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## 2Site specific calibration of a crop model by assimilation of remote sensing 3data : a tool for diagnosis and recommendation in precision agriculture.

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12

### 13 **Abstract**

14Crop models are key tools for helping in decision making in the frame of precision agriculture.  
15However they need a site specific calibration in order to give coherent spatial representation of  
16crop and soil state variables that can be used to make diagnosis and allow recommendations. This  
17paper shows how to perform such a calibration, using the assimilation of external information on  
18crop status obtained from remote sensing images. The improvement in model simulation was  
19evaluated through the improvement in the final yield map estimation.

20

21**Keywords** : Crop model, assimilation, remote sensing, agronomic recommendation

22

### 23 **Introduction**

24Measurement techniques, interpretation models, and information management tools, have  
25progressed in such a way that it is now possible to envisage taking into account field  
26heterogeneity in crop management. The objective can be either a uniform or spatially variable  
27application. It is necessary to build up tools for decision making using soil and climatic data to  
28enable adapted recommendations for applications.

29Crop models are particularly useful in the design of such tools. When provided with relevant  
30climatic, soil and crop data, they allow dynamic simulation of the behaviour of the soil-plant  
31system. Subsequently, they can give dynamic diagnostic information about soil and crop  
32conditions. They allow simulation of their development under different scenarios of operation  
33management and/or climate, thereby providing information for decision making.

34

35Assuming that the models are used within their validity domain, they should meet two specific  
36conditions in order to be applicable in such a methodology. On the one hand, the models should  
37properly describe the processes affected by the operation for which recommendations are  
38expected (for instance the processes linked to nitrogen cycle in the soil and the plant in the case  
39of recommendation in nitrogen fertilisation). On the other hand, they should be able to reproduce  
40the effects of the spatial variability of soil and/or crop conditions at large scale. For this aspect, it  
41is expected: i) to have the set of parameters of the model functions corresponding to each existing  
42situation; ii) to be able to describe the input variables of the model with a spatial resolution

1compatible with the objectives. This last condition can be met by using data assimilation  
2techniques on remote sensing data acquired during the crop cycle (Guérif & Duke, 1998).

3

4Using radiative transfer model inversion, remote sensors in the solar domain give access to  
5canopy state variables such as leaf area index, and leaf chlorophyll content (Moulin et al. 2003).  
6These estimates are available continuously over the entire set of fields, with a spatial resolution  
7of 1 – 10 m, and a given temporal resolution, both related to the platform used (tractor, airplane,  
8satellite). Using optimisation procedures, these canopy state variables allow re-estimation of  
9parameter values and/or input variables and to force the model to simulate as well as possible the  
10"observed values".

11

12These methods have been applied in a project dedicated mainly to the development of a tool for  
13decision making for nitrogen application to winter wheat. The principles and the first results of  
14the method are presented here for one field cultivated with winter wheat.

15

16The objective of this paper was to illustrate how data assimilation acquired during the crop cycle  
17led to a better spatial processing of the model; the evaluation of the method was performed by  
18comparing simulated spatially distributed yields to the observed yield map.

19

## 20 **Material and methods**

21

### 22 *Experimental data*

23The experimental trial (Guérif et al. 2001) was made on two 10 ha fields cultivated alternatively  
24with winter wheat and sugar beet during the first 2 years of experiment (2000-2001). The results  
25presented here refer to one of those fields.

26

27A high resolution soil survey was performed (100 samplings over 10 ha, from 0 to 1.50m depth),  
28recording horizon type, stone content, rooting impedance depth and leading to the definition of  
2951 soil units. Local pedotransfer functions were defined which allowed each type of soil to be  
30related to specific properties (bulk density and water retention at various soil potential). The 0-  
3130cm layer was sampled on a regular grid (36mx36m) and standard physico-chemical analyses  
32were performed. Soil sampling was performed on the grid at different dates (sowing, mid  
33February, and harvest) and for each 30 cm layer, from 0 to 1.50m depth. Soil water and nitrogen  
34contents were measured and interpolated by kriging (Mary et al, 2001). These data provided  
35initial input values at sowing for the model, and validation data for the two other dates.

36

37At several dates between early April and late June, remote sensing measurements were performed  
38with a 2m resolution over the field with a CASI spectrometer mounted on an airplane. These  
39measurements enabled estimation, by inversion of the model Prosail (Moulin et al., 2003), of  
40values of leaf area index (LAI) and leaf chlorophyll content (Cab). These values have been  
41corrected by calibration with data obtained on the ground at the time of the flight. SPOT data

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1were also acquired but not used here. At harvest, a yield monitor operated by the farmer was used  
2to produce yield maps.

