AUTOMATIC CALIBRATION OF A HYDROLOGIC MODEL FOR SIMULATING GROUNDWATER TABLE FLUCTUATIONS ON FARMS IN THE EVERGLADES AGRICULTURAL AREA OF SOUTH FLORIDA†

HOYOUNG KWON1*, SABINE GRUNWALD2, HOWARD BECK3 AND YUNCHUL JUNG3

1International Food Policy Research Institute (IFPRI), Environment and Production Technology Division, NW Washington District of Columbia, USA
2University of Florida, Soil and Water Science Department, Gainesville, Florida, USA
3University of Florida, Department of Agricultural and Biological Engineering, Gainesville, Florida, USA

ABSTRACT

The Shuffled Complex Evolution—Universal Algorithm (SCE-UA) is an automatic calibration algorithm that has shown success in finding a globally optimum objective function with more efficiency than other methods. We incorporated the SCE-UA into our novel modeling environment, utilizing an ontology-based simulation (OntoSim-Sugarcane) framework adapted to analyze groundwater table (WT) fluctuations and drainage practices on four farm basins in the Everglades Agricultural Area of south Florida.

Utilizing two water years (WY96–97) of farm WT fluctuations observed at a portion (<16 ha) of each farm basin, two parameters—lateral hydraulic conductivities of soil profile and vertical hydraulic conductivity of underlying limestone—were automatically calibrated. Regardless of farms, the best parameter sets that minimize the objective function of daily root mean square error could be found after 1500 simulation runs. The quality of matching simulated to observed values of farm WT were further assessed by the Nash–Sutcliffe efficiency coefficient (NSE). The NSE ranged from 0.38 to 0.75 (calibration period, WY96–97) and 0.10 to 0.76 (validation period, WY98–99) on all four farms. These results indicate that this coupling strengthens the capability of OntoSim-Sugarcane to model hydrology by objectively finding the best parameter sets. Copyright © 2014 John Wiley & Sons, Ltd.

KEY WORDS: automatic calibration; hydrologic model; groundwater table management; Everglades Agricultural Area

Received 2 August 2013; Revised 11 September 2013; Accepted 12 September 2013

RÉSUMÉ

L’optimisation par évolution mélangée de complexes de paramètres (SCE-UA) est un algorithme de calage automatique qui est connu pour trouver plus efficacement que d’autres méthodes dans la recherche d’une fonction objective globalement optimale. Nous avons intégré la SCE-UA dans notre environnement de modélisation en utilisant une simulation basée sur l’ontologie (OntoSim-canne à sucre) pour analyser les fluctuations de la nappe phréatique (WT) et des pratiques de drainage sur les blocs hydrauliques de quatre fermes situées dans les marais de la région agricole sud de la Floride.

En utilisant deux années (WY96–97) de données piézométriques observées sur chaque bloc (<16 ha), deux paramètres—la conductivité hydraulique latérale du sol et la conductivité hydraulique verticale du calcaire sous-jacent—ont été automatiquement calés. Indépendamment du bloc, les meilleurs jeux de paramètres qui minissent la racine de l’erreur quadratique moyenne de la fonction objective a pu être trouvée après 1500 cycles de simulations. La qualité de l’appariement simulé à des valeurs observées a encore été évaluée par le coefficient d’efficacité Nash–Sutcliffe (NSE). Le NSE a varié de 0.38 à 0.75 (période d’étalonnage, années 96–97) et de 0.10 à 0.76 (période de validation, années 98–99) sur les quatre blocs hydrauliques. Ces résultats indiquent que ce couplage renforce la capacité de OntoSim-canne en tant que modèle hydrologique à trouver objectivement les meilleurs jeux de paramètres. Copyright © 2014 John Wiley & Sons, Ltd.

MOTS CLÉS: calibrage automatique; modèle hydrologique; gestion de la nappe phréatique; zone agricole des Everglades

*Correspondence to: Dr. Hoyoung Kwon, International Food Policy Research Institute (IFPRI), Environment & Production Technology Division, 2033 K St. NW Washington District of Columbia 20006-1002, United States. E-mail: h.kwon@cgiar.org
†Calibration automatique d’un modèle hydrologique pour simuler les fluctuations de la nappe phréatique dans les fermes de la zone agricole des Everglades du sud de la Floride.

Copyright © 2014 John Wiley & Sons, Ltd.
INTRODUCTION

Groundwater table (WT) management utilizing artificial drainage and/or irrigation systems has allowed the conversion of low-relief and poorly drained areas into fertile agricultural production areas in the United States. However, these also have created negative impacts on the environment, such as the degradation of surface waters by enhancing the transport of major nutrients [nitrogen (N) and phosphorus (P)] to surface waters (Skaggs et al., 1994; Madramootoo et al., 2007). The need to minimize water quality problems has stimulated development of various approaches to enhance our understanding of hydrologic pathways and to develop best management practices (BMPs) for agricultural production.

