Environmental Modelling & Software 79 (2016) 184–196

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

Assessing and modeling economic and environmental impact of wheat nitrogen management in Belgium

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ARTICLE INFO

Article history:
Received 29 April 2015
Received in revised form
10 December 2015
Accepted 8 February 2016
Available online xxx

Keywords:
Tactical nitrogen management
Climatic variability
Probability risk assessment
LARS-WG
Crop model
STICS

ABSTRACT

Future progress in wheat yield will rely on identifying genotypes and management practices better adapted to the fluctuating environment. Nitrogen (N) fertilization is probably the most important practice impacting crop growth. However, the adverse environmental impacts of inappropriate N management (e.g., lixiviation) must be considered in the decision-making process. A formal decisional algorithm was developed to tactically optimize the economic and environmental N fertilization in wheat. Climatic uncertainty analysis was performed using stochastic weather time-series (LARS-WG). Crop growth was simulated using STICS model. Experiments were conducted to support the algorithm recommendations: winter wheat was sown between 2008 and 2014 in a classic loamy soil of the Hesbaye Region, Belgium (temperate climate). Results indicated that, most of the time, the third N fertilization applied at flag-leaf stage by farmers could be reduced. Environmental decision criterion is most of the time the limiting factor in comparison to the revenues expected by farmers.

1. Introduction

Future improvement in wheat yield will rely on the identification of genotypes and/or management practices that are best adapted to the environment (Chenu et al., 2011). However, the complexity of the genotype-environment-management practice interactions (GEM) requires setting up extensive and costly field experiments. Because resources are limited, in practice, breeders typically select new cultivars that are suited to a specific environment (Semenov and Halford, 2009). For practical reasons, such experiments are usually limited to (i) the geographical area targeted by the breeding programme and (ii) the climatic conditions encountered by the plant during the selection program. Furthermore, (iii) the selection is typically performed under management conditions in which sufficient nutrient levels are supplied to the crop. Incorporating a new trait into a crop takes 10–12 years, and only then it will be known if it has been effective in improving yield in the various environments (Asseng and Turner, 2007).

The environment has two main components that induce variability, respectively soil and weather. Within a given field, differences in texture, structure, and organic matter may induce high variability. These soil characteristics greatly affect the soil moisture content and the available water capacity for plants. They not only drive water stress but also, in turn, impact soil nutrient availability (Basso and Ritchie, 2005). Concerning climatic variables, it has long been demonstrated that both the average values of weather variables and the sequencing of weather events greatly impact the dynamics of crop growth (Semenov and Porter, 1995). Interactive stresses may have a greater impact on the final value of crop characteristics of interest (e.g., grain yield) than individual stresses (Riha et al., 1996). For these reasons, the importance of an accurate characterization of soil and weather inputs data increases as the environment becomes more limiting in terms of plant growth and development (Weiss and Wilhelm, 2006).

Concerning the management of crops, nitrogen (N) fertilization is probably one of the most important practices. The optimum N fertilization is known to vary within the same field and with each growing season as a result of the heterogeneity of soil properties, as well as inter- and intra-annual climatic patterns (Basso et al., 2012b). Furthermore, the decision-making process linked to N

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http://dx.doi.org/10.1016/j.envsoft.2016.02.015
1364-8152/

management remains complex because even if a spatial map of soil properties exists, the decision regarding the amount of N fertilizer to apply must be made without any prior knowledge of future weather conditions (Basso et al., 2011b). Consequently, experimentally determining how plant characteristics, either individually or in combination, affect crop performance under a wide range of growing conditions is an intractable task (Hoogeboom et al., 2004). In such a context, determining the optimum amount of and the most appropriate timing for N fertilizer is a challenge (Makowski et al., 2001).

Crop modeling approaches are powerful tools to allow a more comprehensive analysis of real-life processes (Sinclair and Seligman, 1996). Crop simulation models, such as STICS (Brisson et al., 2009), SIRIUS (Semenov et al., 2007), and SALUS (Basso et al., 2012a), are computerized representations of crop development, growth, and yield elaboration. They simulate the functions and impacts of the continuum of soil-plant-atmosphere systems (Hoogeboom et al., 2004). They integrate the current understanding of crop growth derived from physiological studies and phenotypic characteristics measured in various environments (Semenov et al., 2009). By dissociating processes that closely interplay in the real world and cannot be always observed directly, crop models have become engineering tools that extend the potentialities of field experimentation (Casadebaig and Debaeke, 2011). By highlighting gaps in our knowledge, they can be used to guide the direction of fundamental research (Semenov et al., 2007). Furthermore, they have demonstrated to be efficient in assisting in analyzing and deconvoluting any combination of complex GEM interactions (Asseng and Turner, 2007; Chenu et al., 2011). For these reasons, crop models have already proven to be well-suited to supporting decision-making and planning in agriculture (Basso et al., 2011a; Ewert et al., 2011). However, to properly address new environmental issues, the purpose of crop models needs to be widened by encapsulating them in modeling platform (Bergez et al., 2014; Brown et al., 2014) or by surrounding them with appropriate analysis algorithms (Dumont et al., 2014a; Talbot et al., 2014).

