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Integration of remote sensing derived parameters in crop models: Application to the PILOTE model for hay production

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ABSTRACT

The aim of this study is to assess the effects and interests of integrating remote-sensing-derived parameters (LAI, harvest and irrigation dates) in a crop model (PILOTE) that simulates vegetation growth for hay crops. The target variable is the prediction of Total Dry Matter (TDM) production in each of the three growth cycles.

Two scenarios are employed to process the available remotely sensed LAI values, predicting TDM values when forcing in PILOTE either the initial and maximal optical LAI-values, or the initial, maximal and daily interpolated LAI values. The predictions show low deviations compared with the *in situ* TDM values (RMSE of 0.44 t/ha, MAPE of 23%).

The feasibility of using harvest dates that are derived from optical data is examined by feeding the model with randomly perturbed harvest dates. The magnitude of the perturbations is equal to the revisit times of the current optical sensors. Optical images with revisit times lower than 16 days are adequate to feed PILOTE with remotely sensed harvest dates.

Emphasis is placed on the forcing of “uncertain” irrigation dates, derived from Synthetic Aperture Radar images either replacing all true irrigation dates by randomly perturbed dates (using 3-day perturbation magnitudes) or hypothesizing one or several irrigations are “missed” (undetected). The results show negligible errors for the TDM predictions when noisy irrigation dates are used (RMSE of 0.17 t/ha and MAPE of 4.2%). Disregarding one or two irrigations within a period with important rainfalls does not induce significant errors for the predicted TDM values; however, it causes noticeable underestimations in drier periods (maximum of 1.55 t/ha, reference TDM of 3.43 t/ha).

This study enables the identification of a series of conditions in which remote-sensing-derived parameters are suitable to feed the PILOTE model without endangering the reliability of its predictions.

1. Introduction

Pre-harvest yield forecasting is a critical challenge for producers, especially for large agricultural areas, which are a field of predilection both for simplified crop modelling approaches and remote-sensing techniques. Together with occasional, frequent or real-time monitoring of soil and plant statuses, crop models are useful tools for such estimates, providing for example biomass or dry matter assessments for known or adjustable harvest dates. During previous decades, numerous crop models were developed to predict crop growth and yield, most often for wheat or maize (Brisson et al., 1992; Ritchie and Otter, 1985; Weir et al., 1984), and also for grasslands (Mailhol and Merot, 2008). A crop model is a set of equations that describes the growth of plant components, such as leaves, roots, stems and fruits, typically at a daily time step (Oteng-Darko et al., 2013). Crop models require several input parameters that describe soil properties (e.g., field capacity and depths of soil horizons), plant characteristics (e.g., maximal rooting depth and thermal times associated with growth stages) and management options (e.g., sowing dates, irrigation doses and dates, and harvest dates), which are referred to as the soil, plant and management

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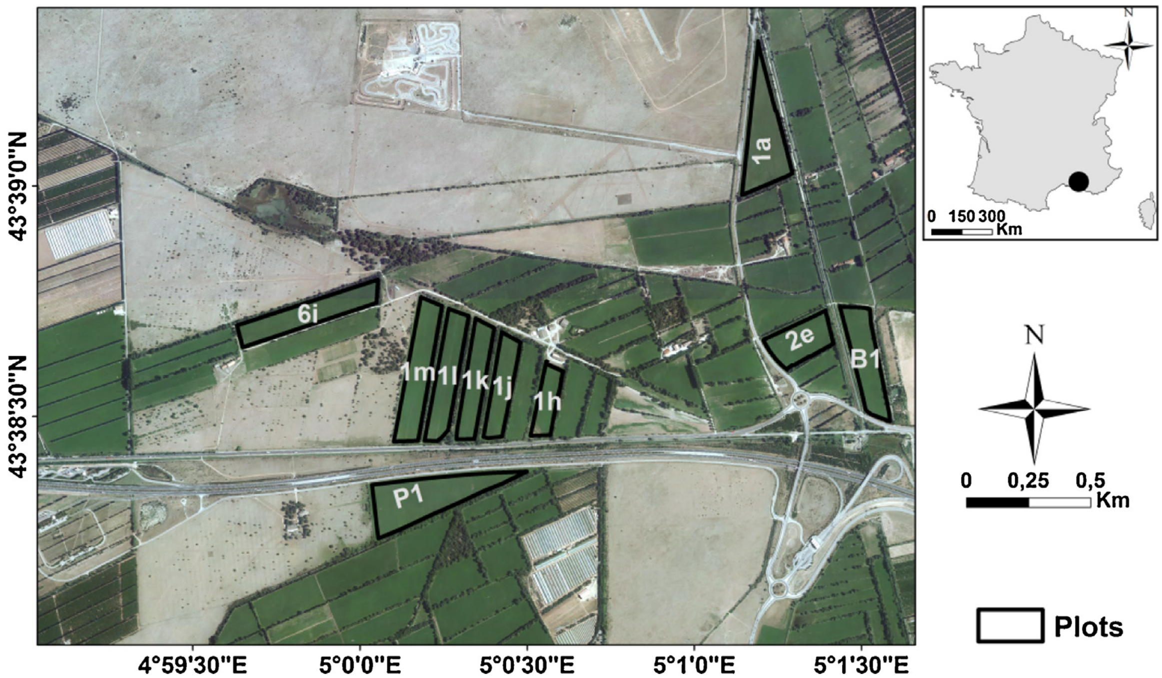

