Available online at www.sciencedirect.com

SCIENCE DIRECT

Reliability Engineering and System Safety 91 (2006) 1142–1147

RELIABILITY ENGINEERING & SYSTEM SAFETY

www.elsevier.com/locate/ress

Global sensitivity analysis for calculating the contribution of genetic parameters to the variance of crop model prediction

David Makowski[a,*], Cédric Naud[b], Marie-Hélène Jeuffroy[a], Aude Barbottin[a], Hervé Monod[b]

[a]UMR Agronomie INRA/INA-PG, B.P.01, 78850 Thiverval-Grignon, France

[b]Unité Mathématique et Informatique Appliqués INRA, Domaine de Vilvert, F78352 Jouy-en-Josas Cedex, France

Available online 9 January 2006

Abstract

Dynamic models are often used to predict the effects of farmers' practices on crop yield, crop quality, and environment. These models usually include many parameters that must be estimated from experimental data before practical use. Parameter estimation is a difficult problem especially when some of the parameters vary across genotypes. These genetic parameters may be estimated from plant breeding experiments but this is very costly and requires a lot of experimental work. Moreover, some of the genetic parameters may account for only a very small part of the output variance and, so, do not deserve an accurate determination. This paper shows how methods of global sensitivity analysis can be used to evaluate the contributions of the genetic parameters to the variance of model prediction. Two methods are applied to a complex crop model for estimating the sensitivity indices associated to 13 genetic parameters. The results show that only five genetic parameters have a significant effect on crop yield and grain quality.

Keywords: Crop model; Extended fast; Genetic parameter; Global sensitivity analysis; Winding stairs

1. Introduction

Crop models are complex nonlinear dynamic models simulating output variables related to crop yield, crop quality, farmer's income, and environment. These models are valuable tools for crop management because they can be used to predict the effects of farmers' practices in function of soil type, climate, and crop characteristics [1].

Crop models can include up to 200 parameters whose values must be estimated from past experiments. The estimation of these parameters is an important step because crop model performances depend for a large part on the accuracy of the parameter estimates [2]. Predictions obtained with crop models are not reliable when inaccurate parameter values are used.

A large amount of data is always required for estimating accurately crop model parameters, in particular when the model includes genetic parameters. As genetic parameters vary across genotypes, the estimation of these parameters must be based on specific measurements collected for each genotype. Such measurements can be performed in plant breeding experiments but this is very costly and requires a lot of experimental work. Moreover, recent studies have shown that crop model predictions are not systematically improved when genotypic parameters are estimated genotype per genotype [3]. This may be due to the small contribution of some of the genetic parameters to the total model output variance.

In this study, we investigate how methods of sensitivity analysis can be used to reduce the quantity of field experiments performed for estimating genetic parameters. The basic principle consists in evaluating the contributions of the genetic parameters to the variance of the model prediction and, then, in estimating genotype per genotype only the key parameters whose uncertainty affects most the outputs. In this paper, two methods of global sensitivity analysis [4] are compared to evaluate the contribution of 13 genetic parameters to the variances of two output variables of a crop model.

*Corresponding author. Tel.: +33 1 30 81 59 92; fax: +33 1 30 81 54 25.
E-mail address: makowski@grignon.inra.fr (D. Makowski).

0951-8320/$ - see front matter © 2005 Elsevier Ltd. All rights reserved.
doi:10.1016/j.ress.2005.11.015

2. Methodology

2.1. The AZODYN model

The AZODYN crop model [5] is a nonlinear dynamic model simulating winter wheat crop. This model can be used as a decision support tool for studying the effects of nitrogen fertilizer management on crop yield, grain quality, and risk of pollution by nitrate in function of soil and climate characteristics [6]. One run of the AZODYN model takes about 0.3 s with a Pentium III bi processor (1.26 Ghz).