The use of hydrologic/water quality models provides a cost-effective way to test various management practices without conducting extensive field studies by modeling water, sediment, and solute movements within defined watershed domains. The level of complexity of these models varies greatly in terms of how models (i) encapsulate and detail ecosystem processes in the form of algorithms, (ii) solve process algorithms analytically or numerically, (iii) populate parameters estimated or empirically derived, and (iv) deal with spatial and temporal scales.

Among many models, DRAINMOD (DRAINage MODel) (Skaggs, 1980) is one of the most widely used especially for testing the performance of drainage and WT control systems. It is a field-scale model to simulate daily drainage flow and surface runoff for a drainage system design using a set of soil and climatic properties. The Green–Ampt equation is used in DRAINMOD to predict infiltration and drainage rates calculated with Hooghoudt’s equation (Hooghoudt, 1940). Importantly, it uses soil moisture characteristics (i.e. water retention curves) to calculate the soil moisture distribution within the soil profile under the assumption of ‘drained to equilibrium’ condition. Such an assumption has also been adapted by other models such as ADAPT (Agricultural Drainage and Pesticide Transport) (Chung et al., 1992) and GLEAMS-WT (Groundwater Loading Effects of Agricultural Management Systems—Water Table) (Reyes et al., 1993). These models have been used to simulate nutrient-enriched drainage flows released from the US Midwestern Corn Belt where the excessive use of N fertilizer for corn production linked with subsurface tile drainage has contributed to the degradation of water quality (Sogbedji and McIsaac, 2006; Nangia et al., 2010).

Recently, algorithms similar to DRAINMOD were utilized in ontology-based simulation (OntoSim) applied to water management systems in low-relief agricultural areas with organic soils of south Florida—the Everglades Agricultural Area (EAA). This model simulated WT fluctuations in farm basins of the EAA where subirrigation and open ditch drainage are commonly practiced (Kwon et al., 2010). Like other complex hydrologic models, it requires a calibration procedure to calculate some measure of ‘fit’ between observed data and simulated results or outputs—the objective function—until an optimum is attained. However, the model calibration was implemented by an iterative process of manually changing parameter values and calculating the objective function (Kwon et al., 2010). Although manual calibration succeeds in finding global optima, the surfaces of objective functions can exhibit many local minima, making it difficult to know whether a manually optimized parameter set corresponds to a global or local optimum. Also, the utility of model results can be limited because the success of these adjustments will depend in part on the experience of the model user (Eckhardt and Arnold, 2001). Thus, manually calibrated models experience limited acceptance by users and are subject to large, unquantified uncertainties in model predictions.

Partly in response to these problems, various algorithms for automatic calibration have been developed (Duan et al., 1992; Grieb et al., 1999). In automatic calibration, a computer algorithm searches the model’s multidimensional parameter space to identify a set of parameters that yields a globally minimized error, or some other optimized objective function, much in the same way that regression minimizes the sum of the squared errors between predicted and observed response variables. The difference is that the relatively simple algebraic equations used in regression modeling are replaced by vastly more complex algorithms.

One successful automatic calibration technique is the Shuffled Complex Evolution—Universal Algorithm (SCE-UA) (Duan et al., 1992). The method includes the best features from several existing methods such as a genetic algorithm-based approach (Goldberg, 1989) and the concept of complex shuffling. It has been successfully applied to the calibration of rainfall–runoff models (Mrochzowski et al., 1997; Franchini et al., 1998), and the SWAT model (Arnold et al., 1998). By this coupling, site-specific model parameters can be automatically and objectively adjusted to provide the best fit between observed and simulated data for a particular site or basin.

The objectives of the present study are to (i) couple the SCE-UA with OntoSim-Sugarcane and test whether such coupling is successful and (ii) utilize and evaluate it to optimize hydrologic parameters that determine vertical and lateral water flux in four farm basins in the EAA.

