PROCESS-BASED MODEL FOR STOCHASTIC SIMULATION OF SUGARCANE GROWTH AND PRODUCTION

Fabio R. Marin[1], James W. Jones[2]

[1] Eng. Agrônomo, Pesquisador da Embrapa Informática Agropecuária, Campinas-SP. Atualmente Professor da ESALQ/USP.
[2] Eng. Agrícola, Professor da Universidade da Florida, Departamento de Engenharia Agrícola, Gainesville-FL-USA

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ABSTRACT: Dynamic simulation models can increase research efficiency and improve risk management of agriculture. Past uses of these models have been criticized in part due to a failure of researchers to quantify uncertainties of crop yield prediction. This paper describes a stochastic sugarcane process-based model that includes an approach for quantifying uncertainty in crop model predictions for regions where it has been parameterized. Classical crop model approaches were used as a framework for this model, and fitted algorithms for simulating sucrose accumulation and leaf development driven by a source-sink approach were proposed. Model was evaluated using data from five growing seasons at four locations in Brazil where crops received adequate nutrients and good weed control. Thirteen of the 27 parameters were optimized using a Bayesian Monte Carlo approach (Generalized Likelihood Uncertainty Estimation - GLUE) algorithm. GLUE was also used to estimate parameters correlations, and the mean parameter values and the covariance matrix were inputs for Toeplitz-Cholesky factorization to generate correlated random variable samples. The correlated random variable approach based on the Toeplitz-Cholesky factorization showed an interesting reduction on the uncertainty of simulations compared with a typical stochastic Monte Carlo simulation. Deterministic model predictions well simulated the sugarcane crop in Southern Brazil, using the parameterization reported here. Predictions were best for stalk dry mass (RMSE=5.38 t ha^{-1}; Eff=0.83), followed by leaf area index (RMSEP=0.85 m^2 m^{-2}; Eff=0.70) and then sucrose content in stalk fresh mass (RMSEP=1.17 %; Eff=0.56).

KEYWORDS: modeling, correlated random, covariance matrix, uncertainty

RESUMO: Modelos de simulação dinâmica do crescimento de plantas podem aumentar a eficiência da pesquisa e melhorar a gestão de risco na agricultura. Usos anteriores deste tipo de ferramenta modelos têm sido criticados em parte por uma falha na quantificação das incertezas da previsão de produtividade das culturas. Este artigo descreve um modelo estocástico baseado em processos para cana-de-açúcar que inclui uma abordagem para a quantificação da incerteza em simulações de crescimento e produtividade. Abordagens clássicas de processos bem estudados em conjunto com algoritmos desenvolvidos para simulação do acúmulo de sacarose e desenvolvimento foliar baseado numa abordagem fonte-dreno. Modelo foi avaliado utilizando dados de cinco experimentos em quatro locais no Sudeste do Brasil, com nutrição adequada e bom controle de plantas daninhas. Treze dos 27 parâmetros foram otimizados usando uma abordagem bayesiana de simulação por Monte Carlo (GLUE). O GLUE também foi utilizado para estimar as correlações entre os parâmetros a matriz de covariância, que foram insumos para a fatorização de matrizes segundo Toeplitz-Cholesky para geração de amostras aleatórias correlacionadas. Esta abordagem resultou numa redução interessante na incerteza das simulações em comparação com uma simulação estocástica típica usando Monte Carlo. Simulações do modelo determinístico foram adequadas para o Sudeste do Brasil com a parametrização obtida. As previsões foram melhores para massa seca de colmos (RMSE = 5,38 t ha^{-1}; Eficiência=0,83), seguido pelo índice de área foliar (RMSEP=0,85 m^2 m^{-2}; Eficiência=0,70) e, em seguida, teor de sacarose no colmo (RMSEP=1,17%; Eficiência=0,56).

PALAVRAS-CHAVE: modelagem, variáveis aleatórias correlacionadas, matriz de covariância, incerteza.

