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Calibration of a crop simulation model using an evolutionary algorithm with self-adaptation.

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Abstract

Calibration of cultivar parameters of a crop simulation model can represent a considerable challenge when observed data for a single cultivar is available for multiple environments. Calibration can be considered as a search of the optimal set of parameters in a multidimensional parameter space. An evolutionary algorithm with self-adaptation has been developed and applied to calibrate parameters of the Sirius crop simulation model for several experimental datasets.

Keywords: Sirius; model calibration and validation; evolutionary optimization.

1. Main text

Calibration of cultivar parameters for a crop simulation model can represent a considerable challenge when observed data for a single cultivar is available for multiple environments (site × year × treatment). Calibration can be considered as a search of the optimal set of parameters in a multidimensional parameter space with a very complex and computationally expensive function as a criterion for optimization. Evolutionary algorithm with self-adaptation can be used to tackle this difficult problem (Back, 1998; Beyer, 1995; Meyer-Nieberg and Beyer, 2007; Schwefel and Rudolph, 1995).

An evolutionary algorithm with self adaptation (EA-SA) includes two sets of parameters: fitness parameters, which belong to the domain of the optimization (fitness) function, and control parameters which control the variation of fitness parameters. Although both parameters are changed randomly during the search, they converge to the optimum state due to direct select for fitness parameters and indirect selection for control parameters. Evolutionary algorithms with self-adaptation do not require fine tuning of control parameters during the search in complex spaces, where predefined heuristic rules are unavailable or difficult to formulate (Semenov and Terkel, 1985; Semenov and Terkel, 2003). We used a new implementation of the Sirius crop simulation model (Jamieson and Semenov, 2000;

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EA-SA {
Initialise $(x, v, \sigma_v, \sigma_l)$(t=0)
Iterate (StoppingRule) {
$\{(x, v, \sigma_v, \sigma_l)^{i,j}(\mathrm{t}), \mathrm{i} < \mathrm{k}_{\mathrm{v}}\ \mathrm{j} < \mathrm{k}_{\mathrm{l}}\}$ = CreateOfsprings $\left((x, v, \sigma_v, \sigma_l)(\mathrm{t})\right)$
$(x, v, \sigma_v, \sigma_l)(\mathrm{t}+1)$ = Select$\{(x, v, \sigma_v, \sigma_l)(\mathrm{t}), (x, v, \sigma_v, \sigma_l)^{i,j}(\mathrm{t})\}$
}
}
CreateOfsprings $\left((\boldsymbol{x}, \boldsymbol{v}, \boldsymbol{\sigma_l}, \boldsymbol{\sigma_v})(\mathbf{t})\right)${
for(i<k $_v$){
$\sigma_v^i = mutate(\sigma_v)$
$v^i = mutate(v, \sigma_v^i)$
for(j<k $_l$){
$\sigma_l^{i,j} = mutate(\sigma_l)$
$x^{i,j} = x + (\sigma_l^{i,j}\ \xi^{i,j})v^i$ where $\xi^{i,j}$ =rand(C^1)
$(x, v, \sigma_l, \sigma_v)^{i,j}(\mathrm{t}) = \left(x^{i,j}, v^i, \sigma_v^i, \sigma_l^{i,j}\right)$
}
}
Select {
if($F(x) \leq F(x^{i,j})$ {
$(x, v, \sigma_v, \sigma_l)(\mathrm{t}+1) = \left(x, v^l, \sigma_v^l, \sigma_l^{l,m}\right),$
$where\ F(x^{l,m}) = min\{F(x^{i,j})\}$
}else{
$(x, v, \sigma_v, \sigma_l)(\mathrm{t}+1) = \left(x^{l,m}, v^l, \sigma_v^l, \sigma_l^{l,m}\right),$
$where\ F(x^{l,m}) = min\{F(x^{i,j})\}$
}
}
Mutate(σ) { return $\left(\sigma\ e^{rand(C^1)}\right)$}
Mutate$(v, \sigma_v^i,)$ { return $\left(norm(v + \sigma_v^i rand(C^n))\right)$ }

Box 1. A schematic representation of a variant of EA-SA used for model calibration.

Lawless et al., 2005; Semenov et al., 2007; Semenov et al., 2009), which contains approximately 44 cultivar specific parameters.

Given experimental data for a single cultivar at multiple environments, we are looking for a set of cultivar parameters which gives the best agreement between observed and simulated data. We used the following implementation of EA-SA (Box 1). The evolving state is described as $(x, v, \sigma_v, \sigma_l)$, where $x \in C^n, v \in S^n, \sigma_v \in [0,1], \sigma_l \in [0,1]$ $(C^n = [-1,1]^n$ and $S^n = \{v \in C^n, |v| = 1\})$; x represents a state in a cultivar parameter space, v represents a vector of mutations for x with scaling parameters σ_v and σ_l . A fitness function F was calculated as weighted differences between observed and simulated values of selected output variables. To reduce the dimension of the search space for calibration, the cultivar parameters have been divided into independent groups, such as parameters controlling phenology or parameters controlling biomass production. EA-SA has been tested for several experimental datasets including a dataset for the N experiment at INRA Clermont-Ferrand, France (1 site × 1 year × 9 treatments), a dataset from the rain-shelter experiment at Lincoln, NZ (1 site × 1 year × 7 treatments), and the BBSRC-INRA N experiment dataset (4 sites × 3 years × 2 treatments). The calibration procedure is incorporated into the Sirius model which allows to automate parameter calibration for new wheat cultivars.

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