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Application of an XML-based genetic algorithm to a rainfall–runoff erosion model

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Abstract Optimization is a common problem in hydrological sciences and Genetic Algorithms (GA) are one approach to manage this problem. This paper presents an application of a configurable and portable GA that uses the eXtensible Markup Language (XML) to solve an optimization problem. The paper describes an application for the calibration of the Watershed Erosion Simulation Program (WESP) model to optimize erosion parameters for estimating sediment yield. The calibration of a rainfall–runoff–erosion model requires finding optimal model parameters. The results show that the XML-based GA tool efficiently defined the WESP erosion parameters. Since any application or platform capable of processing XML could utilize this tool, it may be an important alternative for solving other water resources problems.

Key words XML; genetic algorithms; rainfall-runoff-erosion simulation; WESP model; optimization of parameters

INTRODUCTION

Optimization is a common problem in hydrological sciences (Santos *et al.*, 2003). The optimization of a mathematic function corresponds to the search for its maximum or minimum value. These functions could also have a set of restrictions for the variables to be optimized. Many techniques have been proposed in order to find these values. However, most traditional techniques are less efficient for solving nonlinear optimization problems.

Evolutionary Algorithms (EAs), which are defined as a set of probabilistic optimization methods based on the theory of evolution by Charles Darwin, appear to handle arbitrary types of problems with different objectives and constraints. The species behaviour observed by Darwin is computationally simulated in order to obtain optimized values for the parameters. One of the implementations of EAs, called Genetic Algorithms (GAs), was developed by Holland (1975). Since this pioneering work, many GA implementations have been developed but most of them were built for a specific purpose (e.g. Franchini, 1996; Wang, 1997; Santos et al., 2003). In the present paper, a GA tool is applied to optimize the Watershed Erosion Simulation Program (WESP) runoff-erosion model, which was developed by Lopes & Lane (1988). Then, a GA is proposed which uses the Java® (Sun Microsystems) programming language, eXtensible Markup Language (XML), and some code programming techniques so as to provide a portable and configurable GA tool for general purposes. One application of this XML-based GA tool is described in Soares Junior et al. (2009). Finally, the WESP model is applied to an experimental basin within a semi-arid area of northeastern Brazil, in order to estimate event-based runoff and sediment yield, with the proposed GA being used to optimize the parameters. Thus, this paper presents the general details of the model and the GA tool.

THE GENETIC ALGORITHM

Genetic algorithms are search and optimization methods based on the theory of evolution, in that the better an individual fits in the environment, the greater the possibility that it will survive and generate offspring. According to Michalewicz (1999), a GA must have five components: (a) a genetic representation for solutions; (b) a way to create an initial population of solutions; (c) an

evaluation function that rates solutions in terms of their fitness; (d) genetic operators that alter the genetic composition of the offspring; and (e) values for the various genetic parameters used in the algorithms. A set of solutions is called a population, and individuals are called chromosomes, which represent each possible solution to the problem (i.e. they form a population). Each solution is evaluated and generates a fitness value that is used to select the best individuals.

As shown in Fig. 1, a GA must initially generate a population of individuals. The first population of individuals is then analysed. The fitness for each individual is determined; i.e. how much the proposed solution is better relative to the other individuals. As with Darwin's theory of evolution, the strongest individuals are more likely to be selected and less inclined to be discarded. A GA implementation must also have criteria to stop the population evolution (e.g. the algorithm can stop when 50 populations are evolved). When this criterion is not reached, the algorithm creates new individuals. Through the "modify population" operation, techniques such as crossover and mutation are applied to the selected individuals from the population. These techniques alter the values of the parameters and are the key concepts that make GAs a powerful optimization technique.



Fig. 1 General description of the genetic algorithm.

As stated above, the first step in the implementation of a GA is to generate an initial population of individuals. In the current tool, two techniques can be employed. The user could utilize a random initialization or a grid initialization. In the random initialization, a random set of values for the parameters is generated. In the grid initialization method, the generated values are equally spaced in the search space. After this initialization, the first population is evaluated. One of the main advantages of this GA implementation is that many evaluation approaches can be created. In order to build a general purpose GA implementation, the Object Oriented Paradigm (OOP) was chosen. The key concepts of the OOP are objects, inheritance, polymorphism, classes and subclasses (Watt, 2004). A class defines abstract characteristics of a thing (object), including its attributes, fields or properties. Using such an approach, each part of the GA algorithm is assumed to be a class. When a class is extended the new class (subclass) inherits its attributes and behaviours. To generate an evaluation approach, the user has to extend the Population Evaluation Method (PEM) class. This class has abstract methods that must be implemented again when a new way of evaluation is created. Fig. 2 shows a Unified Modelling Language (UML) diagram. The construction of diagrams that represent the concepts of the system, activities and user iterations.

can be made using the UML. System classes, objects and their conduct after some external event (action of a user) could also be represented by this modelling language (Larman, 2007).