Crop models can help to improve farmers' decisions by assessing the probability that a certain outcome will occur under specific management practices and the given pedo-climatic conditions of a certain field (Basso et al., 2011a, 2012b; Houlès et al., 2004). Dumont et al. (2013, 2014a, 2015a) have recently demonstrated how stochastically generated weather can be used to quantify the uncertainty that impacts on yield and N leaching in order to optimize N fertilization. However, until now, this approach had remained limited to strategic management.

The objective of this study is to optimize N management at the intra-annual level by modeling the within-season environment-management interactions. Winter wheat (*Triticum aestivum* L.) growth was simulated under multiple N strategies and a panel of environments. An environment was here defined by a given soil type and a wide variety of climatic conditions. Stochastically generated climate time series were derived so that the most advantageous and disadvantageous climatic variable combinations could be explored. Such probabilistic climatic scenarios were coupled with historical records made between sowing and the flag-leaf stage. Multi-objective decision criteria were computed to optimize the economic return of the assessed N practices while minimizing the adverse environmental impacts associated with potentially inappropriate N rates.

2. Material and methods

2.1. Field experiment

Between 2008 and 2014, field experiments were conducted to study intra- and inter-annual wheat growth patterns (*T. aestivum* L.) under the agro-environmental conditions of the Hesbaye region (classic loam soil type) in Belgium (temperate climate) and under variable N management practices (Table 1). The cultivar was usually sown between mid-October and mid-November and harvested between very late July and mid-August. The measurements considered for simulation purposes were the results of four repetitions for date, nitrogen level, and crop season. The repetitions were performed on experimental blocks (2 m $\times$ 6 m) that were implemented according to a completely randomized block distribution to ensure measurement independence. During this experiment, biomass (total dry matter and grain yield), plant N uptake, and soil N content were measured twice a month during the growing season, from mid-February until harvest. The measurements were carried out on dried samples corresponding to the sampling of three adjacent 50 cm rows separated from 14.6 cm. Once per month, the biomass samples were crushed, and their N content was analyzed in a laboratory. Once every two weeks, alternating with the sampling of the biomass, the soil N content was measured between 0 and 150 cm in 15 cm soil layers. Because they are time- and/or money-consuming, LAI measurements and soil N measurements were only performed for Exp. 1 and Exp. 4.

During the first four years (2008–2012), crop response was analyzed under seven N fertilization strategies, varying the rate and timing of fertilizer application, as described in the first part of Table 1. Total amounts of N between 0 and 240 kg N ha^{-1} were applied to explore the full response curve of the crop to N. In Belgium, the current N fertilizer management practice consists of splitting a total of 180 kg N ha^{-1} into three equal fractions (60 kg N ha^{-1}) and applying them at the tillering (Zadoks stage 23 – ZS 23), stem extension (ZS 30), and flag-leaf (ZS 39) stages (Zadoks et al., 1974). This practice is presented as Experiment Four (Exp. 4) in Table 1. During the last two years (2012–2014), for reasons detailed and explained in Section 2.4, new experimental N strategies were designed based on the Belgian farmers' current practices (Table 1, second part). For Exp. 8 to Exp. 10, 60 kg N ha^{-1} were applied at the tiller (ZS 23) and stem extension (ZS 30) stages, but increasing fractions were applied at the flag-leaf stage (ZS 39), from 0 to 90 kg N ha^{-1} in 30 kg N ha^{-1} steps.

Table 1
Details of the field trials to study the crop response to variable N management, where different amounts and timing of N applications were investigated.

Fertilization level [kg N ha^{-1}]						
Exp. #	Tiller	T-S	Stem exten.	Flag leaf	Total	Season
Zadoks	23	29	30	39		
Exp. 1	0	/	0	0	0	2008–2014
Exp. 2	30	/	30	60	120	
Exp. 3	/	60	/	60	120	
Exp. 4	60	/	60	60	180	
Exp. 5	/	90	/	90	180	
Exp. 6	60	/	60	120	240	
Exp. 7	/	120	/	120	240	
Exp. 8	60	/	60	0	120	2012–2014
Exp. 9	60	/	60	30	150	
Exp. 10	60	/	60	90	210	