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Potential performances of remotely sensed LAI assimilation in WOFOST model based on an OSS Experiment

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ABSTRACT

An Observing System Simulation Experiment (OSSE) has been defined to assess the potentialities of assimilating winter wheat leaf area index (LAI) estimations derived from remote sensing into the crop growth model WOFOST. Two assimilation strategies are considered: one based on Ensemble Kalman Filter (EnKF) and the second on recalibration/re-initialisation of uncertain model parameters and initial state conditions. The main objective of the OSS Experiment is to estimate the requisites for the remotely sensed LAI, in terms of accuracy and sampling frequency, to reach target of either 25 or 50% reduction of errors on the final estimation of grain yields.

Our results demonstrate that EnKF is not suitable for assimilating LAI in WOFOST as the average error on final grain yields estimation globally increases. These poor results can be explained by the possible differences of phenological development existing between assimilated and modelled LAI values (difference called "phenological shift" in our study) which is not corrected by the EnKF-based assimilation strategy.

On the contrary, a recalibration-based assimilation approach globally improves the estimation of final grain yields in a significant way. On average, such improvement can reach up to approximately 65% when observations are available all along the growing season. Improvements on the order of 20% can be already be attained early in the season, which is of great interest in a crop yield forecasting perspective. If the first objective (25%) of error reduction on final grain yields can be reached in a quite high number of assimilated LAI observations availabilities and uncertainty levels, the field of possibilities is significantly restricted for the second objective (50%) and implies to have LAI observations available all along the growing season, at least on a weekly basis and with an uncertainty level equal or ideally lower than 10%. These requirements are not currently met from neither a technological nor an operational point of view but the results presented here can provide guidelines for future missions dedicated to crop growth monitoring.

1. Introduction

In a context of markets globalization, timely estimation of crop yields at regional to global scale is of prime importance for managing large agricultural lands and determining food pricing and trading policies (Macdonald and Hall, 1980; Hutchinson, 1991 in Lobell et al., 2003). Information on yield and production volumes may indeed support government agencies, commodity firms and producers in planning transport activities, marketing of agricultural products or planning food imports. At global scale, agricultural market prices are affected by information on the supply or consumption of foodstuffs (Supit, 2000).

Crop models simulate crop growth under different environmental and management conditions by dynamically taking various limiting factors (e.g. soil, weather, water, nitrogen) into account, thereby providing good indications on crop growth and enabling to predict yields over large areas (Launay and Guerif, 2005). The success of crop growth monitoring systems based on such models strongly depends on the models' ability to quantify the influence of weather, soil and management conditions on crop yields and on the system's ability to properly integrate model simulation results over a range of spatial scales (De Wit and Van Diepen, 2008).

Unfortunately, crop growth monitoring systems applied over large areas and relying on a spatially distributed crop growth model are typically confronted with large uncertainty in the spatial distribution of soil properties and initial soil conditions, crop parameters, meteorological forcings (Hansen and Jones, 2000) as well as management practices. Within the crop growth model, this uncertainty majorly influences the simulation of two important physiological

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processes: (1) the simulation of crop canopy development, which determines light interception and photosynthetic potential, and (2) the simulation of soil moisture content, which determines the actual evapotranspiration and the reduction of photosynthesis as a result of drought stress (De Wit and Van Diepen, 2007).

Uncertainty in biophysical models can be reduced by the acquisition of more informative and higher quality data (e.g. through the development of improved measurements techniques and observation networks) to improve model calibration and parameterization, by the development of improved models through better representations of physical processes or by the development of efficient techniques allowing a better use of all the available data. The last approach presents obviously room for improvement. There is indeed clearly a need for robust techniques that effectively and efficiently use information from observations into models to produce improved estimations and predictions.

Remote sensing, through its ability to provide synoptic information on growth conditions over large geographic extents and in nearly in real-time, is one of the most frequent data source used for assimilation purposes (Prévot et al., 2003; Launay and Guerif, 2005; De Wit and Van Diepen, 2008; Jarlan et al., 2008; Quaife et al., 2008).

With a variable degree of success and at different spatial resolutions, remote sensing has been indeed used to estimate crop and soil characteristics such as leaf area index (Myneni et al., 2002; Haboudane et al., 2004; Bacour et al., 2006; Baret et al., 2007; Wu et al., 2007; Verger et al., 2008), biomass (Di Bella et al., 2005; Beeri et al., 2007; Liu et al., 2010), chlorophyll contents (Haboudane et al., 2002; Tilling et al., 2007; Zhang et al., 2008), evapotranspiration (Gómez et al., 2005; Mutiga et al., 2010) or soil moisture (Ahmad et al., 2010; Gherboudj et al., 2011). Various algorithms have been developed to retrieve biophysical and biochemical variables from reflectance data (see Dorigo et al. (2007) or Baret and Buis (2008) for a review). Roughly, these algorithms can be subdivided in two categories: statistically/empirically based methods that seek a statistical relationship between the spectral signature and the measured biophysical or biochemical properties of the canopy (Clevers, 1997; Dente et al., 2008; Bsaibes et al., 2009) and physical methods that are based on the principles of radiation propagation within a canopy (e.g. Weiss et al., 2001; Doraiswamy et al., 2004). Hybrid approaches, a combination of both methods, use physical models to establish statistical relationships between the spectral signal and the biophysical variables of interest (Atzberger, 2004).

