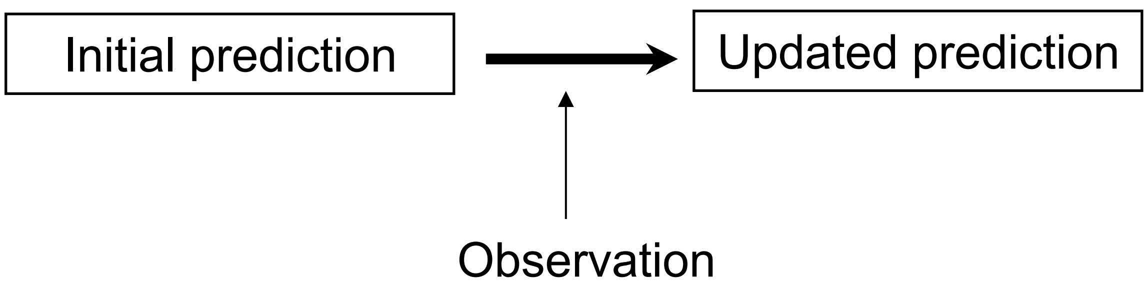
Use of in-season data to update models

David Makowski
INRA Grignon
makowski@grignon.inra.fr

Objective

Improve model predictions by fitting some of the model components to plot-specific data obtained during the season

An attractive approach for improving decision-support models:



How to proceed

- **Collect data on the plot(s) of interest.**
- **Fit some of the model components to plot-specific data**
  1. Parameters,
  2. Input variables,
  3. State variables.

Two types of methods

Parameter estimation

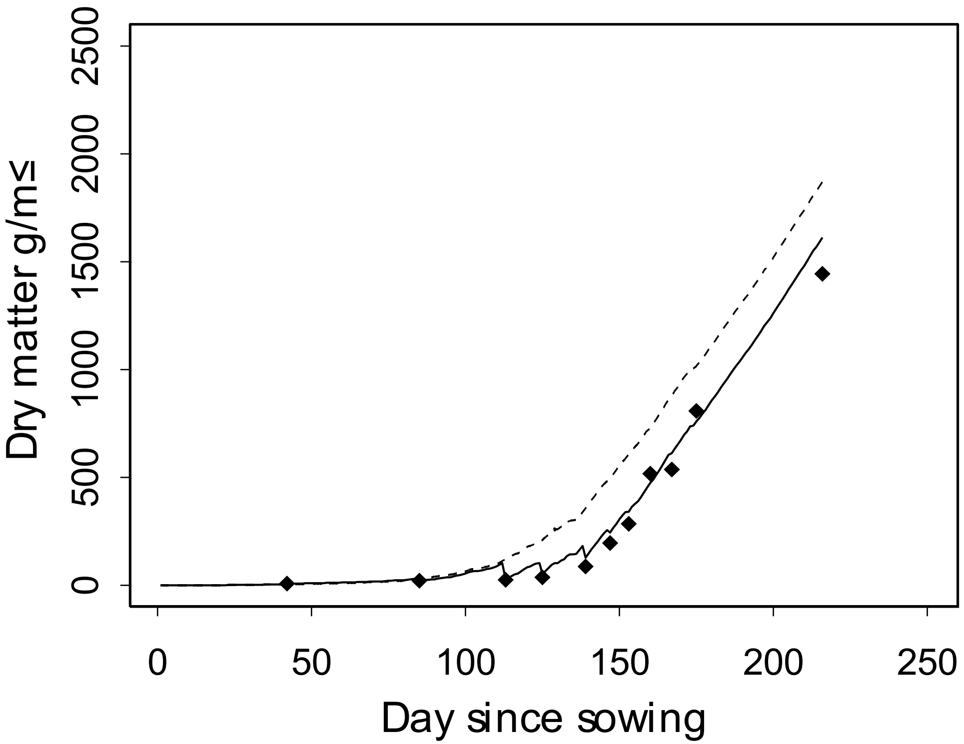
- Least squares,
- maximum likelihood,
- Bayesian estimation method…

Filter

- Kalman filter,
- Extended Kalman filter,
- Ensemble Kalman filter,
- Particle filter…

Basic principle of filtering

Filter = algorithm for **updating** one or several **state variables of a dynamic model** with data



Makowski, Guérif, Jones, Graham (2006).

Three examples

Example 1

Updating the model STICS by estimating some of its parameters

Example 1

Data

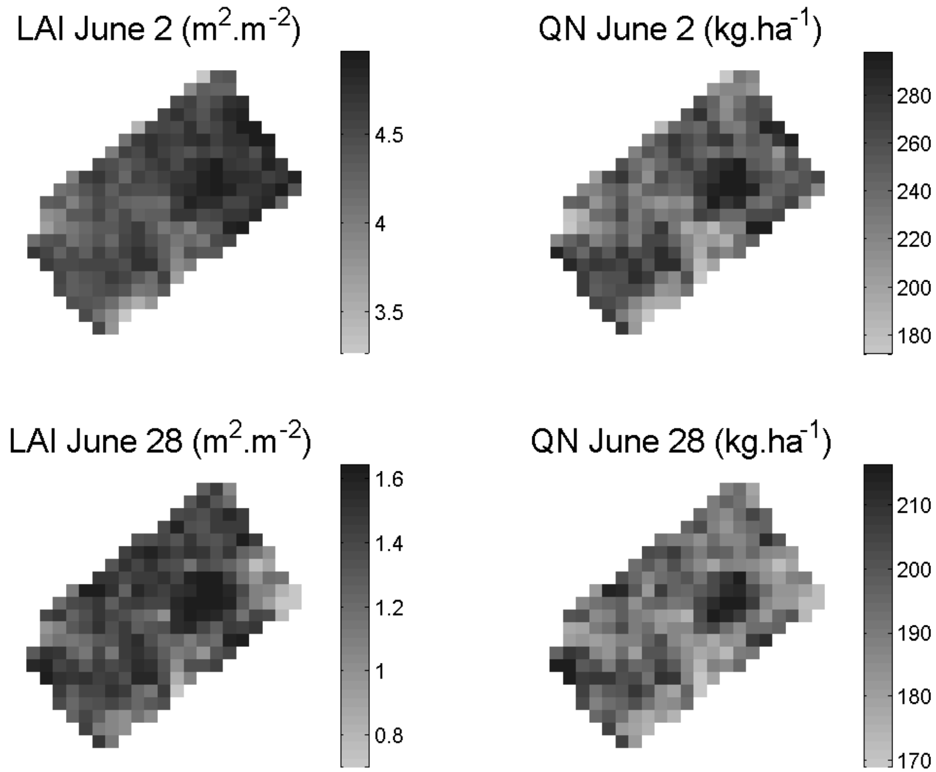
A wheat plot (1999-2000)

= 280 cells (20 m * 20 m).

In each cell:

- four LAI measurements

- four N uptake measurements



Guérif, Houlès, Makowski, Lauvernet (2006).

