

# Optimal Placement of Conservation Practices Using Genetic Algorithm with SWAT

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## **Abstract**

The effectiveness of conservation practices depends on their placement on the fields within the watershed. Cost-effective placement of these practices for maximum water quality benefits on each field requires comparing a very large number of possible land-use scenarios. To address this problem, we combine the tools of evolutionary algorithm with the Soil and Water Assessment Tool (SWAT) model and cost data to develop a trade-off frontier of least cost of achieving nutrient reductions and the corresponding locations of conservation practices. This approach was applied to the Raccoon River Watershed, which drains about 9,400 km<sup>2</sup> of an intensive agriculture region in west-central Iowa. Applying genetic algorithm to the calibrated SWAT modeling setup produced multitudes of optimal solutions of achieving nutrient reductions in relation to the total cost of placing these practices. For example, a 30% reduction in nitrate (and a corresponding 53% reduction in phosphorus) at the watershed outlet can be achieved with a cost of \$80 million per year. This solution frontier allows policymakers and stakeholders to explicitly see the trade-offs between cost and nutrient reductions.

**Keywords:** genetic algorithm, nutrient calibration, Raccoon River Watershed, SWAT.

## 1. Introduction

Conservation practices such as reduced tillage, contour farming, grassed waterways, land retirement, and others have been widely used and are well known for reducing water quality pollutants. However, effectiveness of these practices at the watershed level significantly depends on their placements because of the unique nature of the biophysical relationship between conservation practices and resulting water quality levels. Additionally, multiple conservation practices exist for each field in the sense that there are a potentially large numbers of conservation practices that could be implemented on each field. This means that solving for the optimal solution requires comparing a very large number of possible land-use scenarios. Specifically, if there are “N” conservation practices possible for adoption on each field and there are “F” fields, this implies a total of  $NF$  possible configurations to compare. In a watershed with hundreds of fields and more than a couple of conservation practices, this comparison quickly becomes unwieldy. Added to this complexity, some conservation practices are cost-effective for one nutrient and may have little or no beneficial effect on the other nutrient (even deleterious effects are possible). This implies that the optimal choice of conservation practices will depend on the degree to which control of each separate nutrient is desired.

Recent development of genetic algorithms provides a solution strategy for this sort of problem. Genetic algorithms mimic the process of evolution, which, in effect, is a method of searching for solutions among an enormous amount of possibilities. These algorithms work with populations of candidate solutions iteratively applying stochastic operations of selection, recombination, and mutation in the hope of finding improvements with respect to the optimization objectives. In general, these belong to a class of stochastic optimization methods and are well suited for approximating solutions to complex combinatorial problems (e.g., Deb, 2001; Forrest, 1993). Fewer applications have been made in the area of integrated watershed modeling systems (e.g., Srivastava et al., 2002; Veith et al., 2003; Bekele and Nicklow, 2005; Arabi et al., 2006). These studies have been done on a much smaller scale. In addition, none of these studies examined the trade-offs between two different nutrients.

This study builds upon the previous study by Jha et al. (2009), which established the SWAT modeling framework for the Raccoon River Watershed (Figure 1), conducted the model calibration and validation for streamflow and water quality components including nitrogen and phosphorus, and performed several BMP (best management practice) analyses. The watershed drains about 9,400 km<sup>2</sup> of intensive agricultural land in west-central Iowa. In this application, we

combine the genetic algorithm optimization technique with the calibrated SWAT model for the watershed. Objective functions were built to cost-effectively reduce loadings of two nutrients, nitrogen and phosphorus, at the watershed outlet. The goal of this research is to identify least-cost combinations and placements of conservation practices in the region to achieve nitrogen and phosphorus reductions for the Raccoon River Watershed. Conservation practices chosen include reduced fertilization of row crops, three reduced tillage options, contour farming, installation of grassed waterways, and land retirement. The development of a full frontier will allow policymakers and stakeholders to explicitly see the trade-offs between cost and nutrient reductions as well as the potential trade-offs between the two nutrients.