As can be seen from Fig. 2, if the user cannot describe a problem as a mathematical function, it is necessary to create a new PEM by extending this class. This technique was used in the WESP optimization problem described in this paper. The "evaluate Population" and "is A Valid Solution" methods have to be implemented again in the way that the user needs. The first method consists of evaluating each individual and setting a goodness-of-fit for them. The second one consists of verifying the values of each individual to check the problem constraints. However, if the problem can be described as a mathematical function, the user is able to use the "JEP Evaluation Method". This implementation uses a parser to evaluate the solutions generated in the simulation.



Fig. 2 Unified modelling language diagram for the GA evaluation class.

As mentioned earlier, it is necessary to evaluate stopping criteria to finish the algorithm. In this GA tool, there are three ways the user can configure the algorithm to stop in different situations: when the optimal value is reached; when a finite number of generations are executed; or when some convergence criteria are reached. In the last case, the algorithm could be stopped by setting limits to the quantity of individuals presenting a potential best solution or the number of generations without changes in the potential best solution.

Another point of consideration with this GA tool is to select the best individuals of a given generation. The user can choose between the "roulette wheel" and the "tournament selection". In the former, a probability, which is proportional to the goodness-of-fit, is given to each individual. The individual that has the best "fitness" receives the higher probability to be chosen and generates offspring. In the latter, three individuals are randomly chosen and a tournament is performed among them. The individual that has the best fitness value is chosen to generate offspring.

As mentioned above, the crossover and mutation operations are key concepts of the GA approach. These operations must have a rate of occurrence to be analysed before their application in a chromosome. When one of these operations is invoked, the implementation must generate a number to be compared with this occurrence rate. If this number is less or equal to the configured rate, the operation is allowed to be executed. But if this number is greater than the configured rate, the operation would not occur.

In most applications using GAs, the most common way of coding is to use a binary string of fixed length. This is because the theory of GAs was developed based on this representation.

In the crossover operation, as in nature, parts of the number (bits) are exchanged between two individuals, generating an offspring different from the originals (Table 1). First, a certain amount of bits is randomly chosen to be exchanged between the proposed solutions. In Table 1, four bits were chosen for the exchange. As in genetics, parts are exchanged between individuals and two new individuals are generated.

(a)			(b)		
000010001001 0111	=	solution 1	0000100010011100	=	solution 1
000010101001 1100	=	solution 2	0000101010010111	=	solution 2
000010001001 1100	=	offspring 1	000010 1 01001 0 100	=	offspring 1
000010101001 0111	=	offspring 2	000010101 1 010111	=	offspring 2

Table 1 Examples of (a) crossover and (b) mutation operations within the GA approach.

In the mutation operation, each bit of the offspring has a small probability of being changed to the alternate value (i.e. to be "flipped"). For example, if the mutation occurs in one bit, a 0 becomes a 1 and *vice versa*. Figure 2 shows how this operation is performed. For each bit of an offspring generated by crossover, the mutation operation should be applied, but only if the mutation has been activated.

The use of this binary representation (i.e. 0 or 1) is simpler to use within the GA approach. However, if the problem to be solved has continuous parameters and the user wants to use a good numeric precision, this kind of representation has some problems. To add one more precision number it is necessary to add 3.3 bits in the solution. When there are many parameters to be optimized, the convergence of the GA becomes a problem because the algorithm starts to converge.

To solve this kind of problem, the real number coding representation is used. This approach generates smaller chromosomes and is more readable by the user. Each chromosome is represented by a real number (for example, 34.15). Some studies comparing both approaches are described in Janikow & Michalewicz (1991) and, in most cases, the real number coding approach was more effective and faster.

THE STUDY AREA

The WESP model was used to simulate runoff and erosion in a bare micro-basin, which is one of the four micro-basins of the Sumé Experimental Watershed, in the northeastern region of Brazil. The mean slope, area and perimeter of this micro-basin are 7.1%, 0.48 ha, and 302 m, respectively. This experimental watershed was operated from 1982 to 1991 by SUDENE (Superintendency of Northeast Development, Brazil), ORSTOM (French Office of Scientific Research and Technology for Overseas Development) and UFPB (Federal University of Paraíba, Brazil) to obtain field data for calculating the runoff and sediment yield produced by rainfall in a natural environment (Cadier *et al.*, 1983).

