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Parameter estimation for crop growth model using evolutionary and bio-inspired algorithms

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ABSTRACT

All dynamic crop models for growth and development have several parameters whose values are usually determined by using measurements coming from the real system. The parameter estimation problem is raised as an optimization problem and optimization algorithms are used to solve it. However, because the model generally is nonlinear the optimization problem likely is multimodal and therefore classical local search methods fail in locating the global minimum and as a consequence the model parameters could be inaccurate estimated. This paper presents a comparison of several evolutionary (EAs) and bio-inspired (BIAs) algorithms, considered as global optimization methods, such as Differential Evolution (DE), Covariance Matrix Adaptation Evolution Strategy (CMA-ES), Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) on parameter estimation of crop growth SUCROS (a Simple and Universal CROp Growth Simulator) model. Subsequently, the SUCROS model for potential growth was applied to a husk tomato crop (*Physalis ixocarpa* Brot. ex Horm.) using data coming from an experiment carried out in Chapingo, Mexico. The objective was to determine which algorithm generates parameter values that give the best prediction of the model. An analysis of variance (ANOVA) was carried out to statistically evaluate the efficiency and effectiveness of the studied algorithms. Algorithm's efficiency was evaluated by counting the number of times the objective function was required to approximate an optimum. On the other hand, the effectiveness was evaluated by counting the number of times that the algorithm converged to an optimum. Simulation results showed that standard DE/rand/1/bin got the best result.

Introduction

Mathematical models in agriculture are powerful tools to describe and understand complex systems. These models have been used in plant breeding to simulate the effects of changes in the morphological and physiological characteristics of crops which aid in identification of ideotypes for different environments. The structure of dynamic crop growth models consist in a set of ordinary first order differential equations characterized by non-linearity, multivariate dynamic, complexity and uncertainty [1]. Generally, these equations have a set of coefficients that represent physiological parameters whose values have to be determined with precision to obtain a good fit between predicted variables and measurements. In the development process of a mathematical crop growth model, parameter estimation or model calibration is essential in order to get the objective aforementioned. Which implies, by applying optimization algorithms, to estimate parameters values from measurements that affect more model behavior. The process to determine parameter values can be established as an optimization problem which allowing that a variety of algorithms can be used to look for a solution. Generally, local methods such as LSE (Least Squares Estimation) and SQP (Sequential Quadratic Programming) are used. However, those algorithms have the drawback of leading to inaccurate estimated parameter values (high variance of parameters estimators) and inaccurate model predictions (over parameterization) when they are applied in the estimation of a large number of model parameters (i.e. > 10). This problem is because such algorithms often fail to converge to the optimum value when the parameters are too numerous [2]. Also, due to high non-linearity of models of crop growth and a dependency between the parameters (epistasis), the optimization problem can be non-convex or multi-modal.

In order to solve multi-modal optimization problems, global optimization methods such as evolutionary algorithms (DE, Differential Evolution and CMA-ES, Covariance Matrix Adaptation

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Evolution Strategy) and algorithms inspired by the behavior of biological systems (PSO, Particle Swarm Optimization and ABC, Artificial Bee Colony) can provide good approximations to the global optimal value [3–8,21–24].

In the literature many works devoted to parameter estimation have been focused on greenhouse crop growth models, mainly using evolutionary algorithms (e.g. [9–12]). However, few works have been done to parameter estimation of the crop growth models in open field. Ioslovich and Gutman [13] and Wallach et al. [14] proposed a procedure for parameter estimation of crop models calibrated with field data, but they did not use global optimization methods. Pabico et al. [15] formulated a Genetic Algorithm (GA) to calculate the cultivar coefficients of crop models. However, nowadays limitations of genetic algorithms as optimizers are well known [16]. To our best knowledge no one, so far has applied bio-inspired optimization algorithms to parameter estimation of crop models in open field. Therefore, the objective of the present research was to evaluate the performance through efficiency and effectiveness of the DE, CMA-ES, PSO and ABC algorithms, to estimate 25 parameters of the SUCROS (a Simple and Universal CROp Growth Simulator) model [17] applied to a husk tomato crop, in order to analyze which algorithm generates parameter values that give the best prediction of the model not only to increase the knowledge of the husk tomatoes cropping system but also the potential developing of practical applications. Efficiency or computational cost of an algorithm is the number of times the objective function is evaluated to find an optimum. The effectiveness or performance of an algorithm, to achieve an optimum in a multi-modal optimization problem, is calculated by counting the number of times the algorithm converges to the same optimum with different initial values for the iterative process [18].

Materials and methods

The SUCROS model for potential crop growth

The SUCROS (a Simple and Universal CROp Growth Simulator) is a mechanistic model that explains crop growth on the basis of the underlying processes, such as carbon dioxide (CO_2) assimilation and respiration, as influenced by environmental conditions [19]. It simulates potential growth of a crop, i.e. its dry matter accumulation under ample supply of water and nutrients, in a pest, disease and weed-free environment under the prevailing weather conditions. The potential crop growth model has been described extensively elsewhere [19,17] and a brief summary to emphasize its main properties is given in Tables 1 and 2. The seven ordinary differential equations that make up the model are:

$$\frac{dx_{ds}}{dt} = f(x_{ds,T}) \tag{1}$$

$$\frac{dx_{lai}}{dt} = Growth_{lai} - Death_{lai} \tag{2}$$

$$\frac{dx_{gldw}}{dt} = Growth_{gldw} - Death_{gldw} \tag{3}$$

$$\frac{dx_{dldw}}{dt} = Death_{dldw} \tag{4}$$

$$\frac{dx_{rdw}}{dt} = (1 - fr_{sh}(x_{ds}))TotalGrowth \tag{5}$$

$$\frac{dx_{stdw}}{dt} = fr_{st}(x_{ds})fr_{sh}(x_{ds})TotalGrowth \tag{6}$$

$$\frac{dx_{sodw}}{dt} = fr_{so}(x_{ds})fr_{sh}(x_{ds})TotalGrowth \tag{7}$$

where x_{ds} (dimensionless) represents the development state, x_{lai} ($\mathrm{m^2 m^{-2}}$) is the leaf area index, x_{gldw} ($\mathrm{g\,m^{-2}}$) is the green leaves biomass, x_{dldw} ($\mathrm{g\,m^{-2}}$) is the biomass of death leaves, x_{rdw} ($\mathrm{g\,m^{-2}}$) is the biomass of roots, x_{stdw} ($\mathrm{g\,m^{-2}}$) is the biomass of stems and x_{sodw} ($\mathrm{g\,m^{-2}}$) is the biomass of fruits. Main equations of the model structure are shown on Table 1. The total set of SUCROS parameters are described on Table 2. On the other hand, on Table 1 Δt (d, day) is the integration step size, T_{max} (°C) is the maximum daily temperature, and T_{min} (°C) is the minimum daily temperatures which are the inputs variables for the SUCROS model. Empirical functions in the SUCROS model are the following: $f(x_{ds,T})$ which calculates the development stage rate depending on temperature, $fr_{sh}(x_{ds})$ the fraction total dry matter allocated to shoots, $fr_{st}(x_{ds})$ the fraction of shoot dry matter allocated to stems, $fr_{so}(x_{ds})$ the fraction of shoot dry matter allocated to storage organs, $fr_{leaves}(x_{ds})$ the fraction of shoot dry matter allocated to leaves. All these functions depend on stage of development. Other empirical functions are: $f(x_{st}, x_{ds}, T_{avg})$, $f_1(x_{ds})$, $f_2(x_{lai})$ and $f(d_{emerg})$ is a switching function which output is one as the simulation time is equal to the emergence day, otherwise its output is zero.

Experimental site description

A husk tomato crop (*Physalis ixocarpa* Brot. ex Horm.) was grown during the summer of 2007 in Chapingo, Mexico (19°16′52″ LN and 99°39′0″ LW). The site has a temperate weather with a raining season during the summer and a drought time during winter. The annual average temperature is 15.5°C and the annual rainfall

Table 1
Main equations of SUCROS model for potential crop growth.

Function	Description	Units
$Grwth_{lai} = SLA \cdot Growth_{gldw}$	LAI growth rate during linear phase	$m^2 m^{-2} d^{-1}$
$Grwth_{lai} = \frac{x_{lai} \cdot \exp(RGRL \cdot T_{eff} \cdot \Delta t) - 1}{\Delta t}$	LAI growth rate for exponential phase	$m^2 m^{-2} d^{-1}$
$Grwth_{gldw} = fr_{leaves}(x_{ds}) \cdot fr_{sh}(x_{ds}) \cdot TotalGrowth$	Growth rate for leaves	$g\,m^{-2} d^{-1}$
$TotalGrowth = \frac{Assim - R_m + CONVL \cdot w_{tl} \cdot CFST(30/12)}{ASRQ}$	Growth rate for total plant biomass	$\mathrm{g\,m^{-2}\,d^{-1}}$
$Assim = (30/44)AMX \cdot exp(-EFF \cdot PAR_{abs}/AMX)$	Assimilation rate of CO_2	$\mathrm{g\,m^{-2}\,d^{-1}}$
$R_m = (MAINLV \cdot x_{gldw} + MAINST \cdot x_{stdw} + MAINRT \cdot x_{rdw} + MAINSO \cdot x_{sodw}) \cdot f_{resp}(T) \cdot f_{resp}(x_{ds}) \cdot f(d_{emerg})$	Maintenance respiration rate	$\mathrm{g\,m^{-2}\,d^{-1}}$
$f_{resp}(T) = Q10^{\frac{T_{avg} - TREF}{10}}$	Temperature effect on respiration rate	–
$f_{resp}(x_{ds}) = \frac{x_{gldw}}{x_{gldw} + x_{dldw}}$	Effect of development state on respiration rate	–
$Death_{gldw} = x_{gldw} \cdot \frac{Death_{lai}}{x_{lai}}$	Leaves mortality rate	$\mathrm{g\,m^{-2}\,d^{-1}}$
$Death_{lai} = x_{lai} max(f_1(x_{ds}), f_2(x_{lai}))$	Rate mortality of leaf area	$\mathrm{m^2\,m^{-2}\,d^{-1}}$
$w_{tl} = FRTRL \cdot x_{st} \cdot f(x_{st}, x_{ds}, T_{avg})$	Translocation rate of biomass from stems to storage organs	$\mathrm{g\,m^{-2}\,d^{-1}}$
$PAR_{abs} = 1 - exp(-KDF \cdot x_{lai})$	Function of light interception	$\mathrm{J\,m^{-2}\,s^{-1}}$
$T_{eff} = \max(0, \frac{1}{2}(T_{\max} + T_{\min}) - TBASE)$	Daily effective temperature	°C