Sub-pixel temperatures estimation based on the assimilation of coarse resolution thermal infrared LST using particle filtering

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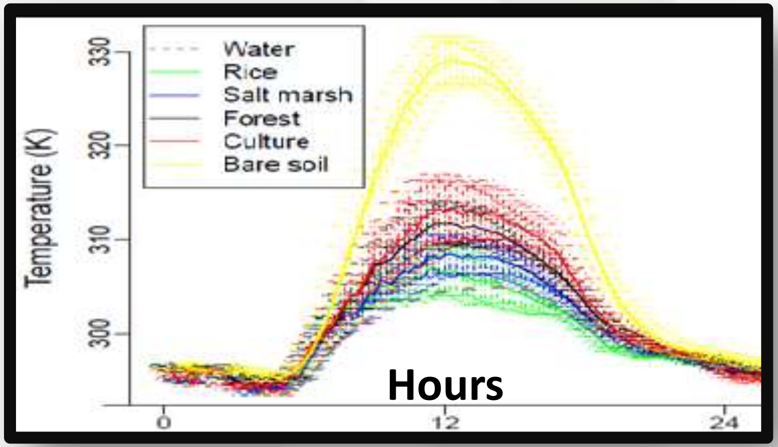
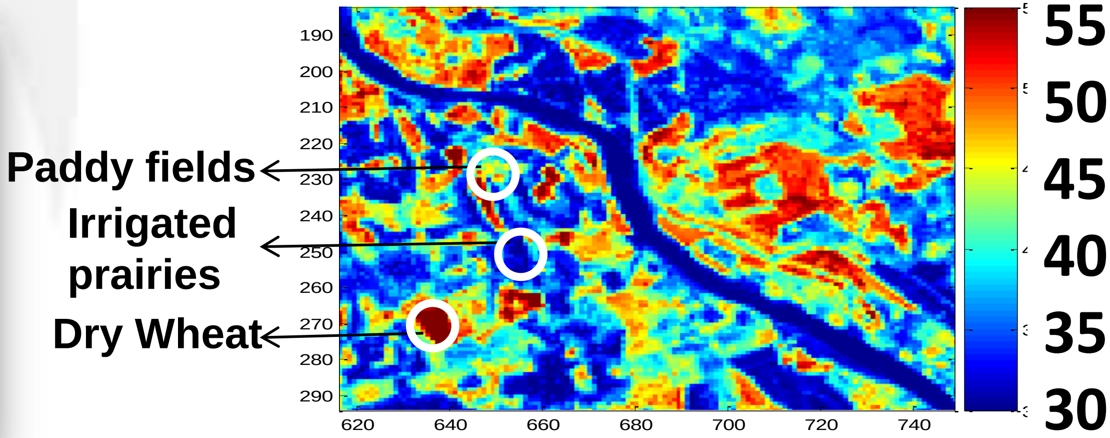
- **LST is a key variable to monitor energy & hydric budgets.**
- **It can be estimated from space , from TIR radiometers .**

	Spatial resolution	Temporal resolution
SEVIRI (MSG)	3000 -5000 m	15 min
MODIS	1000m	~1day
AVHRR	1000m	~2-4 days
ASTER	90m	~ 1 month



➔**High temporal variability**

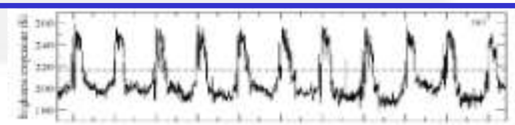


➔**High spatial variability & heterogeneity**

Introduction

- ❑The monitoring of surface budgets requires :
  - ❑To implement methods to estimate high spatial resolution LST from the only up-scaled and irregular observations .
- ❑What we NEED:
  - ❑A model to provide prior LST estimates and to assimilate the up-scaled observations.
    - ➔Land Surface Model (LSM) :
    - ▪ calculates the energy and hydric budgets
    - ▪ calculates the different interactions between soil-vegetation-atmosphere.
    - ▪ **calculates the time evolution of LST**

