Evolutionary algorithms for multiobjective evaluation of watershed management decisions

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ABSTRACT

The comprehensive and systematic management of watersheds is essential for reducing the adverse environmental impacts arising from anthropogenically caused erosion and subsequent sedimentation. This paper describes a computational methodology that is designed to serve as a watershed decision support system and is capable of controlling environmental impacts of non-point source pollution resulting from erosion. In the decision process, the methodology also accounts for other inseparable objectives such as economics and social dynamics of the watershed. This decision support tool was developed by integrating a comprehensive hydrologic model known as SWAT and state-of-the-art multiobjective optimization technique within the framework of a discrete-time optimal-control model. Strength Pareto Evolutionary Algorithm (SPEA), a multiobjective optimizer based on evolutionary algorithms, has been used to generate Pareto optimal sets. For demonstration purposes, the tool was applied to the Big Creek watershed located in Southern Illinois. Results indicate that the methodology is highly effective and has the potential to improve comprehensive watershed management.

Key words | erosion and sedimentation, evolutionary algorithms, multiobjective evaluation, Pareto optimality, watershed management

INTRODUCTION

Soil erosion is a natural phenomena that involves the processes of detachment of sediment particles from a larger soil mass and subsequent transport and deposition of those particles on land surfaces and in water bodies. Most river reaches are naturally balanced with respect to sediment inflow and outflow (Morris & Fan 1998). Today, however, human activities such as deforestation, cultivation, overgrazing, construction and other practices have increased erosion beyond its natural rate. These aggravated rates are responsible for many on-site and off-site impacts. Ritter & Shirmohammadi (2001) indicate, for example, that erosion is the source of 99% of the total suspended loads in the waterways of the United States. The same authors estimate that approximately five billion tons of soils eroded every year in the United States reach small streams. This sediment has a tremendous cost associated with it in terms of stream degradation, disturbance to wildlife habitat, and direct costs for dredging, levees and reservoir storage losses. Sediment is also an important vehicle for the transport of soil-bound chemical contaminants from nonpoint source areas to waterways. According to the U.S. Department of Agriculture (USDA), soil erosion is the source of 80% of the total phosphorus and 73% of the total nitrogen loads in U.S. waterways (Ritter & Shirmohammadi 2001). Attempts that target reduction of sediment yield from a watershed could therefore prevent a significant amount of nutrients from entering water bodies. Proper management of activities in a watershed is the primary key to reducing these adverse impacts, especially those arising from anthropogenic activity.

Any attempt to control erosion and sediment yield should emphasize the three critical stages of these processes: detachment of soil particles, transport of the detached soil particles and deposition. These three stages of erosion are, in one way or another, affected by environmental factors such as geology, slope, climate, drainage density and patterns of human disturbance. While humans have little or no control over some of these factors, other imbalances can be positively impacted with proper planning and management. Mechanisms that aid in reducing levels of soil disturbance and degree of detachment (e.g. tillage practices), that cut long steep slopes and reduce transporting capacity of surface runoff (e.g. structural measures), and that do not expose the soil to the direct impact of falling precipitation (e.g. vegetation) are some available management techniques. While many researchers agree that there is no single dominant factor that explains the wide variability of erosion, using data from 61 gage stations in Southern Kenya, Dunne (1979) demonstrated that land use is a dominant factor explaining variability in sediment yield. This finding indicates that the role of vegetation in reducing erosion and sedimentation is multi-faceted. Vegetation can absorb kinetic energy of the falling rain and reduce its detaching potential. Through its root system, vegetation can bind soil masses together and increase the soil's resistance to detachment. Vegetation also increases soil roughness and reduces transporting capacity of overland flow. These aspects are likely to be the reasons why Morris & Fan (1998) concluded that 'land use improvement is the best and probably the only feasible method'. This study explores the potential role of vegetation and management combinations in addressing the global scale threat posed by erosion. Emphasis herein is specifically placed upon agriculturally dominated watersheds.

Land use management decisions should not only account for a singular objective of reducing environmental impacts of erosion, but also should integrate the feasibility of the designed policy from the socioeconomic perspective of the watershed. With regard to an agricultural watershed with multiple landowners, a likely stakeholder concern may be the economic benefit that he/she may generate from his/her farm. A systematic method of including this individual owner's perspective into a decision support system is crucial for successful implementation of the policy. To address this critical socioeconomic factor, a farm-scale policy that integrates both economic and environmental objectives is adopted in this investigation. The methodology designed here searches for the 'best' land use and management combination that can generate maximum benefit for the farm owner, and at the same time, minimizes erosion and sediment yield from the farm. In this way, all stakeholders in the watershed contribute to the common goal of reducing adverse impacts of erosion from their commonly owned watershed, while preserving their private goals of maximizing farm income.

Effectiveness of this computational methodology is, however, directly influenced by the capability of the model used to estimate erosion and sediment yield for a given land use and management alternative and its ability to account for the various environmental factors that may affect the processes of erosion. Fortunately, over the last three decades, advances in hydrological science and engineering, as well as computer capabilities, have stimulated the development of a wide variety of mathematical simulation models for such estimates. Some of these models integrate Geographic Information System (GIS) technology, thus improving their data management, retrieval and visualization capabilities. The most comprehensive simulation techniques are process-based (physically based), distributed models such as SHE (Abbott *et al*. 1986), AGNPS (Young *et al*. 1987), ANSWERS-2000 (Bouraoui & Dillaha 1996) and Soil and Water Assessment Tool, or SWAT (Arnold *et al*. 1999). These models have replaced traditional lumped, empirical models that relate management and environmental factors to runoff and sediment yield through statistical relations. Distributed models are able to capture the spatial and temporal heterogeneity of environmental factors such as soil, land use, topography and climate variables. This not only makes their resulting estimates more accurate, but also allows policies to be designed on small and more practical scales such as the farm-scale, which has been adopted in this study. SWAT, as mentioned above, is a particularly comprehensive distributed model that is interfaced with Arcview© GIS. Hydrological models themselves, however, are useful only for evaluating *what-if* scenarios and testing potential management alternatives. They are unable directly to solve water resources management and control problems that require the explanation of a range of available alternatives.