The model simulates many output variables like biomass, leaf area, soil mineral nitrogen, yield, and grain protein content. Among all these output variables, yield and grain protein content at harvest are of particular interest for decision makers. Grain yield is an important variable because it determines the farmer's income, and grain protein content is a major grain quality criterion for agro-industries.

The output variables of the model are simulated in function of input variables related to soil characteristics (soil texture, organic matter, soil mineral nitrogen), climate (daily radiation and temperature), and nitrogen fertilization (dates and rates of fertilizer applications). In this paper, the input variables are set equal to the values measured in a field located in northern France (Grignon, 48.51°N, 1.58°E) and harvested in 2001. The soil is a clay-loam. The total amount of applied nitrogen fertilizer was equal to 240 kg ha^{-1}. Meteorological data were recorded daily at the Unité Expérimentale INRA at Grignon in 2001 between the day of the first simulation ($t = 1$) and the day of harvest ($t = 171$).

The AZODYN crop model includes 69 parameters whose values were estimated from literature and from several experiments carried out in France between 1991 and 2002 [3,5]. Among all the parameters, 13 parameters were assumed to vary across genotypes in past studies [3] and their ranges of variation are displayed in Table 1.

For illustration, we present one of the model equations below:

$$B_t = B_{t-1} + \Delta B_{t-1}$$

with

$$\Delta B_{t-1} = \mathrm{Ebmax} \times \mathrm{Eimax} \times \mathrm{PT}_{t-1} \times [1 - \exp(-K \times \mathrm{LAI}_{t-1})] \times \mathrm{PAR}_{t-1}.$$

This equation is used to calculate the wheat biomass on day t as a function of the biomass on day $t-1$ and of the daily incident radiation. Ebmax, Eimax, K are three parameters (Table 1). B_t and LAI_t are two state variables representing, respectively, biomass and leaf area index on day t. PT_t is a penalty term calculated as a function of the daily average temperature and of the nitrogen status of the crop. PAR_t is an input variable representing the incident photosynthetically active radiation on day t.

2.2. Comparing different sensitivity analysis methods on AZODYN

2.2.1. Sensitivity indices

We note further Y the output variable of AZODYN. Y will represent in turn yield and grain protein content at harvest. The total variance of Y, $V(Y)$, is partitioned as follows [4,7]:

$$V(Y) = \sum_{i=1}^{13} V_i + \sum_{1 \leqslant i < j \leqslant 13} V_{ij} + \cdots + V_{1,2\ldots,13}, \tag{1}$$

where $V(Y)$ is the total variance of the output variable Y induced by the 13 genetic parameters, $V_i = V[E(Y|x_i)]$ measures the main effect of the parameter x_i, $i = 1, \ldots, 13$, and the other terms measure the interaction effects. Decomposition (1) is used to derive two types of sensitivity indices defined by

$$S_i = \frac{V_i}{V(Y)}, \tag{2}$$

Table 1
The 13 genetic parameters of AZODYN and their ranges of variation

Parameter	Definition	Range	Unit
RDTMAXVAR	Maximal yield	100–137	q ha^{-1}
Ebmax	Radiation use efficiency	2.7–3.3	g MJ^{-1}
D	Ratio of leaf area index to critical nitrogen	0.02–0.045	—
REM2	Fraction of remobilized nitrogen	0.5–0.9	—
K	Extinction coefficient	0.6–0.8	—
Eimax	Ratio of intercepted to incident radiation	0.9–0.99	
Tep.flo	Duration between earing and flowering	100–200	°C day
R	Ratio of total to above ground nitrogen	1.0–1.5	—
P1GMAXVAR	Maximal weight of one grain	47–65	10^{-3}g
λ	Parameter for calculating nitrogen use efficiency	25–45	—
μ	Parameter for calculating nitrogen use efficiency	0.6–0.9	—
DJPF	Temperature threshold	150–250	°C day
NGM2MAXVAR	Maximal grain number	107.95–146.05	—