Remote sensing and detection of nitrogen status in crops. Application to precise nitrogen fertilization

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ABSTRACT

Remote sensing techniques offer a unique solution for mapping the growth and nitrogen status of crops and monitoring its time course. Therefore these maps are powerful tools for recommending spatially precise cultural practices, and particularly nitrogen dressing. In this paper, we review the main issues to be addressed for estimating crop variables from remote sensing and for using them for managing variable rate fertilizer application.

The derivation of canopy state variables such as the leaf area index (LAI) and chlorophyll content (Cab) is first addressed. It is demonstrated that the inversion of radiative transfer models leads to useful estimates of these variables. However, because of the ill-posed nature of the inverse problem, better accuracy is achieved when using prior information on the distribution of the variables and when multiplying LAI by Cab to get canopy level chlorophyll content. This variable, LAI.Cab is well suited for quantifying canopy level nitrogen content.

The use of such variables for recommending optimal nitrogen rates is addressed further. A first way consists in deriving different indices (index of nutrition, index of deficit of absorption) that can either be substituted into classical empirical methods or directly used to calculate doses. The combination of remote sensing observations with crop models provides a more powerful solution that makes it possible to maximize the farmer gross margin while limiting risks of nitrate leaching.

Key words: Nitrogen, Chlorophyll, leaf area index, Fertilization, Remote sensing, Inversion, Crop model, Assimilation, Precision Agriculture.

INTRODUCTION

Agriculture has to cope with the double objective of increasing yields and limiting injuries to our environment. Precision agriculture is a very efficient way of attaining these objectives, by taking account of within-field variability to recommend variable rate management. For nitrogen fertilization, the challenge is to determine the optimal rate at each place in the field, taking account of the actual status of the crop, its potential growth and soil potential supply.

Remote sensing techniques offer a unique solution for mapping actual crop status. The solar reflective domain (visible to short-wave infrared) is the most informative with respect to canopy variables (leaf area index, *LAI* and chlorophyll content, C_{ab}). At the field level, it has been shown (Baret and Fourty, 1997) that nitrogen content was not an attainable variable from remote sensing observations, nor protein content, even using hyperspectral systems. But through its relationship with chlorophyll content, it is possible to assess the nitrogen status of the crop (Baret et al, 2007).

In a first part, we will present the different ways of linking remote sensing to the nitrogen status of the crop, through the estimation of pertinent canopy variables. In a second part we will present how we can apply these results to nitrogen fertilization recommendations.

REMOTE SENSING AND NITROGEN STATUS

Different variables have been used to characterize the nitrogen status of the crop in order to support decision in fertilization management. Among them, the most popular is the chlorophyll content of the leaves, as shown by the widely spread use of chlorophyll-meters (Hydro-N-Tester of Hydro-Agri, now Yara and SPAD of Minolta), based on the measurement of light absorption by chlorophylls (*e.g.* Piekielek & Fox, 1992; Reeves *et al.*, 1993; Feibo *et al.*, 1998; Shaahan *et al.*, 1999; Chang & Robinson, 2003; Jongschaap & Booij, 2004). The legitimacy of those measurements is linked to the close relationship between chlorophyll content and nitrogen content: this relationship is rarely investigated and generally highly variable.

Beyond the leaves nitrogen content, some authors use more complex variables or indices (the nitrogen nutrition index NNI, or the deficit of absorbed nitrogen which will be defined further).

We will explore in the further sub-parts the way of estimating these variables from remote sensing.

1. ESTIMATION OF LAI AND CHLOROPHYLL CONTENT

The spectral and directional distribution of top of canopy (TOC) reflectance at a given time and location is governed by the canopy structure, the optical properties of the elements including the soil background, as well as the view and illumination geometrical configuration. Because of the numerous variables influencing canopy radiometric response, it is not straightforward to extract specific canopy variables. It requires inverting radiative transfer models, as shown on Fig. 1.