Problem position



SEVIRI, 3-5km, Mixed LST pixel

+

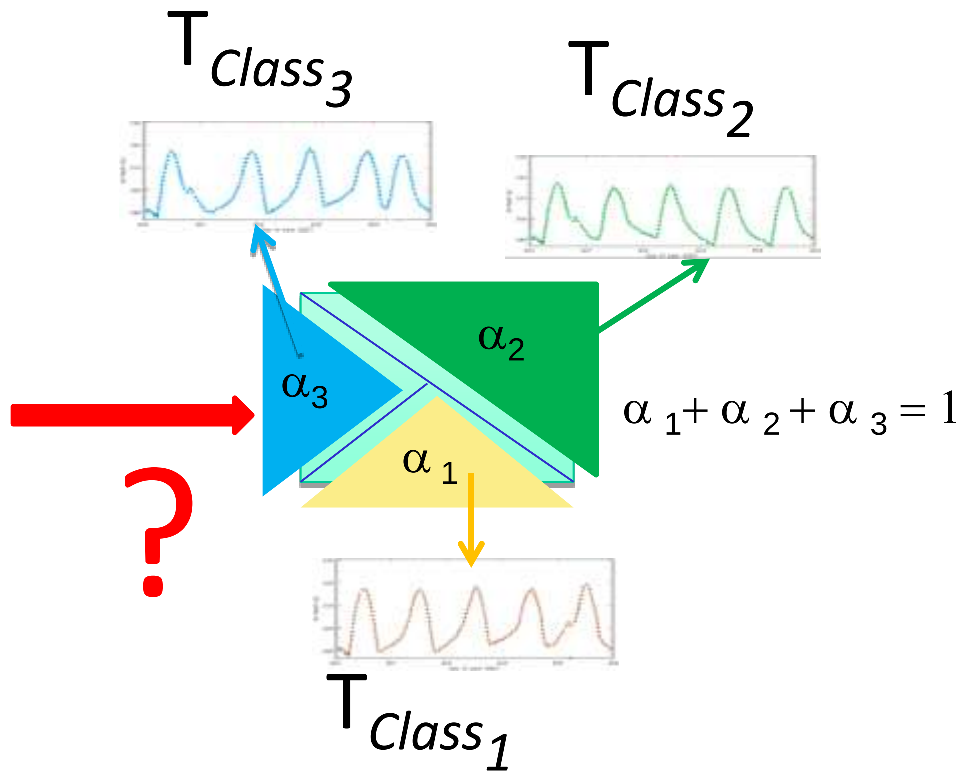
Land Cover map, 20m

+

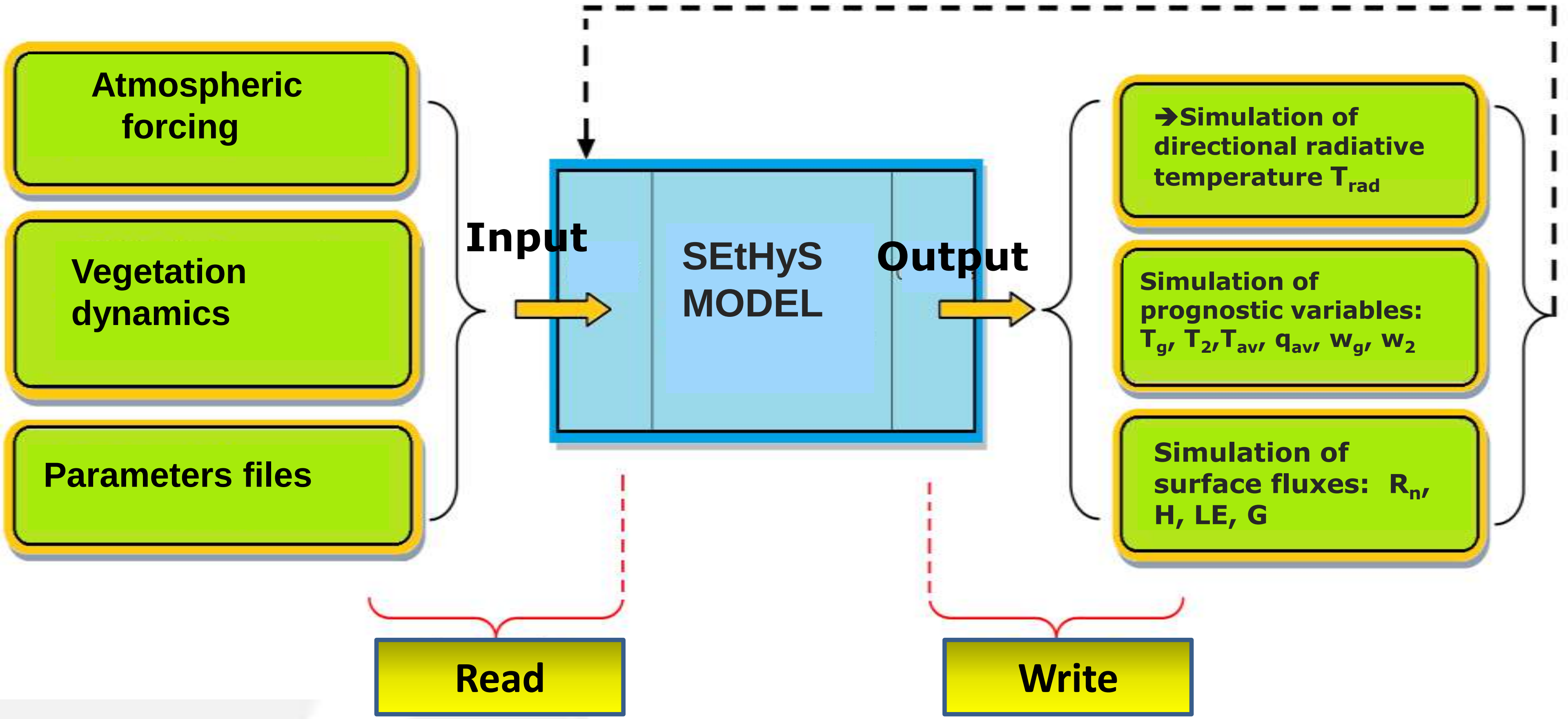
Prior surface temperatures of the N Land cover classes provided by a LS model

+

Data assimilation scheme



Quick insight of the SEtHyS Model



➔SEtHyS will be used to simulate the sub-pixel temperature (T_{class_i})

➔Some of SEtHyS parameters will be calibrated in the downscaling procedure

Data assimilation technique

Particle Filtering (PF)

What's a PF?

- A PF is an ensemble method based on Monte Carlo Sampling to approximate a probability distribution with a discrete sum of samples (ensemble members). It's an ensemble, numeric solution of the Bayesian filtering problem.

Why PF??

- Highly non linear model
- Low dimension problem (finite number of parameters, low number of land classes, etc.)
- Interesting computing time
- facility in PF implementation
- Etc.

Particle Filter general algorithm

Considering a set of particles at the time q=0 ; $\{x_{1,0}, x_{2,0}, x_{3,0}, \ldots, x_{N,0}\}$

➔ Monte Carlo Sampling : $p(x_0) \approx \frac{1}{N}\sum_{i=1}^{N} \delta_{x_{i,0}}(x_0 = x_{i,0}) \quad , N >> 1$

➢ *For all times q we have:*

– ***Prediction:*** $p\left(x_{i,q} | x_{i,1:q-1}\right) \propto p\left(x_{i,q} | x_{i,q-1}\right)$

– ***Analysis / weighting :*** $p(x | y) = \sum_{i=1}^{N} w_{i,q}\, \delta(x_q - x_{i,q})$

with: $w_{i,q} = \frac{p(y_q | x_{i,q})}{\sum_{i=1}^{N} p(y_q | x_{i,q})}$ is the weight associated to the i-th particle

– ***Selection/ resampling :*** $p(x_q) \approx \frac{1}{N}\sum_{i=1}^{N} \delta_{x_{i,q}}(x_q = \hat{x}_{i,q})$

Where $\hat{x}_{i,q}$ presents the most suitable particles selected with the selection/resampling algorithm (genetic algorithm).

