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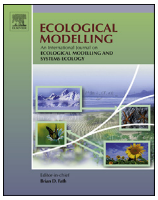

Research paper

Sensitivity of WOFOST-based modelling solutions to crop parameters under climate change

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ABSTRACT

The formalization of novel equations explicitly modelling the impact of extreme weather events into the crop model WOFOST (EMS: existing modelling solution; MMS: modified modelling solution) is proposed as a way to reduce the uncertainty in estimations of crop yield. A sensitivity analysis (SA) was performed to assess the effect of changing parameters values on the yield simulated by the model (both EMS and MMS) for different crops (winter and durum wheat, winter barley, maize, sunflower) grown under a variety of conditions (including future climate realisations) in Europe. A two-step SA was performed using global techniques: the Morris screening method for qualitative ranking of parameters was first used, followed by the eFAST variance-based method, which attributes portions of variance in the model output to each parameter.

The results showed that the parameters related to the partitioning of assimilates to storage organs (FOTB) and to the conversion efficiency of photosynthates into storage organs (CVO) generally affected considerably the simulated yield (also underlying tight correlation with this output), whereas the parameters involved with respiration rate (Q10) or specific leaf area (SLA) became influential in case of unfavourable weather conditions. Major differences between EMS and MMS (which includes a component simulating the impact of extreme weather events) emerged in extreme cases of crop failure triggered by markedly negative minimum temperatures. With few exceptions, the two SA methods revealed the same parameter ranking. We argue that the SA performed in this study can be useful in the design of crop modelling studies and in the implementation of crop yield forecasting systems in Europe.

1. Introduction

Crop models mathematically represent the complex interactions between plant, weather, soil and agricultural practices. They play an important role in understanding and quantifying the relationships, or trade-offs, between crop management and environment on one side, and cropping systems productivity on the other. Crop models have evolved over time, increasing in complexity to meet the increasingly intricate challenges facing agriculture (e.g. Donatelli and Confalonieri, 2011). For instance, the global carbon balance has become an issue of great societal concern in the last decades, when the global emission of CO_2 has continued to increase together with its impact on climate (IPCC, 2013). This has required modelling efforts, for instance, to represent plant responses to CO_2 levels (e.g. Ethier and Livingston, 2004) and thus make crop models responsive to changing climate conditions (Asseng et al., 2013; Bassu et al., 2014; Li et al., 2014). Nowadays, crop models are largely used to understand and anticipate the impacts of climate change on agricultural production (e.g. Ewert et al., 2005; Falloon and Betts, 2010; White et al., 2011; Supit et al., 2012; Nelson et al., 2014), to support the implementation of adaptation strategies (e.g. Tingem et al., 2009; Fernandes et al., 2012; Perego et al., 2014; Cappelli et al., 2015), and to design future crop ideotypes (e.g. Paleari et al., 2017).

However, robust simulation models are needed for diagnosing and prognosing the impacts of environmental factors on the crop

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production systems and, as a matter of fact, some modelling studies have not been completely successful in addressing the impact of extreme weather events on crop production (van der Velde et al., 2012; Zinyengere et al., 2014). Extreme events such as heat waves, cold shocks, droughts and frost affect directly and indirectly cropping systems by altering physiology and behaviour of plants, with impacts on the productivity as well as the seasonality and quality of crop production (e.g. Lesk et al., 2016). Moreover, the additional heat that is generated from ongoing temperature rise has increased the chances for severe heat waves, drought, and other forms of extreme weather (Field et al., 2012). Suggestions have been put forward that most of the existing crop models need an overhaul or an update as they often fail to correctly describe how crops respond to the impact brought about by extreme weather events (Rötter et al., 2011a).

Formalizing the biophysical interactions between the crop and its environment has required the development of customized modelling solutions (Luo et al., 2013) characterized by a large set of interdependent equations representing specific sub-domains of the system. Accounting for such complex interactions has inevitably increased the number of input factors in crop models (variables and parameters) and the uncertainties associated with parameter values and their distributional assumptions, driving variables (climate, soil and management) and model structure (e.g. Gabrielle et al., 2006). The structure of crop models is generally too complex to easily shed light on the relationship between input factors and output variables, even more so the models are continuously improved with novel approaches. Parameter estimation, in particular, is a key challenge in model development, in light of the crucial role in determining the quality of model predictions (Richter and Sondgerath, 1990). There is therefore a need to better understand the behaviour of crop models under a wide range of conditions, also by identifying the parameters that have the greatest influence on outputs (Jacquez and Perry, 1990; Brun et al., 2001; Haag, 2006).