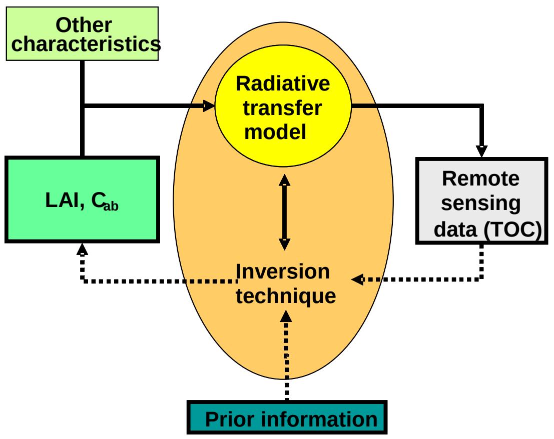

Fig.1 Scheme showing the inputs and outputs required in the forward and inverse problems to estimate canopy state variables (in this case LAI and Cab).

In the general scheme proposed, a radiative transfer model simulates the TOC reflectance in the forward direction from the input variables. These are split into the variables of interest such as *LAI* and C_{ab} and the other characteristics (geometrical view and illumination configuration, other canopy variables such as leaf inclination, leaf water content, soil optical properties…). An inverse technique is then used to extract the variables of interest. It generally requires prior information on the distribution of the input variables to regularize the inversion process (Tarantola, 1987).

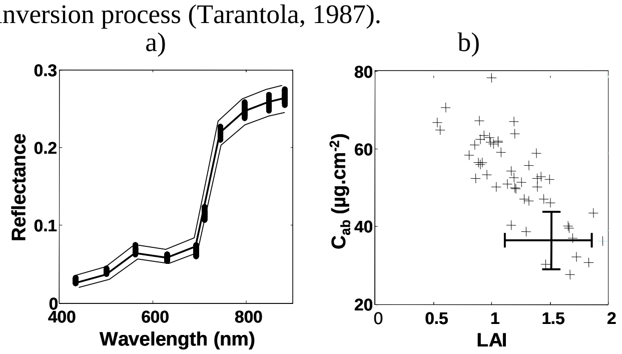

Fig.2

a) actual reflectance measurements (solid lines, with ± standard deviation) and the corresponding closer simulations (dots) achieved with a turbid medium radiative transfer model.
b) the input *LAI* and C_{ab} variables) ('+') used to simulate the reflectance spectra shown on a) plot. The actual *LAI* and C_{ab} measurements (large cross) are shown with their associated confidence intervals (corresponding to 1 standard deviation). Data acquired over a sugar beet experiment conducted in 1990. More details are provided in Combal et al. (2001).

The inverse problem in remote sensing is generally ill-posed (Combal et al., 2002), as several combinations of input variables may provide very similar reflectance simulations that match closely the actual remote sensing observations (Fig.2a). The radiometric information is not sufficient to identify a unique solution: the inverse problem needs to be regularized by exploiting additional information such as prior knowledge on the statistical distribution of canopy radiative transfer model input variables. The possible solutions (Fig.2b) exhibit a strong negative correlation between the retrieved *LAI* and C_{ab} values and have very similar values of canopy integrated chlorophyll content corresponding to the product between the leaf level chlorophyll content (C_{ab}) and *LAI*, named *LAI·Cab*. This variable is a quantity physically sound since it represents the optical path in the canopy where absorption by chlorophyll governs the radiometric signal.