Coupling PF with SEtHyS model

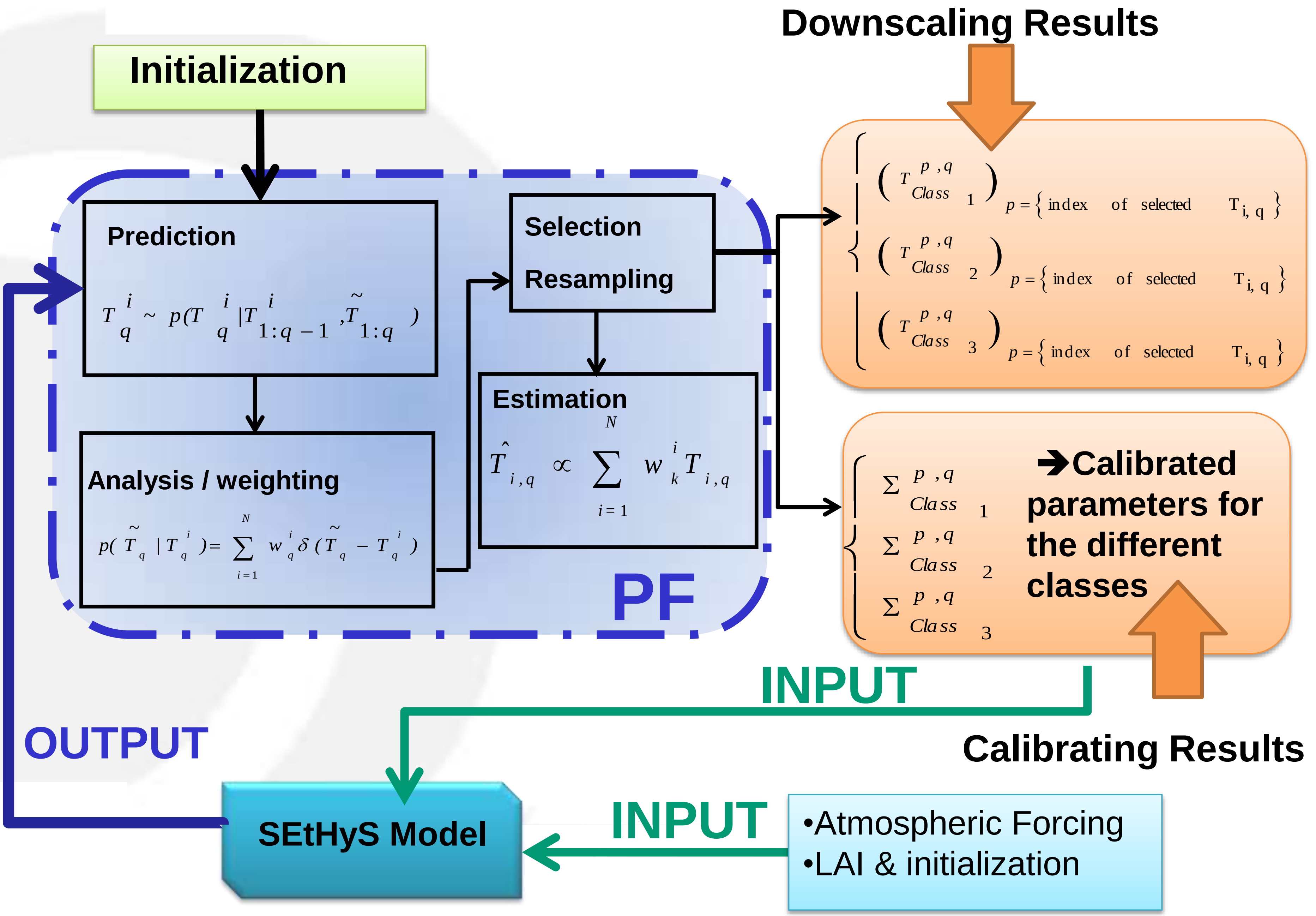
- **What's a particle?** ➔ **The up-scaled LST & the corresponding set of parameters (simulated with SEtHyS model)**
- **Initialization:** **For each land cover we:**

• **Randomly generate an ensemble of 'N' samples for the selected parameters (M parameters / class) with their range of variation**

• **Simulate the initial temperatures relative to the N samples with SEtHyS model on a daily time window.**

- **Assimilation window proceedings**
  - **SEtHyS prediction: computation of the simulated sub-pixel temperatures.**
  - **Particle filtering.**
  - **Actualization of the particles ensemble to be used for model propagation for the next assimilation window.**

Coupling PF with SEtHyS model :General loop scheme



Experience framework

- Initialization step

– Create a synthetic pixel containing 3 land covers equally distributed (forest, wheat and bare soil).

– Use the meteorological forcing of Crau 2006.

– Previous sensitivity analysis : selection of the most sensible parameters (from 22 initial parameters we select 5 parameters / class).

– Generate reference sub-pixel LST for the different classes.