Fig. 1. Location of the study site (Domaine du Merle). Black polygons delineate training irrigated grassland plots, where ground measurements were collected.

families of parameters. Climatic forcings are also required (e.g., rain, radiation, air temperature, and climatic demand). These inputs are usually inferred from previous evaluations or recorded from in situ sensors that are located at fixed locations in the cultivated areas, at the expected drawbacks of "one-shot spot-checks", i.e., measurements that are neither extendable in time nor extendable in space. These measurements are relevant for climatic forcings because when provided climatic data do not significantly vary within an area of interest. Conversely, soil and vegetation parameters or state variables (water content, leaf area index, and total dry matter) frequently present larger spatial heterogeneities due to site history, environmental characteristics, and irrigation practices. The determination of their spatial (and temporal) patterns of values typically falls within the scope of remote-sensing techniques, which provides indirect indications on the agricultural water management strategies.

Remote sensing technology has been extensively applied to identify spatially distributed values of some of the accessible parameters in the soil, plant and management families and to retrieve information about previous and current climatic data (in a broad sense, making no difference between rain or irrigation events). In particular, the SAR (Synthetic Aperture Radar) data were extensively applied to estimate the soil moisture in the top 5 cm of bare and vegetated soils (depending on the soil moisture value and the radar wavelength) on local plot and subplot scales. The estimation of soil moisture over bare soils was performed with an accuracy between 3 and 6 vol.% (Aubert et al., 2011; Baghdadi et al., 2012a,b; Santi et al., 2013; Srivastava et al., 2009; Zribi et al., 2005). Over vegetated agricultural areas (wheat, peas, lentil, fallow, grassland and canola) soil moisture on a local scale was estimated from SAR data with an accuracy between 2 and 8 vol.%, depending on the vegetation conditions and the SAR configurations (Baghdadi et al., 2015; Gherboudj et al., 2011; El Hajj et al., 2016; He et al., 2014; Paloscia et al., 2013; Prévot et al., 1993; De Roo et al., 2001; Kweon et al., 2012; Zribi et al., 2011). Moreover, there are other satellites, such as Soil Moisture and Ocean Salinity (SMOS), that provide soil moisture estimates on a regional scale with a temporal revisit time of 3 days. The spatial resolution of SMOS is 50 km at the swath edges (Kerr et al., 2001). Al Bitar et al. (2012) and Jackson et al. (2012) performed the validation of SMOS soil moisture estimates using in situ soil moisture measurements at a depth of 5 cm. The results showed that SMOS satellites provide soil moisture estimates with an accuracy of approximately 5 vol.%. Given the very low uncertainties mentioned, the usefulness of these indications to constrain crop models is clearly expected to depend on the revisit times.

On the other hand, optical remote sensing data from LANDSAT-8 and SPOT-6 showed significant potential for estimating the Leaf Area Index (LAI) of crop canopies (corn, grassland, maize, wheat, rapeseed and sunflower) with relative uncertainties between 10% and 30% (Bsaibes et al., 2009; Claverie et al., 2013; Courault et al., 2008; Duveiller et al., 2011; North, 2002). The LAI is a derived parameter that was extensively incorporated into crop models to enhance yield estimations; it provides promising yield estimates and "anticipations" (Barnes et al., 1997; Bogh et al., 2004; Doraiswamy et al., 2005; Guerif and Duke, 2000).

Uncertainty in crop model predictions is related to the uncertainty that affects their site parameters or management options

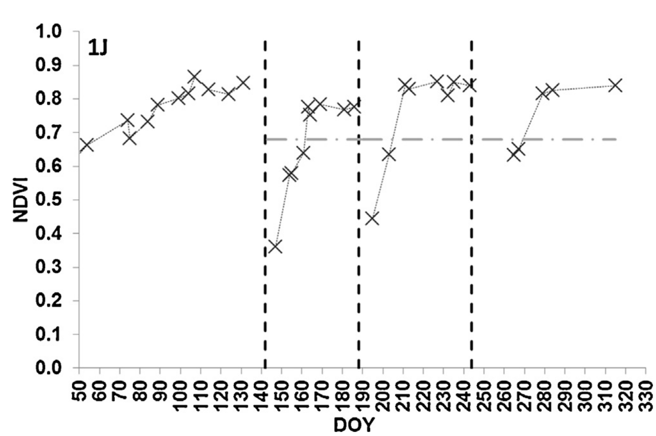

Fig. 2. Temporal evolution of NDVI for a given plot (1J). Black vertical dashed lines represent the harvest dates. Horizontal dashed line corresponds to a NDVI threshold of 0.68, which is found adequate for harvest detection.