Example 1

Objective

Predict crop yield with STICS for each cell by estimating 10 parameters cell by cell

STICS = Dynamic crop model (Brisson *et al*. 1998).

Example 1

Two types of information for estimating the parameters

A. Prior information about 10 parameters

Parameter	Acronym	lower bound	higher bound
Organic nitrogen content (H1) (%)	Norg	0.04	0.17
Lime content (H1) (%)	Calc	0	40
Rooting impediment depth (cm)	Obstarac	50	150
Water content at field capacity (H1) (%)	Hcc(H1)	17	22
Water content at field capacity (H2) (%)	Hcc(H2)	14	22
Water content at field capacity (H3) (%)	Hcc(H3)	14	26
Bulk density (H2) ($g.cm^{-3}$)	DA(H2)	1.45	1.6
Mineral Nitrogen content at sowing (H1) ($kg.ha^{-1}$)	Nmin_ini(H1)	50	85
Life duration of leaves (°C day)	durvieF	140	220
LAI growth coefficient	vlaimax	1.5	2.5

B. Eight measurements in each cell

Example 1

Method

- Bayesian method (Importance Sampling).
- Prior distribution = Uniform distribution.
- Approximation of the posterior parameter distribution from 200,000 values.

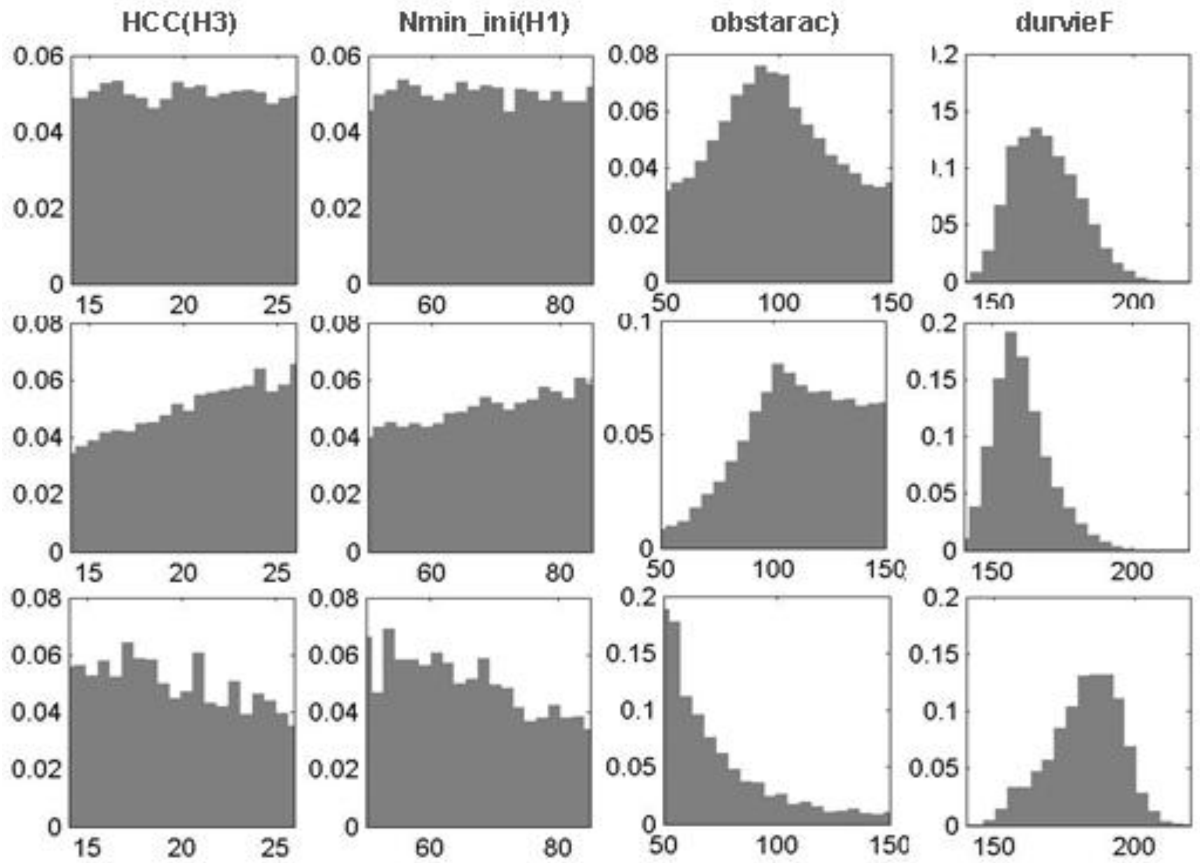
Example 1

Posterior distribution for 4 parameters and 3 cells

Cell. 1

Cell. 2

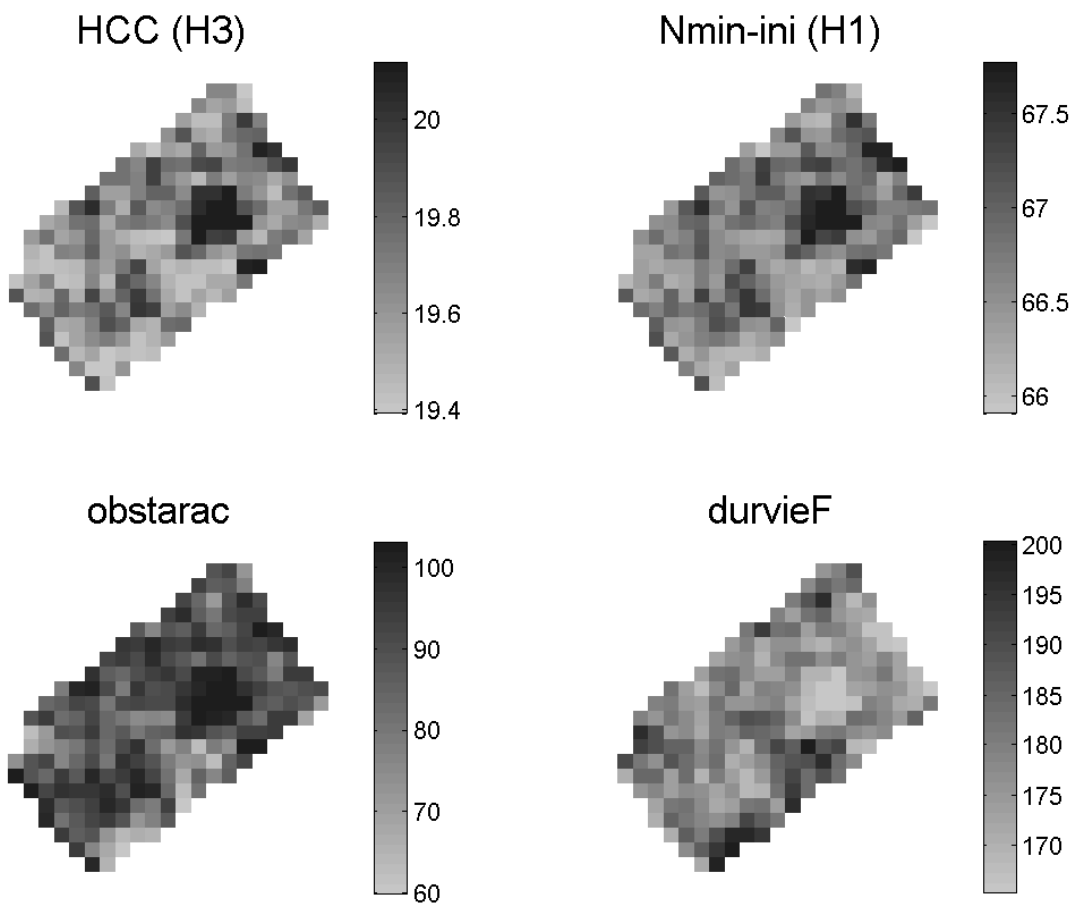
Cell. 3



Guérif, Houlès, Makowski, Lauvernet (2006).