Sensitivity analysis (SA) is the main tool for a comprehensive evaluation of complex models (e.g. Rabitz, 1989; Omlin et al., 2001). It assesses the changes in the model outputs due to changes in the values of input factors (the latter being generated by sampling from inputs' distributional range). As a result, SA provides a valuable method to identify properties that characterize the relationships between model outputs and input parameters and enhance the understanding of the system under study (Saltelli et al., 2000). The distinction – under specific conditions of application (Stearns, 1992) – between influential (relevant) and non-influential parameters is generally based on SA results (Cariboni et al., 2007; Confalonieri et al., 2009a). By ranking model parameters based on their relevance from the most to the least important (Cryer and Havens, 1999), SA offers guidance to the design of experimental programs as well as to more efficient model development and calibration. SA can be implemented either locally to examine the effect of minor variations of the parameter values on model results (Brun et al., 2001), or globally to consider the entire range of parameter values (Xu and Gertner, 2007; Confalonieri et al., 2010a). The latter is generally based on differential analysis through the use of Taylor series (e.g. Pastres and Ciavatta, 2005) and Monte Carlo methods (e.g. Annan, 2001). In particular, there is a challenge in ensuring robust modelling approaches under changing climate conditions, because the implicit assumption that well-designed and calibrated models under current conditions will remain valid under future climate realizations can be an unrealistic one. This is why the importance of improving the understanding of plant responses to the interactive effects of higher temperature and altered patterns of precipitation has been highlighted (e.g. Wang et al., 2012).

This study focused on the generic crop simulator WOFOST (van Diepen et al., 1989), successfully used since years to reproduce growth and development of a variety of crops (de Wit et al., 2012; Boogaard et al., 2013), to forecast crop yields (https://ec.europa.eu/jrc/en/mars), and within model intercomparison and ensemble studies (e.g. Todorovic et al., 2008; Palosuo et al., 2011; Bassu et al., 2014). In this study, we have performed a wide range of SA experiments on WOFOST using two versions of the model: an implementation referred to as existing modelling solution (EMS) and an improved model referred to as the modified modelling solution (MMS), with the latter including a software component (coupled to EMS) that explicitly takes into consideration the impacts of extreme weather events such as high and low temperatures, water deficit and frost (Villalobos et al., 2015). For both modelling solutions, SA was performed for five crops at eight sites representative of contrasting conditions in Europe (Italy, Spain, Switzerland and Ukraine) using two SA methods, and under current and altered weather conditions.

2. Materials and methods

2.1. WOFOST-based modelling solutions

WOFOST (van Diepen et al., 1989) adopts a gross photosynthesis approach to calculate net carbon fixation, explicitly considering phenological development, light interception, gross CO_2 assimilation, transpiration, growth and maintenance respiration. Crop development is reproduced as a temperature-driven process, optionally accounting for photoperiod. Instantaneous gross CO_2 assimilation (estimated at three moments in the day for three depths into the canopy of plant leaves) is computed on the basis of intercepted solar radiation and of a photosynthesis-light response at leaf level. Light interception depends on total incoming radiation, as modulated by photosynthetic leaf area and leaf angle distribution. Assimilates are partitioned to the various organs according to partitioning factors, computed as a function of plant development stage: a fraction of assimilates is allocated to roots first, and then the remainder is split over the above-ground organs (including below ground storage organs such as tubers). The emission of LAI units is driven by temperature in the early stages and it depends on specific leaf area and leaf-partitioned biomass later. Dead LAI units (i.e. leaves no more photosynthetically active) are quantified as a function of self-shading and senescence of old leaves. The model simulates both potential and water-limited production levels, providing information on crop water use, biomass growth and yield. Potential evapotranspiration is calculated via the Penman equation (Frère and Popov, 1979), and water stress is represented by the ratio of actual to potential transpiration. Crop water use is calculated separately for: crop canopy (transpiration), bare soil surface (soil evaporation), and soil surface with ponding (water evaporation).

The capability of the standard WOFOST version (EMS) was enhanced (MMS) thanks to a dedicated component for the impact of extreme weather events (Villalobos et al., 2015; Movedi et al., 2015). In particular, the effects of severe cold and high temperatures, frost and extreme water deficit on crop yields were accounted for by modulating the harvest index (HI) and LAI (only for frost) according to stress-related response functions (0 = maximum reduction; 1 = no effect) computed at a daily time step. These variations are mediated by the time of occurrence of an extreme event, the environmental conditions, and the crop-specific susceptibility. The decline of crop yield can even lead to crop failure in the case of severe extreme weather conditions. Two development phases are identified where crops are most sensitive to weather extremes: (i) around anthesis (+/− 1 week from anthesis) with main effects on pollen viability, fertilization, and grain formation, and (ii) from anthesis to physiological maturity, with impacts related to rates of grain filling. For temperature-related damages, crop temperature is estimated (solving the surface energy balance equation) and used.