– Create the up-scaled observation using the reference sub-pixel temperatures as follows:

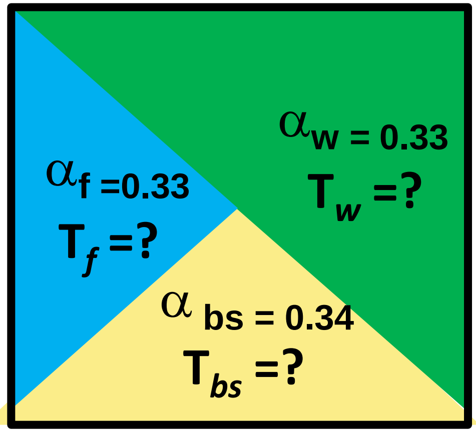
$$T_{obs} = \frac{\left(\alpha_{bs}\sigma_{bs}T_{bs}^{4} + \alpha_{w}\sigma_{w}T_{w}^{4} + \alpha_{f}\sigma_{f}T_{f}^{4}\right)}{\alpha_{bs}\sigma_{bs} + \alpha_{w}\sigma_{w} + \alpha_{f}\sigma_{f}} + N\left(0, \sigma_{obs}\right)$$

– Generate the initial N sets of parameters (definition of parameter space) for the different land covers and simulate the corresponding sub-pixel temperatures .

– Calculate, for each set of parameters, the up-scaled temperatures.

– Proceed to the general loop of PF coupled with SEtHyS .

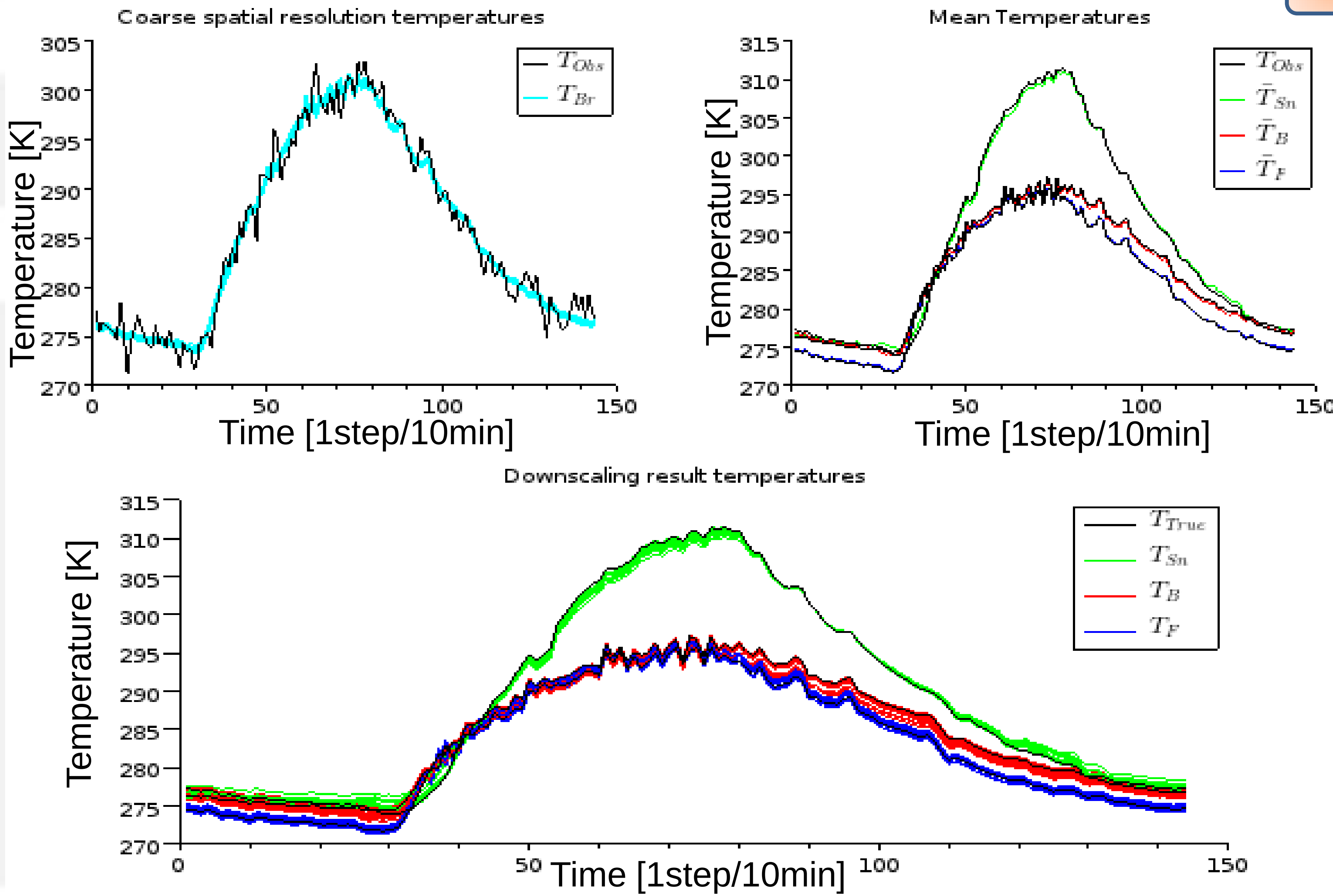
Experience framework



❑ Experience specifications

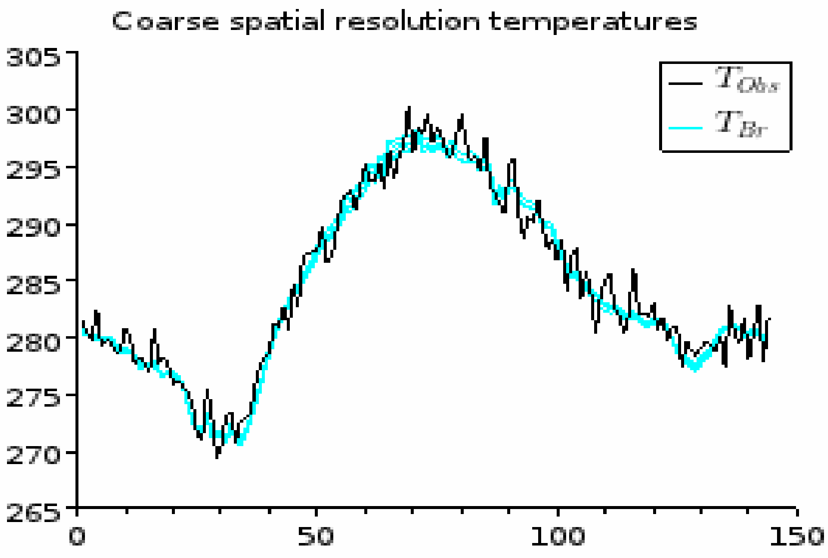
- Assimilation period = 1day
- Observation frequency =1obs/10min
- Observation error variance = 1.5 K
- Size of particles ensemble N= 200
- Number of calibrated parameter/land cover =5
- Total duration of the assimilation experiment= 20 time windows = 20 days = day94 → day 114 of the year 2006
- Resampling Noise = N(0,0.01)