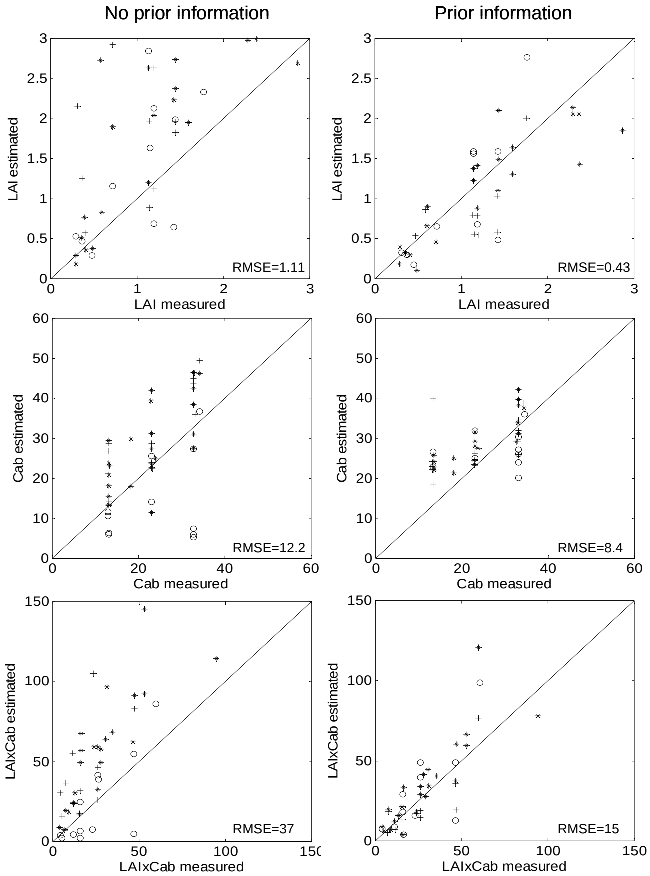

Fig. 3 Comparison of retrieval performances for *LAI* (top), C_{ab} (middle), and *LAI·Cab* (bottom) over sugar beet canopies when using no prior information (left) or with prior information (right). More details can be found in Combal et al. (2001).

The use of prior information on canopy and soil input variables within the inversion process allows to improve the retrieval performances (

Fig. 3). The accuracy and robustness of canopy characteristics estimation is even improved when using canopy level chlorophyll content ($LAI.C_{ab}$) as compared to leaf level contents (C_{ab}). In the following the interest of using canopy integrated chlorophyll content variable will be further demonstrated with reference to its role as a pertinent diagnostic variable.

2. LINKING LAI AND CHLOROPHYLL TO NITROGEN CONTENT

We investigated the relationship between nitrogen and chlorophyll content thanks to a dedicated experiment conducted in Laon in 2000 and 2001 over wheat crops subjected to a range of nitrogen stresses (Houlès et al., 2007). It clearly demonstrated the interest of relating nitrogen to chlorophyll integrated at canopy level rather than at leaf level: while the relationships obtained between N and C_{ab} are highly variable among years and development stages, those obtained at canopy level between $LAI{\cdot}C_{ab}$ and QN are more robust (Fig. 4).

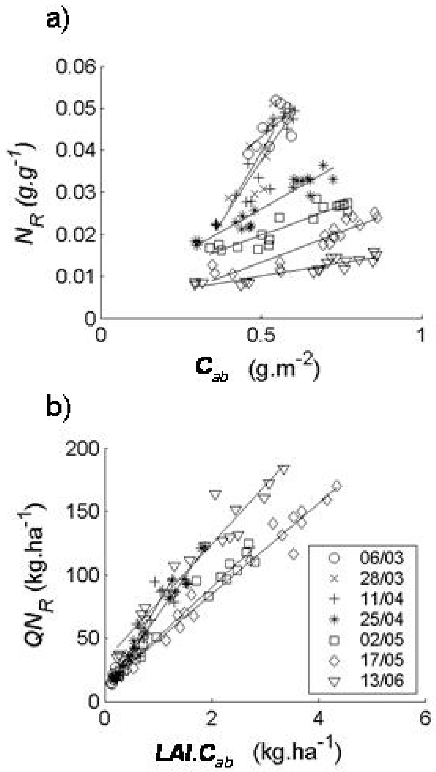

Fig. 4 Relationships between a) C_{ab} and N (top), and b) $LAI{\cdot}C_{ab}$ and QN (bottom) as observed over wheat experimentsconducted at Laon (France) in 2001 (Houlès, 2004).

However, they still slightly depend on development stages: after earing, plants show larger amount of nitrogen for the same chlorophyll amount when a large part of nitrogen is concentrated in the grains (Fig. 4). For the younger stages having also more nitrogen for the same amount of chlorophyll, this might be due similarly to dilution of nitrogen in the structural biomass with leaf development as confirmed by the strong relationship between leaf nitrogen and leaf chlorophyll content per unit soil area. This clearly shows the complexity of the processes associated to nitrogen and chlorophyll distribution in plants.