INTRODUCTION

Dynamic simulation models can increase research efficiency by allowing the analyst to search for strategies and analyze system performance, improve risk management, and interpret field experiments that deal with crop responses to soil, management, genetic or environmental factors (Keating et al., 1999). Sugarcane (Saccharum spp.) is of major social and economic importance in Brazil (Goldemberg, 2007). Worldwide, there have been several models developed specifically for sugarcane crop simulation (Pereira and Machado, 1986; Langellier and Martine, 2007; Keating et al., 1999; Inman-Bamber, 1991). Most of these models are based on a range of concepts described in Jones et al. (2003), and they balance the need for comprehensive description of the observed variation in crop performance over diverse environments and the need to avoid excessive complexity with large numbers of difficult to measure parameters (Keating et al., 1999). Recent literature contains relatively little work on parameter estimation for crop models. Makowski et al. (2006) point out the importance of raising the quality of calibration in crop models with automatic procedures for parameter adjustment. Also, crop models are increasingly being used for different purposes including evaluation of climate change impacts on crop yields and opportunities for adapting management to future conditions. However, past uses of these models have been criticized in part due to a failure of researchers to quantify uncertainties of crop yield prediction. Monte Carlo simulation is one way to estimate the effect of uncertainty in crop models and include spatial variability in soil, weather, and crop cultivar parameters inside crop models, using a moderate-sized random sample of all input combinations. In general, the randomly generated values for different input parameters were assumed to have no significant correlations among them, but this may not necessarily be true in the field (Aggarwal, 1995). In fact, in the nature, these parameters are likely to be correlated and this should be considered in stochastic simulations, avoiding nonexistent uncertainties in the model and keeping variability regarding the uncertainty source considered within a consistent range(Baigorria & Jones, 2010). A new sugarcane model was developed that builds on well-tested relationships used in existing models, adding new features (such as for photosynthesis, leaf development driven by a source-sink approach, and sucrose accumulation algorithms) based on recent literature and experiments. This new model also incorporates a stochastic approach using correlated random variables and an objective calibration procedure based on Generalized Likelihood Uncertainty Estimator (GLUE) to ensure consistent and reliable adaptation of the model for applications in Brazil. The purpose of this paper is to describe the functional basis of this stochastic model and to evaluate it for Southern Brazil, with a diverse range of planting dates, soils and water availability.

MATERIAL AND METHODS

The model simulates sugarcane growth and development using process-based algorithms including phenology, canopy development, tillering, biomass accumulation and partitioning, root growth, and water stress. State variables (Table 1) are updated using Euler integration with a one-day time step. The model is designed to simulate the entire plant, stalk and root biomass, sucrose concentration, plant phenology and other variables. The model requires soil parameters that regulate the soil water balance (field capacity, wilting point, water saturation, and soil depth), daily weather variables (solar radiation, maximum and minimum temperatures, precipitation), and irrigation. The model engine and modules are coded in FORTRAN 90 because this language continues to be the predominant programming language of simulation modeling in agriculture and due to the ease of obtaining available free code for specific algorithms used in this model. The description of the biophysics of the model can be found in Marin & Jones (2013).

Table 1. Model state variables, descriptions, units and categories.

State Variables	Description	Units	Category
NSTK	Number of stalks per area unit	stalk m^{-2}	Phenology
LN	Number of green leaves per stalk	Leaves $stalk^{-1}$	Leaf Development
LNTOTAL	Number of green plus dead leaves per stalk	Leaves $stalk^{-1}$	Leaf Development
LA	Leaf area	m^2	Leaf Development
W	total plant dry matter weight	ton ha-1	Photosynthesis
WA	aerial dry matter weight	ton ha^{-1}	Biomass accumulation
WR	root dry matter weight	ton ha^{-1}	Biomass accumulation
WSDM	stalk dry matter weight	ton ha^{-1}	Biomass accumulation
WSFM	stalk fresh matter weight	ton ha^{-1}	Biomass accumulation
WL	leaf dry matter weight	ton ha^{-1}	Biomass accumulation
WSUC	Sucrose weight	ton ha^{-1}	Sucrose accumulation
SLENG	Stalk length	m	Plant extension
RLD	Root length density for L layer	cm cm^{-3}	Root and water stress
SWC_a	actual soil water storage in the profile	mm	Soil Water