Example 1

Posterior means for 4 parameters and all cells

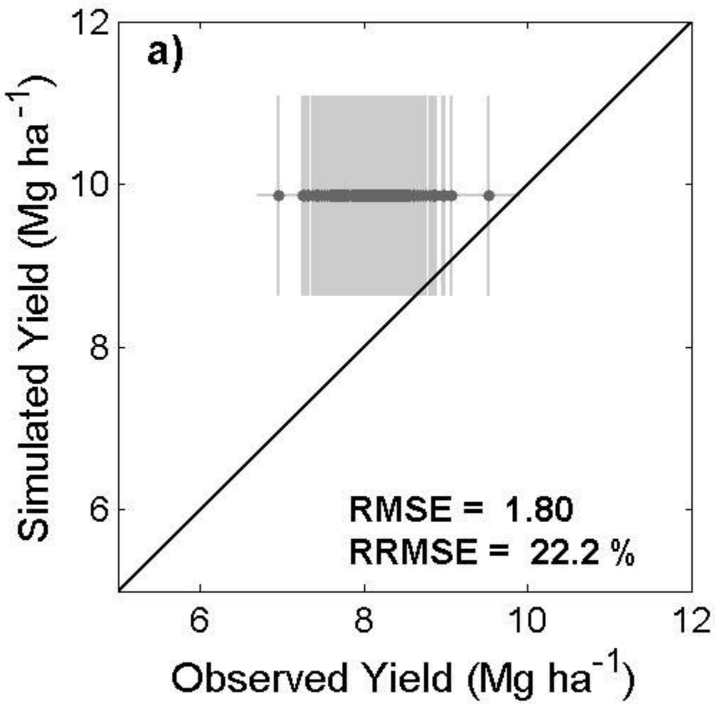


Guérif, Houlès, Makowski, Lauvernet (2006).

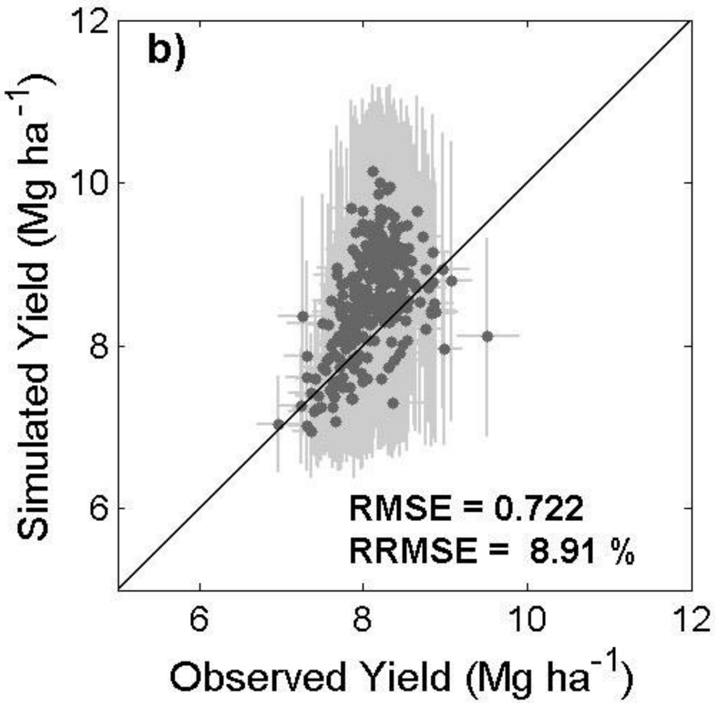
Example 1

Yield predictions with and without parameter estimation

Without



With



Guérif, Houlès, Makowski, Lauvernet (2006).

