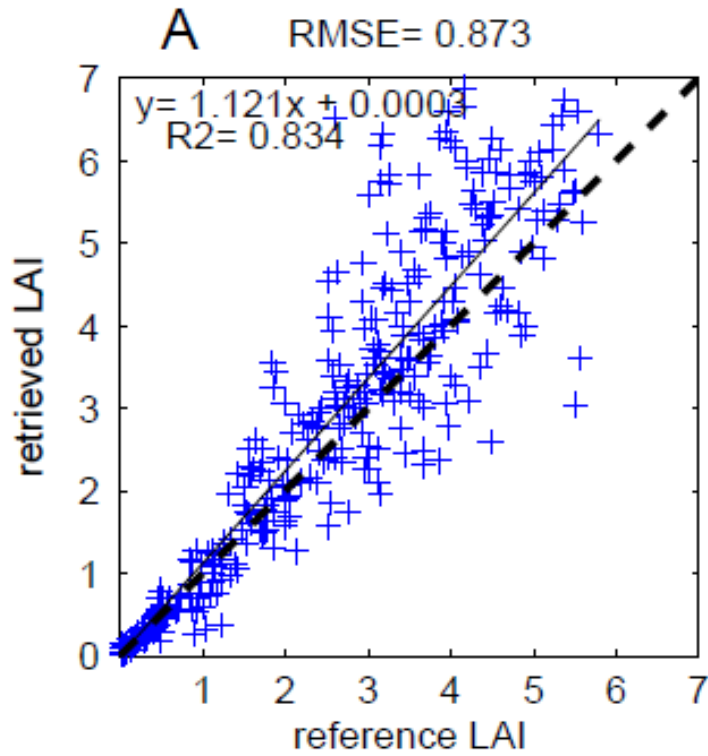
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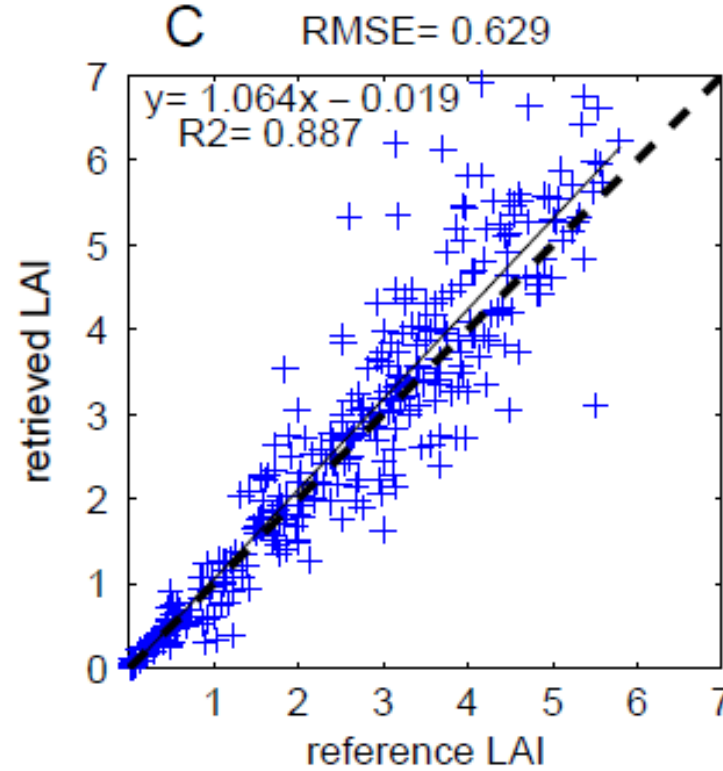
Modeling temporal changes in surface spatial heterogeneity over an agricultural site