The experimental watershed includes four micro-basins, nine erosion plots of 100 m^2 , and several micro-plots of 1 m^2 operated under simulated rainfall within a basin of 10.7 km^2 . The surface conditions and the slopes varied between the plots and micro-basins. Rainfall data were obtained from four standard raingauges and two recording raingauges, installed close to the micro-basins and erosion plots. Measurements of water and sediment discharge at the outlet of the micro-basins were obtained using a rectangular collector, which had a 90° triangular weir at the end. The collector held all the surface runoff and sediment yield for most of the low to medium rainfall events, thereby providing an effective means for measuring runoff and sediment yield. Based on the work of Santos *et al.* (1994), 21 events were selected between 1987 and 1988, and 25 events were selected between 1988 and 1991, giving a total of 46 events. These periods were chosen because the micro-basin was maintained bare (i.e. no or limited vegetation cover) under controlled conditions during these events.

THE WESP MODEL

Lopes & Lane (1988) developed a physically-based distributed model called WESP, which computes runoff and sediment yield based on kinematic wave approximation for the surface flow

due to excess rainfall r_e (m s⁻¹). In turn, r_e is obtained by the subtraction of the infiltration rate f(t) from the rainfall intensity *I*, i.e., $r_e = I - f(t)$. The model was developed to generate hydrographs and sedigraphs for small basins. The infiltration process is modelled with the Green-Ampt equation (Green & Ampt, 1911), which can be written in the form:

$$f(t) = K_s \left(1 + \frac{\Delta \theta \psi}{F(t)} \right) \tag{1}$$

where, K_s is the effective saturated soil hydraulic conductivity (m s⁻¹), F(t) is the cumulative depth of infiltrated water (m), ψ is the average suction head at the wetting front (m), $\Delta\theta$ is the change in the moisture content, and t is the time variable (s). The moisture content θ and suction head ψ may be expressed as a single parameter, the soil moisture-tension parameter N_s , such that:

$$N_s = \Delta \theta \psi_i = (\theta_s - \theta_i) \psi_i \tag{2}$$

where θ_s is the soil moisture content at saturation (which is almost equal to the soil porosity) and θ_i is the initial soil moisture content. The surface flow is considered to be either overland flow (on planes) or channel flow.

Overland flow

The spatially variable overland flow is considered one-dimensional and is described by Manning's turbulent flow equation:

$$u = \frac{1}{n} R_H^{2/3} S_f^{1/2}$$
(3)

where *u* is the local mean flow velocity (m s⁻¹), $R_H(x, t)$ is the hydraulic radius (m), S_f is the friction slope and *n* is the Manning friction factor. Thus, the local velocity for plane flow can be obtained using the hydraulic radius equal to the depth of flow ($R_H = h$) and using the kinematic wave approximation resulting in the friction slope being equal to the plane slope ($S_0 = S_f$) as:

$$u = \alpha h^{m-1} \tag{4}$$

where *h* is the depth of flow (m), α is a parameter related to surface slope and roughness, equal to $(1/n) S_0^{1/2}$, and *m* is a geometry parameter whose value is set to 5/3 for wide rectangles.

The equation of continuity for a one-dimensional plane can then be written as:

$$\frac{\partial h}{\partial t} + \alpha m h^{m-1} \frac{\partial h}{\partial x} = r_e \tag{5}$$

From equations (4) and (5), the overland flow velocity and depth (u, h) can be calculated for a given rainfall excess r_e . The beginning of surface runoff is obtained by determining the ponding time (the time elapsed between the start of rainfall and the time water starts to pond on the soil surface, t_p) for an unsteady rain event.

Sediment transport is considered as the erosion rate in the plane minus the deposition rate within the reach. The erosion occurs due to raindrop impact as well as surface shear. Thus, the continuity equation for sediment transport is expressed as:

$$\frac{\partial(ch)}{\partial t} + \frac{\partial(cuh)}{\partial x} = e_I + e_R - d \tag{6}$$