Example 2

Filtering

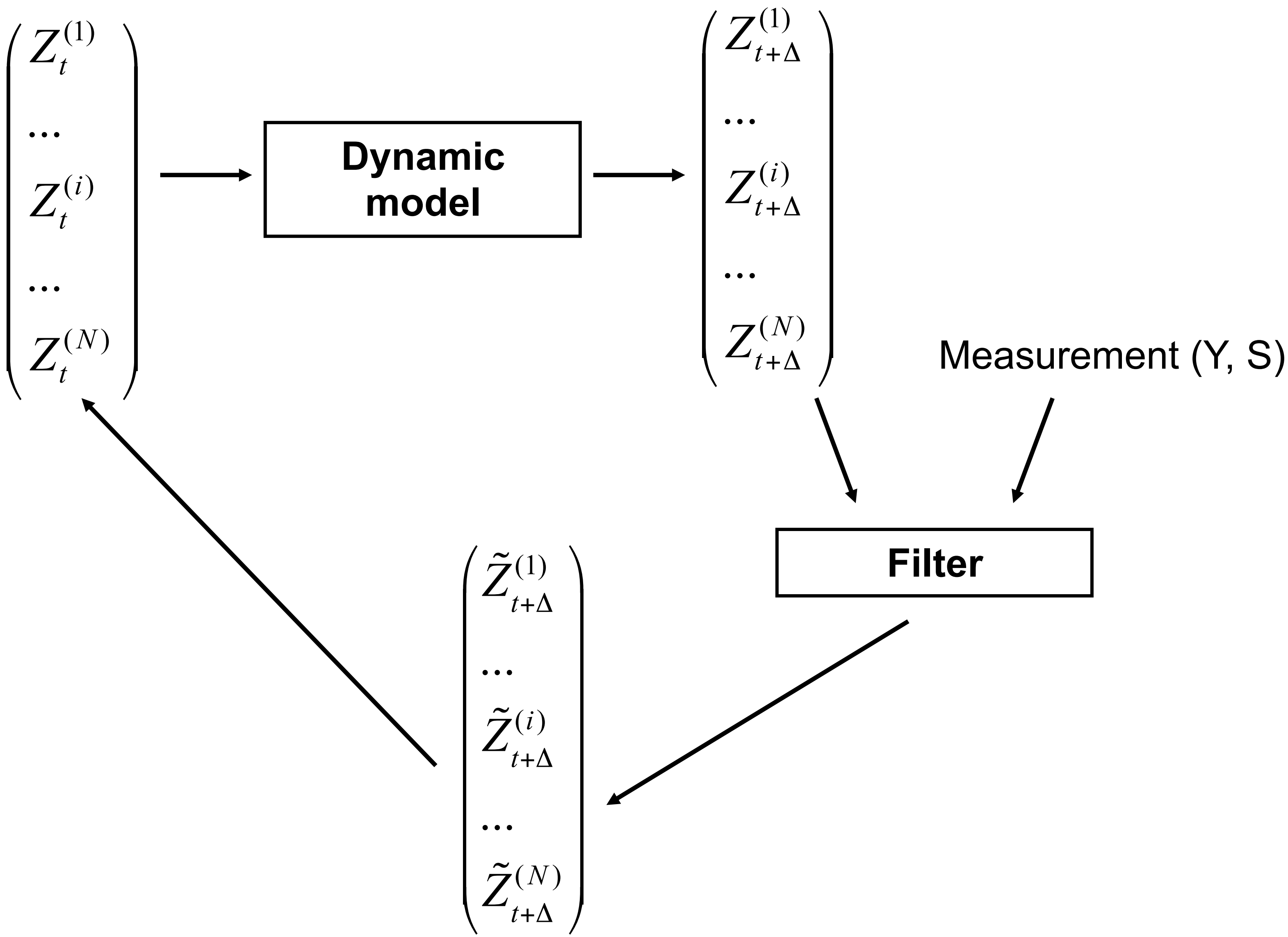
Objective

Predict the risk of wheat nitrogen deficiency with AZODYN by using one or several plot-specific measurements

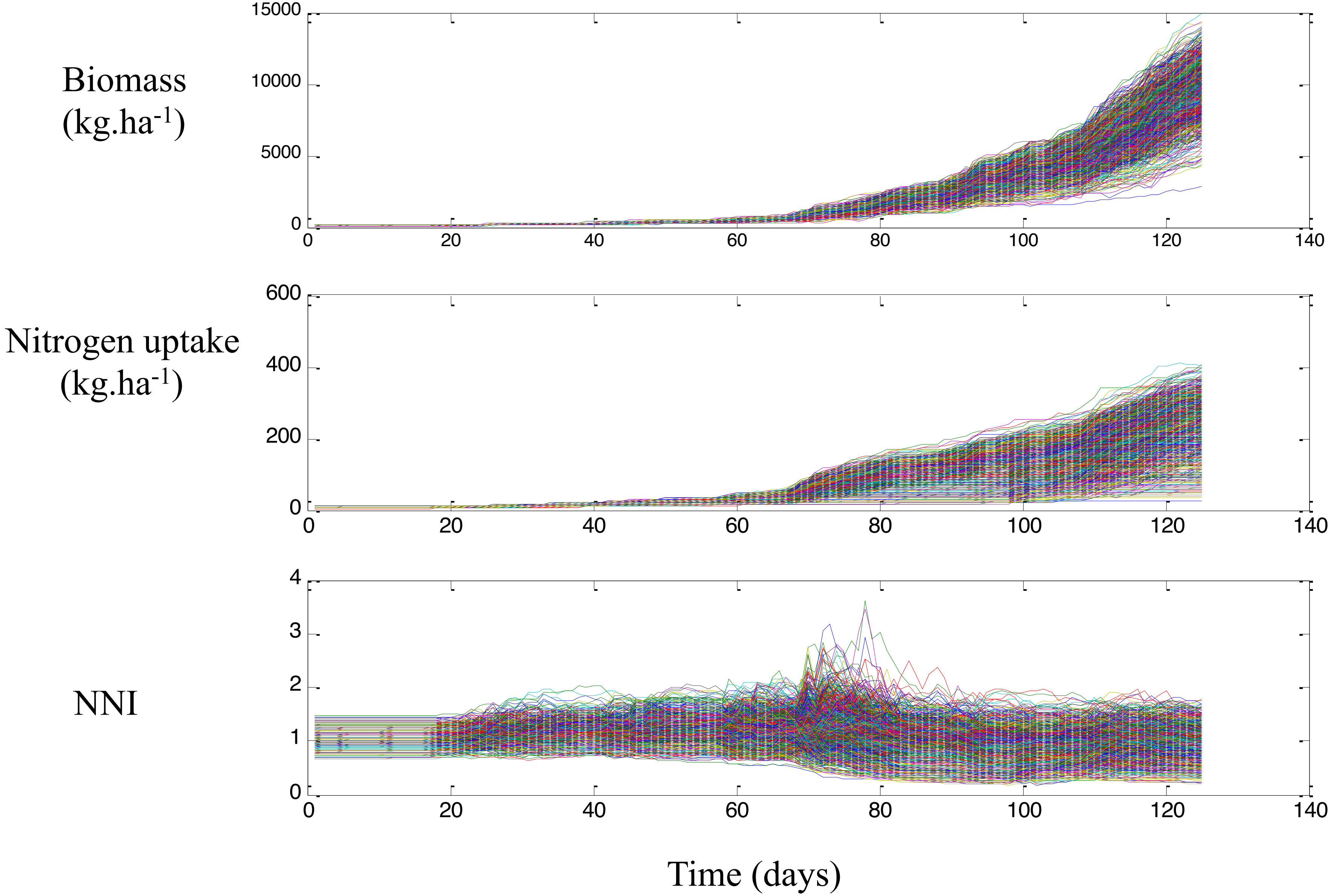
AZODYN = Dynamic crop model (Jeuffroy et Recous, 1999).