MATERIALS AND METHODS

Ontology-based simulation (OntoSim)

Since the late 1990s, the term ‘ontology’ has been used by artificial intelligence research communities to facilitate the sharing and reuse of knowledge among humans as well as machines. Currently it has become widespread in many fields such as intelligent information integration, information retrieval.
on the Internet, and knowledge management (Studer et al., 1998). One popular definition of ontology is ‘a formal explicit specification of a shared conceptualization’ (Gruber, 1993; Borst, 1997) and more practically it can be defined as real-world semantics and consensual terminologies interweaving human and machine understanding (Fensel, 2003). Recently, ontology-based technology was used to develop a platform for simulation modeling of dynamic soil–plant–nutrient processes in agro-ecosystems, which is called ontology-based simulation (OntoSim) (Beck et al., 2010). In the OntoSim, complex processes, such as soil organic matter decay, water fluxes, and crop growth, are defined and described by a set of symbols and mathematical equations (Figures 1(a) and (b)). Then, all associated knowledge about the symbols and equations including operators (+, −, ×, /, =, and many others) are represented as ontology objects so that it becomes machine-readable information as well as being better documented for use in sharing models within the modeling community (Figure 1(c)). Finally the information is utilized to automatically generate computer code in Java and build programs needed to execute the model simulation of soil–plant–nutrient processes (Figure 1(d)).

**Description of OntoSim-Sugarcane**

**Modelled area and processes.** The OntoSim-Sugarcane (Kwon et al., 2010) is a daily time-step and field-scale model developed to simulate complex soil–crop–nutrient processes in EAA farm basins of south Florida (Figure 2). It has been developed within the OntoSim framework specifically to model farm basins in sugarcane production. The EAA farm basins, dominated by sugarcane production, have been established by installing an extensive system of main canals, lateral ditches, and farm pump stations since the late 1940s (Diaz et al., 1993). At the pump station of each farm basin, the water levels of a main farm canal are controlled by off-farm discharge pumping from the main farm canal into the basin drainage canal. While the main farm canal runs from the main farm pump station to the far reaches of the farm basin, farm laterals branch off the main canal at right angles...
and farm ditches emanate at right angles from the farm laterals (Figure 3). These networks of laterals and ditches within an entire farm basin create rectangular areas (~ 16 ha) that are considered the basin water management unit. In these farm basins subirrigation or open ditch drainage practices are used to either raise or lower the main farm canal levels (Bottcher and Izuno, 1994).

The processes modelled include (i) first-order kinetic soil organic matter decay based on the mathematical framework of the CENTURY model (Parton et al., 1998), (ii) dynamics...
of soil inorganic nutrients (P) (Sharpley et al., 1984), and (iii) sugarcane growth and its nutrient uptake based on a modified version of the DSSAT (Decision Support System for Agrotechnology Transfer)—CANEGRO (CANE GROwth) model (Inmanbamber, 1994).

Regarding hydrologic processes, it models soil moisture content using van Genuchten’s (1980) equation (Table I). Empirical parameters in the equation were estimated by fitting this function and the data measured for the soil–water retention relationship. Evapotranspiration (Allen et al., 2005), upward water flux (Anat et al., 1965), and infiltration (Green and Ampt, 1911) are subsequently calculated. Finally lateral drainage (\(Q_L\), cm h\(^{-1}\)) and deep seepage (cm h\(^{-1}\)) are calculated (Table I). Detailed descriptions of modeling of the hydrologic processes in the EAA can be found in Kwon et al. (2010).

**Automatic calibration tool.** We incorporated the SCE-UA genetic algorithm into OntoSim-Sugarcane to allow automatic calibration of the model. The automatic calibration was created as a type of ‘plug-in’ into the OntoSim environment that would allow users to perform automatic calibration on any model built with OntoSim. Similar to other automatic calibration methods, an iterative process is used to change (input) parameter values and calculate some measure of fit between simulation results and empirical observations. This allows us to attain an optimum of the objective function. It uses the approaches combining the downhill simplex procedure of Nelder and Mead (1965) with random search, competitive evolution, and complex shuffling (Agyei and Hatfield, 2006) (Figure 1(e)). First, a number of points are generated for the entire sample population, which is confined by lower and upper limits of the parameter values given by users. Then values are obtained from an objective function calculated at each point. Second, the points are sorted in order of increasing criterion value so that the first point represents the point with the smallest criterion value and the last point represents the point with the largest. Third, the sorted points are partitioned into several complexes, each consisting of \((2n+1)\) points, \(n\) being the number of parameters to be optimized. Fourth, each complex evolves independently in a manner based on the downhill simplex procedure, moving from the points where the value of an objective function is largest to the opposite points. Finally, the population is periodically shuffled and new complexes formed so that the information gained by the previous complexes is shared. The evolution and shuffling steps repeat until the objective function value ceases decreasing. Further details of the algorithm can be obtained in Duan et al. (1992) and Agyei and Hatfield (2006).