**Fig. 1** Location of the Raccoon River Watershed and delineated subwatersheds

## **2. Raccoon River Watershed**

The Raccoon River Watershed is a typical Midwest agricultural basin. It drains a watershed of about 9,400 km<sup>2</sup> in west-central Iowa (Figure 1). Current land use is predominantly

agricultural with row crops of corn and soybeans comprising 76% of the watershed. Agricultural grasslands (alfalfa, brome, pasture, and land retirement) comprise 17% of the watershed, whereas forest (4%), urban areas (2%), and water (1%) comprise the remaining land area. The river is impacted by sediment, phosphorus, and nitrogen pollution, which originate primarily from nonpoint sources. The nutrient input sources include widespread use of fertilizers, livestock manure applications, legume fixation, and mineralization of soil nitrogen. Nitrate pollution is a particularly acute problem and is transported primarily through groundwater discharge via baseflow and tile drainage (Schilling and Zhang, 2004). The watershed's high concentrations of nitrate have exceeded the federal maximum contamination level standard of 10 mg/L with enough frequency since the late 1980s to warrant the installation and operation of the world's largest nitrate removal facility by the Des Moines Waterworks. Sections of the Raccoon River have also been listed in Iowa's Federal Clean Water Act 303(d) list of impaired waters because of the elevated nitrate levels.

### **3. Modeling setup with the Soil and Water Assessment Tool (SWAT)**

The SWAT model is a watershed-based hydrologic and water quality model. It is capable of modeling the impact of different land-use and management practices on hydrology and water quality of the watershed (Arnold and Fohrer, 2005). SWAT is a long-term continuous simulation model that operates on a daily time step. Major model components are hydrology, weather, soil temperature, crop growth, nutrients, bacteria, and land management. Watersheds are subdivided into subwatersheds, which are further delineated by hydrologic response units (HRUs) that consist of homogeneous soil, land-use and management characteristics. The HRUs represent percentages of a subwatershed area and thus are not spatially defined in the model. Routing of water and pollutants are simulated in the model from the HRUs to the subwatershed level, and then through the stream network to the watershed outlet. Neitsch et al. (2005) provide detailed documentation of the current SWAT2005 model. SWAT validation and scenario applications have been reported worldwide for a wide variety of watershed scales and environmental conditions (Gassman et al., 2007).

In the modeling framework developed by Jha et al. (2009), the watershed was divided into a total of 112 subwatersheds and more than 3,000 HRUs. The SWAT model was adequately calibrated and validated for the overall watershed hydrology, and for streamflow, nitrogen, and

phosphorus at the watershed outlet. Successful calibration and validation with strong correlation was established by statistical analyses with coefficient of determination and model efficiency.

#### **4. Conservation options and cost**

Several in-field conservation activities can reduce nitrogen and/or phosphorus loadings from agricultural fields. In this study, we include conservation tillage (mulch, ridge, and no-till), contour farming, grassed waterways, terraces, retirement of land from crop production in favor of perennial cover, and reduction of fertilizer application. With the exception of land retirement, all other practices are modeled in conjunction with the cropping system currently in place. Conservation practices and cropping systems observed in the baseline are preserved; i.e., the algorithm can add, but not subtract, conservation practice options. In total there are 32 sensible combinations of these conservation practices. These 32 options combined with an option of retiring entire cropland results in 33 possible land-use options for each HRU.

Land retirement was modeled by assigning a permanent grass cover to the HRU; fertilizer reduction was modeled by reducing the application by 20% for all crop rotations; and in-field practices (tillage, grassed waterways, contour farming, and terraces) were modeled by adjusting the SWAT model parameters (Arabi et al., 2007; Secchi et al., 2007).

Detailed information on the costs of all the options was obtained from multiple sources. Costs of terraces, no-till, and contouring were gathered from the Natural Resources Conservation Service's Web site. The costs of grassed waterways were obtained from the Conservation Reserve Program office and converted to a per acre protected, annualized basis using a 5% discount rate and a 20-year useful life term. The costs of land retirement were proxied by the cash rental rates. The costs of nitrogen reductions were developed using the yield curves inferred from Iowa State University Extension's N-Rate Calculator information for geographic zones and corn-soybean crop sequences. Reduced profits predicted by the yield reductions multiplied by the price of corn served as the cost estimate.