A comprehensive decision-making framework for watershed management requires the integration of a hydrological simulation model and a suitable optimization technique that is capable of solving complex control problems. This integrative method, referred to here as a discrete-time optimal control methodology, has been increasingly popular in water resources related fields and has provided solutions for large-scale problems in areas of reservoir management (Yeh 1985; Unver & Mays 1990; Nicklow & Mays 2000), bioremediation design and groundwater management (Wanakule *et al.* 1986; Yeh 1992; Minsker & Shoemaker 1998), design and operation of water distribution systems (Cunha & Sousa 2000; Sakarya & Mays 2000) and watershed management, (Muleta & Nicklow 2001; Nicklow & Muleta 2001). Nicklow (2000) provides a comprehensive review of the benefits of the approach, which include a reduced need for additional simplifying assumptions about the problem physics in order to reach an optimal policy and a decrease in size of the overall optimization problem. Furthermore, if the developer is able to incorporate existing simulation procedures that have been widely accepted in engineering practice, the optimal control model attempts to improve the practical utility of the approach. When applied to a typical nonpoint source pollution reduction problem, the approach allows the direct determination of land-use patterns and tillage practices that solve the following formulation:

minimize: annual average sediment yield and *maximize* annual average economic benefits on a farm scale

subject to: (i) water quality and hydrological relationships that govern erosion and sedimentation processes
(ii) crop management constraints, such as feasible crops according to season and cropping sequence.

There have been minimal applications of this type of integrative modelling technique for comprehensive watershed management. Dorn *et al.* (1995) and Harrell & Ranjithan (1997) used a similar technique to determine the optimal design of storm water detention ponds to achieve sediment removal requirements on a watershed scale. Sengupta *et al.* (2000) developed a spatial decision support system capable of evaluating the effect of proposed watershed conservation policies by linking the Agricultural Non-Point Source Pollution (AGNPS) model and a linear programming model known as GEOLP. GEOLP is an enhanced version of an economic farm model developed by Kraft & Toolhill (1984) and was used to maximize annual farm income, rather than control nonpoint source pollution. Nicklow & Muleta (2001) presented an application of this methodology in which SWAT and a genetic algorithm were coupled for purposes of watershed management under consideration of a single objective of minimizing sediment yield from a basin. In this paper, the methodology is expanded for solution to a typical multiobjective problem involving both nonpoint source pollution and economic goals. The methodology is designed to yield directly the land use pattern that simultaneously minimizes sediment yield and maximizes net farm-level profits from a watershed, subject to specified constraints. The particular approach used here interfaces SWAT with an evolutionary multiobjective global search strategy known as SPEA (Zitzler & Thiele 1999) to locate non-dominated Pareto optimal solutions. Capabilities of the methodology and resulting integrative model are demonstrated through an application to the Big Creek watershed, a Southern Illinois watershed placed on the 303(d) list by the Illinois Environmental Protection Agency (ILEPA) as a result of its excessive sediment yield.

PROBLEM FORMULATION

For the multiobjective problem being studied, the vector of decision variables is represented as seasonal cropping and tillage practices that define an agricultural landscape. The important state variables under consideration are sediment yield and economic benefit that occur in response to the applied land-use pattern. The problem can be expressed mathematically as

$$\text{Min } Z = \frac{\sum_{t=1}^{T} (y_t)}{T} \tag{1}$$

and

$$\text{Min } Z = \frac{\sum_{t=1}^{T} (-P_t)}{T} \tag{2}$$

subject to the transition constraints

$$y_t = f(C_s, X_s, T_s, t, s) \tag{3}$$

$$P_t = f(C_s, X_s, T_s, M, t, s) \tag{4}$$

and crop management constraints, expressed in functional form as

$$g(C_s, X_s, T_s, t, s) \leq 0 \tag{5}$$

where Z represents the functions to be minimized; y_t is annual sediment yield; P_t is the net annual economic benefit to be maximized; T is the number of years in the simulation horizon; C_s and T_s represent crops planted and tillage practices implemented during season s of year t; X_s is a generic term that represents all other hydrological and hydraulic factors that may affect sediment yield and crop yield during season s of year t, and M is an average market price for crop C over the decision period T.

WATERSHED AND CROP GROWTH SIMULATION MODEL

The transition constraints provided in the current problem formulations are best solved using a comprehensive watershed simulation model and crop growth model. With respect to the variety of models available, distributed models are better suited to solve watershed management problems than empirical and lumped routing models because of their use of spatially dynamic parameters. The USDA's watershed management model, SWAT, represents a prime example of one such model. SWAT is a continuous-time (e.g. long-term yield) simulator developed to assist water resource managers in routine assessment of water supplies and the effects of nonpoint source pollution in large river basins (Arnold *et al*. 1998; ASCE 1999). The model operates on a daily time interval and allows a watershed to be subdivided into natural sub-watersheds, upon which distributed routing of flows is based. In addition, each sub-watershed can be further subdivided into a number of Hydrological Response Units (HRUs), defined by a unique combination of land use and soil type heterogeneity. All factors such as soil type, land management practice and climate are considered homogeneous on an HRU scale.

