USING MSG THERMAL INFRARED SURFACE TEMPERATURE TO IMPROVE SVAT MODEL SIMULATIONS

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ABSTRACT

Interesting perspectives concerning the calibration of Soil Vegetation Atmosphere Transfer (SVAT) models are offered thanks to the higher acquisition frequency of the thermal infrared (TIR) brightness temperature provided by MSG.

SVAT models are useful for the monitoring of root zone soil moisture, sensible and latent surface fluxes. They may be helpful for meso-scale meteorological models initialisation, or for hydrological and agricultural applications. It was recently proven that SVAT models could be correctly calibrated thanks to thermal infrared data. However, this was only shown at the local field scale on homogeneous covers with ground-based data.

The purpose of this presentation is to present the potentialities of TIR brightness temperatures acquired by MSG in order to calibrate SVAT model over patchy regions. The feasibility studies are performed with simulated data to test calibration and desegregation methodologies.

Key words: SVAT model, calibration, assimilation, thermal infrared temperature, MSG, soil moisture.

1. INTRODUCTION

This paper deals with the potentialities of thermal infrared remote sensing, to improve SVAT model (soil moisture) simulation.

The main objective is the development of methodologies improving total soil moisture monitoring at the agricultural fields scales. Such a methodology would be helpful for better management of water resources in agricultural applications. For this purpose, a soil, vegetation, atmosphere, heat and water transfer model (SVAT model) is used. When atmospheric and vegetation states are known, this kind of model is efficient provided that it is used over homogenous vegetation and when soil and vegetation characteristics are well-known. These conditions would be addressed by:

- using the available information, in particular using thermal infrared temperature and ,
- resolving the scale and atmospheric attenuation problem

This paper focuses only on the first point: atmospheric data corrections and desagregation problems are not treated. The ability of the model to be calibrated from thermal infrared temperature data is checked.

This paper is organized as follows: in section 2, SVAT model is described. Section 3 presents the simple strategy, employed to calibrate the model, thanks to TIR temperature. It was tested on Alpilles-ReSeDa experiment database as briefly explained in section 4. Section 5 presents the results obtained from this database and section 6 closes the paper with a conclusion and prospects.

2. THE SETHYS SVAT MODEL (TO BE COMPLETED) (FIGURE 1)

The SEtHyS SVAT model is derived from Deardorff model (Deardorff, 1978; Taconet et al., 1986). It is a 2 sources (soil and vegetation) and 2 layers (surface and root zone) model. SVAT models compute from meteorological forcing, vegetation, and soil states, the water and energy budgets. SEtHyS model calculates separately soil and vegetation temperatures and the soil moisture in the two layers. It is coupled with a radiative transfer model which allows the calculation of the directional thermal infrared brightness temperature.

The SVAT model is based on meteorological data as air temperature, air humidity, wind, solar and atmospheric radiation, and rainfall rate at an hourly time scale as well as information about vegetation state, as leaf area index, and cover height. The initial soil

Proc. Second MSG RAO Workshop, Salzburg, Austria
9 – 10 September 2004 (ESA SP-582, November 2004)

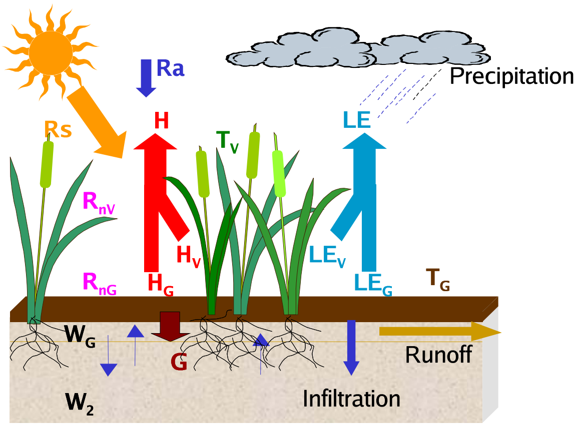


Figure 1. The SEtHyS SVAT model. Ra, Rs and Rn are the atmospheric, global and net radiation; H, LE and G are the sensible, latent and ground heat fluxes. T and W are the temperature and the soil moisture. The subscripts g and v correspond to the ground and the vegetation.

state (soil moisture and temperature) should be prescribed. Finally, a set of parameters describing the vegetation, and soil characteristics should be fixed. These parameters are often badly known, and need to be calibrated.

