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A framework to use crop models for multi-objective constrained optimization of irrigation strategies

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ABSTRACT

This paper discusses an innovative framework to use crop models which combines sensitivity analysis, uncertainty analysis and constrained optimisation runs for irrigation optimisation purposes, facing competing constraints on several agricultural variables (e.g. crop yield, total irrigation amount, financial expectations). For simplicity, this ex-post optimisation relies on direct calculations only, exploiting the dispersions on the target variables. The screening of the parameter space for sensitivity analysis yields a reference dispersion which is expectedly reduced by reducing the uncertainties in the sensitive parameters and/or climatic forcings. Additional dispersions are calculated to evaluate if the management controls on irrigation strategies (amounts, triggers, periods) are more influential on model predictions than the remaining uncertainties on the soil, plant, irrigation and climatic inputs, eventually allowing optimisation. As a case study, the Optirrig model is used. A discussion proposes future ways to convert diagnostics into real-time near-optimal decision rules, for example through learning algorithms.

Software availability

Neither the Optirrig model nor the presented irrigation optimisation code are downloadable as open-source material, due to the licensing strategy of Irstea (the French National Research Institute of Science and Technology for Environment and Agriculture). Both have been developed in FORTRAN but will be recoded in Python: new Graphical User Interface is planed and the software will be distributed at this time.

1. Introduction

Crop models aim to predict agricultural yields from selected soil properties, plant characteristics and climatic forcings, and possibly dependent on irrigation strategies. Even if they are of limited extent, the random uncertainties in source data (Nonhebel, 1994; Aggarwal, 1995; Heinemann et al., 2002; Rivington et al., 2006; Spank et al., 2013) can combine and propagate through the models, whose predictions should therefore include statistical confidence intervals or at least relevant, dedicated estimates of the error terms or trends affecting model outputs (Monteith, 1996; Challinor et al., 2009, 2010; Wallach et al., 2012; Asseng et al., 2013). Noticeable differences exist between model structures, purposes and responses, especially for climate change scenarios, hence the difficulty to decipher absolute, normative evaluations. This, in turn, outlines the interest in model intercomparison methodologies (Rötter et al., 2011; White et al., 2011; Asseng et al., 2013) that help positioning any tested model among possible alternatives or help choosing between several candidate models.

Whatever the selected model, model exploration, sensitivity analysis and uncertainty assessment always need intensive calculations which typically fall within the scope of model automation procedures: these can then provide both the agricultural scenarios and their associated dispersion envelopes. As a result the

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optimisation of irrigation strategies consists of comparing what may be gained from appropriate resources management, taking into account the dispersion in model predictions that arises from intrinsic uncertainties in source data, or from hypotheses of climate change and increased variability (Rosenzweig and Parry, 1994; Rosenzweig et al., 2014) with the associated deficit irrigation issues (English, 1990; Reca et al., 2001; Pereira et al., 2002; Geerts and Raes, 2009). Several simulation platforms have been developed in the recent years, based on some of the most popular crop models. However, agronomical modelling still seems to miss a framework that relies on model automation to propose successive steps towards the identification of the context-dependent best irrigation strategies. Moreover, these “multi-variable constrained optimisation” strategies can be inferred from objective functions that not only rely on crop yield levels (Sun et al., 2006; Cetin and Uygan, 2008).

Advances in computer science have facilitated the automation of crop models. For example, the connection to environmental and socio-economic issues, with a clear trend to use biophysical models within integrated system and economic viability assessment (Vatn et al., 1999; Berntsen et al., 2003; Belcher et al., 2004; Janssen and van Ittersum, 2007). In addition, the inclusion of crop models in simulation platforms related to communication between models based on common databases or input/output formats. For example, AqYield (Nolot and Debaeke, 2003; Murgue et al., 2014; Constantin et al., 2015) may now be run on the MAELIA platform (Gaudou et al., 2013) to handle low-water management issues and multi-agent spatial planning, STICS (Brisson et al., 2003, 2009) runs on the RECORD platform (Bergez et al., 2013) that integrates farming practices into agro-ecosystems and APSIM (McCown et al., 1995; Keating et al., 2003) now embeds the PMF - Plant Modelling Framework (Brown et al., 2014) as a sub-model. Not long ago, the HarvestChoice (2010) platform already allowed scenarios and regional-scale decision-making on the basis of data issued from APSIM or DSSAT (Jones et al., 2003). Other composite (SAFYE, Duchemin et al., 2006; 2008) or generic crop models (RZWQM, Hanson et al., 1998; Ma et al., 2006) offer many of the above possibilities, while Aquacrop (Steduto et al., 2009; Raes et al., 2009) was used in combination with an economic model to optimise irrigation management (García-Vila and Fereres, 2012). Irrigation management, as a part of ecosystem responses to climate changes, has been addressed by APSIM (Ludwig and Asseng, 2006), WOFOS (Wolf and van Diepen, 1995; Reidsma et al., 2009; Supit et al., 2012), RZWQM (Ko et al., 2011; Islam et al., 2012) and STICS (Singh et al., 2014), among others.