S. Garrigues ^{a,*}, D. Allard ^b, F. Baret ^c

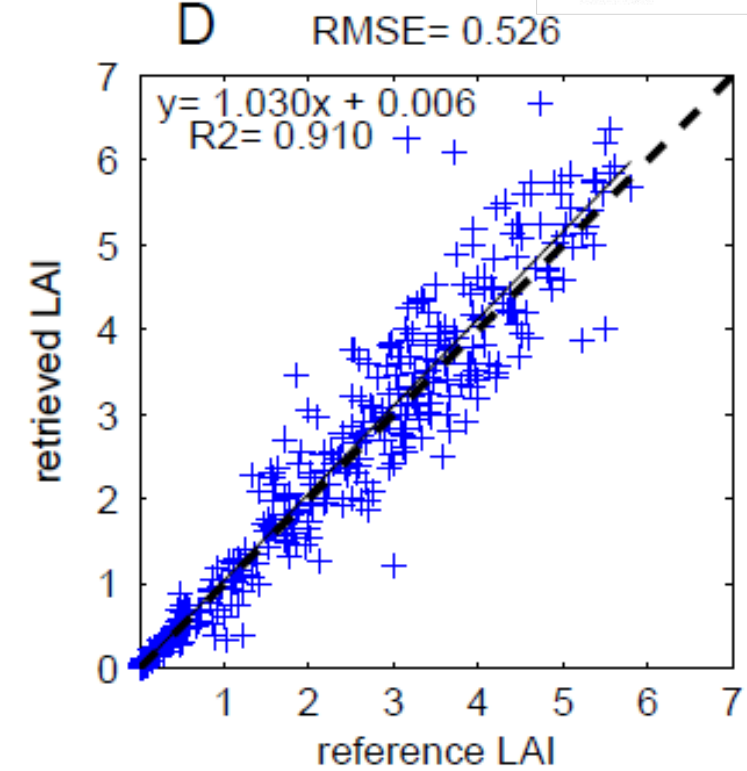
Efficacité des contraintes temporelles



Estimation indépendante pour chaque date d'observation



Estimation sous contrainte d'un Modèle de dynamique de LAI



Simple lissage temporel

Available online at www.sciencedirect.com



Remote Sensing of Environment 95 (2005) 115–124

Remote Sensing of Environment

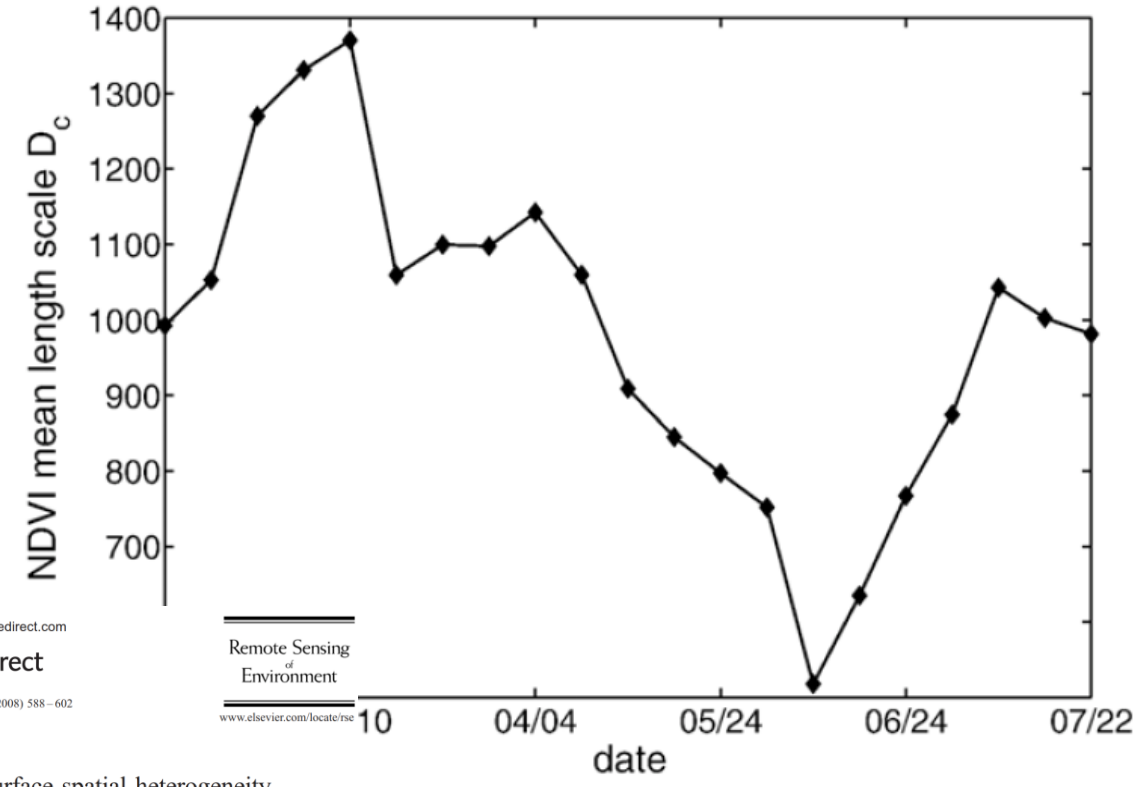
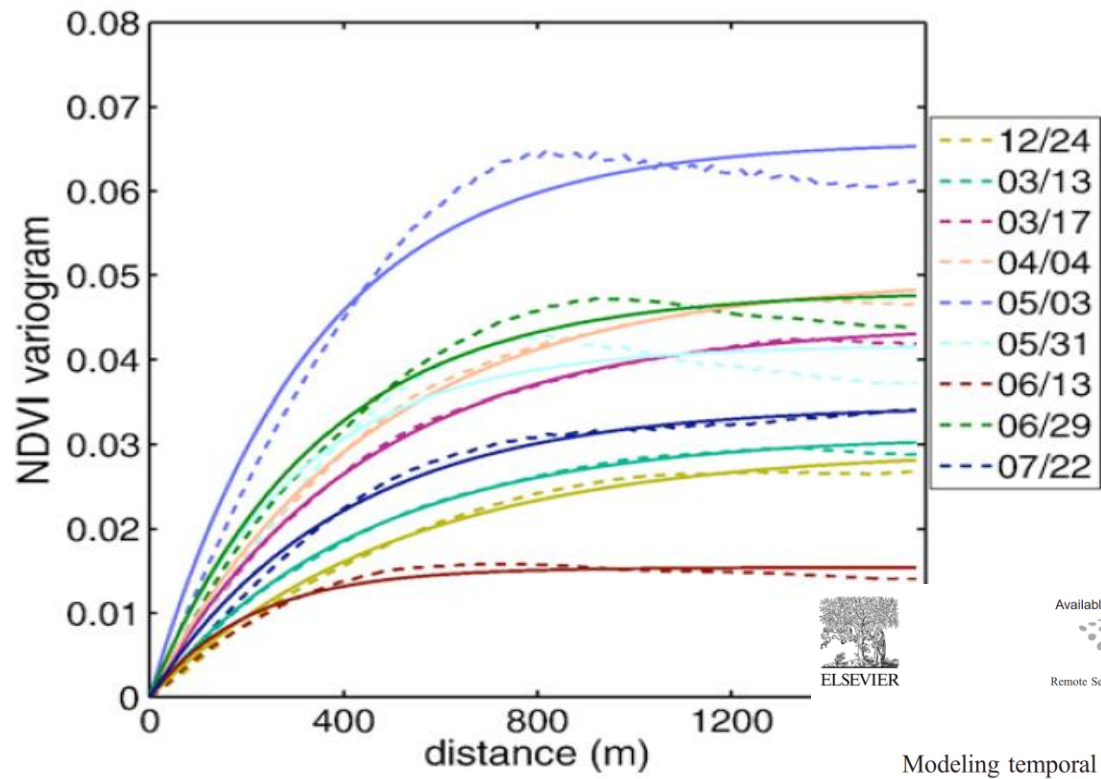
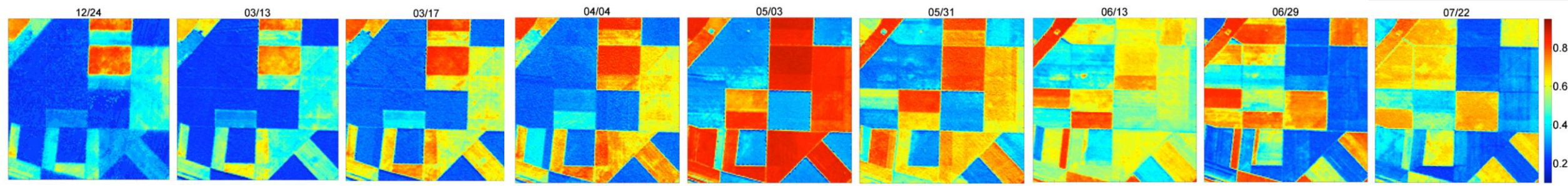
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Use of coupled canopy structure dynamic and radiative transfer models to estimate biophysical canopy characteristics

Temporal variability of the spatial heterogeneity

The proposed approach: type of constraints for the input variables

- Spatial constraints
 - Local scale (3x3 cell depends on the heterogeneity: variogram)
 - No constraint (default)
 - Local spatial gradient (D-referent)
 - $\partial^2 f(x,y) = \partial^2 f(x,y) = \partial^2 x + \partial^2 y$
 - Equality (L-variogram)
 - Field / Plot scale
 - No constraint
 - Equality
- Temporal constraints
 - Local scale (small temporal window < 10 days)
 - No constraint
 - Smoothness (small local variability)
 - Growth cycle scale (or part of it for real-time estimation)
 - No constraint
 - Equality



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Modeling temporal changes in surface spatial heterogeneity over an agricultural site