**Table I. Equations related to hydrologic process modeling**

<table>
<thead>
<tr>
<th>Process</th>
<th>Equation</th>
<th>Variable</th>
</tr>
</thead>
</table>
| Soil moisture content (cm\(^3\) cm\(^{-3}\)) | \(\theta(h) = \theta_r + (\theta_s - \theta_r) \left[ \frac{1}{1 + \frac{|\theta_s - \theta_r|}{\alpha}} \right]^n \) | \(\theta_r\): residual soil water content (cm\(^3\) cm\(^{-3}\))  
|                                       |                                                                          | \(\theta_s\): saturated soil water content (cm\(^3\) cm\(^{-3}\))  
|                                       |                                                                          | \(h\): the soil matrix potential or capillary pressure head (cm)  
|                                       |                                                                          | \(\alpha\) (cm\(^{-3}\)) and \(n\): empirical parameters  
|                                       |                                                                          | \(m = 1 - 1/n\)  
| Upward water flux (cm h\(^{-1}\))     | \(U_{FLUX} = VK_{SAT} \left(1 + \frac{1.886}{\eta} \right)^{-\eta} \left( \frac{\eta h}{\eta - 1} \right)^{-\eta} \) | \(VK_{SAT}\): vertical saturated hydraulic conductivity (cm h\(^{-1}\))  
|                                       |                                                                          | \(\eta = 2 + 3 \cdot n \cdot (1 - 1/n)\)  
|                                       |                                                                          | RD: root zone depth (cm)  
|                                       |                                                                          | \(b_h\): bubbling pressure (cm) and determined from the relationship between effective saturation and \(h\)  
| Soil air volume (cm)                 | \(AirV = a_1 \cdot WTD^2 + a_2 \cdot WTD\)                              | \(a_1\) and \(a_2\): empirical parameters  
| Infiltration (cm h\(^{-1}\))         | \(f = \frac{\phi}{n} + B\)                                             | \(f\): the infiltration rate which is equal to the downward flux  
|                                       | \(A = VK_{SAT} (\theta_s - \theta) h_b \left( \frac{\eta}{\eta - 1} \right)\) | \(F\): the cumulative infiltration (cm h\(^{-1}\))  
|                                       | \(B = VK_{SAT}\)                                                        |                                                                          |
| Lateral drainage (cm h\(^{-1}\))     | \(Q_L = K_f \left(\frac{WT_{farm} - WT_{ditch}}{S_a}\right)\)            | \(K_f\): an effective lateral saturated hydraulic conductivity (cm h\(^{-1}\))  
|                                       |                                                                          | that is a function of lateral saturated hydraulic conductivity of soil profiles \(LK_{SAT}\)  
|                                       |                                                                          | \(WT_{farm}\) and \(WT_{ditch}\) (cm): the WT at the farm water management unit and ditch based on above mean sea level  
| Deep seepage (cm h\(^{-1}\))        | \(Q_V = \frac{WK_{SAT - bedrock} (WT_{farm} - WT_{ditch})}{d_{bedrock}}\) | \(S_a\): the distance from the middle of a farm unit to ditch (cm)  
|                                       |                                                                          | \(VK_{SAT - bedrock}\): a vertical saturated hydraulic conductivity of the underlying limestone bedrock (cm h\(^{-1}\))  
|                                       |                                                                          | \(d_{bedrock}\): limestone bedrock thickness (cm)  

Copyright © 2014 John Wiley & Sons, Ltd. *Irrig. and Drain.* (2014)
Simulation of groundwater table fluctuations

Data. We selected four farm basins (Figure 2) in the EAA in which comprehensive BMP research has been conducted from 1992 to 2002 by the South Florida Water Management District (SFWMD). These farm basins were selected to represent a typical range of farm sizes, soil types, crop rotations, water management and geographical distribution across the EAA (Daroub et al., 2009). The farm basins were dominated by Pahokee and Dania soil series and sugarcane was mainly cropped (>90%) for consecutive water years (WYs) from May 1995 (WY96) through April 1999 (WY99). The basins vary in terms of basin sizes, i.e. 129 ha (UF9202A), 518 ha (UF9200A), 1243 ha (UF9209A), and 1865 ha (UF9203A). At the farm pumping station of each farm basin, main canal water levels, off-farm discharge volumes, and rainfall were recorded by the SFWMD. Canal water levels were measured using pressure transducers (Wika Instrument Corp., Lawrenceville, Ga) every 5 min and averaged and stored hourly. The data were converted to WT by subtracting the water level data from the ground average mean sea level (Garcia et al., 2001) to derive the distance of WT from a zero ground reference (AMSL). Rainfall was measured using a tipping bucket rain gage (Texas Electronics, Inc., Dallas, Tex.).