Method = Particle filter

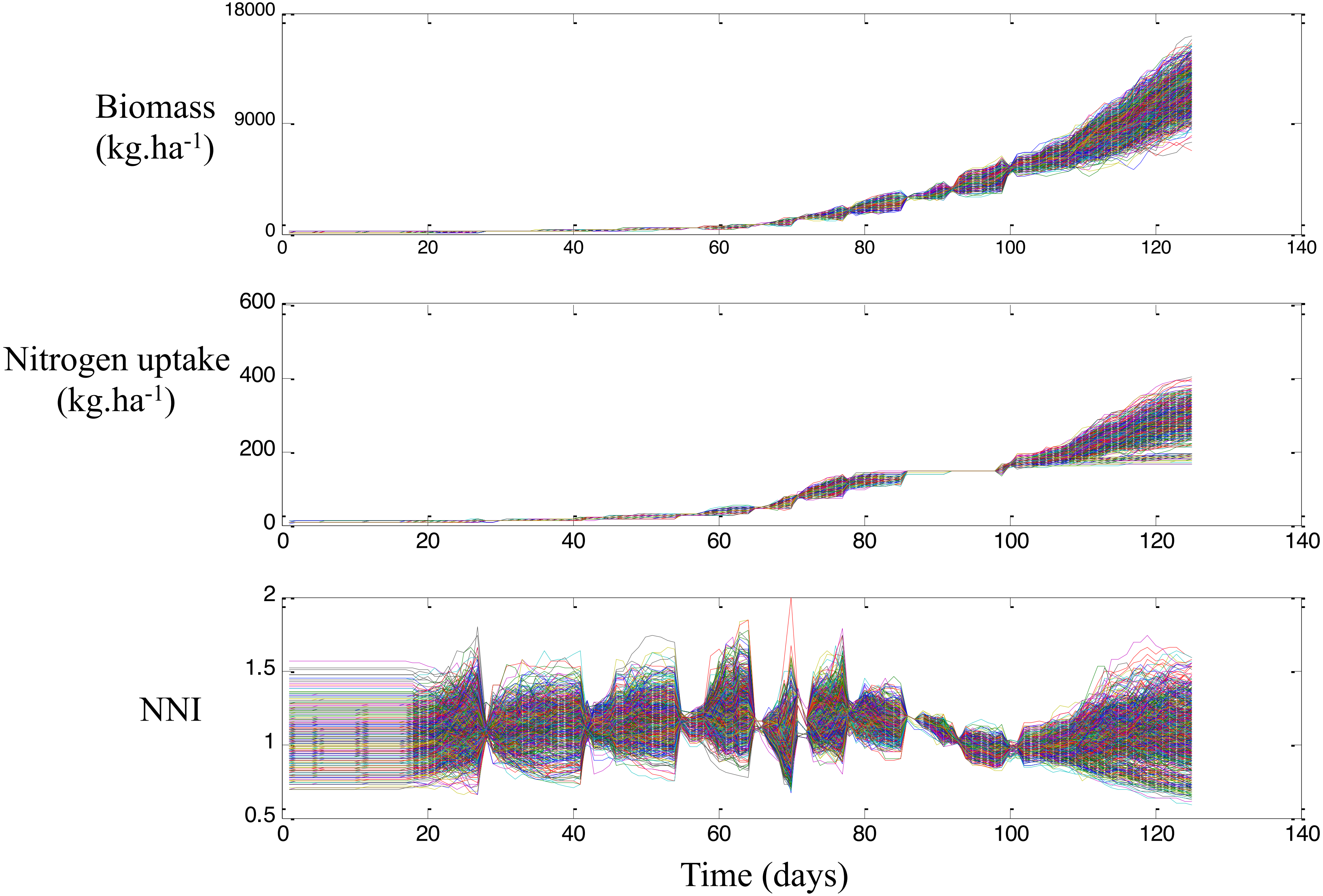
$$\begin{cases} Z_t = \begin{pmatrix} MS_t \\ QN_t \\ Ncumu_t \end{pmatrix} = Z_{t-1} + f\left(Z_{t-1};\theta\right) + \varepsilon_{\text{t-1}} \\ Z_0 \sim N\left(\mu_0, \Sigma_0^2\right) \end{cases}$$


$Z_t^{(1)}$
…
$Z_t^{(i)}$
…
$Z_t^{(N)}$
Dynamic model
$Z_{t+\Delta}^{(1)}$
…
$Z_{t+\Delta}^{(i)}$
…
$Z_{t+\Delta}^{(N)}$
Measurement (Y, S)
Filter
$\tilde{Z}_{t+\Delta}^{(1)}$
…
$\tilde{Z}_{t+\Delta}^{(i)}$
…
$\tilde{Z}_{t+\Delta}^{(N)}$

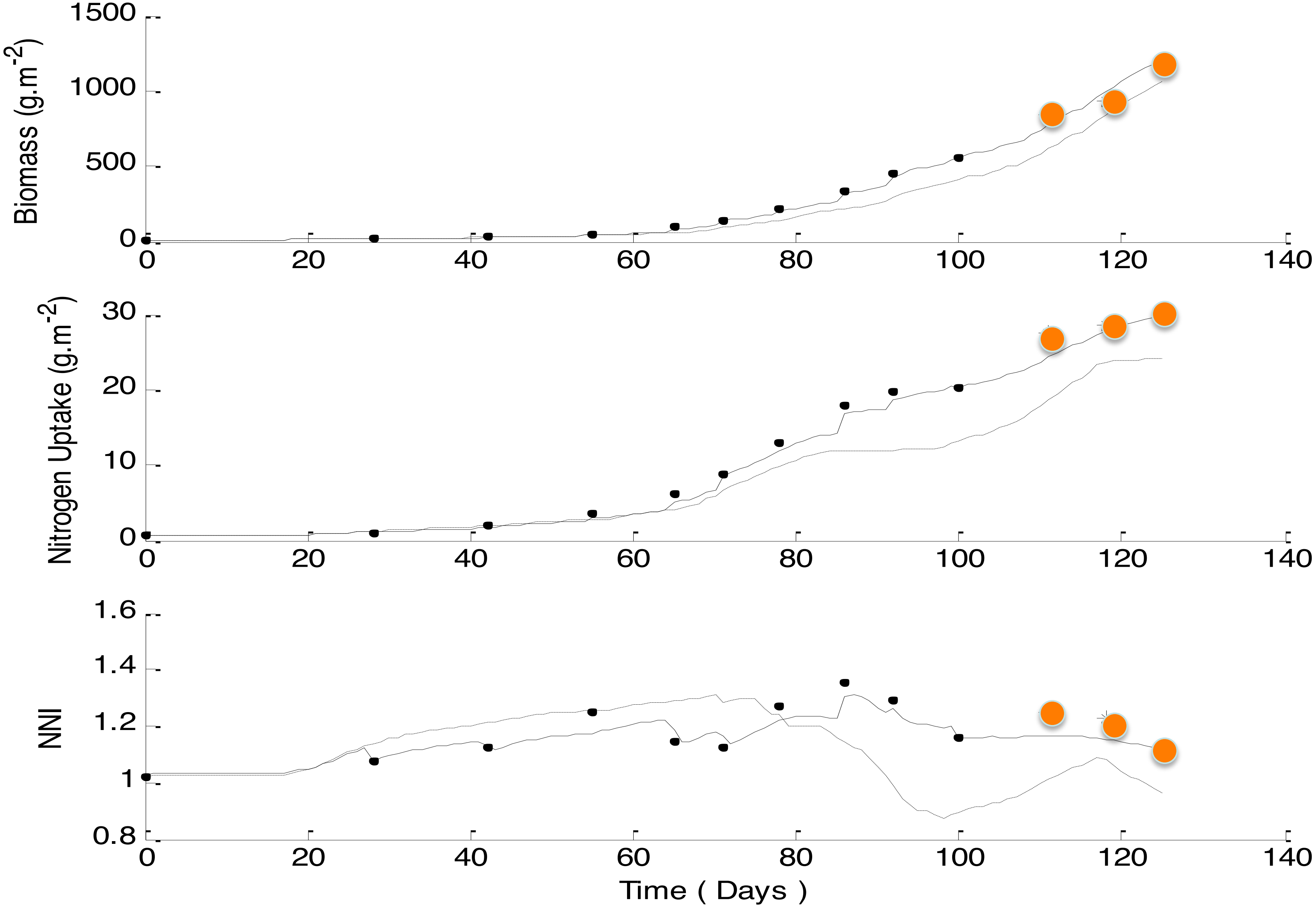
Simulations without correction for one wheat plot (site-year)
N=1000, λ=1, ρ=0