Finally, a typical evolution through the last decades is that of the Wageningen crop models (e.g. WOFOS, van Diepen et al., 1989; Boogaard et al., 1998; van Ittersum et al., 2003) from their original formulations in the 1980's (often in FORTRAN 77) to object-oriented and modular programming structures (e.g. PCSE - Python Crop Simulation Development, de Wit, 2015) at the assumed risk of slower model execution. In summary, what is sought in general is (i) simulation engines running multi-agent scenarios, (ii) the flexibility of modular designs that use crop models as plug-ins and (iii) interfaces between models based on common exchange file formats. The framework presented here is compatible with such approaches as (i) it offers the possibility to perform multi-objective constrained optimisation from the analysis of a wide variety of user-defined irrigation scenarios, (ii) most of the automated crop models fit in this framework, provided (iii) they communicate through input/output text files. The newly-automated version of the Optirrig model (formerly the PILOTE model, Mailhol et al., 1997, 2011; Khaledian et al., 2009; Feng et al., 2014) has been chosen here for application of the proposed framework, providing guidelines for the identification of optimal irrigation parameters from successive direct calculations (sensitivity analysis, uncertainty analysis then constrained optimisation runs) associated with decreasing dispersion on the target variables (i.e. convergence towards one or several equifinal parameter sets).

Section 2 of this paper highlights the successive stages of the framework that leads to the multi-objective constrained optimisation of irrigation strategies, across preliminary sensitivity and uncertainty analyses, also indicating ways to evaluate the effect of management decisions versus parameter and forcing uncertainties (Section 2.1). For simplicity, the Optirrig model developed at Irstea is chosen for these applications (Section 2.2) but the framework was designed to be as generic as possible. Section 3 presents the results of the sensitivity analysis (Section 3.1), uncertainty analysis (Section 3.2) and constrained optimisation runs (Section 3.3). The discussion (Section 3.4) highlights the specificities, strengths and limitations of this framework (Section 3.4.1) as well as possible adaptations for the search of real-time near-optimal decision rules (Section 3.4.2). Section 4 is the conclusion.

2. Material and methods

2.1. Framework for multi-objective constrained optimisation

2.1.1. Scope and overview

This framework indicates how to perform scenarios of agricultural yield from irrigation strategies (e.g. dates, doses, trigger criteria), acknowledging uncertainties on both the model parameters (e.g. soil and plant parameters) and its climatic forcings (e.g. rain, potential evapotranspiration, radiation and temperature), possibly handling hypotheses of climate change and variability. However, irrigation optimisation is defined here as extracting the user-defined best cases from a series of scenarios, which typically requires the definition of one or several objective functions, in addition to the agricultural yield (Y). Other candidates are the total irrigation amount (I), the irrigation water use efficiency (IWUE) and an economic cost function related to financial expectations (F) that combines the selling price of the harvested crop and the cost of the irrigation water. In the following, a multi-objective constrained optimisation framework targets these variables, calculated by most crop models. Fig. 1 shows an overview of this framework, that involves three successive run series (A. Sensitivity analysis: Subsection 2.1.2, B. Uncertainty analysis: Subsection 2.1.3 and C. Constrained optimisation: Subsection 2.1.4) with five stages in each series (Stage 1- Conceptual case preparation, Stage 2- Technical case preparation, Stage 3- Controls and settings, Stage 4- Calculation loop and Stage 5- Post-treatments). The description of the stages is the same whatever the run series.

Stage 1 is where the modeller builds a mental model of the problem and selects a strategy to address it. The subsequent stages are all automated, provided (i) an automated version of the crop model is available, (ii) it uses a single parameter file (where parameter sets to process appear on successive lines in this file) and (iii) it uses a climate file in which the values of forcings in time appear in columns. Although not shared by all crop models, these requirements were found sufficiently easy to meet to justify the automation of the other stages.

Stage 2 is where the selected scenarios are encoded in source files.

- If the scenarios decided in Stage 1 do not involve random perturbations (neither of the parameters nor of the forcings) then the automated model will run (in Stage 4) on the parametric scenarios previously placed in its parameter file, using the current climate file.