The model was parameterized and evaluated using plant cane and first ratoon data from the SP83-2847 cultivar, collected in four locations in Southern Brazil. The experimental data were collected and measurement frequency are fully described in Marin et al. (2011) (Table 2). All experiments received adequate N, P and K fertilization and regular weed control and were planted using healthy cuttings with 13 to 15 buds m–2. Row spacing varied from 1.4 m to 1.5 m. One of the datasets had two treatments (irrigated and rainfed), and all the remaining experiments were rainfed.

The generalized likelihood uncertainty estimate (GLUE) (Beven and Binley, 1992; Franks et al., 1998; Shulz et al., 1999) method was used for the crop model optimization to determine the best set of parameters from such a number of samples. GLUE was also use to generate the covariance matrix of model parameters, which in turn was used to generate the correlated random variables through the Toeplitz-Cholesky factorization.

Table 2. Overview of experimental data from cultivar SP83-2847, soil and climate characteristics of each experiment site.

Dataset	Site	Planting and Harvest Dates	Crop Cycle[1]	Climate[2]	Treatments
1	Piracicaba/SP, 22º52' S, 47º30' W, 560m asml	29 Oct 2004 and 26 Sept 2005	PC	21.6 ºC, 1230mm, CWa	1) Irrigated, 2) Rainfed
2	Aparecida do Taboado/MS, 20º05'19" S, 51º17'59" W, 335m asml	1 July 2006 and 8 Aug 2007	R1	23.5 ºC, 1560, Aw	3) Rainfed
3	Colina/SP, 20°25' S 48°19' W, 590m asml	10 Feb 2004 and 15 June 2005	PC	22.8 ºC, 1363mm, Aw	4) Rainfed
4	Olimpia/SP, 20°26' S, 48°32' W, 500m asml	10 Feb 2004 and 15 June 2005	PC	23.3 ºC, 1349mm, Aw	5) Rainfed

[1] PC - Plant cane crop; R - ratoon crop and following number is the ratoon rank; [2] Respectively: mean annual temperature, annual total rainfall, Koeppen Classification.

RESULTS AND DISCUSSION

Running the model under a deterministic approach, simulations for stalk dry mass well compared with Singels and Bezuidenhout (2002), or O'Leary (2000) and Marin et al. (2011) using several versions of CANEGRO for simulations or values from Cheeroo-Nayamuth et al. (2000) using the APSIM-Sugar model to simulate sugarcane growth in Mauritius. We found RMSEP=5.38 t ha^{-1} and modeling efficiency (eff)=0.85 (Fig. 1). Uncertainties in crop parameters resulted in variations in simulated stalk dry mass and sugar content (POL), but this uncertainty was variable among the evaluated sites (Fig. 2). Matter to highlight that Aparecida Taboado being the hotter and dryer site compared to Piracicaba. For the boundary conditions used here, the variability in stalk dry mass was generally higher than the variability obtained for sucrose content (Fig. 3). Percent deviation for stalk dry mass showed a 32.9% probability that the deviation in sugar content was greater than 20%.