3. LINKING LAI AND CHHOROPHYLL TO CROP NITROGEN INDICES.

1.1 Nitrogen Nutrition Index and Nitrogen Absorption Deficit

The nitrogen nutrition index is the ratio between the actual nitrogen concentration in shoots to the ideal N concentration of a crop having the same biomass and whose growth is not limited by N availability (Lemaire and Gastal, 1997). It is defined as:

$$NNI = \frac{N_R}{N_C} \qquad [1]$$

where N_R is the actual shoot N concentration and N_C is the 'critical nitrogen' concentration. N_C is a function of shoot biomass and is defined by the 'critical dilution curve'. The dilution curve is defined on a graph of biomass (on the abscissa) against nitrogen content (on the ordinate) of the aerial parts of the plant stand (Justes *et al.*, 1994) (Fig. 5a). It represents a situation of optimal nitrogen nutrition. For every species it can be constructed from all of the points corresponding, for a given date, to the nitrogen content above which the aerial dry weight does not increase significantly despite an increase in the nitrogen supply.

For C3 plants, including wheat, it can be parameterized as follows (Justes *et al.*, 1994):

$$N_C = 5.35 \text{ if } W_R \leq 1 \text{ t.ha}^{-1} \qquad [2]$$

$$N_C = 5.35.\ W_R^{-0.442} \text{ if } W_R \leq 1 \text{ t.ha}^{-1} \qquad [3]$$

where N_C is the critical nitrogen content expressed in g N per 100 g of dry matter and W_R is the dry weight of the aerial shoots in t.ha^{-1}. This equation does not depend on the variety.

This critical dilution curve delimits three zones on the graph. If the real nitrogen content of a given plant, denoted N_R, equals N_C, the crop is optimally supplied with nitrogen. If $N_R < N_C$, it is deficient, and if, on the contrary $N_R > N_C$, it is over-fertilised.

From the critical curve we can easily move to a critical nitrogen absorption curve (Fig. 5b): multipling the ordinate by the dry weight give the curve of the quantity of nitrogen absorbed under optimal conditions (QN_C) as a function of the biomass.

a)

b)

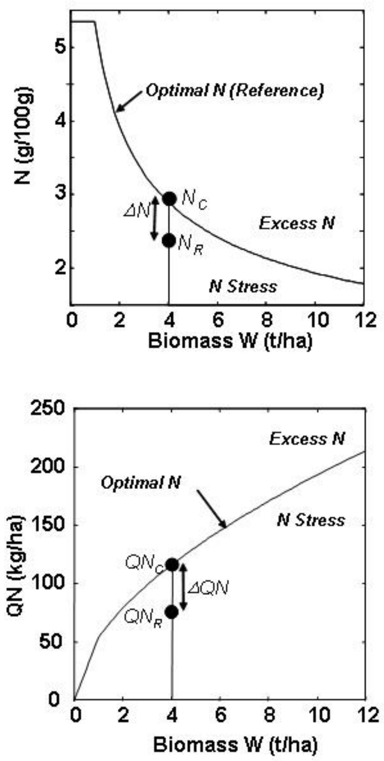

Fig. 5 Critical curve corresponding to the optimal nitrogen concentration in the plant as a function of plant biomass (top). The optimal canopy nitrogen content is shown as a function of the biomass (bottom).

Thus one can determine, for experimental points giving the nitrogen absorbed by a crop (QN_R) and its biomass (W_R), the excess or deficit of nitrogen uptake (ΔQN):

$$\Delta QN = QN_R - QN_C \quad [4]$$

Both indices may be used in order to detect nitrogen stress and manage the N fertilization.

1.2 Estimating *NNI* and ΔQN from *Cab* and *LAI*

Blondlot *et al.* (2005) suggest estimating *NNI* by empirical relations with the value of *Cab* obtained from remote sensing data. In order to make the estimate more precise, we proposed to use not only *Cab* but also *LAI* (which informs on the crop biomass W_R), as both variables are available from remote sensing measurements (Houlès et al, 2007). Once *NNI* and W_R are estimated, ΔQN is easily deduced. In the following, we illustrate the comparison of 3 methods for estimating ΔQN (Fig. 6).

The variable *LAI* can be used to estimate through empirical relationships W_R which therefore gives access to N_C and QN_C via the dilution curve (equations [2] and [3]). Knowing *NNI* and N_C, equation [1] enables one to find N_R and from there, QN_R, thanks to W_R (fig. 6a) (method 1).

