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Simulation-Optimization Model for Non-point Source Pollution Management in Watersheds: Application of Cooperative Game Theory

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Abstract

A new cooperative watershed management methodology is designed for developing an equitable and efficient Best Management Practice cost allocation among landowners in a watershed. The approach intends to control the total sediment yield in the watershed, considering landowners' conflicting interests. Wet detention ponds, are considered as the only available options to the landowners. The quality of the storm water is evaluated by the Total Suspended Solid loading from the watersheds. The proposed methodology combines a watershed simulation model, named Soil Water Accounting Tool (SWAT), with an Ant Colony Optimization (ACO) module and the cooperative game theory approach. Integration of SWAT and ACO modules provide the best set of designs for any constraints on target sediment removal set forth by non-cooperative and cooperative behaviors of the stakeholders to participate in the coalition to minimize the total cost of management practice. Nash Bargaining Theory is used to investigate how the maximum saving on cost of the participating players in a coalition can be fairly allocated. The proposed method is illustrated by a hypothetical example. The results demonstrate the applicability of the methodology. For the hypothetical case example, the proposed methodology with grand coalition leads to approximately 48 percent cost saving.

Keywords: *Ant Colony Optimization (ACO), cooperative game theory, detention ponds, nash bargaining theory, Best Management Practices (BMP), SWAT*

1. Introduction

An effective storm water management program must contain elements and control practices to be the most cost-effective system. The combinations of practices that are most efficient for a specific area must be selected based on many site specific conditions and local objectives. In almost all cases, the use of wet detention ponds is an important storm water control that should be given serious consideration.

Wet detention basins are among the most common Best Management Practices (BMPs) being implemented to comply with United States (US) Phase II storm-water rules and impending to exceed Total Maximum Daily Load limits. Wet ponds are designed to have a permanent pool of water, which prevents the re-suspension of sediments in the pond from previous storm events. Microorganisms and plants in the permanent pool assist in biological uptake and degradation of pollutants. Additional storage is provided above the permanent pool level to detain the storm water. Properly designed wet ponds can achieve both pollutant removal and peak discharge reduction. If well designed and properly maintained, wet ponds can remove 70 to 90% of Total Suspended Solids (TSS), 60 to 70% of nutrients and 60 to 95%of heavy metals (United States Environmental Protection Agency (US-EPA) 1999). Wet ponds can also be designed to obtain significant flood control benefits, controlling post-development peak discharge rates to pre-development level for a determined design storm.

The runoff water is detained for varying periods of time, depending on the pond detention volume and the storm runoff flow rate and duration. Detention times (*residence*) can vary from several minutes for small ponds receiving high flows to many days for large ponds receiving relatively small flows. The permanent water is stored and treated until the runoff of next storm. In general, a higher level of nutrient removal and better storm water quantity control can be achieved in wet detention ponds than in other BMPs practices (US-EPA, 1999).

Ponds are usually designed individually, and so their interactions in integrated scheme are very often disregarded. Generating cost-effective pond locations and configurations that meet system-wide targets for total target sediment removal might be much more effective and efficient (Harrell and Ranjithan, 2003). Guang *et al.* (2004) developed a mathematical model of pollutant

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removal by wet ponds based on the mass balance principle and the release storage equation of linear and nonlinear depending on the wet pond shape and the spillway crest features. The pollutant removal and flow routing models were tested with data obtained from an actual wet pond for treating highway runoff. The predicted flow discharges and pollutant concentrations compared well with the observed data. Guo (1999) proposed a consistence procedure for sizing wet detention ponds for small urban watershed that minimizes discrepancy in the volumes between the inflow and outflow hydrographs. Mallin *et al*. (2002) evaluated and compared the pollutant removal efficiency of three wet detention ponds. In a fairly recent work, Emerson *et al.* (2005) evaluated a system of storm water detention basins at the watershed scale level.

Most of the proposed models for watershed simulation are based on simple equations and can only model the runoff in the basins. Therefore, employing either a fully or partially distributed model for simulating TSS at the watershed scale is adequate and essential to represent the physical processes. In this research, the Soil Water Accounting Tool (SWAT) platform is used to build a watershed simulation model (Arnold *et al.*, 1998). SWAT has been applied in several fields of water management. A very comprehensive application has been reported by Abbaspour *et al.* (1997). They used the SWAT platform for simulating all related processes in water quantity, sediment and nutrient loads in the Thur watershed in Switzerland. Later, Tolson and Shoemaker (2004) applied SWAT to New York City water supply reservoir named Cannonsville. They found that SWAT is a valuable tool that can be used to help evaluating the long-term effects of various phosphorus management options for mitigating pollutant loading to the reservoir. Rostamian *et al.* (2008) employed SWAT to successfully estimate runoff and sediment in two mountainous basins.

Facing conflict in water resource management is unavoidable. In many water resource projects, conflict arises in cost sharing of joint projects or over allocating the benefits of a coalition. Developing an efficient approach to conflict resolution in water resource management is essential. In recent years, game theory has successfully been applied to resolve conflicts in various national and international water resource management problems (Madani, 2010; Teasley and McKinney, 2011). Game theory has provided important insights into decision making in various fields of science and engineering. Nevertheless, game theory has not been used by its full capacity into system analysis in water resource management; “thus, game theory’s value might remain unclear to the water resources community due to lack of understanding on its basic concepts” (Madani, 2010).