We selected one farm unit (Table II) where the SFWMD installed a monitoring well at an approximate center of the unit in order to monitor farm WTs. The farm WTs were recorded on an hourly basis using mechanical strip chart recorders (Leopold and Stevens, Inc., Beaverton, Ore.). A reference point on each well was surveyed to AMSL which allows conversion of all the strip data to a common datum. For this study, all the data were averaged to derive daily values. Other data such as daily temperature and total solar radiation were derived from the Belle Glade weather station (ID 33430) operated by the SFWMD. The soil parameters required for estimating soil moisture distribution were calculated by fitting the data with the van Genuchten equation.

Table II. Characteristics of farm water management units utilized for hydrologic simulations of OntoSim-Sugarcane

<table>
<thead>
<tr>
<th>Farm water management unit</th>
<th>Size (ha)</th>
<th>Unit-to-farm basin ratio (%)</th>
<th>Distance from a farm well to a farm ditch (m)</th>
<th>Depth of soil (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UF9200A</td>
<td>15.3</td>
<td>2.95</td>
<td>96</td>
<td>120</td>
</tr>
<tr>
<td>UF9202A</td>
<td>7.2</td>
<td>5.58</td>
<td>95</td>
<td>50</td>
</tr>
<tr>
<td>UF9203A</td>
<td>16.0</td>
<td>0.86</td>
<td>100</td>
<td>96</td>
</tr>
<tr>
<td>UF9209A</td>
<td>16.0</td>
<td>0.013</td>
<td>100</td>
<td>88</td>
</tr>
</tbody>
</table>

*The distances were calculated by Euclidean distance in ArcGIS.

For this study, its empirical parameters, $a$ (cm$^{-1}$), $n$ and $m$ were set as 0.024, 1.19, and 0.16, respectively.

The capability of SCE-UA to estimate test parameter values. Before model calibration using real (field) observations, we tested whether the coupling of OntoSim-Sugarcane with the SCE-UA is successfully completed. First, we generated a synthetic farm WT set, i.e. an output of OntoSim-Sugarcane simulation using model parameter values and real rainfall and canal WT records available at the farm basin UF9209A. Among model parameters, the lateral hydraulic conductivity of the soil profile ($L_{K_{SAT}}$) and the vertical hydraulic conductivity of underlying limestone ($V_{K_{SAT}}$ – bedrock) were arbitrarily prescribed as 'test' values.

By treating the synthetic farm WTs as observed WTs, we ran the coupled SCE-UA–OntoSim-Sugarcane to derive the convergence of optimized parameters fitting a global optimum between simulated and synthetic WTs. In this preliminary analysis the goal was to identify whether the SCE-UA can retrieve the 'test' values of $L_{K_{SAT}}$ and $V_{K_{SAT}}$ – bedrock which were used to generate simulated farm WTs. Following this preanalysis, our investigation focused on calibrating the two parameters using real field observations because these site-specific parameters are not often measured but are sensitive among several tested parameters to control farm WT fluctuations in OntoSim-Sugarcane by controlling the gradients between the farm WT and canal WT (Kwon et al., 2010).

Model calibration and validation. Properties to parameterize hydrology algorithms in the OntoSim-Sugarcane model for farm units are summarized in Table II. Two hydrologic parameters ($L_{K_{SAT}}$ and $V_{K_{SAT}}$ – bedrock ) were selected to be calibrated by minimizing the objective function of root mean square error (RMSE) between simulated and observed farm WT utilizing the SCE-UA.

Arguably, the most important parameter of the SCE-UA is the number of complexes because the number of model simulations is proportional to the number of complexes, and thus, increases the probability of converging into the global optimum (Madsen, 2003). We used 10 complexes to compromise between simulation runs and converging into a global optimum and used the other recommended algorithmic parameters suggested by Duan et al. (1992) (Table III).

Then we ran the model simulation for three WYs (WY95–97) to spin up the model for WY95, perform model calibrations for two WYs (WY96–97), followed by independent model validation for WY98–99 where we applied the calibrated parameter values for simulation.

The goodness of fit for both calibration and validation periods was further estimated using the Nash–Sutcliffe efficiency (NSE), the coefficient of residual mass (CRM), and average deviation (AD).
\[
\text{NSE} = 1 - \frac{\sum_{i=1}^{i} (W_{T\text{sim}}^i - W_{T\text{obs}}^i)^2}{\sum_{i=1}^{i} (W_{T\text{obs}}^i - W_{T\text{obs}}^i)^2} 
\]

(1)

\[
\text{CRM} = \left( \frac{\sum_{i=1}^{i} W_{T\text{sim}}^i - \sum_{i=1}^{i} W_{T\text{obs}}^i}{\sum_{i=1}^{i} W_{T\text{obs}}^i} \right) \cdot 100 
\]

(2)

AD = \frac{\sum_{i=1}^{i} |W_{T\text{sim}}^i - W_{T\text{obs}}^i|}{t}

(3)

with \(i\) the number of observations and \(t\) daily time steps. \(W_{T\text{sim}}\) and \(W_{T\text{obs}}\) indicate simulated and observed WT, respectively. \(\overline{W_{T\text{obs}}}\) is the average of \(W_{T\text{obs}}\) for the calibration and validation periods, respectively.