3

#### 4*The crop model.*

5The STICS-winter wheat model (Brisson et al., 1998) was used in its latest version (V5.0). Its  
6sensitivity to the expression of the variability of soil characteristics has been checked (Houlès et  
7al., 2002). Its ability to properly reproduce the effect of nitrogen fertilisation has been verified.  
8An empirical function was introduced which simulates the leaf chlorophyll content as a function  
9of the nitrogen amount in the canopy. This is based on the data obtained by Houlès et al. (2001).

10

#### 11*Spatial resolution of the working units*

12We defined squared grid units of 20m x 20m. Soil data (permanent and non-permanent) and crop  
13state data (LAI, Cab) were collected into a GIS. The intersection of the 20m x 20m grid with  
14different information layers allowed to characterise the different soil grid units and to derive the  
15necessary input variables for running the crop model.

16

#### 17*The method used for remote sensing data assimilation*

18A simplex type method has been used which allowed re-estimation of some parameters or input  
19variables of the model. The method minimises a distance criterion between the values estimated  
20by the model and the values “observed” by remote sensing.

21

22 Parameters and variables to be re-estimated were chosen according to two criteria. One  
23 referred to the probable spatial variability due to soil characteristics, cultivation technique  
24 effects and soil - plant interactions. The other one referred to their importance shown by the  
25 sensitivity analysis of the model (Ruget et al., 2002). Three variables were outlined. The  
26 potential maximum depth of rooting (this is a key variable in the water and nitrogen  
27 absorption process and has been assessed during the soil survey) ; loss of nitrogen due to  
28 volatilisation of the fertiliser and the depth of the soil layer which is concerned by organic  
29 matter mineralisation.

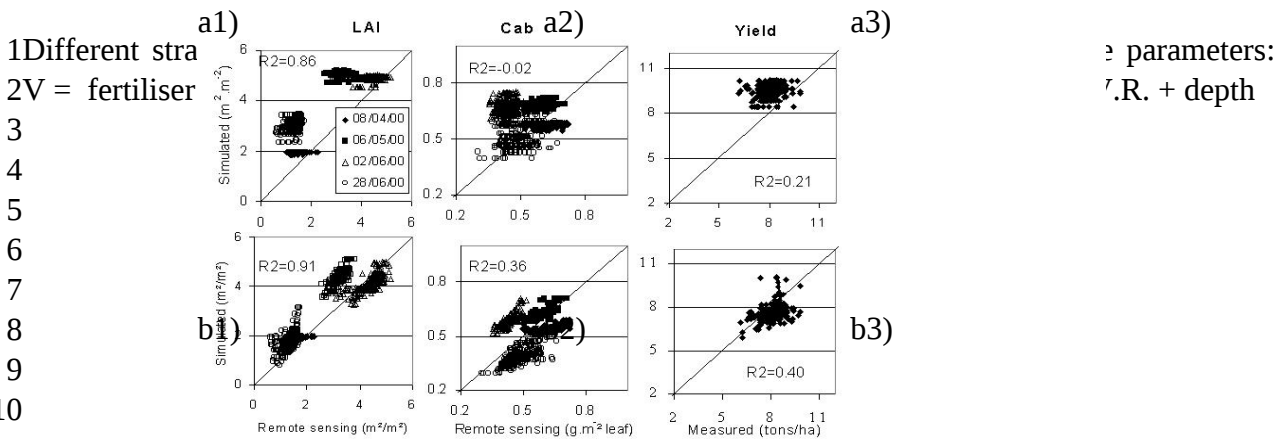
30

## 31 **Results**

32

33Direct simulation, without assimilation, led to a similar overestimation of LAI (Fig. 1, a1).  
34Moreover, the simulated values of LAI for each date expresses very little spatial variability and a  
35poor correlation with the observed LAI. The global bias was less for the chlorophyll content  
36(Fig. 1, a2), but we still notice the incapacity to reproduce spatial variability and the lack of  
37correlation between observed and simulated data. As a consequence of LAI overestimation, the  
38simulated yield was also overestimated (Fig.1 a3).

39



20 Figure 1. Simulation results a) with the model alone and b) after LAI and Cab data assimilation  
 21 for 4 dates 1) simulated LAI, 2) simulated Cab, 3) simulated final yield

22  
 23 of mineralisation of the organic matter. Table 1 shows the efficiency of the different strategies to  
 24 reduce the RMSE and the RRMSE. The results (LAI, Cab, & final yield) obtained with the  
 25 different strategies are compared to the simulations with the model alone.