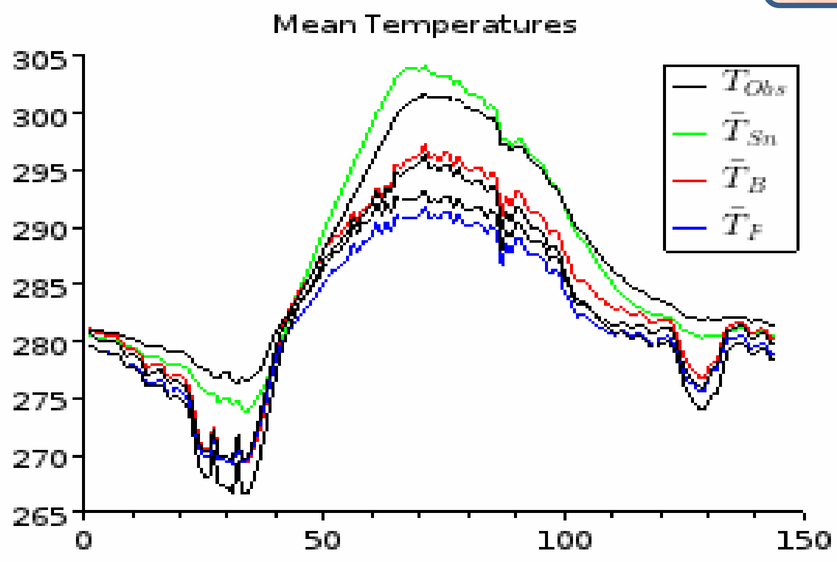
Downscaling results

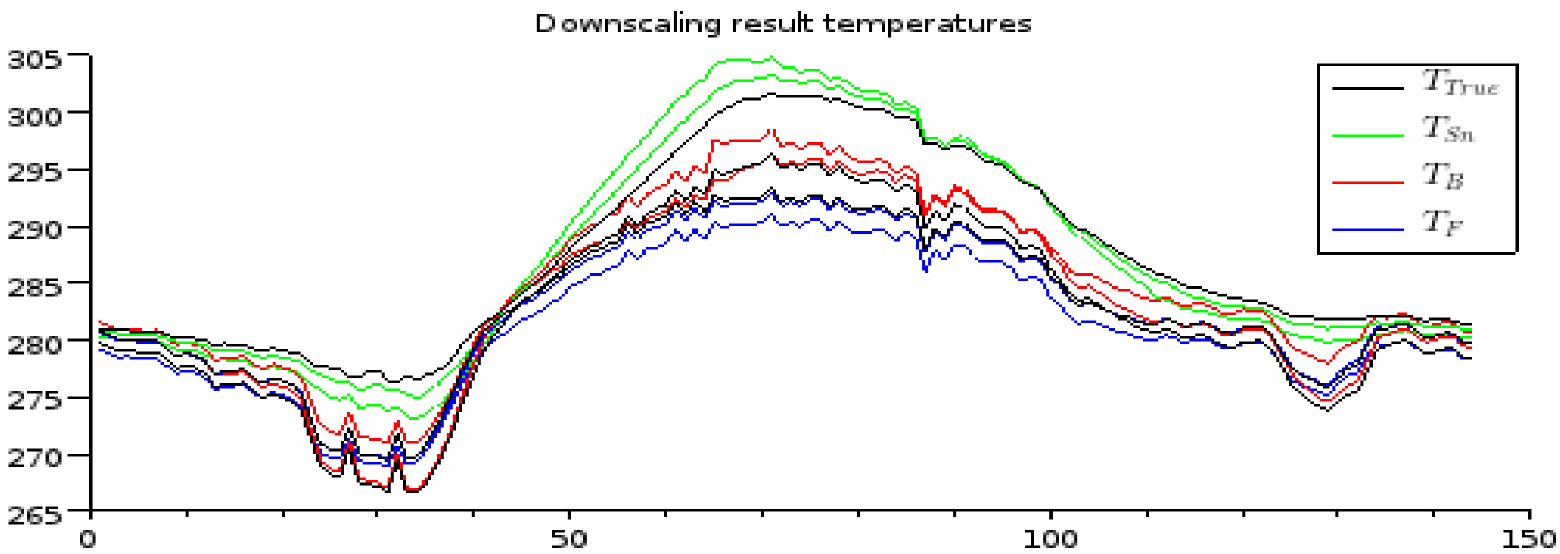


Downscaling result for the 20th assimilation window

Downscaling results



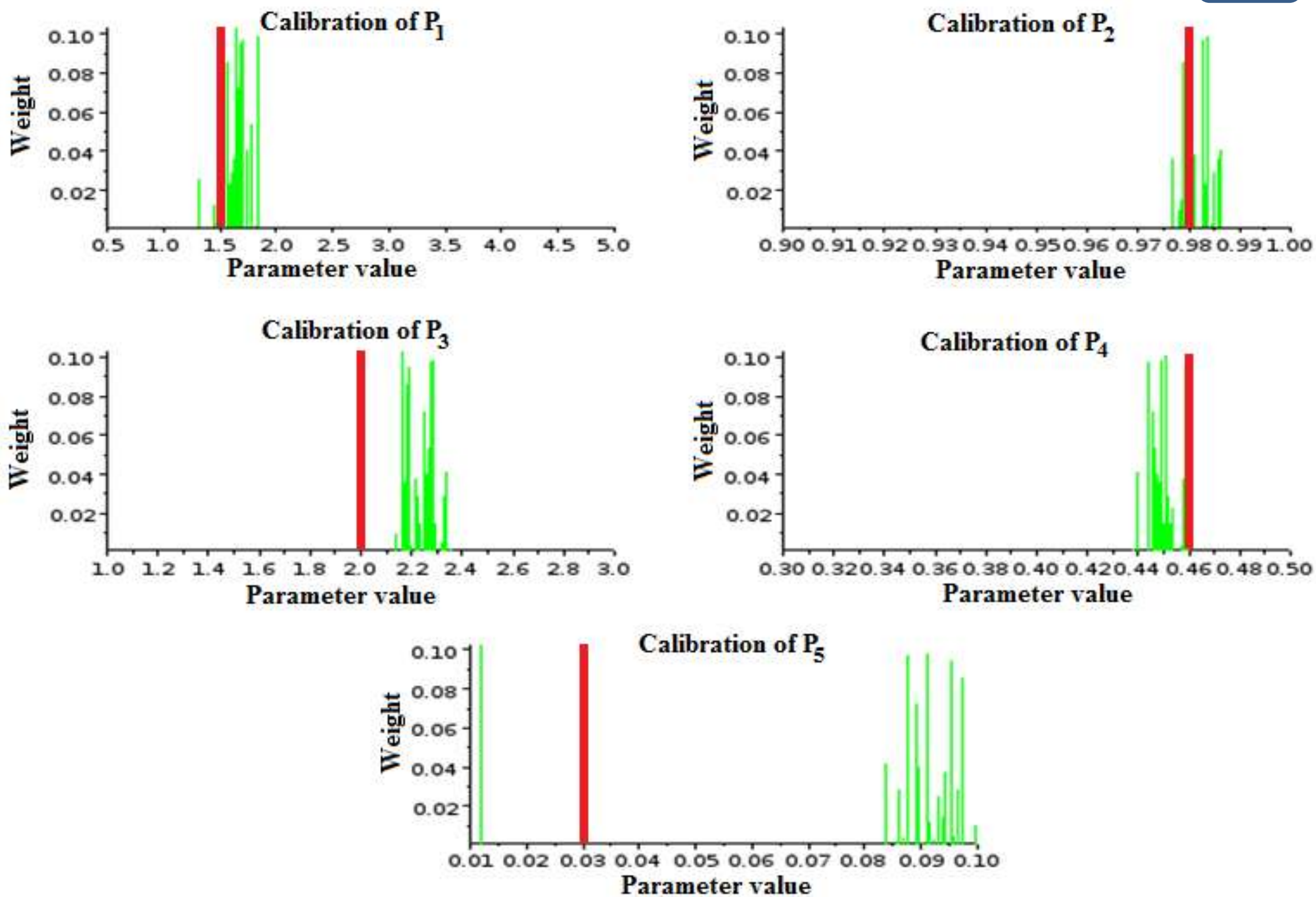




Downscaling result for the period day 94 → day 114

Calibration results

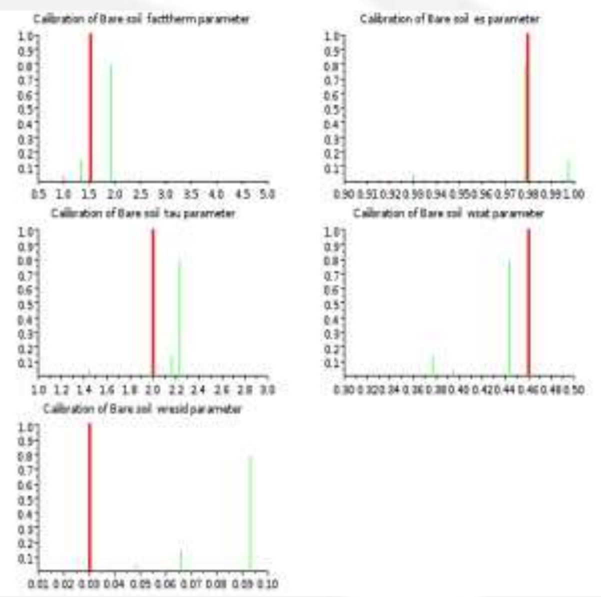
- Bare soil

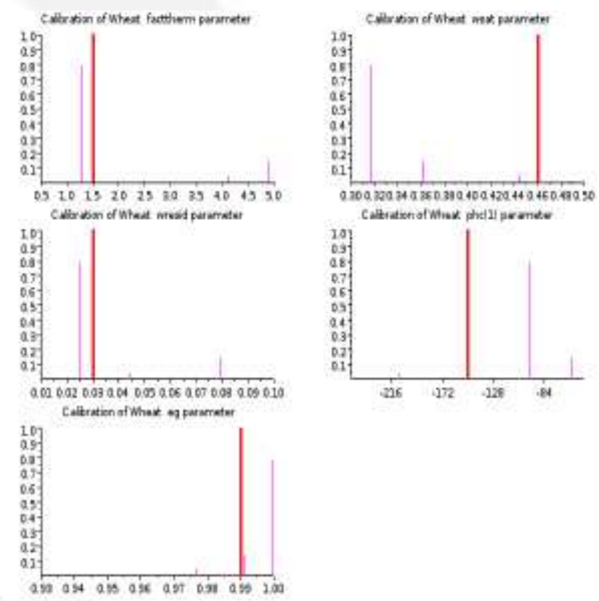


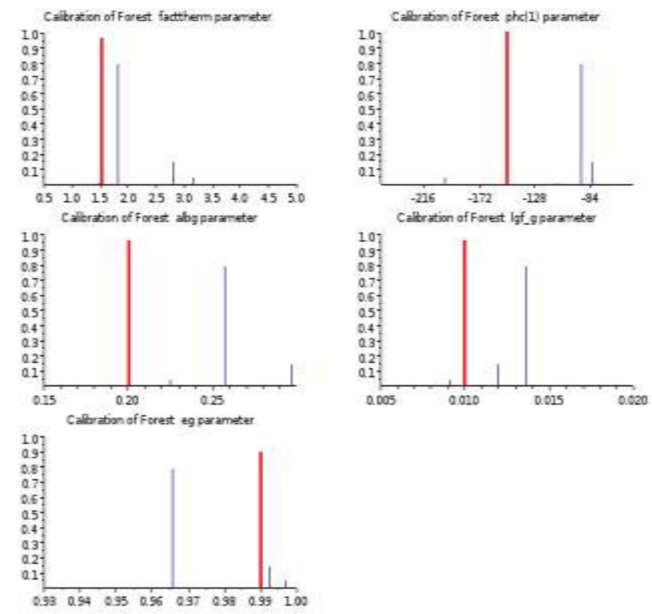