3. METHODOLOGY

An automatic calibration methodology based on a statistical approach is proposed. It is derived from Bastidas and Gupta approach (Gupta et al., 1999; Demarty et al., 2004). It consists in initialising the SVAT model with several parameter sets, randomly generated from initial ranges. The parameters sets leading to the best brightness temperature simulation are keep. The reference brightness temperature is measured.

At each calibration step, and for each parameter, a cumulated probability distribution functions is drawn (see figure 2). It corresponds to the best sets. The analyses of this curve allows the determination of the values range for which the brightness temperature is well computed. The values range of each parameter is also reduced at each calibration step. The most sensitive parameters are calibrated by this methodology. Some strategic choices have to be made according to the calibration quality and the computation limits :

- the number of sets used: according to the performed tests, one thousand sets seems to be enough to determine the interval of the most sensitive parameters,
- the number of sets assumed as good sets: the first 10% of the sets are assumed to correspond to the best sets group,
- the range reduction ratio: in order to reduce the parameters values range, the values corresponding to the range [10;90%] of the cumulated probability distribution function of the best sets group is retained.

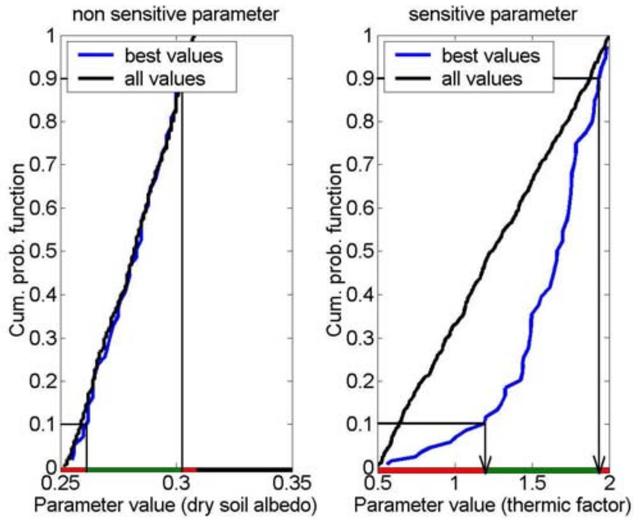


Figure 2. Cumulted probability function of a non sensitive and a sensitive parameter. The green range corresponds to the new parameter range obtained by retaining the parameter values corresponding to the [0.10;0.90] range of the prabibility function.

This work was performed with a complete sensitivity study (Coudert et al., 2004). According to this study, temperature diurnal cycle information can be used as unique constraint, provided some conditions, like a good soil moisture initialisation. This solution, that is easier to be operationally implemented, is shown in this communication.

4. DATABASE AND METHODOLOGY APPLY

This methodology was applied in the framework of the Alpilles ReSeDa experiment (Olioso et al., 2002). This experiment set up in 1996, in the south east of France. It took place in a small agricultural area, characterized by a large diversity of crops, and lasted about one year. All the forcing variables needed for this study were available :

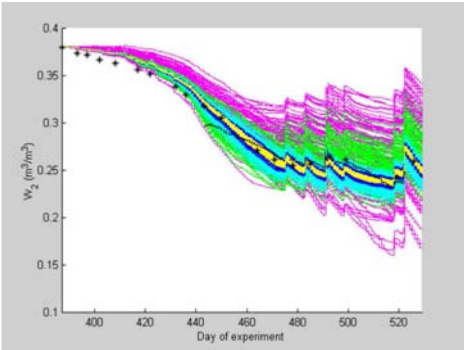


Figure 3. Total soil moisture in function of time obtained at several steps of the calibration methodology. The purple curves correspond to the first calibration step whereas the yellow curves are related to the last calibration step. The black stars represents the observed soil moisture.

- standard meteorological data (wind, relative humidity, temperature, rainfall, incident radiations),
- vegetation characteristics (height, leaf area index),
- soil characteristics (temperature, soil moisture profiles),
- brightness temperature.

Soil moisture was measured by several methods: capacitive, TDR and neutron probes, gravimetric sampling methods. Brightness temperature was obtained with thermal radiometers, with the same temporal resolution, on several agricultural fields.

To take into account the availability of brightness temperature data, the theoretical cloudy free solar radiation were compared with the observed solar radiation. Then, a data file, giving the availability information about the brightness temperature has been built.