While SWAT can be used to study more specialized processes such as bacteria transport, the minimum data required for execution are commonly available from government agencies, thus boosting its practical utility. SWAT inputs can be divided into the following categories: hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides and applied agricultural management techniques. Weather variables that drive the hydrological model include daily precipitation, maximum and minimum air temperature, solar radiation, wind speed and relative humidity. For watersheds lacking adequate weather data, a stochastic weather generator can be used for all or several variables and is based on monthly climate statistics that are calculated from long-term measured data from a weather station that is geographically near the watershed. In addition, weather data can be permitted to vary according to specific sub-watersheds, depending on data availability.

SWAT is designed to simulate major hydrological components and their interactions as simply, and yet realistically, as possible (Arnold & Allen 1996). Hydrological processes that are modelled include surface runoff, estimated using the SCS curve number or Green–Ampt infiltration equation; percolation, modelled with a layered storage routing technique combined with a crack flow model; lateral subsurface flow; groundwater flow to streams from shallow aquifers; potential evapotranspiration by the Hargreaves, Priestley–Taylor and Penman–Monteith methods; snow melt; and transmission losses from ponds. For additional detailed information, the reader is referred to Arnold *et al*. (1998).

Sediment yield is computed for each HRU using the Modified Universal Soil Loss Equation (MUSLE). Whereas the original Universal Soil Loss Equation (USLE) uses rainfall as an indicator of erosive energy, the MUSLE uses the quantity and rate of runoff to simulate erosion and sediment yield. The substitution results in a number of benefits including increased prediction accuracy, elimination of the need for a sediment delivery ratio, and the computation of sediment yield on a single storm basis. The MUSLE can be expressed as

$$y = 11.8V(q_p)^{0.56}KCP(LS) \tag{6}$$

where y is the sediment yield from an HRU in tons; V is the surface runoff column for the HRU in m^3; q_p is the peak flow rate for the HRU in m^3/s; K is a soil erodibility factor; C is a crop management factor, which accounts for crop rotations, tillage methods, crop residue treatments, and other cultural practice variables; P is an erosion control factor; and LS is the slope length and steepness factor (Yang 1996; Arnold *et al*. 1999). A quick observation of the MUSLE reveals a range of possibilities for reducing sediment yield from watersheds. As described earlier, these include the minimization of erosive potential of rainfall using alternative ground covers, the usage of tillage practices that cause less soil disturbance, the reduction of long, steep slopes through construction of terraces and check dams, and the proper choice of land use and management combinations. Land use and tillage practices in particular play a significant role in reducing erosive power of rainfall by binding the soil and reducing soil mobility and by increasing roughness to retard transport.

Within SWAT, crop growth is simulated over a daily time step, and crop management factor values in the MUSLE are calculated for all days that runoff occurs, thus accounting for stage of crop growth and improving accuracy of model results. Using crop-specific input parameters that are included in the model as a database, one can simulate a variety of annual and perennial crops. Agricultural management practice options include tillage techniques, planting and harvesting dates of crops, fertilizer and pesticide types, application dates and dosages, and cropping sequences. The model also provides an estimate of crop yield and accounts for crop yield reduction that may arise due to stresses such as the lack of sufficient precipitation and/or fertilizer. This crop yield estimate, along with information on production expenses and market price of the crops, helps in predicting economic implication of a decision policy. In addition, SWAT operates on an Arcview© GIS platform, which greatly assists in the generation of model input parameters and visualization of model output. Finally, SWAT and its source code are public domain and available online free of charge (http://www.brc.tamus.edu/swat/). It is a well-supported model and is widely used in solving broad water resources problems ranging from nonpoint source pollution control to climate change studies. These numerous features make SWAT a comprehensive mechanism for assessing both environmental and economic effects of alternative land management practices, and as such, a suitable tool for solving the transition constraints of the current optimization problem.

MULTIOBJECTIVE EVALUATION

Multiobjective optimization, without loss of generality, can be defined as a technique for simultaneously minimizing or maximizing several non-commensurable and often conflicting objectives. Although single-objective optimization problems may have a unique optimal solution, this is not the case for many realistic multiobjective optimization problems (MOPs). Typically, MOPs have no unique, perfect solution but rather a set of non-dominated, or non-inferior, alternative solutions, also known as the Pareto-optimal set.

For an m-dimensional minimization problem $F(\boldsymbol{x}) = (f_1(\boldsymbol{x}), \ldots, f_m(\boldsymbol{x}))$ subject to constraints $g_i(\boldsymbol{x}) \le 0$, $i = 1, \ldots, k$, $\boldsymbol{x} \in \Omega$, Veldhuizen & Lamont (2000) defined Pareto dominance and Pareto optimality as follows:

- A vector $\boldsymbol{u} = (u_1, \ldots, u_m)$ is said to dominate another vector $\boldsymbol{v} = (v_1, \ldots, v_m)$ if u is partially less than v, i.e. $\forall i \in \{1, \ldots, m\}$, $u_i \le v_i \wedge \exists\, i \in \{1, \ldots, m\}$: $u_i < v_i$.
- A solution $x \in \Omega$ is said to be Pareto optimal with respect to Ω if there is no $x' \in \Omega$ for which $\boldsymbol{v} = F(x') = (f_1(x'), \ldots, f_m(x'))$ dominates $\boldsymbol{u} = F(x) = (f_1(x), \ldots, f_m(x))$.

These Pareto optimal solutions may have no clearly apparent relationships other than that they form a set of solutions whose corresponding vectors are non-dominated with respect to all other comparison vectors, the comparison vectors being the m-dimensional functional values. A decision maker then implicitly chooses an acceptable solution (or solutions) by selecting one or more from the Pareto-optimal set based on his/her own additional criteria. When applied to the two objective non-point source pollution problem discussed here, $\boldsymbol{x}$ is a vector of land use patterns and tillage operations over the decision period (T), and $F(\boldsymbol{x})$ is a vector of the minimization function Z given in Equations (1) and (2), where $f_1(\boldsymbol{x})$ is mean annual sediment yield (Equation (1)) and $f_2(\boldsymbol{x})$ is mean annual net profit (Equation 2). Transition equations and system constraints given in Equations (3)–(5) are analogous to $g_i(\boldsymbol{x})$. For any decision policy to be a member of Pareto optimal set, the vector of decision variables chosen (i.e. land covers and corresponding tillage practices) should result in a mean annual sediment yield and mean annual dollar values that are at least as good as those obtained by any other alternative policies investigated and should be better than those alternatives in at least one of the two objectives.

