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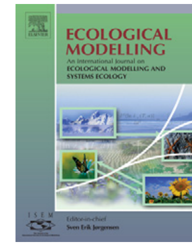

Application of an interacting particle filter to improve nitrogen nutrition index predictions for winter wheat

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ABSTRACT

Dynamic crop models predict several state variables at a daily time step and thus provide useful information for optimizing agricultural techniques. But the prediction errors of these models are often large due to uncertainties in parameters, initial state values, and equations. Monte Carlo sequential methods, like the interacting particle filter [Del Moral, 1996. Nonlinear filtering: interacting particle solution. Markov Process. Relat. Fields 2, 555–580], can be used to update the state variable values predicted by nonlinear dynamic models from a set of measurements and thus reduce the prediction errors. An interesting feature of these methods is that they do not require a linearization of the original nonlinear model. Up to now, these methods have never been applied to complex dynamic crop models. In this paper, the interacting particle filter was used to update the Azodyn model, a dynamic winter wheat crop model, at 10 or 11 dates, from biomass and nitrogen uptake measurements, and to predict a variable of practical interest, the nitrogen nutrition index. We showed that the implementation of this method can reduce the root mean squared error by 66.7–79.7% for the nitrogen nutrition index, but that the filter is highly sensitive to the assumptions made about the probability distribution of the model errors. We also showed that the particle filter gives stable results with 10,000 Monte Carlo simulations and that this number of simulations can be performed in a very reasonable calculation time.

1. Introduction

Numerous dynamic crop models have been developed by agronomic researchers since the 1960s (*e.g.* de Wit, 1965; Wilkinson et al., 1983; Ritchie and Otter, 1985; Spitters et al., 1989; Brisson et al., 1998; Jeuffroy and Recous, 1999; Loyce et al., 2002; Jones et al., 2003). Crop models predict a large number of state variables like the crop biomass, the leaf area index, the crop nitrogen (N) uptake, and the Nitrogen Nutrition Index as functions of soil characteristics, weather and farmers' practices. Some of these models can be used to improve agricultural practices like, for instance, the amounts of applied N fertilizer (Jeuffroy and Recous, 1999; Makowski et al., 2001; Houlès et al., 2004; David et al., 2004, 2005). Nonetheless, their errors are often large due to uncertainty in parameters, input variables and equations (Houlès et al., 2004; Schnebelen et al., 2004; David et al., 2005; Barbottin et al., 2006).

The Nitrogen Nutrition Index (NNI) is a variable of practical interest. NNI is an indicator of crop nitrogen deficiency (Lemaire and Gastal, 1997; Lemaire and Meynard, 1997) and it was shown that this variable is correlated to the loss of grain number and grain yield due to N deficiency (Jeuffroy and Bouchard, 1999), and to grain protein content (Justes et al., 1997b). NNI can be predicted by using crop models such as Azodyn (Jeuffroy and Recous, 1999) or STICS (Brisson et al., 2002) before the date of fertilizer application. The predicted

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values can then be used to identify the crop fields in which nitrogen fertilizer must be supplied. NNI values derived at a daily time step by dynamic models can also be used to determine optimal dates of N fertilizer application and optimal N doses.

The purpose of this paper is to study the interest of a data assimilation technique to improve the prediction of NNI in winter wheat crops (*Triticum aestivum* l.). Data assimilation consists of using a set of measurements to update some of the model parameters and/or some of the model state variables. Measurements of state variables are in fact more and more commonly available, due to progress in detection and transmission capability. Satellite systems give information about plant biomass, LAI, or leaf chlorophyll content. Tensiometers can be used to give information about soil moisture. Several tools provide information about plant nitrogen status like SPAD® (Minolta), Hydro N-tester® (Yara) and N-sensor® (Yara) and ®GPN (Grande Paroisse). In each case, model predictions could be modified taking into account these measurements.

Two families of methods can be used for data assimilation. The first consists of estimating some of the model parameters. This approach has already been used with several dynamic crop models (*e.g.* Faivre et al., 1991; Guérif and Duke, 1998; Wallach et al., 2001; Tremblay and Wallach, 2004; Guérif et al., 2006). An important limitation of this method is that the parameters are often very numerous in crop models (up to 200) and it is very difficult to determine which parameters must be estimated from the data (Houlès et al., 2004).

The second family of methods is often referred to as filtering. A *filter* is an algorithm that provides an efficient computational means to estimate the state of a dynamic system from a series of measurements. Here the dynamic system is defined by the successive values of the model state variables. The state variables are updated sequentially, *i.e.* each time an observation is available. The best-known algorithm for doing this is the *Kalman filter*, an analytical method which applies if the model is linear and the errors have a normal distribution (Kalman, 1960). See Makowski et al. (2006) for an application to a simple dynamic crop model.