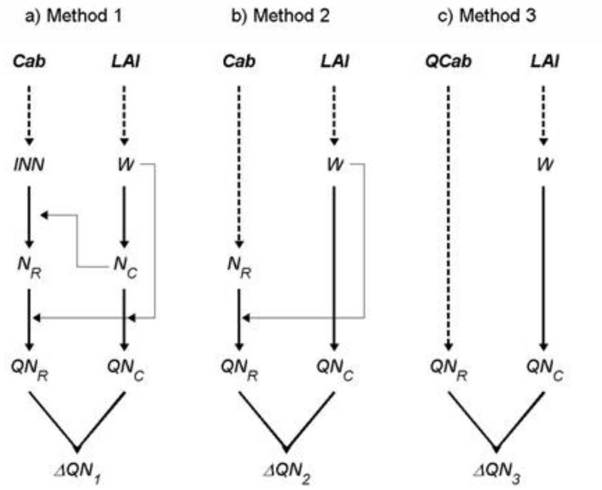

Fig. 6 Three methods of calculating the absorption deficit ΔQN. a) by taking *NNI* as an intermediary; b) by taking N_R as an intermediary; c) by using *QCab* to calculate QN_R directly. The dotted arrows represent experimental relations, the plain arrows the relations given by equations 1 to 4. (from Houlès et al, 2007).

A second method is therefore proposed (fig. 6b) which consists of calculating N_R directly from *Cab* using experimental relationships. Just as for the first method, one can arrive at the quantities absorbed by estimating W_R from *LAI*. To further simplify the calculations and to use the integrated variable *QCab*, which is in principle best evaluated by remote sensing, one can choose to evaluate QN_R directly from the latter: this we will call method 3 (Fig. 6c).

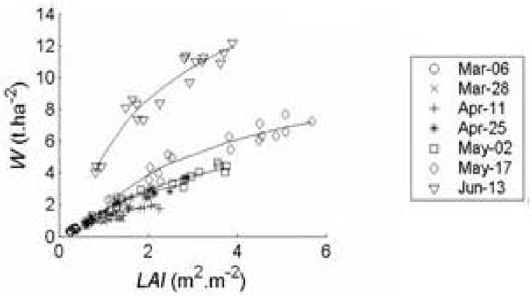

Fig. 7 Experimental relations between *LAI* and W (from Houlès et al, 2007).

Figure 7 shows the relationship between *GLAI* and W_R established on the experiment previously described. The relation quite well described by a logarithmic function:

$$W_R = a_1 . \ln(GLAI) + b_1 \quad [5]$$

The correlation coefficients between ln(*LAI*) and W_R are mostly above 0.9.

The relation between *Cab* and *NNI* is well described for each date and by a simple linear relationship (Fig. 8).

$NNI = a_2. Cab + b_2$ [6]

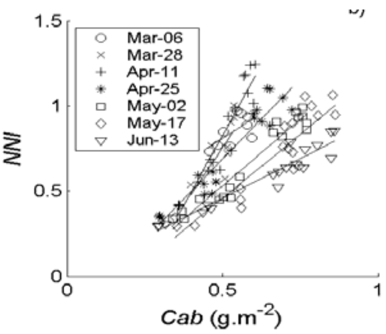

Fig. 8 Experimental relations between *NNI* and *Cab* (from Houlès et al, 2007).

The correlation coefficients are mostly above 0.92
The relations between *Cab* et N_R (*cf* Fig. 4a), are also well described by a linear fit:

$N_R = a_3. Cab + b_3$ [7]

The slope strongly depends on the date and the stage of the crop. They are also expressed as functions of the temperature sum since sowing. Moreover, early sampling dates also show a poorer fit than the others.

As shown earlier, the relationships between the measurements of *QCab* and QN_R are also linear (fig. 4 b) and mostly have correlation coefficients very close to 1.

$QN_R = a_4. QCab + b_4$ [8]

Again, the slope and intercept depend on the crop stage. Two groups of points appear: before the 2-node stage and from then onwards, i.e. when the stems begin to be of a significant size in relation to the leaf area, which can bring about changes in the metabolism and in the chlorophyll/nitrogen ratio.

