Surface Temperature Downscaling based on Genetic Particle Smoother

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Abstract

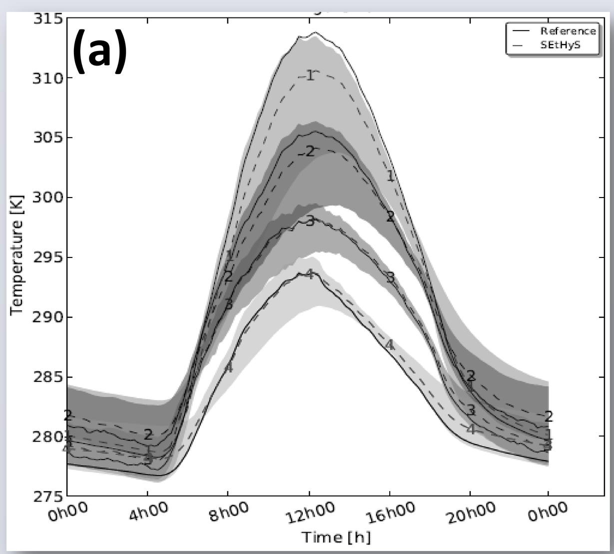
Thermal infrared (TIR) data are efficiently used for surface fluxes estimation giving the possibility to assess energy budgets through surface temperature. An accurate knowledge of such data at high spatial/temporal resolution is not possible considering the present instruments on board satellites It is then, necessary to develop methodologies to enhance both spatial and temporal resolutions to better monitor fluxes at appropriate scales. Our approach consists in the development of a new downscaling method based on the Genetic Particle Filter (*GPF*) or more precisely Particle Smoother (PS) to extract sub-pixel variables from large scale data measurements. This methodology consists in constraining surface temperatures trajectories simulated by a dynamic model and aggregated at the scale of the observations. The ***SETHYS*** land surface model [1] was used for that purpose. The first step was to develop and test our approach on a synthetic database based on the French "Crau-Camargue" region landscape and climate The synthetic case study results of PS LST downscaling approach [2] showed that *PS* performances decrease with observation error amplitude and rise with observation frequency. The second step was to apply the *PS* downscaling approach on actual data and at larger scale. The comparison based on the assimilation of *METEOSAT-**SEVIRI*** Coarse Spatial Resolution ***(CSR)*** observations and the efficiency of the downscaling method compared to ***ASTER*** High Spatial Resolution ***(HSR)*** images showed promoting results.

Synthetic case study results

Downscaling results and observation error amplitude impact on GPS performances

Table 1: Efficiency rates for different observation error amplitudes

Land cover class	$\mathcal{I}^k_{\sigma_O=0.5K}$	$\mathcal{I}^k_{\sigma_O=2.0K}$	$\mathcal{I}^k_{\sigma_O=4.0K}$
1: Bare Soil	54%	56%	53%
2: Prairie	33%	30%	26%
3: Wheat	60%	59%	54%
4: Rice	48%	46%	43%



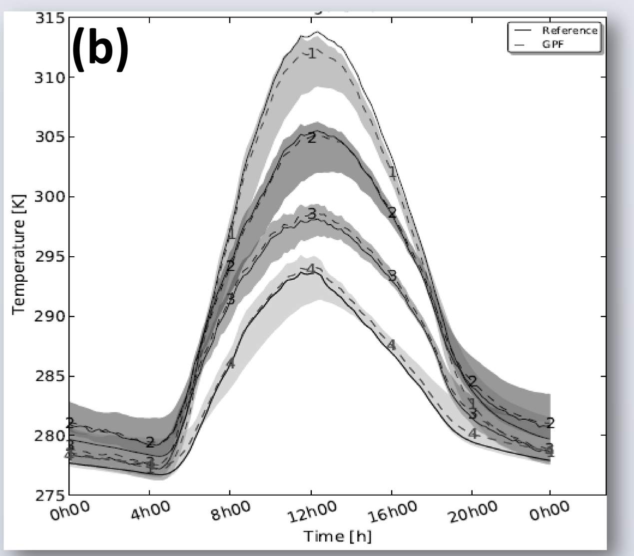


Figure 1 : Mean diurnal cycle over 20 days of assimilation. Figure (a) presents the prior downscaled temperatures compared to reference ones and figure(b) presents the GPS downscaled temperatures when CSR observation are assimilated. Line markers '1', '2', '3' and '4' design respectively 'bare soil', 'prairie', 'wheat' and 'rice' classes. Continuous lines correspond to "truth" sub-pixel temperatures.