Various extensions of this method were developed for non-linear models (Gordon et al., 1993; Del Moral, 1996; Burgers et al., 1998; Pastres et al., 2003). Among all these techniques, the interacting particle filter (Del Moral, 1996) is very promising because its implementation is based on Monte Carlo simulations and therefore does not require a linearization of the original model, which, like all crop models, is non-linear. In addition, the convergence properties of this method are satisfactory for a variety of model error distributions (Del Moral and Guionnet, 1998, 1999). The interacting particle filter has already been applied to simple dynamic models (Doucet et al., 2001) but never to complex dynamic crop models.

In this paper, the interacting particle filter is used to update three state variables of the winter wheat dynamic crop model Azodyn (Jeuffroy and Recous, 1999) in order to predict the NNI. Three questions of practical importance are addressed: (i) is it possible to improve the NNI predictions with an interacting particle filter? (ii) What is the sensitivity of the filter to the distribution assumptions of the model errors? (iii) How many simulations are required to obtain accurate results?

2. Materials and method

2.1. *The Azodyn model*

Azodyn was developed by Jeuffroy and Recous (1999) in order to help farmers to determine dates and amounts of nitrogen fertilizer application for winter wheat crops. It includes 69 parameters and numerous input variables related to climate (daily temperature and global radiation), to soil characteristics (%clay, %$CaCO_3$, nitrogen supplied by the soil), and to the wheat crop stages (end-of-winter, beginning of stem elongation, flowering). Once set up, the Azodyn model computes several daily state variables like wheat biomass, nitrogen uptake, cumulative amount of mineral nitrogen in the soil, and the nitrogen nutrition index. NNI indicates whether the crop suffers from a nitrogen deficiency (NNI < 1) or not (NNI ≥ 1). Justes et al. (1997a) defined a method to derive nitrogen fertilizer recommendations based on an indicator highly correlated to this variable.

In this study, we consider four state variables simulated by the model on a daily time step: crop biomass, nitrogen uptake, cumulative amount of soil mineral nitrogen, and NNI. We briefly describe below the equations used to compute these variables from the initialization date of the model (end-of-winter) to the flowering stage.

The biomass (B, $\mathrm{g\,m^{-2}}$) is calculated as a function of daily radiation as follows:

$$B_t = B_{t-1} + f_1(B_{t-1}) = \begin{cases} B_{t-1} + 5E_b(\mathrm{NNI}_{t-1})E_{i\,\max}(1-\mathrm{e}^{-K\,\mathrm{LAI}_{t-1}})\mathrm{Teff}_{t-1}C\,\mathrm{RG}_{t-1} & \text{if } t < \text{beginning of stem elongation} \\ B_{t-1} + 10E_b(\mathrm{NNI}_{t-1})E_{i\,\max}(1-\mathrm{e}^{-K\,\mathrm{LAI}_{t-1}})\mathrm{Teff}_{t-1}C\,\mathrm{RG}_{t-1} & \text{else} \end{cases} \quad (1)$$

where B_t represents the value of the biomass at day t, NNI_t and LAI_t are the nitrogen nutrition index and the leaf area index, respectively, Teff_t is a function simulating the effect of the temperature on the crop growth rate, $\mathrm{Teff}_t = 1 - ((T_t - T_{\mathrm{opt}})/(T_{\min} - T_{\mathrm{opt}}))^2 \mathrm{II}_{\{T_t \in]T_{\min};T_{\mathrm{opt}}]\}} - ((T_t - T_{\mathrm{opt}})/(T_{\max} - T_{\mathrm{opt}}))^2 \mathrm{II}_{\{T_t \in]T_{\mathrm{opt}};T_{\max}[\}}$, T_t is the daily average temperature, RG_t the daily global radiation. $E_b(\cdot)$ is a function computing the radiation use efficiency, $E_{i\,\max}$, C, K, T_{opt}, $T_{\min}$, and $T_{\max}$ are six parameters.

The nitrogen uptake (NU, amount of nitrogen in the aerial parts of the crop, $\mathrm{g\,m^{-2}}$) is expressed as:

$$\begin{aligned} \mathrm{NU}_t &= \mathrm{NU}_{t-1} + f_2(\mathrm{NU}_{t-1}) \\ &= \mathrm{NU}_{t-1} + [\min(V_{\max}T_{t-1}, \mathrm{Ne}_t - \mathrm{Ne}_{t-1}, \mathrm{Na}_{t-1})]^+ \end{aligned} \quad (2)$$

where $A^+ = \max(0,A)$, Ne_t the nitrogen crop requirement at day t ($\mathrm{g\,N\,m^{-2}}$) and is calculated as follows (Justes et al., 1994): $\mathrm{Ne}_t = R \times B_t[(M/100)\mathrm{II}_{\{B_t<L\}} + (N/100)(B_t/1000)^P \mathrm{II}_{\{B_t \geq L\}}]$, $V_{\max}$, R, M, N, L and P are six parameters. Na_t is the amount of soil mineral nitrogen available for the crop ($\mathrm{g\,N\,m^{-2}}$) and expressed as $\mathrm{Na}_t = \mathrm{CumN}_t - \mathrm{NU}_t + \mathrm{NU}_0$, where CumN_t is the cumulative amount of mineral nitrogen in the soil from the end-of-winter