where *c* is the sediment concentration in the surface flow (kg m⁻³), e_I is the rate of sediment erosion due to rainfall impact (kg m⁻² s⁻¹), e_R is the erosion rate due to shear stress (kg m⁻² s⁻¹), and *d* is the rate of sediment deposition (kg m⁻² s⁻¹). The rate of soil/sediment erosion due to rainfall impact e_I is a function of the rate of detachment by raindrop impact and the rate of transport of sediment particles by shallow flow. A simple functional form of detachment by raindrop impact can use rainfall intensity as a measure of the erosivity of raindrop impact (Foster, 1982). In order to include the process of sediment transport by shallow flow on hillslopes, Lane & Shirley (1985) included rainfall and expressed e_I as:

$$e_I = K_I I r_e \tag{7}$$

where K_I is the soil detachability parameter (kg s m⁻⁴). The rate of sediment erosion due to shear stress e_R is expressed by an entrainment rate proportional to a power of the average shear stress acting on the soil surface (Croley, 1982; Foster, 1982) as:

 $e_R = K_R \tau^{1.5} \tag{8}$

where K_R is a soil erodibility factor for shear (kg m N^{-1.5} s⁻¹), and τ is the effective shear stress (N m⁻²), which is given by $\tau = \gamma h S_f$, with γ being the specific weight of water (N m⁻³). Entrainment and transport of sediment occur when the erosive forces exceed the resisting forces. Water flowing over the soil surface exerts shear forces on the soil particles that tend to move or entrain them. On bare soil surface and stream beds, the forces that resist erosion by flowing water depend on the size and the distribution of the sediment particles. For coarse sediments, the forces resisting entrainment are mainly frictional forces that depend on the weight of the particles. Finer sediments that contain appreciable fractions of silt and/or clay resist entrainment mainly due to cohesion, rather than friction. Also, in fine sediments, groups of particles (aggregates) get entrained as single units, whereas coarse non-cohesive sediments are moved as individual particles. Thus, the amount of entrainment is related to the magnitude of total shear stress as expressed in equation (8) rather than to a "critical" shear stress. Finally, the rate of sediment deposition *d* in equation (6) can be expressed as (Einstein, 1968):

$$d = \varepsilon_p V_s c \tag{9}$$

where ε_p is a coefficient that depends on the sediment and fluid properties, set to 0.5 in the present study based on Davis (1978), c(x, t) is the plane sediment concentration in transport (kg m⁻³), and V_s is the particle fall velocity (m s⁻¹) computed by Rubey's equation:

$$V_s = F_o \sqrt{\frac{\gamma_s - \gamma}{\gamma}} g d_s \tag{10}$$

and,
$$F_o = \sqrt{\frac{2}{3} + \frac{36\nu^2}{gd_s^3\left(\frac{\gamma_s}{\gamma} - 1\right)}} - \sqrt{\frac{36\nu^2}{gd_s^3\left(\frac{\gamma_s}{\gamma} - 1\right)}}$$
(11)

where γ_s is the specific weight of sediment (N m⁻³), ν is the kinematic viscosity of water (m² s⁻¹), d_s is the mean diameter of the sediment (m), and g is the acceleration of gravity (m s⁻²).

Channel flow

The concentrated flow in a channel is also described by continuity and momentum equations. The momentum equation can be reduced to the discharge equation with the kinematic wave approximation as:

$$Q = \alpha A R_H^{m-1} \tag{12}$$

where Q is the discharge (m³ s⁻¹), and A is the cross-sectional area of flow (m²). The continuity equation for the channel flow is given by:

$$\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = q_A \tag{13}$$

where q_A is the lateral inflow per unit length of channel. Equations (12) and (13) enable the calculation of channel flow. Since the effect of rainfall impact is negligible in the channel, the continuity equation for sediment is expressed without the rainfall impact component by:

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$$\frac{\partial AC}{\partial t} + \frac{\partial CQ}{\partial x} = q_s + e_r - d_c \tag{14}$$

where C(x, t) is the sediment transport concentration in the channel (kg m⁻²), q_s is the lateral sediment inflow into the channel (kg m⁻¹ s⁻¹), d_c is the rate of sediment deposition in the channel (kg m⁻¹ s⁻¹), and e_r is the erosion rate of the channel bed material (kg m⁻¹ s⁻¹). The components of the net sediment flux for the channel segment are given as follows: the erosion rate of the channel bed material e_r is obtained from a general equation, initially developed for bed-load transport capacity (Croley, 1982; Foster, 1982):

$$e_r = a(\tau - \tau_c)^{1.5} \tag{15}$$

where *a* is the sediment erodibility parameter (kg m² N^{-1.5} s⁻¹), and τ_c is the critical shear stress for sediment entrainment (N m⁻²), which is given by $\tau_c = \delta(\gamma_s - \gamma)d_s$, where δ is a coefficient, set to 0.047 in the present study, γ_s is the specific weight of sediment (N m⁻³), and d_s is the mean diameter of sediment particles (m). The rate of sediment deposition within the channel d_c (kg m⁻¹ s⁻¹) in equation (14) is expressed by (Mehta, 1983):

$$d_c = \varepsilon_c T_W V_s C \tag{16}$$

where ε_c is the deposition parameter for channels, considered as unity in the present case based on the study of Einstein (1968), and T_W is the top width of the channel flow (m). From equation (14), the sediment transport rate (*CQ*) can be calculated for the overland flow with *A* and *Q* obtained from equation (13).