The estimation of soil and crop biophysical variables derived from satellite imagery is uncertain for several reasons. First of all, the measurement device is not perfect inducing small measurement errors to which is added a significant noise due to atmospheric conditions. Secondly, the observations models relating satellite observations to the soil or crop biophysical variables (e.g. empirical or radiative transfer models) are not perfect. Third, the spatial and temporal scale on which the measurement are made is rarely the one on which the observation is required. Observation models and interpolation of these observations implies hypotheses or requires ancillary information that induces new uncertainties (Pellenq and Boulet, 2004).

Despite these uncertainties, crop variables derived from satellite imagery represent an additional source of information on crop growth that could be favourably incorporated in crop growth models. Indeed, if simulations or observations by themselves are not able to provide an accurate description of the considered system, combining them should improve both predictive and retrospective models capabilities. Ground data can be also used in this context but it can hardly compete with the synoptic spatial and temporal coverage provided by remote sensing imagery. Ground data are also tainted with considerable measurement errors and their collection is expensive as well as time consuming.

Combining both model and observations is the task of data assimilation methods (Reichle, 2008; Lahoz et al., 2010). These methods aim at minimising uncertainties in the estimation of a given modelled state (as e.g. LAI) in an optimal way, i.e. based on statistical criteria. All of these methods aim at reducing the discrepancy between the measured and the simulated observations by adjusting either uncertain model parameters and/or initial conditions (Prévot et al., 2003; Launay and Guerif, 2005; Dente et al., 2008) or the model state variables (De Wit and Van Diepen, 2007; Reichle et al., 2008a).

The performance of data assimilation strongly depends on the assimilation protocol and the uncertainty specification (Pellenq and Boulet, 2004). The assimilation method, the level of uncertainty on both modelled and observed variables, the availability of the observations assimilated in the model or the objectives pursued are indeed some of the elements to consider. A comprehensive assessment of the performance of an assimilation scheme based on real observations is unfortunately not conceivable as it requires too many observations. In order to systematically investigate the assimilation performance, an approach based on synthetic data called "Observing System Simulation Experiment" (OSSE) has been developed. OSS Experiments have been initially developed (Arnold and Dey, 1986; Atlas, 1997) and mainly used (Raicich and Rampazzo, 2003; Reichle et al., 2008b; Wei and Malanotte-Rizzoli, 2010) in meteorology and oceanography. Applications of OSSE in agronomy are currently limited (Pellenq and Boulet, 2004; Pauwels et al., 2007).

This paper presents the results of an OSS Experiment assessing the efficiency of the assimilation of leaf area index (LAI) derived from satellite in the World Food Studies (WOFOST) crop growth model. LAI, defined as one-half of the total green leaf area per unit of horizontal ground surface area (Chen and Black, 1992), is indeed an important vegetation biophysical variable widely used notably for crop growth monitoring and yield estimation or land surface process simulation (Xiao et al., 2011). Improving its retrieval is also one of the focuses of the remote sensing community.

Two assimilation methods are considered, the first based on model parameters recalibration and the second on Ensemble Kalman Filter (EnKF). It is expected that these assimilation methods improve the estimation of final grain yields. The magnitude of the final grain yields estimation improvement is supposed to be, among other things, in connection with the uncertainty on the LAI derived from remote sensing in addition to the uncertainty of the model itself. In this context, besides the comparison of both assimilation approaches, the OSS Experiment also assesses the accuracy and temporal availability required on the retrieved LAI to reach a given objective in terms of errors reduction on the estimation of final grain yields.

2. Materials and methods

2.1. Crop growth model

We used the WOFOST (WOrld FOod STudies) crop simulation model as a basis for our work (Diepen et al., 1989; Van Ittersum et al., 2003). WOFOST is a mechanistic crop growth model that describes plant growth by using light interception and CO_2 assimilation as growth driving processes and by using crop phenological development as growth controlling process. The model can be applied in two different ways: (1) a potential mode, where crop growth is purely driven by temperature and solar radiation and no growth limiting factors are taken into account; (2) a water-limited mode, where crop growth is limited by the availability of water. The difference in yield between the potential and water-limited mode can be interpreted as the effect of drought. Currently, no other