#### **5. Genetic algorithm**

Three major components were integrated to arrive at the final modeling framework. The first component is the logic and the fitness assignment method of a multi-objective evolutionary optimization algorithm, SPEA2 (Zitzler et al., 2002). The second component is a publicly available C++ library of genetic algorithms, GALib, originally developed by Wall (2006), with

the current version available online. The third component is the water quality model, SWAT ver. 2005, coupled with a Windows-based database control system, i\_SWAT (CARD, 2007). SPEA2 provides the fundamental multi-objective optimization logic, while GALib provides the basis that is needed to implement an evolutionary search algorithm. Finally, SWAT and i\_SWAT provide a framework to model the different conservation practices considered in this study and their watershed-level environmental impacts.

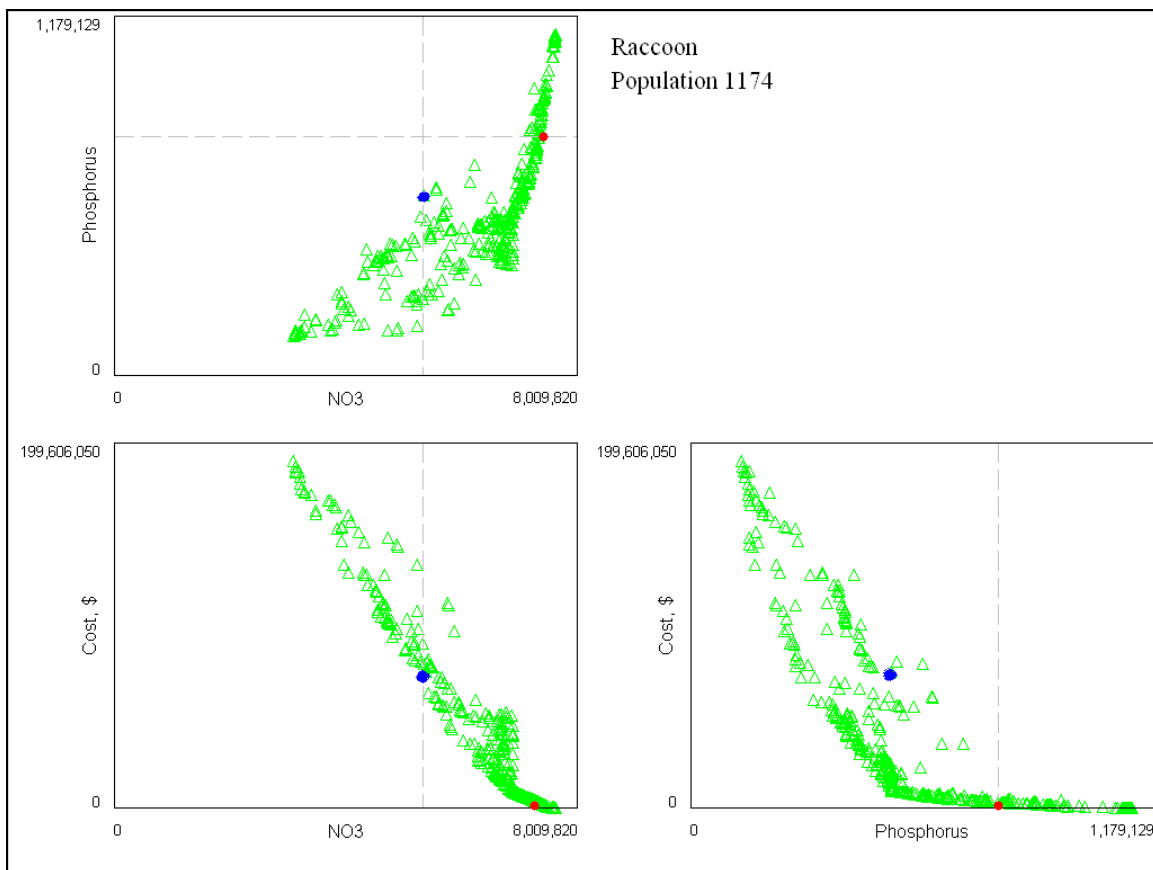
The genetic algorithm was initialized with a population of 50 individuals (scenarios). In order to efficiently exploit prior domain-specific knowledge, the initial population was not created completely at random. First, the initial population was seeded with an individual representing the baseline allocation of conservation practices and an individual representing a scenario of all cropland being retired from production and placed under permanent grass cover. These individuals represent the boundary points on the trade-off frontier: the “baseline” individual results in the lowest cost and highest nutrient loadings, while the “all cropland retired” individual results in the highest cost and lowest nutrient loadings. To further cover the search space, an additional 32 individuals, each of which represent a uniform application of each of the conservation practice combinations, were included in the initial population. The purpose of such seeding is twofold. First, a good coverage of the objective space is achieved. Second, the land-use options, which are immediately judged to be “good,” help define the direction of the stochastic search and improve the algorithm’s efficiency. The rest of the initial population was generated by randomly assigning 1 of the 33 options to each cropland HRU in the watershed.