**RESULTS AND DISCUSSION**

The capability of SCE-UA to estimate test parameter values

Because of potential errors introduced in a procedure, the success and completeness of the coupling of several models and/or algorithms should be tested before use. However, only a few in the literature have explicitly reported such tests (Gupta and Sorooshian, 1985; Vrugt et al., 2003). In our study, the optimization patterns of parameters were derived from the automatic calibration results using OntoSim-Sugarcane/SCE-UA along with the synthetic WTs as model inputs (Figure 4). When calibration was conducted to estimate ‘test’ values of two hydrologic parameters, ‘noise’ was evidently present in the parameter values for calibration runs. However, values began to stabilize and came closer to the global optimum at about 1500 model runs. Although SCE-UA was conducted with three different starting values of the predetermined parameters, the parameter values

---

Table III. Parameter sets for Shuffled Complex Evolution—Universal Algorithm

<table>
<thead>
<tr>
<th>Description of parameter</th>
<th>Value used in this study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum number of trials allowed before optimization is terminated</td>
<td>1500</td>
</tr>
<tr>
<td>Number of shuffling loops in which the criterion must improve by the specified percentage or else optimization will be terminated</td>
<td>5</td>
</tr>
<tr>
<td>Percentage by which the criterion value must change in the specified number of shuffling loops or optimization is terminated</td>
<td>0.01</td>
</tr>
<tr>
<td>Number of complexes used for optimization search</td>
<td>10</td>
</tr>
</tbody>
</table>

---

Figure 4. The convergence patterns of two parameter estimates ((a) LKSAT and (b) VKSAT-bedrock) utilizing three different starting points for the automatic calibration using the Shuffled Complex Evolution – Universal Algorithm and synthetic data. The synthetic data was generated by assembling all input data such as rainfall and canal water tables recorded at one farm, UF9209A and using “test” values of the model parameters.
obtained at the end of the optimization process were close enough to the ‘test’ values that were used to generate the synthetic WT data (Figure 4), regardless of their starting values. The absolute differences between predetermined and optimal values were only 0.001% when the objective function of RMSE values was minimized (after 1500 runs). It indicated the capability of SCE-UA to retrieve ‘test’ parameter values due to the successful coupling of the two models.

### Simulation of groundwater table fluctuations

**Statistical measures of calibration results.** We utilized the SCE-UA’s algorithm to search parameter sets, which provide the lowest RMSE between simulated and observed farm WT, among randomly selected parameter sets using 1500 runs. Such model calibrations were conducted at four different farm units for the period of WY96–97 (Table IV).

The results showed that the RMSE ranged from 5.78 (UF9202A) up to 17.09 cm (UF9200A) during the calibration period. The lowest RMSE at UF9202A can be explained by the fact that UF9202A is a small farm at the end of a communal drainage ditch and drainage events were not as dramatic, making it easy to get good fits. Although the size of UF9209A is similar to that of either UF9200A or UF9203A, the RMSE at the former was better than those of the latter because ditches cut into the bedrock, leading to relatively uniform drainage at the site. The highest RMSE was calculated at the farm unit of UF9200A (Figure 5(a)) mostly due to the discrepancy between simulated and observed WT during a few major WT fluctuations. A similar situation occurred at the farm unit of UF9203A across different seasons and years (Figure 5(b)).

Some underlying reasons to explain the discrepancies are that (i) other model parameters (other than $L_K^{SAT}$ and $V_K^{SAT-\text{bedrock}}$) which were not calibrated lead to erroneous simulations of WT, (ii) the algorithms used in OntoSim-Sugarcane imperfectly represent processes, or (iii) negligence in spatially discretizing the farm basins may have led to erroneous simulations of WT.