- Efficiency rates in Table(1) show that PF performances for downscaling LST decrease with observation error amplitude.
- Figure 1 shows that assimilating CSR observations improve significantly downscaling result (RMSE(*prior*) = 1.2K, RMSE(*posterior*)=0.3K)

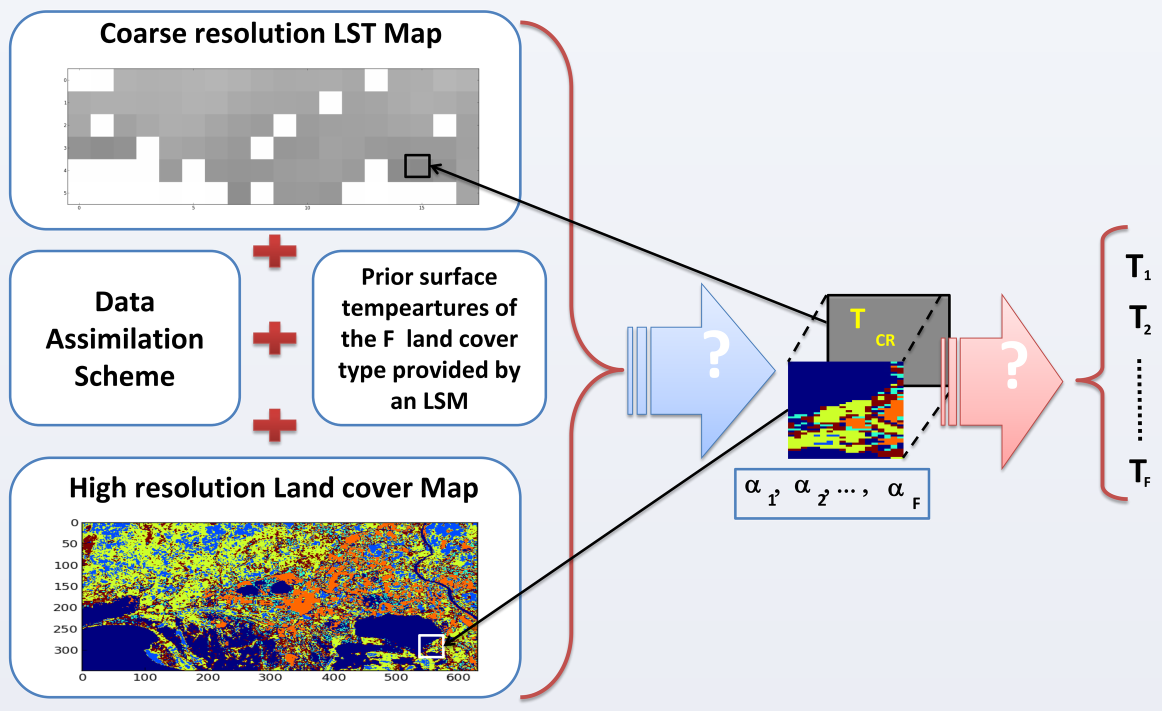
Impact of observation sampling on GPS performances