The calibrated SWAT model was run separately with each of 50 initial individuals. Non-dominated individuals were then selected based on the evolutionary algorithm’s multi-objective optimization function of minimizing (1) the cost of nonpoint source pollution control, (2) the mean annual nitrate loadings at the watershed outlet, and (3) the mean annual total phosphorus loadings at the watershed outlet. Those selected individuals were used to create the next population of 50 individuals. A set of Pareto-nondominated individuals surviving after several hundred generations (iterations of the evolutionary algorithm) provides an approximation to the true frontier.

## **6. The trade-off frontier and the cost of nutrient reduction**

Figure 2 shows two-dimensional projections of the trade-off frontier of possible solutions. Each point on the frontier corresponds to a unique individual watershed configuration, i.e., a prescription for the application of conservation practices in the watershed. Figure 2 provides

interesting insight into the interactions between conservation practices considered and the two nutrients. For a given set of practices considered, once nitrate loadings are reduced by 30% (highlighted in red in Figure 2 in nitrate-cost space), an automatic reduction of about 53% in phosphorus loadings follows. Greater reductions in nitrates lead to simultaneous reductions in phosphorus, suggesting complementarities in the set of practices used to achieve greater nitrate reductions. Alternatively, least-cost watershed configuration to reduce phosphorus by 30% (highlighted in blue in Figure 2 in phosphorus-cost space) reduces nitrate loading by only 4%.



**Fig. 2** Two-dimensional projections of trade-off frontier (loadings are in kg)

Further examination of the conservation practices chosen for these two individuals (watershed configurations) sheds light on this finding. Each individual in the frontier is encoded with a unique identification number. The red individual, which achieves a 30% nitrate reduction, is identified as #638, and the blue individual is #1252 (see Table 1). With a control cost of over \$80 million/year, individual #638 achieved a 30% reduction in nitrates and a 53% reduction in phosphorus. This is significantly more expensive than individual #1252, which has a cost of about \$4 million/year and achieves a 30% phosphorus reduction, but only about a 4% nitrate



reduction. The detailed allocation of conservation practices for these two watershed configurations reveals that the algorithm favors “grassed waterways” for phosphorus reduction whereas “fertilizer reduction” is favored for a small reduction in nitrate and “land retirement” is favored for a medium to large reduction in nitrate loadings. The cost of nitrate reduction increases dramatically with the use of land retirement. Table 1 also lists individual #1146, which can achieve a 15% reduction in nitrate with a least cost of about \$23 million/year (substantially lower than the cost of 30% reduction) and as a by-product achieves a 54% phosphorus reduction.

**Table 1.** Example trade-off relationship between the cost of pollutant reductions

Frontier Individual ID#	Nitrate	Phosphorus	Cost of achieving reductions (million \$/year)
	% reduction from baseline		
638	30.5	53.2	80.1
1252	3.9	30.2	3.6
1146	15.4	54.6	22.9

## 7. Conclusion

Because of the unique nature of the biophysical relationship between conservation practices and resulting water quality levels, the effectiveness of a given conservation practice on a given field depends on the placement of conservation practices and cropping systems in the watershed. Additionally, a large number of conservation practices could be implemented on each field. In this study, we combine the tools of evolutionary algorithms with the calibrated SWAT model and cost data to develop a frontier of least-cost combinations and locations of conservation practices to achieve various nitrate and phosphorus reductions. With the help of evolutionary algorithm and cost data, a trade-off frontier has been developed. This frontier provides the trade-off relationship between nutrient reduction and the corresponding cost of placing a selected set of conservation practices. For example, a total cost of \$23 million/year (due to the adoption of selected conservation practices) is predicted to achieve a 15% reduction in nitrate and corresponding 45% reduction in phosphorus at the watershed outlet.