As an additional measure of model fit, the CRM, NSE, and AD were calculated. The CRM, which is a measure of the model’s tendency to over- or underestimate the observed values, showed slightly negative values ($-0.06$ and $-0.08\%$) at UF9200A and UF9209A. On the other hand, positive values of less than 1% were observed at the other two farm basins for the calibration period, indicating that the OntoSim-Sugarcane model slightly overestimated the daily WT$^{obs}$. The NSE has a maximum value of 1.0 for a perfect model and zero for a model that is no better than the mean of the observations. Values of NSE ranged from 0.38 to 0.75 (calibration period WY 96–97) and the highest was calculated in farm basin UF9202A (Table IV). Based on both RMSE and NSE, model calibration within the farm unit of UF9202A can be considered the most successful among the tested farm basins. However, such success can also be contributed to no fluctuations of WT during about half of the studied WYs (Figure 5(b)) due to zero WT in soil profiles. The NSE of the other farm units were 0.67 (UF9203A) and 0.59 (UF9209A) during the calibration period, indicating that OntoSim-Sugarcane is able to simulate farm WT. The AD showed a similar pattern as RMSE where UF9202A and UF9209A have lower values than the other two, indicating better performance of models at the former two.

The values of RMSE, CRM, and NSE calculated from this autocalibration work at UF9202A and UF9209A were compared to those from previously manual calibration study at the same farms (Kwon et al., 2010). Similar values were obtained from both auto- and manual calibration. For example, at UF9202A, the RMSEs of calibration and validation

<table>
<thead>
<tr>
<th>Farm basin</th>
<th>$L_K^{SAT}$ $^{a}$&lt;sup&gt;1&lt;/sup&gt; ($\text{cm h}^{-1}$)</th>
<th>$V_K^{SAT-\text{bedrock}}$ $^{b}$</th>
<th>Calibration period (WY96–97)</th>
<th>Validation period (WY98–99)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UF9200A</td>
<td>123.22</td>
<td>2.6E-05</td>
<td>17.09 (-0.06)</td>
<td>27.48 (8.42)</td>
</tr>
<tr>
<td>UF9202A</td>
<td>126.64</td>
<td>0.028</td>
<td>5.78 (0.92)</td>
<td>5.77 (-0.21)</td>
</tr>
<tr>
<td>UF9203A</td>
<td>125.8</td>
<td>1.3E-05</td>
<td>13.8 (0.45)</td>
<td>17.14 (1.54)</td>
</tr>
<tr>
<td>UF9209A</td>
<td>342.6</td>
<td>0.026</td>
<td>9.09 (-0.08)</td>
<td>8.3 (2.3)</td>
</tr>
</tbody>
</table>

*1* Lateral saturated hydraulic conductivity of soil profile.  
*2* Vertical saturated hydraulic conductivity of the underlying limestone rock.

---

Copyright © 2014 John Wiley & Sons, Ltd. *Irrig. and Drain.* (2014)
periods from autocalibration were 5.78 and 5.77 cm, while those from manual calibration were 6.35 and 5.08 cm. However, considering that we calibrated one $L K_{S A T}$ rather than two for the entire soil profile utilized in the manual calibration, these results indicate better performance of automatic calibration than manual calibration.

However, we should point out that it took 2 days to optimize the parameters using an Intel Core 2 Duo 3.16 GHz personal computer although we calibrated only the two parameters using the SCE-UA. If more parameters are simultaneously optimized, this calibration will require more model runs and will therefore be computationally intensive. This might be a weakness of any automatic calibration, although it is still generally faster than manual adjustment of parameters and the results are more certain to reflect a global optimum (Solomatine et al., 1999). One advantage of utilizing the SCE-UA among many autocalibrations would be its parallel procedure of the algorithm, and thus, if the procedure is coded to make use of parallel processors, faster program execution will be obtained (Sharma et al., 2006).

Statistical measures of validation results. For the validation period of WY98–99, the calibrated parameter values were used for subsequent simulation runs. The RMSE increased by about 50% at two farm basins (UF9200A and UF9203A), resulting in relatively poor model fits between observed and simulated WT (Figures 5(a) and (c)). However, the RMSE did not increase at the units of UF9202A and UF9209A and the same was observed in case of the AD (Table IV).

The CRM and NSE were noticeably changed. Except for UF9202A, the CRM calculated exceeded more than 1% with maximal 8.42% at UF9200A, resulting in overestimating the daily $WT_{obs}$. The NSE decreased remarkably during the validation period when compared to the calibration period, except in UF9209A where it even improved (Table IV). The latter was because the NSE of 0.49 during WY96 contributed to an overall lower NSE during the calibration period and the same did not occur during the validation period.

Among the four farm units we modeled, the one at UF9200A showed the largest discrepancy between simulated and observed WT based on the worst measures for all the
statistical measures. Such differences occurred for both calibration and validation phases (RMSE and NSE) and validation phase (CRM). This might indicate the necessity of calibrating other parameters in the model and the lack of spatial discretization rather than the possibility of inadequate algorithms to represent processes.