Calibration results for result for the 20th assimilation window

Calibration results

- Bare soil
- Wheat
- Forest







Calibration results for the period day 94 → day 114

Particle Filtering efficiency

❖Experience framework:

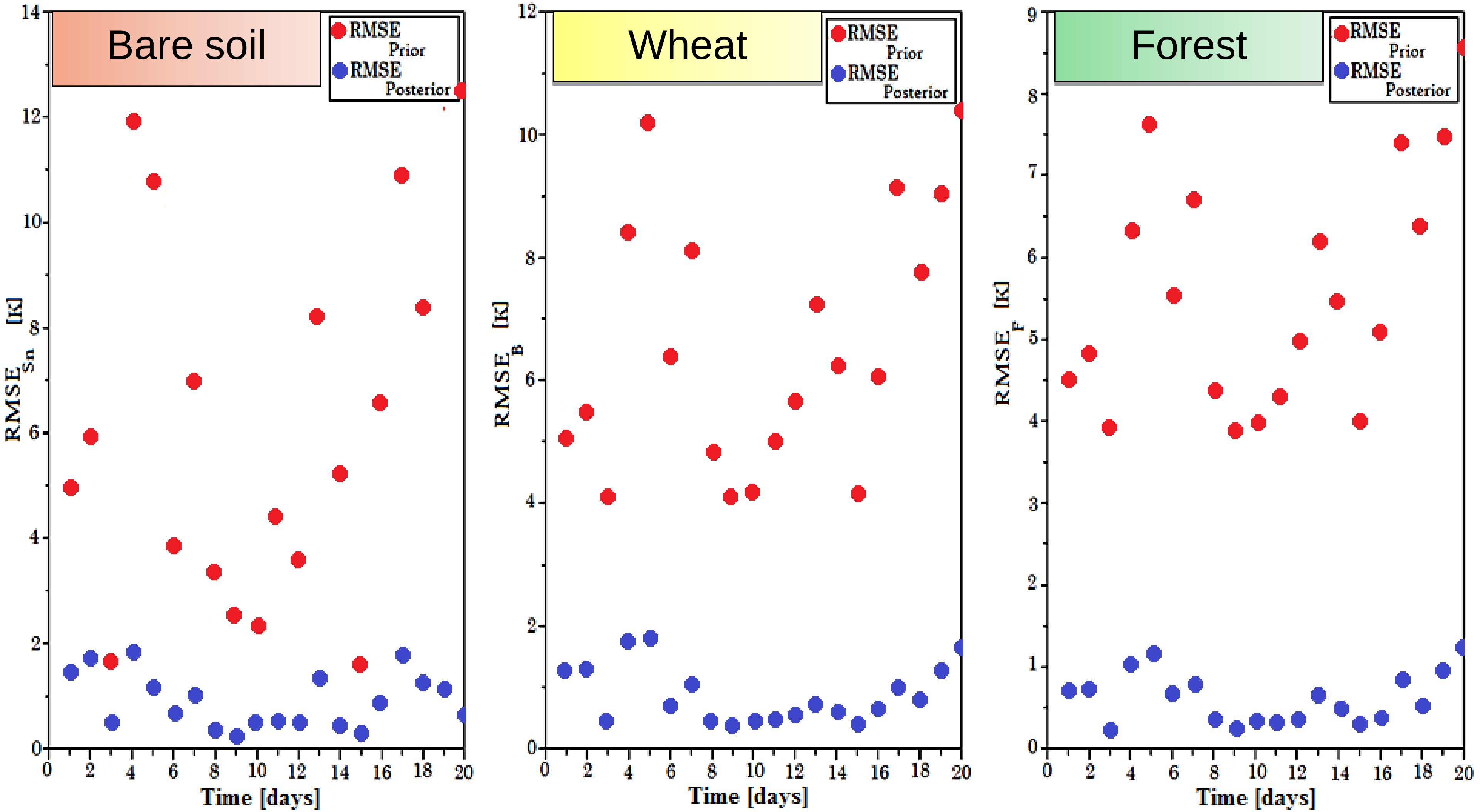
- Time window= 1day
- Observation frequency =1obs/10min
- Observation error variance = 1.5 K
- Size of particles ensemble N= 200
- Number of calibrated parameter/land cover =2 (bare soil :P_1= $fact_{therm}$, P_2= e_s; forest: P_1= $fact_{therm}$, P_2= e_g ; wheat : P_1= $fact_{therm}$, P_2= e_g)
- Assimilation period = 20 time windows = 20 days = day94 → day 114 of the year 2006
- Resampling Noise = $\mathcal{N}(0,10^{-2})$

❖The efficiency index is evaluated as follow : $$I = mean_{10\ experiences}\left(1 - \frac{RMSE_{posterior}}{RMSE_{prior}}\right)$$

❖We repeat the experience 10 times and average the results on 10 experiences.