5. RESULTS

The methodology has been applied on three periods corresponding to several vegetation states periods :

- bare soil,
- wheat during maturation period,
- wheat during senescence period.

It was moreover applied over a great period including the 3 small ones.

Table 1. Root mean square error of the latent heat flux with the calibration step.

Calibration step	RMSE(LE) [W m^{-2}]
1	67
2	76
4	58
7	54
10	53

Figure 3 represents the time evolution of total soil moisture, according to the several parameters sets, randomly generated during the calibration steps. Each curve is related with the simulation obtained with one parameter set. Purple lines correspond to the first calibration step whereas the yellow lines correspond to the last calibration step. The black curve corresponds to the observations obtained by a capacitive and neutron probe. Note on this figure, that soil moisture was intentionally well initialised. The dispersion of the purple curves group is large since the model run with parameters values included in large initial ranges. The yellow curves agree well with the black line corresponding to the observations. Note that the simulation of heat latent fluxes are improved too (see table 1).

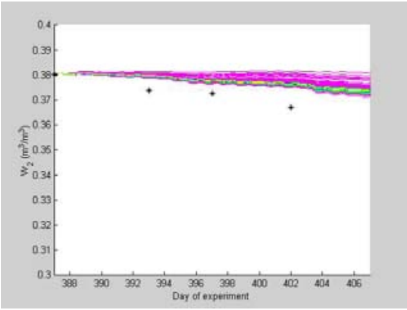
The same figures have been plotted for the three short periods mentioned above. They represent the calibration performed on these short periods independently of the others periods.

Figure 4 shows a very few scattering between the simulations. All the simulations lead to a slight overestimation. However, the yellow curve corresponding to the last calibration step is closer to the observation as the curve corresponding to the first calibration step.

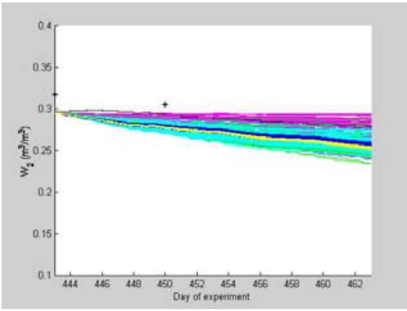
On the second and the third period, the scattering is larger, the last calibration step do not seem to be the more efficient. The heat latent flux is not improved when calibration is performed on the short period independently of the large period even with a correct initialisation. Table 2, 3 and 4 show the root mean square error of the latent heat flux when the calibration is perfomed : (a) on the short periods or (b) on the semester.

6. CONCLUSION

This study confirms that thermal infrared brightness temperature is useful for root zone soil moisture monitoring, and that SVAT models may be controlled using an automatic calibration methodology. The next step will be the application of this methodology to



(a)



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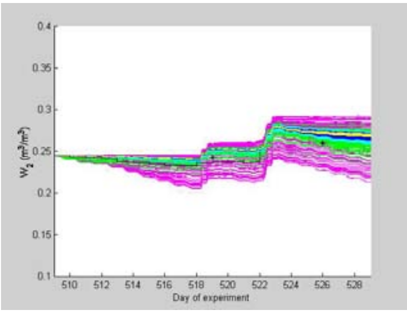

(c)

Figure 4. As in Fig. 3 but during (a) bare soil period, (b) maturation period and (c) senescence period.

Table 2. Root mean square error of the latent heat flux with the calibration step during bare soil period. The column (a) represents RMSE when the calibration is performed on the semester and the column (b) represents RMSE when the calibration is performed on the bare soil period.

Calibration step	RMSE(LE) [W m^{-2}] (a)	RMSE(LE) [W m^{-2}] (b)
1	30	30
2	27	29
4	28	29
7	28	29
10	28	29

Table 3. As in table 2 but for maturation period.

Calibration step	RMSE(LE) [W m^{-2}] (a)	RMSE(LE) [W m^{-2}] (b)
1	74	54
2	54	56
4	75	38
7	85	36
10	83	36

Table 4. As in table 2 but for senescence period.

Calibration step	RMSE(LE) [W m^{-2}] (a)	RMSE(LE) [W m^{-2}] (b)
1	92	65
2	95	79
4	103	74
7	103	66
10	103	64

remote sensing data, in particular, instruments sampling the diurnal cycle of the surface temperature like MSG thermal infrared data. The resolution at 45° latitude is about 3×5 km^2 that is much larger than the agricultural field scale. So, the desagregation problem has to be addressed.

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