		Model alone	Model with assimilation		
		(a)	V (b)	V,R (c)	V,R,P (d)
<i>LAI</i>	RMSE (m <sup>2</sup> .m <sup>-2</sup> )	0.133	0.069	0.071	0.070
	RRMSE (%)	51.2	26.7	27.1	26.9
<i>Cab</i>	RMSE (g.m <sup>-2</sup> )	0.015	0.011	00.11	0.011
	RRMSE (%)	27.7	19.8	19.9	19.8
<i>Yield</i>	RMSE (T/ha)	1.6	0.83	0.79	0.85
	RRMSE (%)	19.1	10.2	9.7	10.4

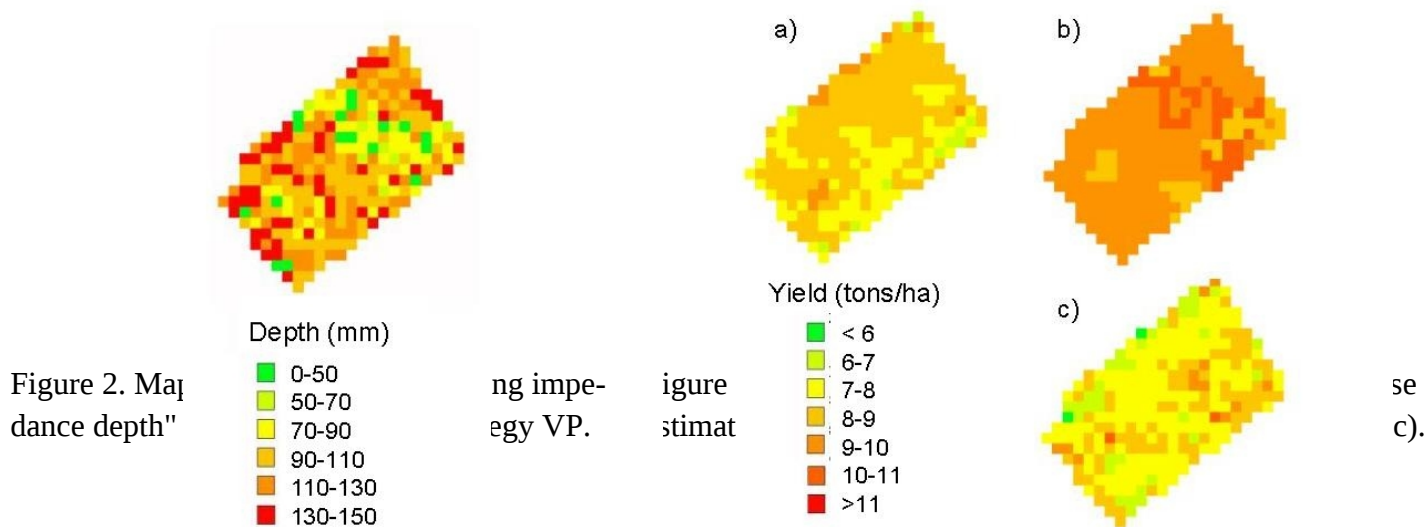
27 Table 1. Performance of direct simulation as compared with assimilation of LAI and Cab data

28  
 29

1The 3 strategies appeared to be rather similar. The VR strategy allowed reduction of the yield errors from 19.1 to 9.7%. Figure 1 (b1,b2,b3) shows how the variability simulation had been improved as well as for the LAI, Cab and yield with the VR strategy.

4

5The spatial display of the “rooting impedance depth” parameter suggested the interest of the method to estimate the spatial distribution of some of the unknown soil characteristics (Figure 2). In our case, we can compare this map with the one surveyed by the pedologist and outline the mismatches, which should be then validated. The map of simulated yields (Figure 3) shows that the assimilation has allowed better fitting of the range of simulated yields to that of the measured ones. Moreover, it allowed incorporation into the simulation of the spatial variability, which was existing in the images, obtained by remote sensing.



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16 **Discussion**

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18These first results showed the potential of the method in attaining a site adjusted simulation of the crop status. The performance of the method depends a lot on the number of data to be assimilated and their distribution along the crop season (Guérif & Duke, 1998). In our case the results should have been improved by images acquired earlier during the crop establishment. Apart from the soil-linked parameters that we tried to estimate, a global re-estimation of more specific plant parameters should be undertaken in a previous step.

24This type of method is applicable to the assimilation (or inversion) of any information acquired during the cropping season: measure of the water content by electric resistivity, remote sensing data at different wavelengths, automated measure of yield. The assessment of the field permanent characteristics, in the case where they are unknown, could be performed by inversion of

1“collections” of yield map, using a model such as STICS, which allows simulation of crop  
2rotations.

3

#### 4**Conclusion**

5

6The combined use of the assimilation of data acquired during the crop growth, and of spatially  
7distributed data obtained by an exhaustive characterisation (by geophysics or remote sensing) or  
8by interpolation with geostatistics, allows relevant localised simulations of the plant and soil state  
9variables. This spatial distribution is the first step of a method to develop nitrogen fertilisation  
10recommendations. The next step of this method will consist of simulating fertiliser application  
11and climatic scenarios, and finding the optimum of a cost function built on both production  
12(yield, quality) and environmental variables relative to nitrogen losses.

13

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6