Table 2: Efficiency rates for different observation scenarios

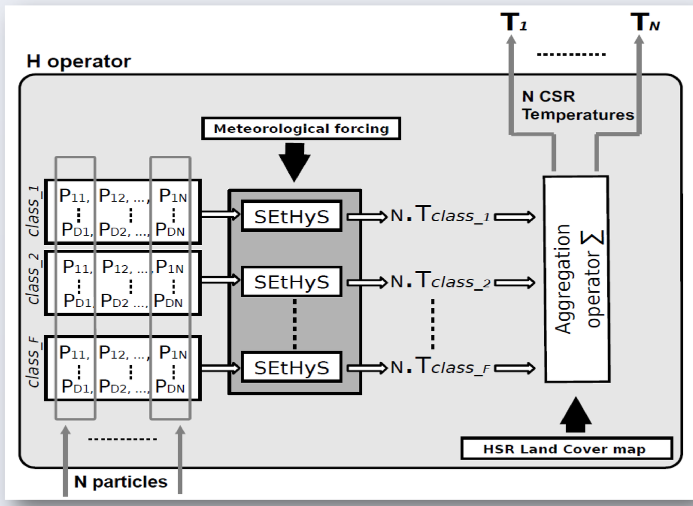
Scenario Id	Obs number	Bare soil	Prairie	Wheat	Rice
1	72	56%	30%	59%	46%
2	25	55%	26%	56%	42%
3 Daytime	13	54%	26%	55%	40%
4	1	39%	20%	44%	34%
5 Nighttime	49	55%	30%	57%	47%
6	25	53%	28%	54%	45%

- Efficiency rates in Table(2) show for the same number of observation (scenarios 2 and 6) better efficiency rates are obtained at nighttime for wet lands (prairie, rice) and inversely true for dry lands(bare soil, wheat).
- Better efficiency rates are obtained when more observations are considered.
- Result of scenario 4 (only one observation at midday) show that even with a single observation , GPS efficiency rates are still positive (RMSE(*posterior*) >RMSE(*prior*)).