In order to take account of the dependency of the relationships on the stage of the crop, we expressed the coefficients (ai, bi) for i=1,…,4 , as functions of the sum of temperature since sowing (ΔT). We optimized these coefficients based on least squares between the observed and calculated absorption deficits by each of the three methods. The result for the whole dataset of the fitting for the calculation of absorption deficits, ΔQN, is presented on the first line of table 1. A cross validation was done in order to evaluate the predictive capacity of these relations (Table 1, line 2).

According to these values, method 1 describes the nitrogen absorption deficit less well than the 2 others. Method 3 appears the best, as it leads to a smaller degradation of the prediction within the cross-validation process.

Table 1. RMSEP values for prediction of ΔQN compared to values of RMSE. (CV) indicates values calculated by cross-validation.

	Method 1	Method 2	Method 3
RMSE	19.4	15.0	15.2
RMSEP (CV)	30.2 (+10.8)	23.0 (+8.0)	18.0 (+2.8)

It predicts the nitrogen absorption deficit with an error of about 20 kg.ha^{-1}, whereas for the others it is about 30 and 25 respectively. It therefore seems preferable to calculate ΔQN from *QCab* and *LAI*.

APPLICATION TO PRECISE NITROGEN FERTILIZATION

Remote sensing techniques allow to estimate different variables, more or less complex, that are linked to the nitrogen status of the crop : N content (*N*, %), N uptake in the shoots (*QN*, kg ha^{-1}), N nutrition index (*NNI*, sd) or the deficit of N absorption (ΔQN, kg ha^{-1}). Different ways of using these variables are possible:
- taking them as proxies of the indices determined with the customary tools that exist on the market;
- or using them to spatialize a crop model whose predictions are used to determine the optimal dose on any point of the field.

In any case, remote sensing brings the spatial extension of the information on the whole fields.

1. USING CROP NITROGEN INDICES

In the case of the usual empirical approaches such as the N-Tester or Jubil (Justes et al, 1997), they can be generalised on the within-field scale by replacing the usual measurement of nitrogen status by the estimation of *Cab* ΔQN by remote sensing. In this case, one will be working in terms of thresholds: above a certain value of ΔQN, an extra dose will not be applied; below it, it will. In this case, one will have, on any given date, only two kinds of zone in the field.

As ΔQN expresses the deficit of N absorption by the plant, it can be used directly to calculate the doses to apply. This involves making assumptions about the efficiency of the fertiliser, which can however be estimated from the absorption deficit and the amounts. The recommendation map will then be made up of numerous zones which will reflect the variability observed by remote sensing. A simplification of the map should therefore be necessary so that the recommendations can be applied by the variable rate fertiliser spreader.

The decision rules which serve here as a pattern (e.g. N-tester) were developed primarily to optimise the yield. The problems of the sustainability of agriculture both from the environmental and the economic points of view require a consideration of these factors when calculating fertiliser requirements. This then involves modifying these decision rules which are decided on the basis of empirical databases. Crop models are particularly useful in this objective

2. USING CROP MODELS

Crop models offer many advantages as compared to methods based on nitrogen indices. As they take account of the different components of the system (soil, plant, cultural practices and climatic condition) and of their interaction, they can allow to diagnose the actual cause of a N stress : it may be effectively due to N shortage but also to a limitation of growth by another stress (water stress). Crop models also make it possible to evaluate the performance of different technical scenarios and optimize them according to multiple criteria (crop yield, quality, nitrogen loss,…); they allow also to run climatic scenarios and make predictions.

The difficulty lies in the possibility of getting the necessary input variables in any place of the field.

In the following, we will illustrate how exploiting a crop model (STICS model, Brisson et al, 1998) to quantify nitrogen stresses and proposing an optimal strategy for fertilizer application on wheat crops (Houlès et al, 2004, Guérif et al, 2005).

The approach is decomposed into 2 steps:

- re-calibration of the model inputs using remote sensing observations. This corresponds to the assimilation step.
- definition of a decision rule based on a criterion derived from the crop model state variables that account for both economic and environmental constraints. This corresponds to the recommendation step.