Results obtained with the particle filter using biomass and nitrogen uptake measurements

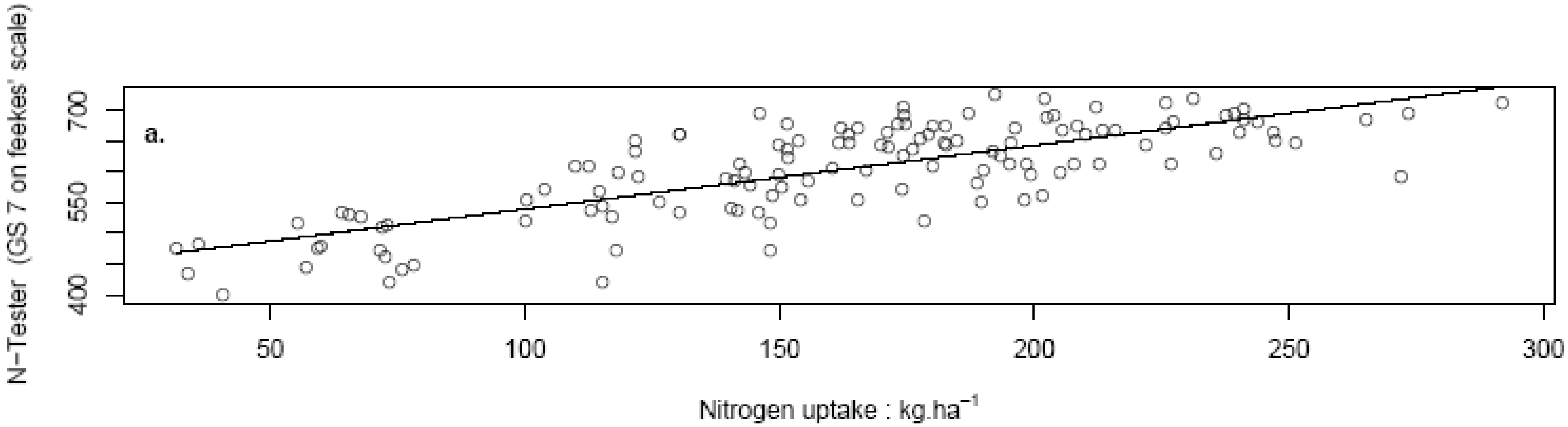


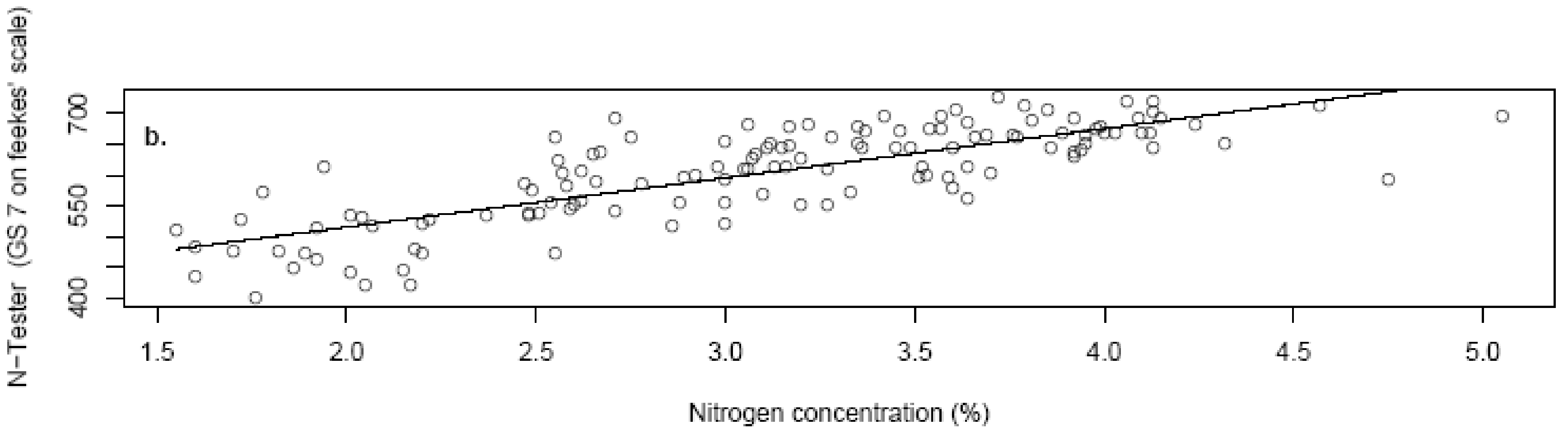
Averaged values without and with correction using biomass and nitrogen uptake measurements



Implementation of the filter with transmitance measurements

Relationship between transmitance and a model state variable

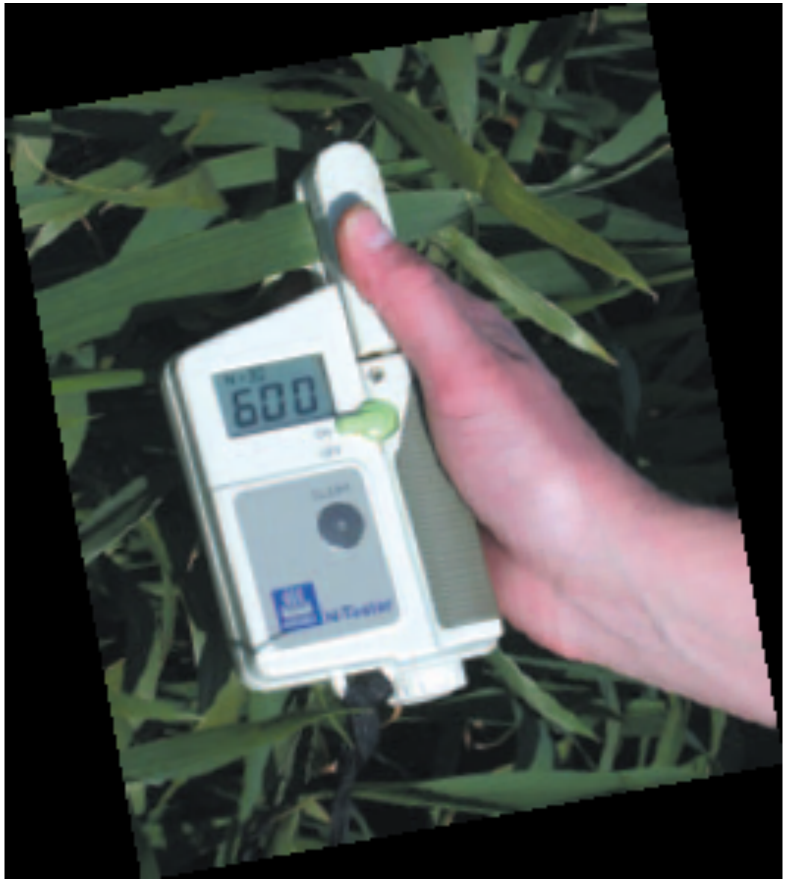




Naud, Makowski, Jeuffroy (2007, 2008)