Traditionally, there have been many methods of solving MOPs including those which find a single optimal solution in one simulation run (Deb & Horn 2000). These methods, however, need to be used repeatedly with hopes of finding a different Pareto-optimal solution each time. Moreover, they have difficulties in solving problems having a non-convex search space. Alternatively, evolutionary algorithms (EAs), search and optimization algorithms inspired by the process of natural evolution and that work on populations of candidate solutions, are a natural choice for multicriteria evaluation since they can generate a number of Pareto-optimal solutions in one simulation run. Current evolutionary approaches include evolutionary programming (EP), evolutionary strategies (ES), genetic algorithms (GAs) and genetic programming (GP). For details of these techniques, the reader is referred to Back *et al*. (2000). Candidate solutions in EAs are evaluated and assigned fitness values based on their relative performance, represented through objective functions. Proportional to their fitness value, better individuals are then given the opportunity to reproduce themselves with the philosophy that the new generation could better fit the environment than the parents from which the new individuals were created. Offspring produced are modified by means of mutation and/or recombination operators in order to control premature convergence. To apply this logic to MOPs, the key is the conversion of the multiple performance measures, such as objective function values, into a scalar fitness measure.

Based on techniques of mapping multiple performance values to a single fitness value, usually termed as fitness assignment, Fonseca & Fleming (2000) grouped current EA approaches to solving MOPs into plain aggregation approaches, population-based non-Pareto approaches and Pareto-based approaches. As the name implies, aggregation methods numerically combine the objectives into a single objective function that can be optimized using single function optimization techniques. A weighted-sum approach is the classical example of this technique. The shortcoming of the method, however, lies in the assignment of relative importance of the multiple objectives. In population-based non-Pareto approaches, different objectives affect the selection of different parts of the population. The Vector Evaluated Genetic Algorithm (VEGA) (Schaffer 1985) is a typical example of algorithms that adopt this technique. In VEGA, selection is carried out for each objective function separately. Pareto-based techniques make use of Pareto dominancy criteria for fitness evaluation and population ranking.

Motivated by the diversity of algorithms and the lack of comparative performance studies of the different approaches, Zitzler *et al*. (2000) provided a systematic comparison of six multiobjective EAs from the three classes. The basis of the empirical study was formed by a set of well-defined, domain-independent test functions that allow investigation of independent problem features. Test functions having features that pose difficulties for EAs with regard to convergence to the Pareto-optimal front (Deb 1999) (i.e. convexity, non-convexity, discrete Pareto fronts, multimodality, deception and biased search spaces) were used in the comparison study. As such, the authors were able to compare systematically the approaches based on different kinds of difficulties and determine more exactly where certain techniques are advantageous or have trouble. The conclusions of their comparison study included a clear hierarchy of algorithms with respect to the distance to the Pareto-optimal front. The Strength Pareto Evolutionary Algorithm (SPEA) was ranked first and outperformed all other algorithms on five of the six test functions, and was ranked second on the sixth-test function that incorporated deceptive features. Based on this comprehensive comparison study and inspired by the excellent performance of SPEA on these carefully chosen test functions, SPEA has been integrated into the solution methodology for the multiobjective watershed management problem.

SPEA (Zitzler & Thiele 1999) is an algorithm that makes use of both well-established techniques and new concepts in finding Pareto-optimal solutions. Specifically, it incorporates concepts such as elitism, niching and clustering, and Pareto dominancy. The algorithm begins with initial solution alternatives, P, that are randomly generated, and objective function evaluation is performed for each of these decision policies. Based on the definition of Pareto dominance, non-dominated solutions are sought from these initial solutions and are copied to temporary storage P'. The fitness of each individual in P, as well as P', is then calculated. The fitness assignment is a two-stage process. First, fitness of individuals in the external, non-dominated set P' is evaluated. The number of individuals in P that are dominated by an individual i in P', denoted here as n, are counted, and the fitness value (f_i) for individual i in P' is then determined according to

$$f_i = \frac{n}{N+1} \tag{7}$$

where N is the total number of individuals in P. This process is repeated for all individuals in P'. Afterwards, to determine fitness of individuals in P, say for individual j, fitness values of all individuals in P' that dominated individual j will be added and a value of one is added to this total to ensure that members of P' have better fitness than members of P:

$$f_j = 1 + \sum_{i, i \geq j} f_i. \tag{8}$$

Based on their fitness values, individuals from P and P' are ranked and selected according to a user-defined scheme until the mating pool is filled. Problem-specific crossover and mutation operators are then applied. On subsequent generations (iterations), dominance is checked within P', and those solutions that are dominated are removed. If the number of solutions (Pareto optimal set) stored in P' exceeds a user specified maximum number of niches (N'), P' is pruned by clustering. For this study, an average linkage method was used for clustering. Unless the convergence criteria is satisfied, another iteration begins by searching for non-dominated solutions and copying them to P'. Figure 1 presents the structure of SPEA. For further detail of the algorithm, including fitness assignment and the clustering approach, the reader is referred to Zitzler & Thiele (1999).