While computationally intensive, this integration can produce very detailed information on least-cost approaches for the implementation of conservation practices, even with a large number of locations and options. However, there may be several significant limitations to this approach, including the enormity of the search space for the most efficient solution, the limited set of

conservation practices considered and the assumptions in their cost estimates, and the SWAT model's ability to replicate the impacts of conservation practices on water quality. This study is limited to a certain set of practices. Inclusion of other possibly relevant practices may alter the results. Both wetlands and buffer strips are important options but are omitted from the set because SWAT is not yet capable of reliably simulating these practices. Nonetheless, many more options are considered here and at a much finer spatial scale than in previous analyses. Finally, this tool could be very helpful for policymakers and stakeholders to explicitly see the trade-offs between cost and nutrient reductions.

## References

- Arabi, M., R.S. Govindraj, and M.M. Hantush. 2006. Cost-effective allocation of watershed management practices using a genetic algorithm. *Water Resources Research* 42, W10429, doi:10.1029/2006WR004931.
- Arabi, M., J.R. Frankenberger, B.A. Engel, and J.G. Arnold. 2007. Representation of agricultural conservation practices with SWAT. *Hydrological Processes* 22(16): 3042-3055, doi:10.1002/hyp.6890.
- Arnold, J.G., and N. Fohrer. 2005. SWAT2000: Current capabilities and research opportunities in applied watershed modeling. *Hydrological Processes* 19(3): 563-572.
- Bekele, E.G., and J.W. Nicklow. 2005. Multiobjective management of ecosystem services by integrative watershed modeling and evolutionary algorithms. *Water Resources Research* 41, W10406, doi:10.1029/2005WR004090.
- CARD (Center for Agricultural and Rural Development). 2007. Interactive SWAT (i\_SWAT). Iowa State University. Available at [www.public.iastate.edu/~tdc/i\\_swat\\_main.html](http://www.public.iastate.edu/~tdc/i_swat_main.html). (accessed February 2008).
- Deb, K. 2001. *Multi-Objective Optimization using Evolutionary Algorithm*. New York: John Wiley & Sons.
- Forrest, S. 1993. Genetic algorithms: principles of natural selection applied to computation. *Science* 261: 872-878.
- Gassman, P.W., M.R. Reyes, C.H. Green, and J.G. Arnold. 2007. The soil and water assessment tool: historical development, applications, and future research directions. *Transactions of the ASABE* 50(4): 1211-12850.
- Jha, M., C.F. Wolter, P.W. Gassman, and K.E. Schilling. 2009. TMDL analysis with SWAT

- modeling for the Raccoon River Watershed, Iowa. Manuscript submitted for publication.
- Neitsch, S.L., J.G. Arnold, J.R. Kiniry, and J.R. Williams. 2005. Soil and Water Assessment Tool Theoretical Documentation, version 2005. Temple, TX: USDA-ARS Grassland, Soil and Water Research Laboratory. Available at [www.brc.tamus.edu/swat/doc.html](http://www.brc.tamus.edu/swat/doc.html). (accessed February 2008).
- Schilling, K.E., and Y.K. Zhang, 2004. Baseflow contribution to nitrate-nitrogen export from a large agricultural watershed, USA. *Journal of Hydrology* 295: 305-316.
- Secchi, S., P.W. Gassman, M. Jha, L. Kurkalova, H.H. Feng, T. Campbell, and C.L. Kling. 2007. The cost of cleaner water: assessing agricultural pollution reduction at the watershed scale. *Journal of Soil and Water Conservation* 62(1): 10-21.
- Srivastava, P., J.M. Hamlett, P.D. Robillard, and R.L. Day. 2002. Watershed optimization of best management practices using AnnAGNPS and a genetic algorithm. *Water Resources Research* 38(3): 1-14.
- Veith, T.L., M.L. Wolfe, and C.D. Headwale. 2003. Optimization procedure for cost-effective BMP placement at a watershed scale. *Journal of American Water Resources Association* 39(6): 1331-1343.
- Wall, M. 2006. GALib: A C++ Library of Genetic Algorithm Components, ver. 2.4.6. Available at <http://lancet.mit.edu/ga> (accessed February 2008).
- Zitzler, E., M. Laumanns, and L. Thiele. 2002. SPEA2: Improving the Strength Pareto Evolutionary Algorithm for multiobjective optimization. P. 95-100. In K. Giannakoglou et al. (Eds.) *Evolutionary Methods for Design, Optimization and Control*. Barcelona, Spain: CIMNE.