Objective: Updating the crop model with in-season measurements

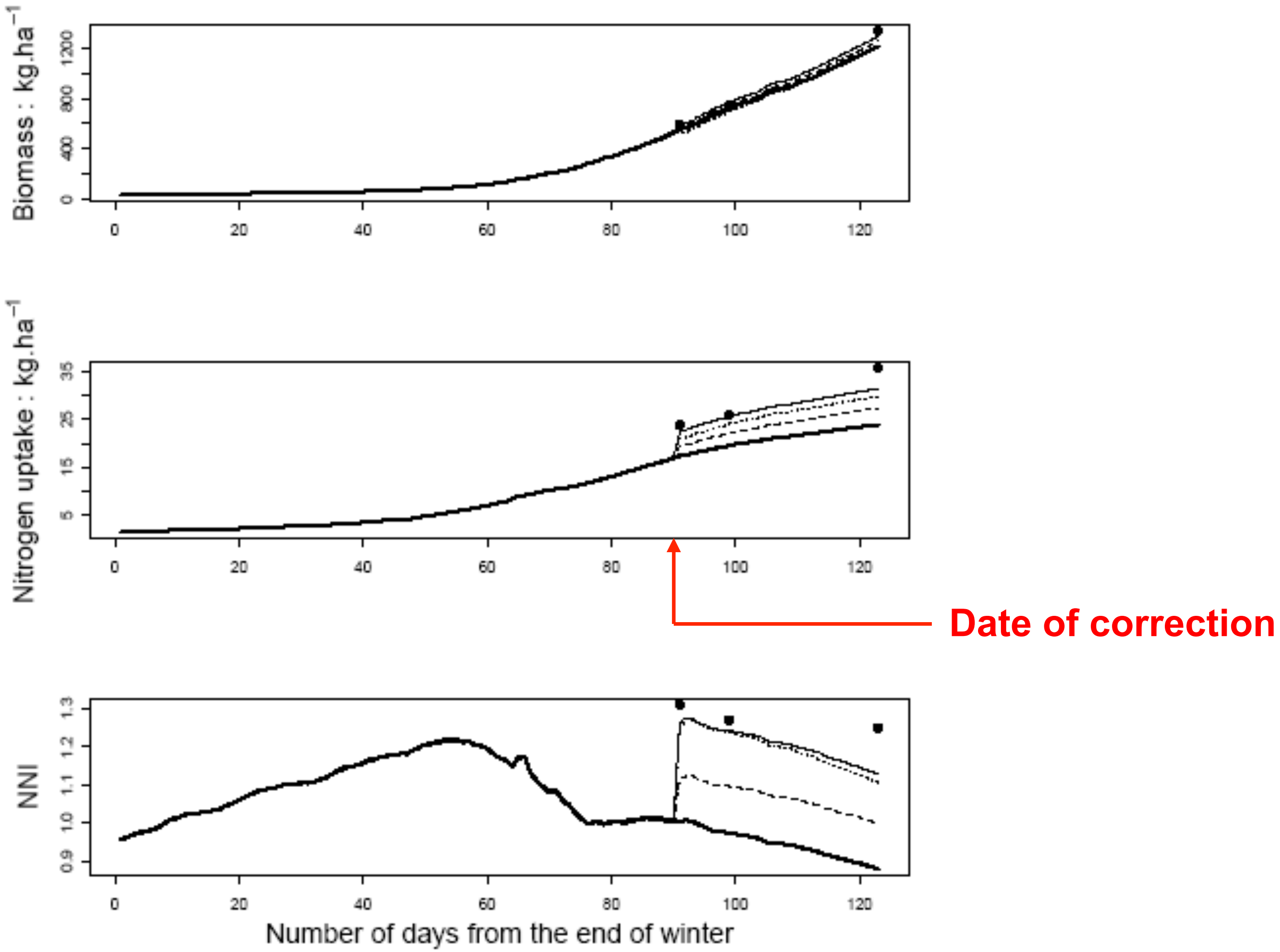
- **Biomass and nitrogen content measurements**
- **Transmitance measurement (correlated with nitrogen content)**



HN tester, Yara

Implementation of the filter with transmitance measurements

Updating model predictions



Naud, Makowski, Jeuffroy (2007, 2008)

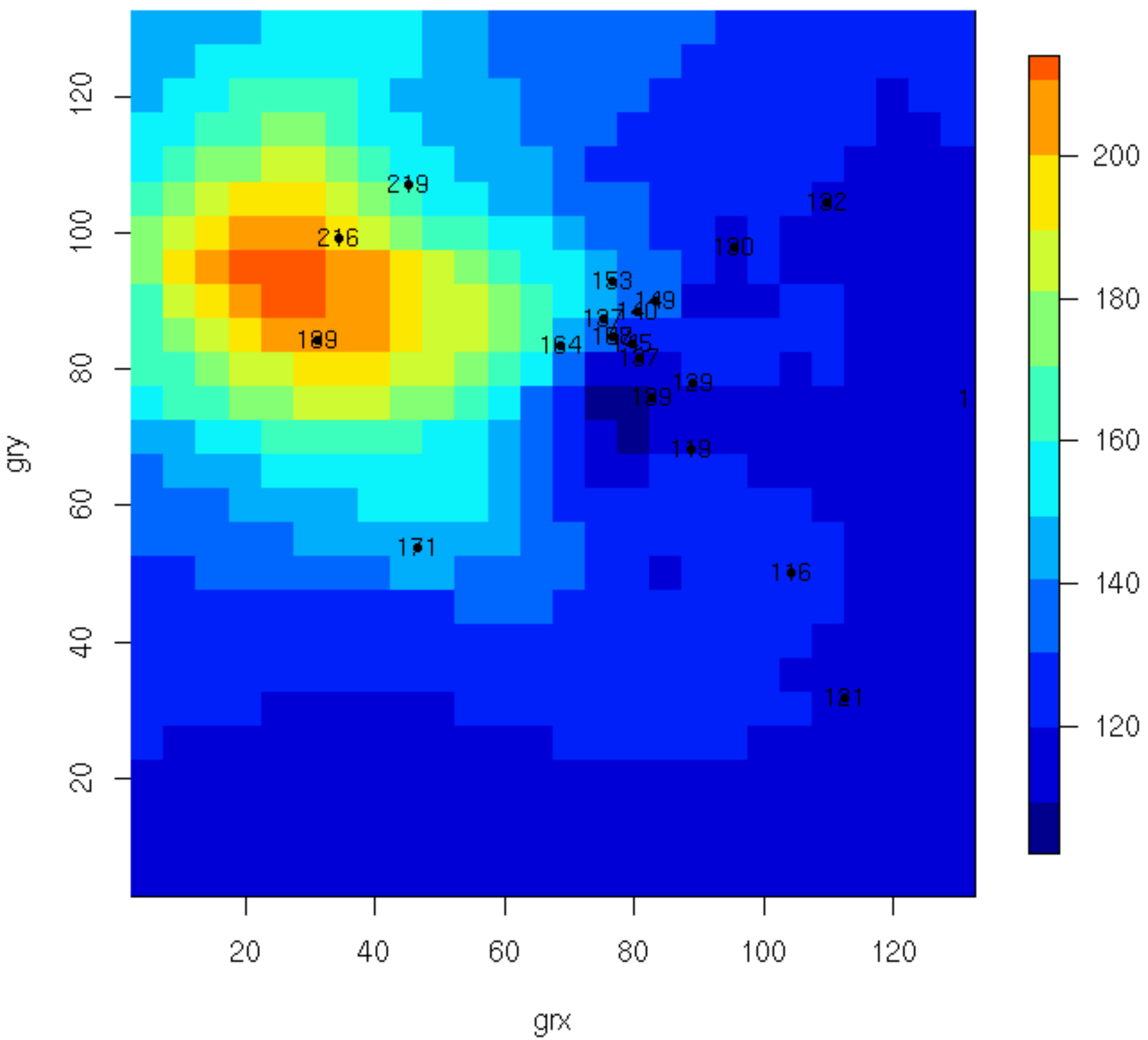
Many elements influence the results of the filter