Equations (1) and (2) are the objective functions to be minimized and represent the mean annual sediment yield and mean annual economic benefit generated from a farm field, respectively. The functions implicitly depend on a particular landscape and climate conditions through the governing dynamics of water quality and hydrological phenomena. The transition constraints, Equations (3) and (4), represent the laws that govern water quality, hydrological processes, crop growth and subsequent crop yield, and market conditions and are used to describe the stage-by-stage response of the watershed system and economics according to an imposed land-use pattern. The transition equations for the current problem are comprised of relationships for water and sediment continuity, the soil loss equation, plant growth model, and many others solved by SWAT. Equation (5) defines a feasible range for decision policies. These policy constraints, together with the transition constraints, define the feasible solution space for this multiobjective watershed management problem.

SOLUTION METHODOLOGY

The optimal control methodology developed to solve the multiobjective problem relies on an interface between SWAT and SPEA, as illustrated in Figure 2. Design of the SWAT–SPEA linkage was performed systematically with two critical goals: minimizing computational resources, particularly CPU time, and preserving the originality of SWAT so as to simplify upgrading efforts of the optimal

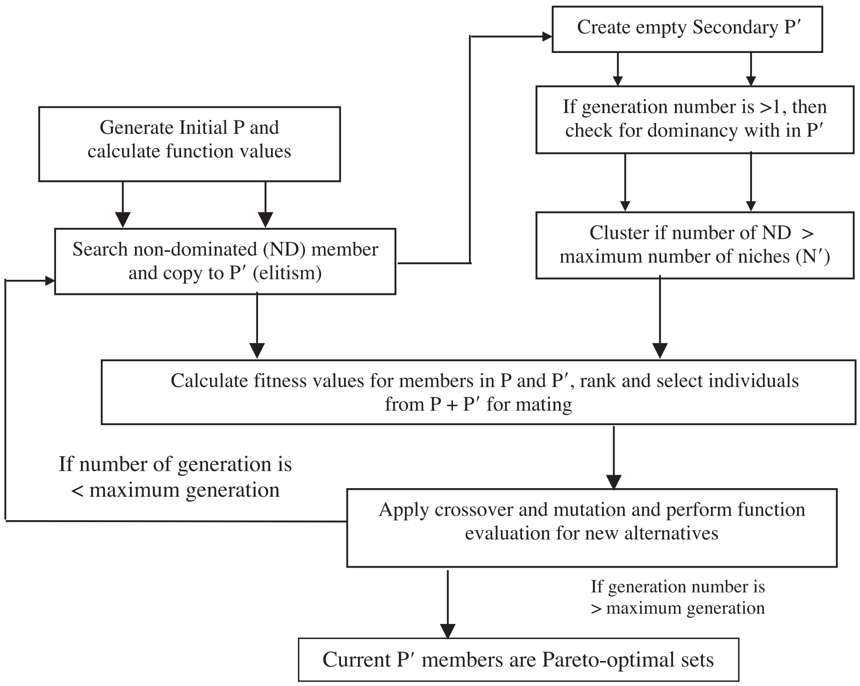


Figure 1 | Logical flow diagram of SPEA.

control tool with future, newer versions of SWAT. SWAT is a model designed to make one simulation run starting from variable declaration and initialization, to the processes of reading inputs, computation of hydrological processes, and writing outputs to file. The optimization model developed here, however, requires an iterative search for which a number of function evaluations, or SWAT calls, are necessary. To avoid performing some of the unnecessary operations that demand considerable computational time, such as reading inputs, only computational subroutines of SWAT were directly involved in the search process. Input reading was performed only once in operation of the overall model. Likewise, subroutines for reinitializing variables to their original values after every function evaluation were carefully designed and incorporated to the model. The process of iteratively writing outputs to a file was fully suppressed. Output was written only on completion of the overall optimal control model.

In this control model, decision variables, or genes, are cropping and tillage practice combinations for a particular HRU, which are permitted to change over subsequent seasons. A set of decision variables, or chromosome, that defines a particular landscape then represents a potential solution to the posed problem. Within this study, Table 1 provides examples of genes (land cover and tillage practice) and their assigned integer codes for some of the land covers considered in this search operation. An operational management database and economic database were developed for all potential land covers believed to be commonly grown in the study watershed. After a sequence of genes for a chromosome, or policy, is chosen, the model uses the database to automatically assign management operations for each crop in the chromosome. This subsequent management schedule is ultimately used by SWAT in hydrological simulation. The operational management schedule dictates the type of land cover chosen for a particular season, tillage type used, planting and harvest dates for the crop, chemical (fertilizer and pesticide) application dates and dosages, end of year operations, curve number to be used in estimating surface runoff taking into account soil type in the HRU and crop type selected for the season and its tillage type, potential heat units required for the