2.1 Assimilation step

We hypothesised that the main sources of spatial variability was the soil, and neglected the heterogeneity due to cultural practices and pests. The model inputs to be estimated concerned soil reservoir capacity, roots growth and organic N in soil. The observations which were available from remote sensing concerned *LAI* and C_{ab}. C_{ab} values were transformed into *QN* values, according to the relationship presented above. Cultural practices and climatic variables measured during the experiments were used as model inputs.

Recalibration of crop models is an inverse problem, which is ill-posed similarly to the of canopy state variables retrieval from remote sensing. The GLUE Bayesian method was therefore used (Beven and Binsley, 1992; Makowski et al., 2002), exploiting prior distribution of the variables and parameters to be estimated to get the optimal values for their posterior distribution. This method is summarized into the following three steps (for more details, see Houlès et al, 2004 and Guérif et al, 2006):

– a large number of parameter vectors (200 000) are randomly drawn within their prior distribution defined from expert knowledge and previous experiments.
– the output variables corresponding to *LAI* and *QN* observations, derived from remote sensing observations, are simulated for each parameter vector using the STICS model;
– observed LAI and QN values are then compared to the simulated values, and the likelihood of each parameter vector is computed. The posterior distribution of each parameter is estimated using the weights attributed to each parameter vector as derived from its corresponding likelihood.

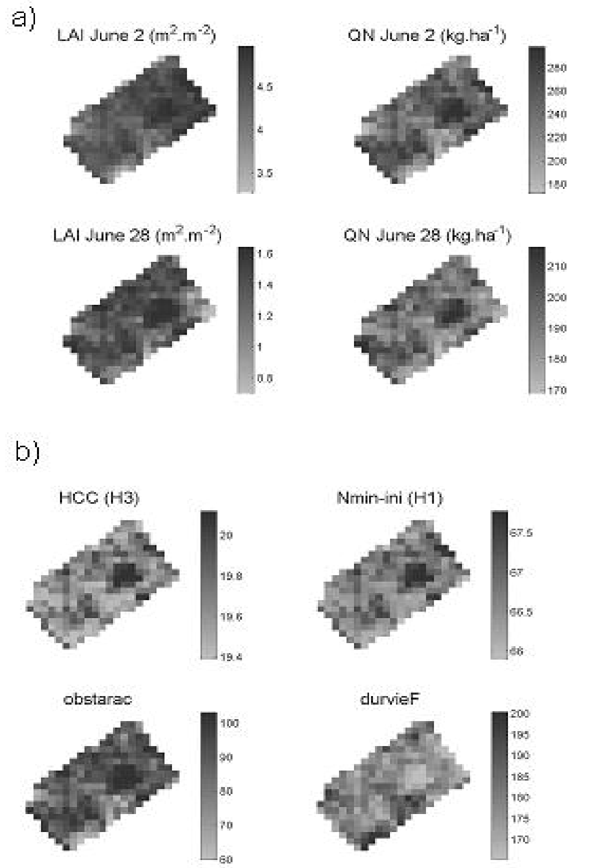

Fig. 9 Spatial distribution of a) observed *LAI* and *QN* values at two dates in the 280 cells of the plot and, b) as a result of the assimilation procedure, four estimated parameters. The pixel size is 20 m * 20 m.

Figure 9 illustrate the results of the process applied to a 10 ha wheat field, using four dates of *LAI* and *QN* observations (Fig. 9a) for estimating 13 inputs parameters.

The retrieved values of the parameters (Fig. 9b) exhibit the same spatial pattern as the *LAI* and *QN* observations.