- The level of complexity of the equations
- The number of stochastic state variables
- The probability distribution of the random error terms
- The number, type, and accuracy of the measurements

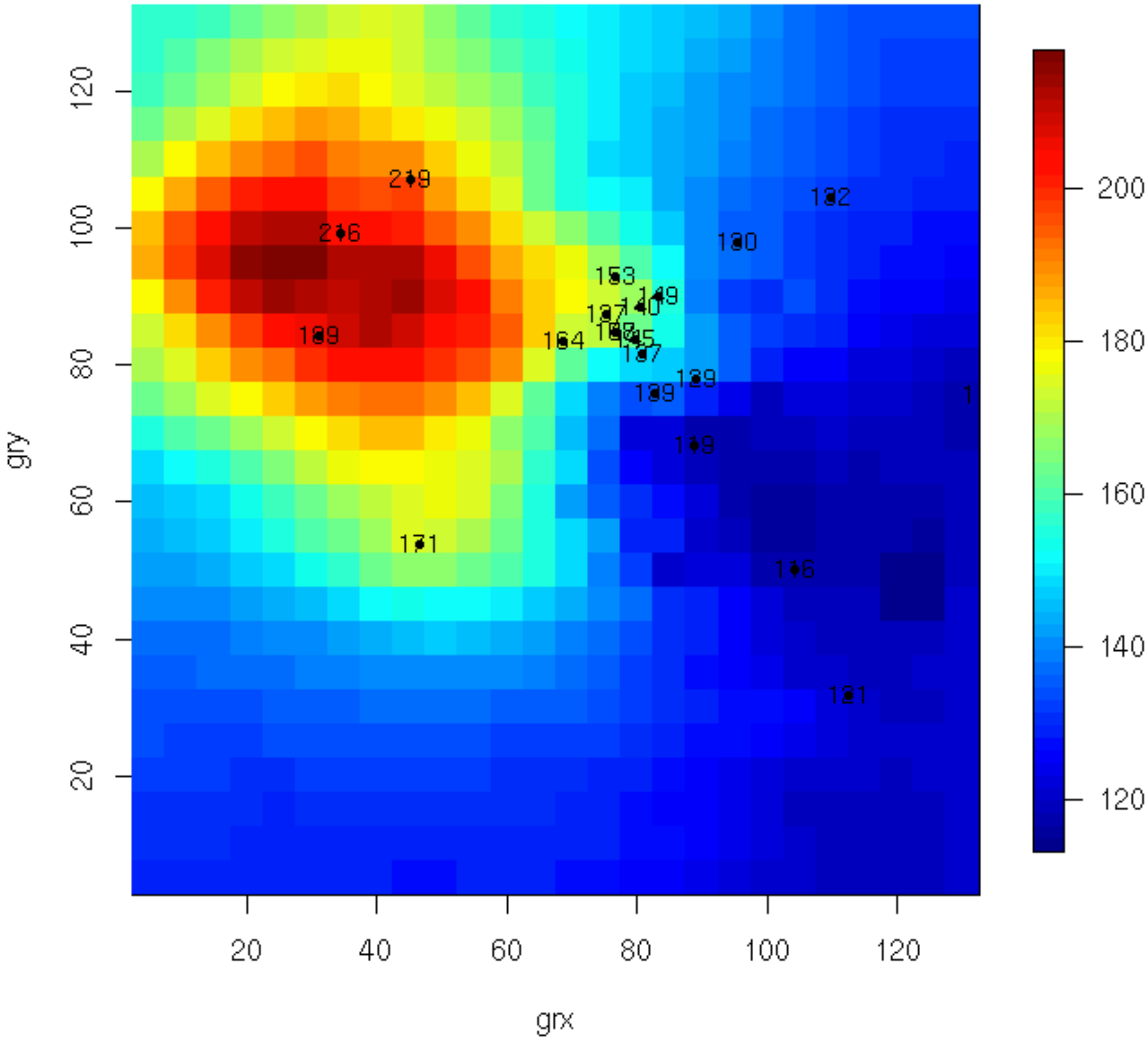
An efficient computational tool is required to build a large variety of models and update their predictions with observations

Example 3

Krigging on model errors



gry
grx
20
40
60
80
100
120
140
160
180
200


gry
20
40
60
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100
120
grx
20
40
60
80
100
120
200
180
160
140
120

Conclusion

These techniques allow modellers **to fit models to local measurements (plot-specific)**

They can be used to **decrease prediction errors**

BUT

- The measurements can be costly
- Computations can be complex

STAGE 2012 INRA – Arvalis

Mise au point d'une méthode de couplage spatialisé des prédictions d'un modèle de conseil phytosanitaire (septoriose du blé) avec les observations d'un réseau de surveillance

Stagiaire : Lygie Esquirol

Encadrants : David Makowski et David Gouache

OBJECTIF DU TRAVAIL :

- Identifier des méthodes de couplage et les adapter aux spécificités du problème agronomique posé

- Construction d'un jeu de données pertinent à partir des bases de données existantes
  - Simulations de la sévérité de la septoriose
  - Mesures d'incidence/sévérité de septoriose

- Mise en œuvre de modélisations géostatistiques des erreurs du modèle de prévision

- Evaluation de l'amélioration de la qualité prédictive du modèle par le couplage avec les données d'observations

RESULTATS ATTENDUS :

- Fonctions R génériques pour représenter graphiquement des simulations et des mesures à diverses échelles spatiales (région, pays)

- Méthodes opérationnelles de couplage modèles/mesures

- Evaluation et réduction des erreurs d'un modèle simulant la sévérité de la septoriose du blé

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