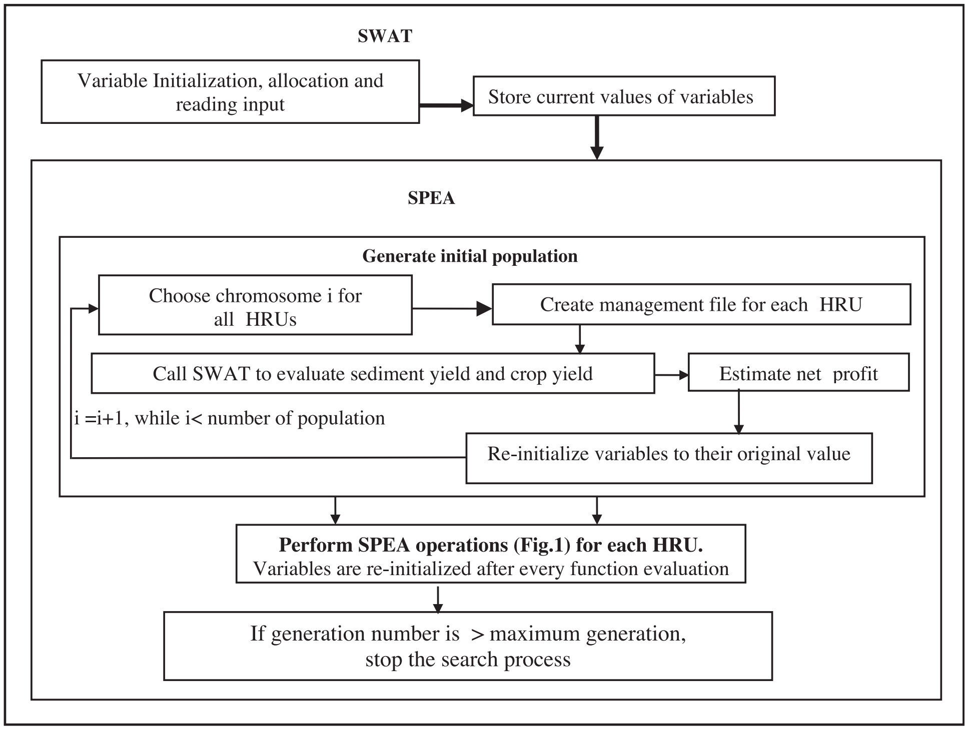


Figure 2 | Structure of SWAT–SPEA interface.

particular crop to reach maturity which heavily influences crop yield, and other practices. This operational management schedule varies from HRU to HRU within the same search iteration and also varies within the same HRU from iteration to iteration. As a result, its allocation is dynamic and should be updated each time a new policy is designed for an HRU. The economic database supplies information on production expenses, both variable and fixed costs, and the selling price of all crops included in the decision process.

Table 1 | Example of genes defining crop types and tillage practice

Crop	Tillage practice	Acronym	Integer code
Soybean	No tillage	SYNT	1
Corn	No tillage	CRNT	4
Sorghum	Conservation tillage	SGCT	8
Wheat	Fall tillage	WWFT	19
Wheat	No tillage	WWNT	17
Soybean after wheat	Conservation tillage	SYWC	10
Alfalfa	No tillage	AFNT	12
Pasture	No tillage	PSNT	14

The solution methodology assumes that each HRU represents a particular farm field that is singularly or commonly owned by a landowner. Under this assumption, a landowner's decision concerning land uses and tillage types will have no influence on the decisions made by neighbouring landowners. Expressed differently, the methodology allows each landowner within the watershed to make independent decisions, but contributes towards the overall goal of minimizing sediment yield to a receiving water body. This approach supports ILEPA's recognition that watershed planning and management begins with the responsibility of farmers and other landowners who have ownership rights within

Table 2 | Sample management alternatives

Chromosome	Crop 1 Warm season	Crop 2 Winter crop	Crop 3 Warm or perennial crop	Crop 4 Warm or perennial season	Crop 5 Winter or perennial season
1	1 (SYNT)	17 (WWNT)	12 (AFNT)	12 (AFNT)	12 (AFNT)
2	8 (SGCT)	19 (WWFT)	10 (SYWC)	4 (CRNT)	14 (PSNT)

the watershed. Their land use choices directly affect their personal income and affect their shared responsibility to maintain environmental quality. Effective decision making in such cases should thus recognize different stakeholder perspectives. It may be argued that such decision policy needs to be performed on the scale of a watershed rather than a farm field. Unlike the farm-based decision, however, a watershed scale decision may be that which economically favours one landowner over the other within the same watershed and may suffer from severe socioeconomic issues.

Farm management decisions are not typically based on single-year concerns, but rather under consideration of multi-year criteria, such as crop rotation. In this study, it is assumed that a farm management policy dictates the seasonal sequence of crops to be grown on an individual farm field for a three-year time horizon. In the decision process, only field crops are considered and a maximum of two crops per year are permitted to grow. The second crop of the year can be planted only after the preceding crop is harvested. Planting and harvesting dates of crops are assumed to be consistent within the dates recommended for specific crops in the watershed of study, and a crop year is assumed to commence in January. With any three-year rotation, a maximum of five crops can be grown. The first crop planted in the three-year period is a warm season crop and is harvested in late September. A winter crop is then planted in early October and is harvested in June. Next, using a double cropping system, warm season crops, such as soybean, that can grow following harvest of winter crops are planted. The fourth crop is a warm season crop that is planted in March or April, and finally the fifth and the last crop of the sequence is a winter crop. In addition, once planted, perennial crops such as hay and pasture are allowed to remain on the field until the end of the three-year plan. These criteria represent crop management constraints, which were expressed generally through Equation (5).

The solution methodology begins with randomly generated chromosomes for each HRU, each consisting of five genes, which represent the sequence of land covers and tillage practices to be implemented over a three-year period for that farm field. By design, each chromosome is feasible according to the specified crop management constraints described above. Satisfaction of the management constraints is checked not only during initial random generation of alternative solutions, but also on crossover and mutation operations. This was performed using the systematically assigned crop codes (see Table 1), and supplying minimum and maximum values (codes) that a certain season's gene may assume. For further illustration, Table 2 provides two examples of potential chromosomes. Considering the second alternative in the table, sorghum with conservation tillage is a warm season crop and is chosen as gene 1; then wheat with fall tillage is a winter crop chosen as gene 2; soybean with no tillage which can be grown over the summer after harvesting wheat is the third land cover; and the last land cover selected over the decision time horizon is pasture with no tillage. In alternative 1, silage with spring tillage was proposed as the first gene and the second gene was chosen to be perennial land cover, which is alfalfa with no tillage option. The third, fourth and fifth genes of the chromosome were then automatically assigned the same land cover (i.e. alfalfa with no tillage) to satisfy the management constraints due to perennial cropping.