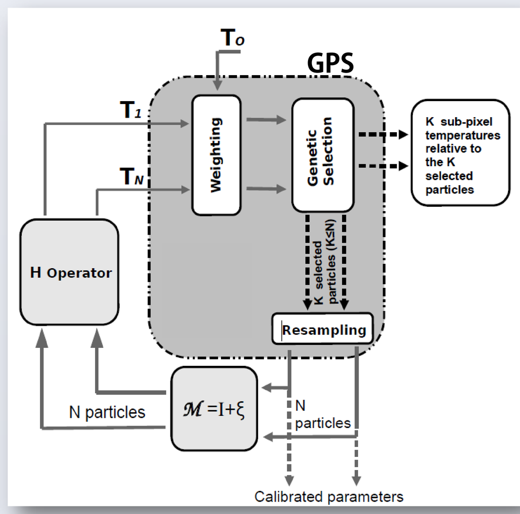
Context



Downscaling-Calibration Process Scheme



H operator diagram



Downscaling-Calibration loop diagram

Real Data Downscaling Results

Actual Data presentation

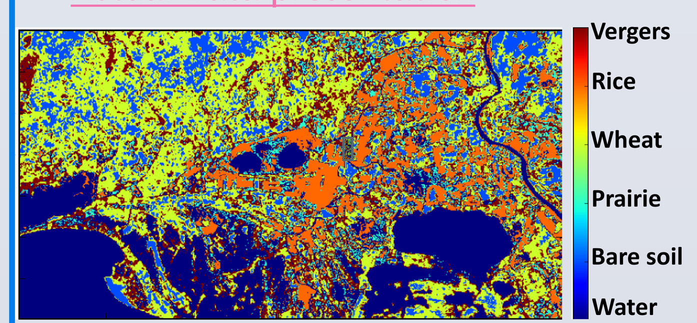


Figure 2 : ASTER 90m LAND cover/use map

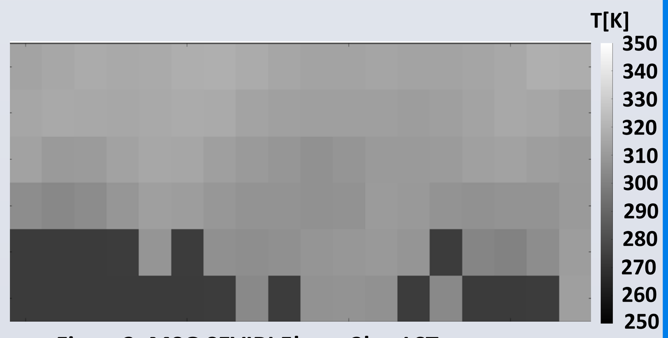


Figure3: MSG SEVIRI 5km x 3km LST map

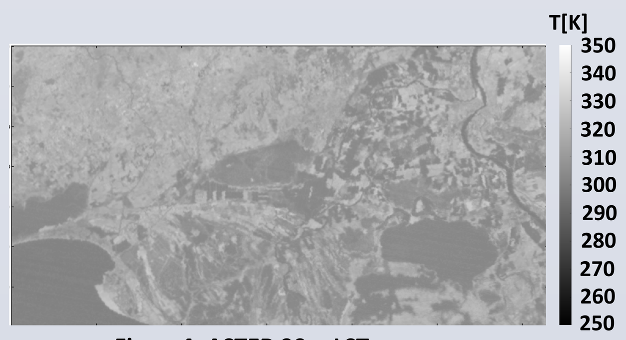


Figure4: ASTER 90m LST map

Downscaled MSG-SEVIRI LST map VS high spatial resolution ASTER LST map

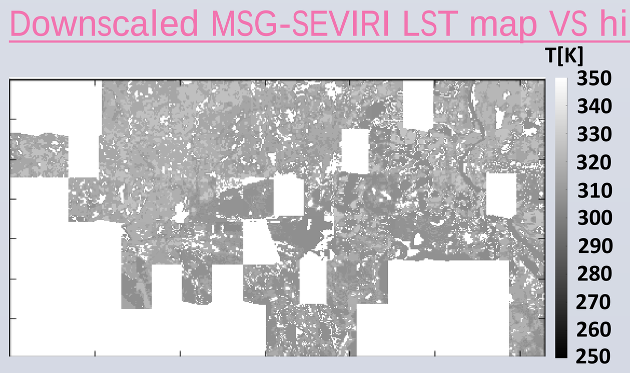


Figure 5: MSG SEVIRRI downscaled 90m LST map

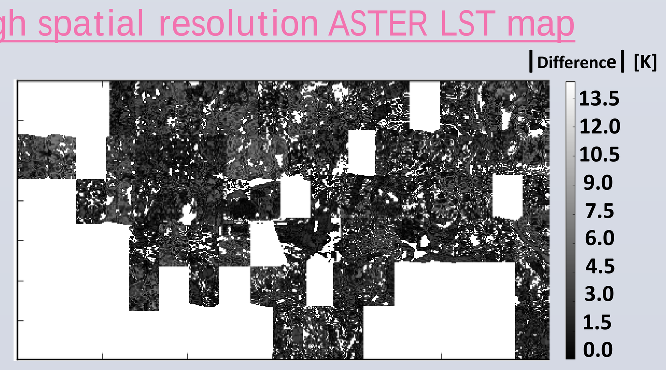


Figure 6: Absolute differnce between ASTER 90m and downscaled SEVIRI 90m LST map

Table 3: GPS downscaled LST map results

	Water	Bare soil	Prairie	Wheat	Rice	Vergers
RMSE [K]	2.9	2.8	2.2	3.0	1.8	3.4
MAE [K]	2.4	2.4	1.9	2.5	1.5	3.0
Bias [K]	-1.4	1.4	1.0	-1.9	0.7	-3.0

- Table 3 shows good performances for GPS in downscaling actual data (RMSE of the whole image is equal to 2.9K, MAE = 2.4 K and Bias = -1.14 K).