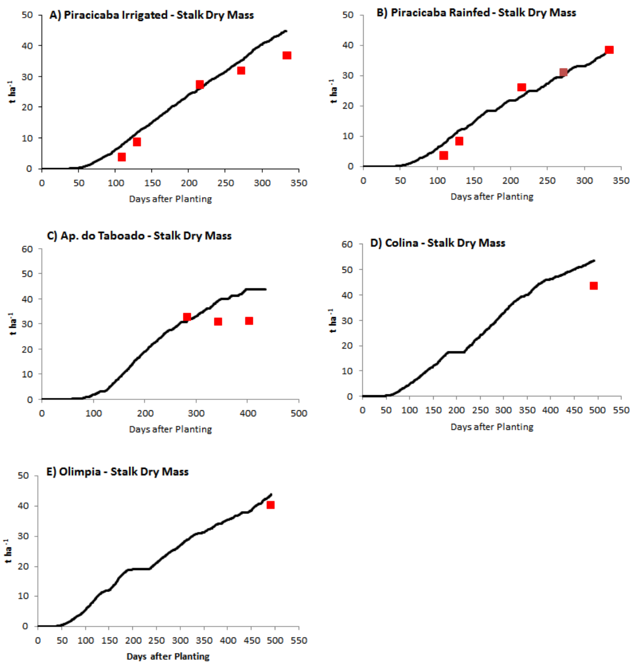

Figure 1, Time variation of observed and deterministically simulated stalk dry mass for five datasets of cultivar SP83-2847 in Southern Brazil.

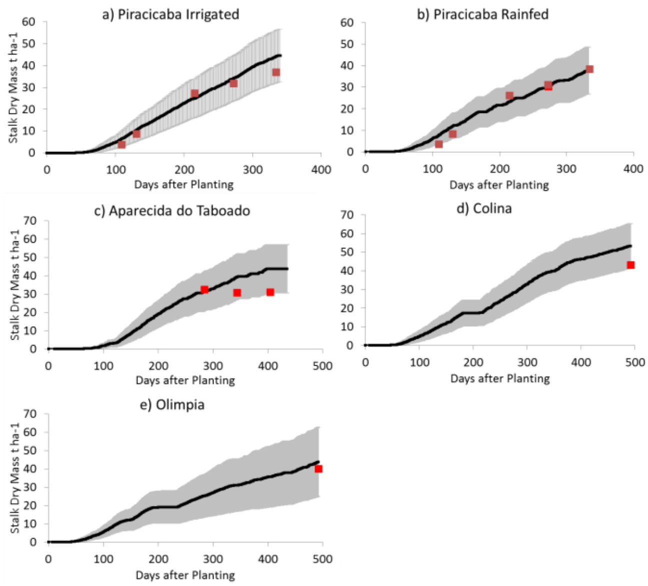

Fig. 2. Time variation of observed and stochastically simulated stalk dry mass for five datasets of cultivar SP83-2847 in Southern Brazil. Black line is the mean of stochastic simulations and grey area is representing one standard deviation around mean.

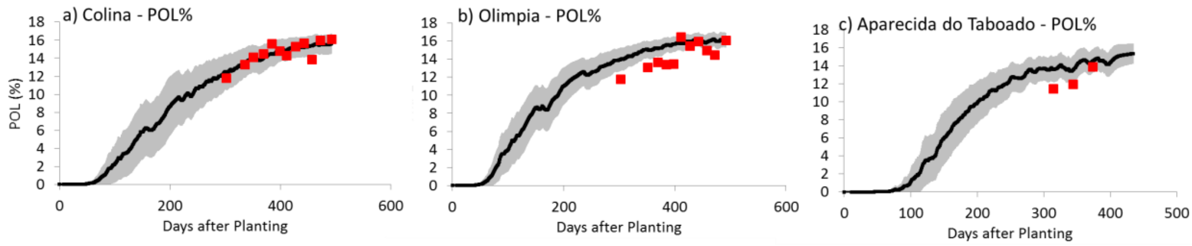

Fig. 3. Time variation of observed and stochastically simulated sugar content in the stalk (POL%) for five datasets of cultivar SP83-2847 in Southern Brazil. Black line is the mean of stochastic simulations and grey area is representing one standard deviation around mean.

CONCLUSIONS

This model provided a reasonable explanation of the growth of the experiments analyzed. The calibration using GLUE coupled with the cross-validation technique permits the use of diverse datasets that would be difficult to use separately because of the heterogeneity of measurements and measurement strategies. Using the calibration proposed, the model deterministically well simulated sugarcane growth and production under water-limited and irrigated conditions in Southern Brazil. The correlated random simulation seems useful to include the uncertainty in the crop growth and yield estimates, and the use of correlated random approach reduces the uncertainty in respect of model structure and parameter meaning. The uncertainty varies with the environment.

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