Once a single, random decision policy is chosen for an HRU in the watershed, the task of assigning operational management schedules for the HRUs is accomplished. This process is repeated for all HRUs in the watershed where potentially different policies are chosen for different HRUs, according to the process described above. After having decision alternatives for all HRUs in the watershed, the water quality and hydrological simulator is used to solve implicitly the transition constraints for each chromosome. The objective function value returned from SWAT represents a three-year average annual sediment yield and crop yield of the five genes in a chromosome that occur in response to implementation of a particular alternative. Net profit that accrues as a result of implementing this policy is then estimated by using the economic database and the crop yield estimated for each gene. Finally, variable reinitialization is performed since the original SWAT processes of variable initialization and input reading are suppressed for the mere reason of reducing computational time. This process is repeated until the user-defined number of chromosomes for each HRU is reached. The mean annual sediment yield and mean annual net profit values establish the basis for searching non-dominated solutions by SPEA. If the number of non-dominated solutions is beyond the maximum niche number assigned by a user, clustering is performed. Binary tournament selection is applied to the fittest pairs of chromosomes to evaluate policies that are privileged to mate during a random, uniform crossover scheme. Before progressing to the next generation (search iteration) of the SPEA, genes are mutated according to a user-specified frequency and function evaluation is performed for the new offspring and mutated alternatives. This cyclic process is continued for a user-defined number of generations. The ultimate result is the evolution of a set of land-use patterns (Pareto-optimal sets) that are best suited to the multiple criteria problem considered in this study.

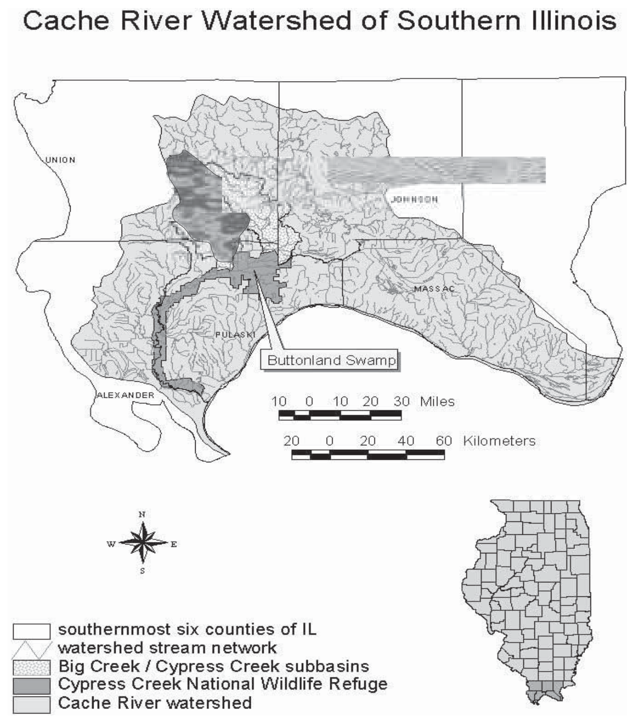


Figure 3 | Location map of Big Creek watershed.

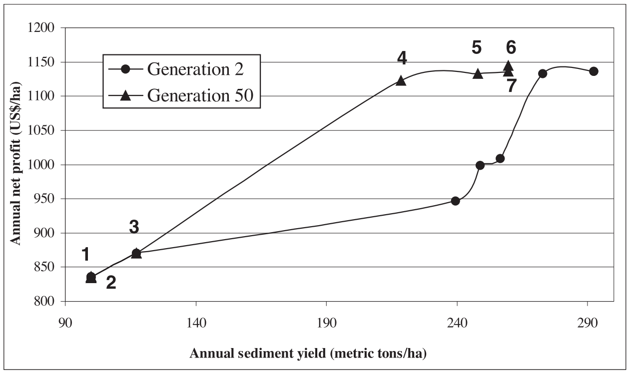
APPLICATION TO THE BIG CREEK WATERSHED

The Cache River basin, shown in Figure 3, is located in Southern Illinois near the confluence of the Mississippi and Ohio Rivers. Big Creek watershed is one of the major tributaries draining into the Lower Cache River, near the internationally recognized Cache River Wetlands, including Buttonland Swamp. This watershed not only contributes significant amounts of water to the Lower Cache River, but also carries a higher sediment load than other tributaries in the area. According to data from 1985–1988, Big Creek watershed contributed more than 70% of sediment inflows into the Lower Cache (Demissie *et al.* 2001). Because of its high sediment yield and influence on the Lower Cache River, multiple agencies and organizations have identified the Big Creek watershed as a priority area for improved watershed management. As a result, it is undergoing extensive study as part of the Illinois Pilot Watershed Program, through cooperation between the Illinois Department of Natural Resources

(IDNR), the Illinois Department of Agriculture, ILEPA, and the U.S. Natural Resources Conservation Service (IDNR 1998).