2.2 Recommendation step

We proposed a criterion that combines gross margin maximisation and the limitation of the risk of nitrogen losses. Gross margin is calculated from two state variables provided by the model: yield (Y) and protein content (Pg) plus the nitrogen fertiliser dose (N_D) and price (P_N): $GM=Y{\cdot}Pg\ (N_D)– N_D.P_N$.
The risk of nitrogen losses is approached by the nitrogen balance between inputs as fertiliser (D_N) and outputs as grain protein: $NB = N_D – 10.\ Y.\ Pg/5.7$. To limit the risk, we impose the constraint on *NB* to be inferior to a threshold (e.g. NB_T= 50kg/ha).
The best strategy leading to optimal N rate is the strategy maximising *GM* among all the strategies satisfying the constraint on *NB*. If no strategy can satisfy the constraint, the strategy giving the lowest value for *NB* is selected.
This process applied over all the pixels of the field provides the optimal nitrogen application map as illustrated by Fig. 10 for another 10 ha field. Note that no nitrogen application was required over about 20% of the field area, because canopy requirements are small enough to be covered by soil contribution. A homogeneous nitrogen application would lead to excess nitrogen left in the soil with some possible leaching downwards the water table. Conversely, applying a unique average nitrogen rate to the areas requiring the larger nitrogen amounts would reduce the yield and the farmer's income.

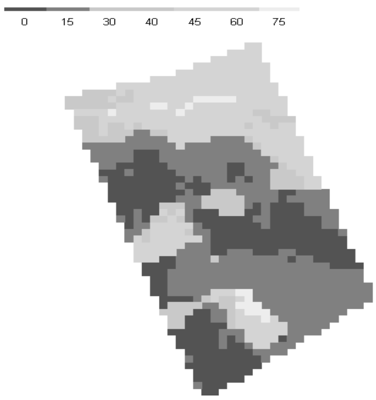

Fig. 10 Optimal nitrogen application map (Nitrogen amounts in kg/) for the third application as derived from the combination of remote sensing observations and crop model. Pixel size: 20 m * 20 m.

CONCLUSION

Remote sensing observations in the visible and near infrared spectral domains allow mapping canopy leaf area index and leaf chlorophyll content. Those are key variables for giving information on crops, both in terms of growth and in terms of nitrogen status, at different moments within the growing season. Knowing these variables with a high spatial resolution (from 5 to 20 m as in the case of data from satellite SPOT) makes it possible to use them for promoting precise agriculture and especially variable rate nitrogen fertilization.
It is here demonstrated that the canopy chlorophyll content is more strongly related to the canopy nitrogen content. This provides the necessary link between remote sensing observations and the canopy state variables used as indicators of nitrogen status. Fortunately, chlorophyll content is better estimated at the canopy than at the leaf levels. This is mainly explained by the possible compensations observed in the inversion process between leaf level chlorophyll content and leaf area index: several combinations of *LAI* and *Cab* may lead to very similar spectral reflectance responses. However, the uncertainties associated to canopy nitrogen content are still significant, around 20 to 30 $kg{\cdot}ha^{-1}$, which is at the limit of the acceptable level. Sources of uncertainties are coming in first place from remote sensing estimates of canopy chlorophyll content, both because of measurement uncertainties, and of the lack of realism of the radiative transfer models used. In addition, the relationships between canopy and nitrogen chlorophyll contents may vary slightly depending on the situations encountered.
We presented different ways to exploit those variables obtained from remote sensing for recommending spatially variable nitrogen fertilizer application. The first way consists to estimate indices as *INN* or ΔQN that inform on nitrogen absorption by the crop and the possible deficit. These indices should be used in the same way as the manual measurements made in some usual empirical method (Ntester, Jubil), having the advantage to be more explicit and reliable. They should be also used to directly to determine a dose, as ΔQN means the actual deficit of absorption. However, this deficit of absorption may not be linked to a nitrogen deficit in the soil but to a water stress. Prescribing a large amount of fertiliser as a consequence of a high value of ΔQN would not solve the problem of absorption limitation and would increase the risk of further nitrate leaching. Therefore, the use of crop models which allow to have a diagnostic on all the components of the system (soil, crop), avoids this kind of error. They make it possible to build an agro-environmental criterion that can be optimized over a number of technical and climatic scenarios to calculate an optimal nitrogen dose. The development of methods for spatializing the model, by assimilating the observations on *LAI* and *QN*, permits to account for the within field variability and work out spatially variable optimal doses over the whole field.
Progress is still expected in the precision of *LAI* and *QN* estimation thanks to improvements in radiative transfer

modelling. The performance of data assimilation methods is also being improved, as we have a lot to learn from other areas of research (hydrology, meteorology, oceanography) were assimilation is performed since a long time. Finally, the performance will also be improved in the future with the increasing the number of available observations that will be affordable in the future projects of satellite clusters.

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