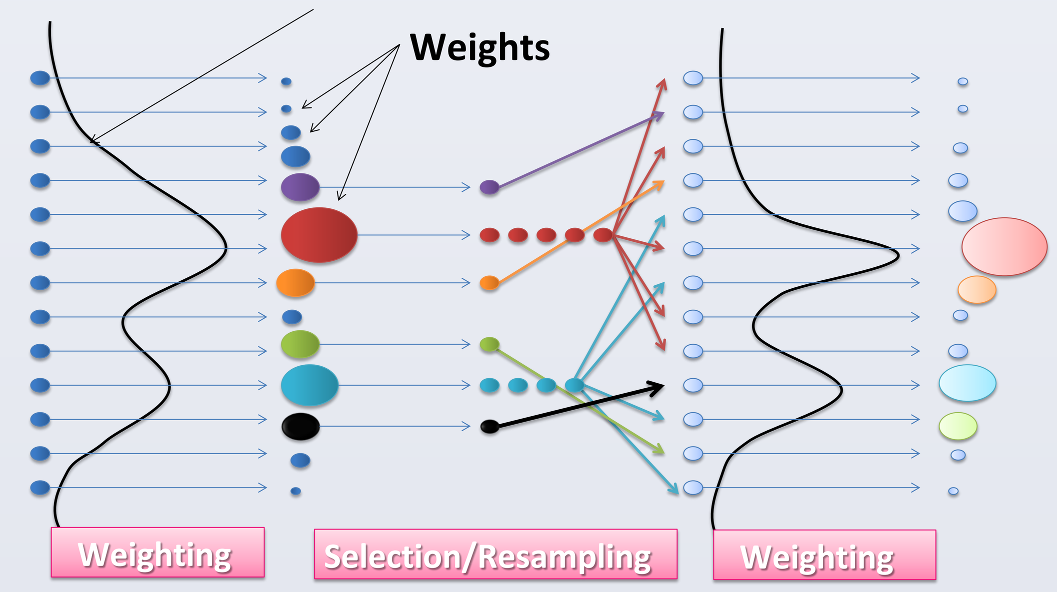
Methodology

$$\mathcal{H}(x_q^k) = \left[\frac{\sum_{i\in[1:4]} \alpha_i\epsilon_i\{SEtHyS(x_q^k)\}^4}{\sum_{i\in[1:4]}\alpha_i\epsilon_i}\right]^{\frac{1}{4}} = \left[\frac{\sum_{i\in[1:4]} \alpha_i\epsilon_i T^4_{i,q}}{\sum_{i\in[1:4]}\alpha_i\epsilon_i}\right]^{\frac{1}{4}}$$

Particle filter approach : Assimilation in a land surface model

- **In this study, we present how to use particle filtering to assimilate the coarse resolution observations in a land surface model representing the pixel heterogeneity by a tile approach.**
- **The calibration of the model parameters and initial states for each tile, allows to estimate the optimal temperature for each type of land cover/land use.**
- **The application of our downscaling-calibration is performed on a synthetic study case to assess the new approach performance and then on actual data .**

Particle Filter Scheme



Conclusions

- Good performances of GPS in downscaling low spatial resolution temperatures in both synthetic and real cases.
- Consider spatial correlation to better estimate sub-pixel temperatures for adjacent pixels (posterior correction, estimation of spatial correlations for the different classes, etc.)

Perspectives

- **Relax the hypothesis of no spatial correlation and include spatial correlation modelisation into the GPS downscaling approach.**
- **Extend the validity of the approach to multiscale observations (e.g.: combine METEOSAT and MODIS data).**
- **Compare our downscaling approach to other ones (Inamdar 2008; Inamdar 2009; Kallel & al., 2012 ; Bechtel & al.,2012 , etc.)**

References

[1] Coudert, B. , C. Ottlé, B. Boudevillain, J. Demarty, and P. Guillevic , "Contribution of Thermal Infrared Remote Sensing Data in Multiobjective Calibration of a Dual-Source SVAT Model," *Journal of Hydrometeorology*, vol.7 , no.3, pp. 404-420, June 2006.

[2] Mechri, R., C. Ottlé, O. Pannekoucke and A. Kallel. "Genetic Particle Filter application to Land Surface Temperature Downscaling," *Geophysical Research Letters*, submitted.

[3] Agam, N., W. P. Kustas, M. C. Anderson, F. Li, and C. M. Neale, "A vegetation index based technique for spatial sharpening of thermal imagery," *Remote Sensing of Environment*, vol.107, no.4, pp. 545-558, April 2007.

[4] Kallel, A., C. Ottlé, S. Le Hegarat-Mascle, F. Maignan, and D. Courault, "Surface Temperature Downscaling From Multiresolution Instruments Based on Markov Models," *IEEE Transactions on Geoscience and Remote Sensing*, vol.51, no.3, pp. 1588-1612, March 2013.

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