A 30 m resolution U.S. Geological Survey (USGS) Digital Elevation Model (DEM), an IDNR land use map, and a soils map were obtained for the region of study. The land use map had been generated from LandSat imagery collected between April 1991 and May 1995. The Big Creek watershed was delineated from the DEM using the United States Environmental Protection Agency's (USEPA) BASINS model, which provides a GIS extension for SWAT2000, and was subsequently divided into 73 sub-basins. BASINS was used in this study since the Arcview© interface for the latest version of SWAT, SWAT2000, was not yet released (as of July 2001) from the USDA. The land use map and soils map were then superimposed over the subdivided watershed to identify HRUs. For this application, dominant soils types and land uses from each sub-basin were used in establishing HRUs, a statement that implies that each farm field consists of a single soil type and land cover during any one season and that the number of HRUs is equal to the number of sub-basins (i.e. 73). A search for an optimal land use pattern was applied to HRUs whose existing land cover was not forest, water, wetland and/or urban. Historical data related to daily precipitation, daily maximum temperature and daily minimum temperature were obtained from the U.S. National Weather Service for Anna, IL, a nearby weather station. A database of 19 suitable cropping and tillage practice combinations was prepared for the Big Creek watershed. This database contains additional information on planting dates, harvesting dates, dates to apply tillage, fertilizer and pesticide types, application dates and dosages, heat units required for a plant to reach maturity, and curve numbers the land cover may assume for all hydrological soil groups for AMC II (i.e. Soil Groups A, B, C and D). Information for the watershed's management database was collected from the Illinois Agronomy Handbook (UIUC 2000) and from National Agricultural Statistics Service (USDA 2000). Additionally, an economic database for all crop type and tillage combinations was prepared. This database provides data on production expenses and selling prices of these land uses. The production expenses were broadly classified as variable costs and fixed costs. Variable costs include expenses for seed, chemical, insurance and interest for machinery, labour and trucking. Fixed costs are related to cost of owning land and machinery and were not used in the optimization process. A 10-year (1990–1999) average of production expenses and selling price data for the study area were collected from various sources, and these data were used in the decision process. The major resources used in preparing the economic database were the University of Illinois at Urbana-Champaign (UIUC) Farm and Resource Management Laboratory (FaRM Lab) (UIUC 1999), Illinois Census of Agriculture (USDA 1997a), and Cost and Returns Estimator model (CARE) farm budget for Southern Illinois (USDA 1997b).

The optimal control model was applied using inputs collected for Big Creek watershed and executed for each HRU with an initial population of 100 chromosomes, an upper limit of 100 generations and a mutation rate of 15%. To search solutions for the 73 HRUs in the entire 130 km^2 watershed required a CPU time of about 63.25 h on a Pentium 4, 1.3 GHz PC. However, it should again be noted that a 3-year policy is designed for the watershed during this 63.25 h of CPU time. To demonstrate solution convergence, search results for one particular HRU is presented in the plot shown in Figure 4. The plot shows Pareto-optimal fronts obtained at generation 2 and generation 50. The search was continued until generation 100, but no significant improvement was found after generation 50. One can clearly see that none of the alternatives at any corresponding generation are better than any other as to the criteria that were supplied to the model. Alternatively stated, improvement in one of the objective functions comes only at the expense of deterioration of the other objective and no solution is better than the other solution according to the model criteria. The policy maker can add his/her own criteria to decide on which of these seven alternatives to implement. At the same time, the ability of the model to guide the search to a region that improves both objectives simultaneously is demonstrated. This is evident from a comparison of the Pareto front found at generation 50 with that obtained at generation 2. It is also interesting to see that the optimal land covers chosen make a clear compromise between erosion protection and generating profit. Considering the



Notes:

A. Optimal land covers on generation 50 in ascending order of their sediment yield:

1.	CRNT	HYCT	HYCT	HYCT	HYCT
2.	CRST	HYCT	HYCT	HYCT	HYCT
3.	CRNT	PSNT	PSNT	PSNT	PSNT
4.	CRCT	WWNT	SYWN	CRCT	WWNT
5.	CRNT	WWCT	SYWN	CRST	WWNT
6.	CRCT	WWCT	SYWC	CRNT	WWNT
7.	CRCT	WWCT	SYWC	CRST	WWNT

B. The first two letters of each acronym refer to crop type and the last two to tillage type:

Crop Types	Tillage Types
CR: Corn	NT: No tillage
HY: Hay	ST: Conventional spring tillage
PS: Pasture	CT: Conservation tillage
WW: Wheat	WN: No tillage for soybean grown after harvesting wheat
SY: Soybean	WC: Conservation tillage for soybean grown after wheat

Figure 4 | Convergence plot of SWAT–SPEA application to Big Creek watershed.

plot for generation 50, for example, land covers that correspond to alternatives on the lower portion of the curve (i.e. those which generate less profit, but have better erosion protection capability) are mainly hay and pasture with conservational tillage or no tillage option. Those on the extreme opposite side of the curve are cash crops with less erosive tillage options, which can generate higher profit, but at relatively high sediment yield. Lack of alternatives in the middle of the curve is due to extreme differences between field crops and perennial crops with respect to erosion protection and market prices and not due to the inadequacy of SPEA in locating smoothly distributed optimal solutions over the range of the front.

It should also be noted that no calibration was performed as part of this particular study since sufficient calibration data does not exist at this time. This makes the actual figures (average sediment yields and annual dollar values) given in the convergence plot less informative, apart from their relative comparison. This data, however, is currently being collected, thus permitting extensive calibration efforts in the near future. Nevertheless, application of the model and presentation of results at this stage allow the demonstration of the tools developed in this research and their capabilities.

CONCLUSIONS

This study explains a multiobjective, discrete-time optimal control computational model for watershed decision support. The tool may potentially play a significant role in addressing adverse environmental impacts of non-point source pollution and, at the same time, boost the agricultural economy of a watershed. The model framework is based on an interface between a comprehensive hydrological and water quality model known as SWAT and an evolutionary algorithm-based, multiobjective optimization technique known as SPEA. Application of the methodology to a study region located in Southern Illinois demonstrates the effectiveness of the tool in presenting non-dominated decision alternatives to policy makers, who may then decide upon which policy to adopt, based on their own additional criteria. The solution methodology applied in this study integrates local, social dynamics in multiple ownership watersheds with environmental issues and is more likely to be granted validity and trust by stakeholders of a watershed. Future work will address calibration concerns and issues related to the reliability of the model under uncertainty of inputs. Techniques that may reduce computational demand of the current methodology are also under investigation. Finally, the methodology and computational watershed decision support model may play a significant role in assisting watersheds in meeting criteria such as Total Daily Maximum Loads (TMDLs).

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