Bare soil	Wheat	Forest
I=0.85	I=0.78	I=0.89

Particle Filtering efficiency



Impact of the observation error variance

❖Experience framework:

- Observation error variance values : σ_o = [0.5K, 0.75K,1K, 1.25K,1.5K,1.75K, 2K,2.25K, 2.5K,2.75K, 3K,3.25K, 3.5K,3.75K, 4K]
- We vary the value of the observation error variance and evaluate the RMSE for each land cover type.

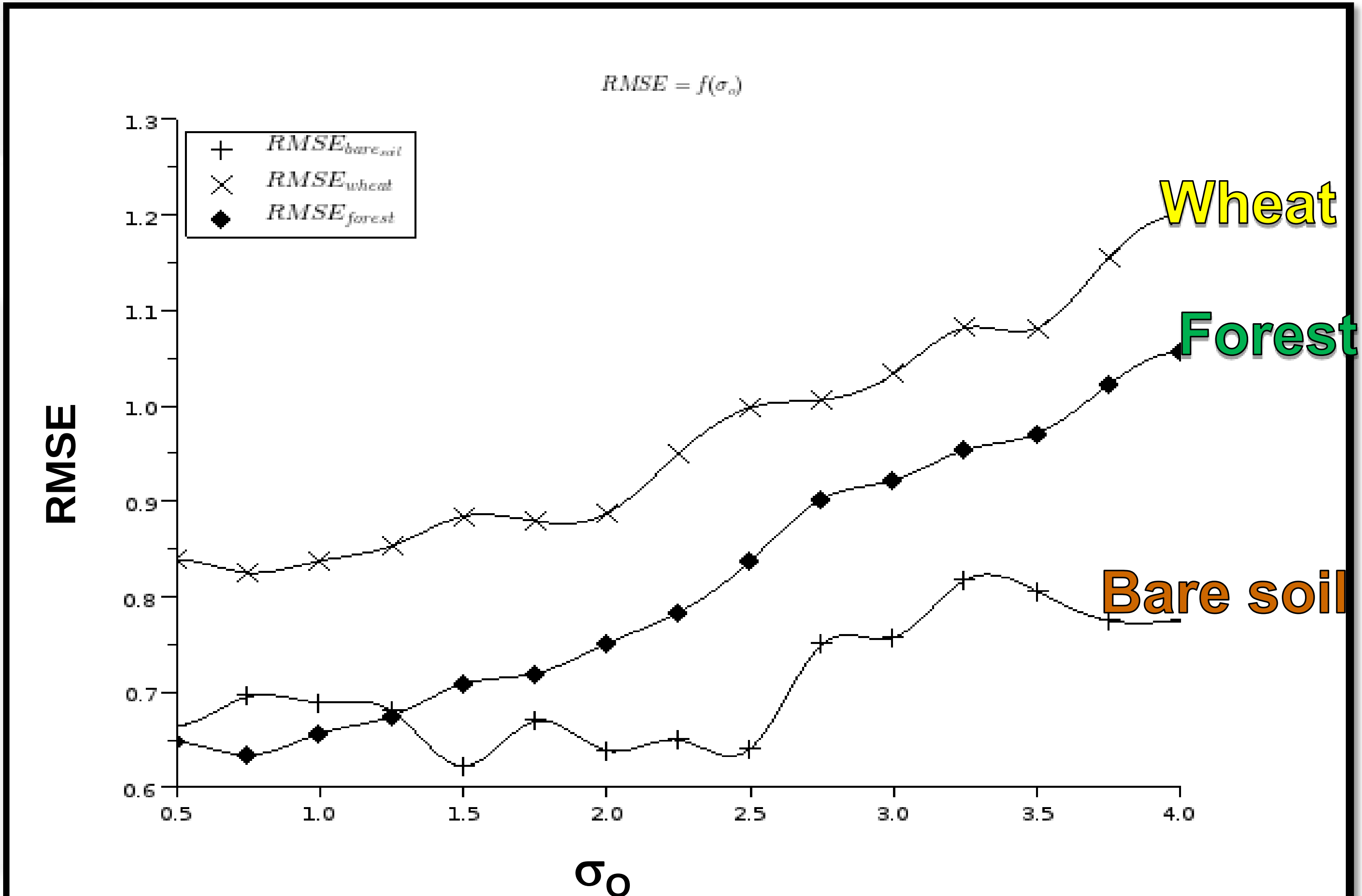
$$RMSE_{i,j} = \frac{1}{N_{period}} \sum_{m=1}^{N_{period}} \left[\sqrt{\frac{\sum_{q=1}^{K} \left(T_{ref_q}^{i,j} - T_{m,q}^{i,j} \right)^2}{K}} \right]$$

Where;

- **'i'** is the land cover index
- **'j'** is the σ_o index
- **'m'** is window index
- **'q'** is the time step index

➔We repeat the experience 19 times and average the results on the 19 experiences.

Impact of the observation error variance



Conclusion and perspectives

Conclusions

- Good performances of PF on the downscaling of low spatial resolution temperatures
- Good performances of the calibration of the most sensitive parameters
- The particle filter performances decrease with the observation error variance .

Perspectives

- ✓Application of our approach on real TIR data and at larger scale (image)
- ✓Application on multi-scale data (combine METEOSAT and MODIS data).
- ✓Compare our downscaling approach to other ones (Inamdar 2008; Inamdar 2009; Kallel & al., 2012 ; Bechtel & al., 2012)

** THANKS FOR **

** YOUR ATTENTION **