APPLICATION AND RESULTS

The parameters whose values are fixed *a priori* are: the Manning friction factor, which was assumed as 0.02 for planes and 0.03 for channels based on the soil type, its grain size composition and surface characteristics; the specific weight of water (9.8 kN m⁻³); and the specific weight of sediment (2.6×10^4 kN m⁻³). However, there are some parameters that are specific for this area which should be determined by field tests such as the saturated soil hydraulic conductivity K_s (whose average value was set to 5.0 mm h⁻¹) and the mean diameter of sediments d_s (whose value was assumed to be equal to the d_{50} , 0.5 mm). The other parameter values should be based either on the literature or determined by calibration with an optimization process.

There are four parameters in the WESP model to be determined by optimization. The first parameter to be calibrated in the WESP model is the soil moisture-tension parameter N_s of equation (2), and the remaining three parameters (a, K_R and K_I) are related to the erosion process. Since there are no universally applicable values for these four runoff–erosion parameters, they were optimized using the GA implementation. The range for these parameters was determined to be $0.1-200 \text{ mm} (N_s)$, $0.001-0.1 \text{ kg m}^2 (a)$, $0.1-10.0 \text{ kg m N}^{-1.5} \text{ s}^{-1} (K_R)$, and $0.1 \times 10^8 \text{ to } 10.0 \times 10^8 \text{ kg m}^{-4} \text{ s}^{-1} (K_I)$. As stated earlier, the deposition parameters for plane and channel (ε_p and ε_c) were set as $\varepsilon_p = 0.5$ (Davis, 1978) and $\varepsilon_c = 1.0$ (Einstein, 1968).

The initial values of the runoff and erosion parameters were randomly set. The following objective function, to be minimized, was chosen in order to include both the runoff and erosion processes:

$$J = (E_{\rm o} - E_c)^2 + (L_{\rm o} - L_c)^2$$
(19)

where E_o and E_c are the observed and calculated sediment yield (kg), respectively, and L_o and L_c are the observed and calculated runoff depth (mm), respectively. The optimization of the parameters for each of the 46 events resulted in different values of the soil moisture-tension parameter N_s for a specific event, which ranged from 1 to 75 mm, and the mean values of the erosion parameters were determined to be $a = 0.01 \text{ kg m}^2$, $K_R = 3.12 \text{ kg m N}^{-1.5} \text{ s}^{-1}$, and $K_I = 5.17 \times 10^8 \text{ kg m}^{-4} \text{ s}^{-1}$.

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Figures 4 and 5 show comparisons between the observed and calculated runoff depth L and event-based sediment yield E, respectively, using the optimized values of N_s and the mean values of the erosion parameters. Generally, it can be seen that the calculated erosion values are fairly close to the observed ones, except in the case of the largest event (event 28). Considering that the erosion and deposition processes are simplified in the WESP, the results shown in Figs 4 and 5 should be considered as satisfactory.



Fig. 3 Observed and calculated total runoff depths.



Fig. 4 Observed and calculated event-based total sediment yields.

CONCLUSION

Event-based runoff depth and sediment yield were modelled based on data from an experimental watershed in the semi-arid region of Brazil. The main conclusions are: (a) an XML-based GA tool for finding the minimum value of a nonlinear function with many variables, proved to be useful for the optimization of the four parameters in the runoff-erosion model; (b) as the soil moisture-tension parameter N_s also depends on the initial moisture content, then it should be different for each rainfall event; (c) the channel erosion parameter a, the soil detachability factor K_R , and the sediment entrainment by rainfall impact parameter K_I , were constant for almost all rainfall events in the experimental basin, i.e. $a = 0.01 \text{ kg m}^2$, $K_R = 3.12 \text{ kg m N}^{-1.5} \text{ s}^{-1}$, and $K_I = 5.17 \times 10^8 \text{ kg m}^{-4} \text{ s}^{-1}$.

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