Parameter estimates. The values of two hydrologic parameters were automatically calibrated using farm WT and canal WT data during the period of WY96–97. As seen in the autocalibration test using synthetic data, noise was observed before 600 model runs, regardless of modeling units. Then the parameter values began to stabilize and approached the global optimal values of the objective function (Figure 6). As the final values after 1500 model runs, the $V_{K_{SAT}}$–limerock showed differences among farm units. These were not close to zero at farm units UF9202A and UF9209A, while those were close to zero at farm units UF9200A and UF9203A, indicating that there might be significant deep seepages from the former two farm units. The other parameter $L_{K_{SAT}}$, ranged from ~123 to 342 cm h$^{-1}$. However, except for one at UF9209A, the $L_{K_{SAT}}$ were similar among the three farm units (Table IV). In fact, the $L_{K_{SAT}}$ is nearly twice as large on UF9209A compared to other farms. This might be due to (i) the higher ratio of discharge to rainfall at this farm unit compared to others (Table II), and (ii) the differences in terms of land management (i.e. timing of rotations) that are not available.

Because model calibration often involves adjusting some parameters that cannot be derived directly from knowledge of physical farm characteristics (Hogue et al., 2000), like our study, it is important to test if the calibrated results make sense. For this purpose, we calculated water budgets for the

![Figure 6](image)

Table V. Water balance calculated for four farm units for the period of water years 96–99. Values in parentheses indicate the percentage of each variable in the input or output.

<table>
<thead>
<tr>
<th>Farm basin</th>
<th>Precipitation (mm)</th>
<th>Sub-irrigation (mm)</th>
<th>ET$^a$ (mm)</th>
<th>Vertical Seepage (mm)</th>
<th>Lateral drainage (mm)</th>
<th>change$^b$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UF9200A</td>
<td>4290 (82)</td>
<td>967 (18)</td>
<td>2811 (54)</td>
<td>5</td>
<td>2411 (46)</td>
<td>30</td>
</tr>
<tr>
<td>UF9202A</td>
<td>4741 (98)</td>
<td>98 (2)</td>
<td>3098 (62)</td>
<td>879 (18)</td>
<td>1006 (20)</td>
<td>-143</td>
</tr>
<tr>
<td>UF9203A</td>
<td>4199 (76)</td>
<td>1310 (24)</td>
<td>3169 (58)</td>
<td>4</td>
<td>2296 (42)</td>
<td>40</td>
</tr>
<tr>
<td>UF9209A</td>
<td>4923 (62)</td>
<td>3043 (38)</td>
<td>3193 (40)</td>
<td>2444 (30)</td>
<td>2444 (30)</td>
<td>-115</td>
</tr>
</tbody>
</table>

$^a$ET = evapotranspiration.  
$^b$Net change = input – output.
entire simulation period using observed precipitation along with simulated outputs (i.e. subirrigation, ET, and drainage) (Table V). While annual precipitation comprised almost all the total water input into UF9202A, due to a small amount of subirrigation, it was at most 62% of total water input at UF9202A. In terms of water outputs, the percentage of ET in the water losses ranged from 40 to 62%, and lateral drainage and deep seepage were pronounced at farm units UF9202A and UF9209A. Note that surface runoff is considered to be negligible at these farms due to rapid vertical hydraulic conductivity within soil profiles (> 20 cm h⁻¹) (Bottcher and Izuno, 1994) and the flat topography within the farms.

CONCLUSIONS

To simplify the calibration process to enable farmers and practitioners to use OntoSim-Sugarcane, we incorporated the SCE-UA as an automatic calibration algorithm into the model. This coupling facilitates model parameters to be automatically and objectively adjusted to provide the best fit between observed and simulated data for a particular basin or watershed. In this study, we demonstrated the application of the SCE-UA for the purpose of analyzing WT fluctuations in farms of the EAA by optimizing site-specific parameters describing vertical and lateral water fluxes.

When recalibration is necessary because parameters have different values in different farms even in an area such as the EAA which is relatively homogeneous, this can be accomplished now using SCE-UA. This will strengthen the model’s capability to simulate hydrologic and nutrient dynamics by objectively finding the best parameter sets in multiple farm basins in support of accurate hydrologic and water quality predictions. This will further guide optimization of water management practices and recommendations to improve water quality.

ACKNOWLEDGEMENTS

This project is supported by grant WM837 from the Florida Department of Environmental Protection. The authors are very grateful to Dr Samira H. Daroub and Timothy A. Lang for providing farm basin data.

REFERENCES

American Society of Agricultural Engineers: St Joseph, MI.