Different versions of game theory have successfully been applied to variety of equitable, efficient, and fair allocation of cost or net benefit to the stakeholders (Lejano and Davos, 1995; Dinar and Howitt, 1997; Axelrad and Feinerman, 2008; Niksokhan *et al.*, 2009; Wang *et al.*, 2008; Wang *et al.*, 2007) and conflict resolution (Adams *et al.*, 1996; Supalla *et al.*, 2002; Tao and Wang, 2009). In recent studies, different game theory-based models have been employed for comparing incentives of stakeholders (Fernandez, 2005), managing water allocation and pollution conflicts (Wei *et al.*, 2010), water sharing conflicts in transboundary basins (Teasley and McKinney, 2011, Kucukmehmetoglu, 2012), water reallocation problem (Pfaff and Velez, 2012), trading water along a river and inter-basin water transfer (Wang, 2011; Mahjouri and Ardestani, 2009). In a most recent application Madani (2012) used Nash and Nash–Harsanyi bargaining solutions to explore the Federal Energy Regulatory Commission relicensing process, in which owners of non-federal hydropower projects in the United States have to negotiate their allowable operations, with other interest groups, mainly environmental groups. An interesting Multi-Objective Game-theory Model (MOGM) was developed and applied by Lee (2012) for assistance in decision making and balancing economic and environmental concerns in reservoir watershed management.

The objective of this paper is to develop and present an integrated simulation-optimization approach for the best management strategy for TSS loading from different sub-basins that are controlled by independent land owners. The proposed modeling scheme couples an Ant Colony Optimization (ACO) algorithm, as an efficient optimizer, with a SWAT model for simulating the watershed behavior to select the optimum decision vectors and associated payoffs for each landowner to optimally control the sediment release from their own basin in pre and post development conditions. The developers (players) are free to participate in a coalition to minimize the total cost of the pond constructing in a cooperative form. Nash Bargaining theory is used to investigate how the maximum saving cost of the participating players in a coalition can be fairly allocated to the players. Game theory has been used by the authors, as an alternative tool for analyzing strategic interactions between economic development (land use and development) and environmental preservation (water-quality protection and phosphorus release). Applicability and performance of the proposed modeling scheme is demonstrated using a hypothetical example. Although the idea of simulation-optimization modeling for developing the most desirable decision for TSS loading is not a novel idea, the concept of integrating full scale SWAT, ACO, and game theory model in a large scale problem for minimizing the total cost of a BMP and equitable cost sharing is of recent origin and has only been presented in this work.

2. Methodology

The presented simulation-optimization approach benefits from integration of three main components: (1) an optimizer (ACO), (2) a hydrological watershed simulator (SWAT) and (3) Nash Bargaining method as the cooperative game theory approach. Fig. 1 depicts the interrelation between the three modules; it shows the methodology starts with the generation of initial solutions with the proposed ACO model to be tested in the simulation model. Then, the simulation model receives the controlling inputs (proposed values for decision variables) from the optimizer to evaluate their performances considering both their feasibilities and fitness defined by the total management cost incurred.

The model objective is to obtain the least possible sediment removal cost to satisfy the pre-set environmental requirement on TSS loading to the downstream receiving water body. This aim can be achieved through the construction and operation of ponds of different sizes in different locations at each sub-basin. The proposed modeling scheme intends to develop a solution strategy that provides an economic incentive for the players to participate in the coalition. To achieve this objective, one has to define the primary optimum allocation of loads to the players in a non-cooperative environment.

In the proposed approach, the primary optimum load allocation is addressed by using a single objective load optimization model. In this model, each player tries his best to control the TSS from his own sub-basin while satisfying the requirement set by the environmental agency. Therefore, the methodology starts with minimizing the design and/or operation cost of the ponds for all individual players working independently to manage their own basin. To reach the target sediment removal for each individual player, ACO algorithm has been coupled with a SWAT model. The results of these solutions define the primary allocation of TSS loading to downstream water-bodies in a non-cooperative scheme. Then, the landowners as the players use their primary TSS loading to participate in different coalitions. These coalitions are formed to reduce their shares from the total cost. In other words, the cooperative game tries to minimize the whole cost of achieving total target sediment removal by forming a coalition and applying the simulation-optimization scheme. Finally, Nash Bargaining Theory is used to investigate how the maximum saving cost of the participating players in a coalition can be fairly allocated to each player.

Due to lack of adequate and supportive data for a real case of study, the proposed method is applied and illustrated in a hypothetical case of study. The methodology is illustrated in a watershed with few sub-basins in which the total TSS loading to the downstream water-body must be controlled according to the authorities' specifications. It is assumed that each sub-basin is managed by independent individuals (e.g., landowners or decision makers). To satisfy some equity criteria, each landowner is asked to control TSS loading from his watershed to the downstream water body in a predefined value. In this case, each landowner must control the TSS outflow from his catchment in a specified rate to satisfy the environmental restrictions. Without loss of generality in modeling scheme and solution methodology, it is assumed that wet pond construction is the only available alternative and feasible strategy. Therefore, the locations and dimensions of the wet ponds in the sub-basins are to be determined.

It is imperative to know that the players' rationale is the main assumption underlying any game theory based solution to the problem. In fact without this assumption the basic principles of the game theory is violated and its application is not justified. In this problem the players will participate in the coalition only if the participations in the coalition provide them more benefits, compared to the primary loading allocation scheme. In the non-cooperative form of the game (i.e., the primary loading allocation) the players try to satisfy the environmental restrictions individually. In this part, ACO algorithm is applied for each player separately in order to define the minimum cost for the reduction of the loading sediment.

At first, an ACO algorithm is used to evaluate the minimum pond constructing cost and its volume for a specified TSS loading reduction. Then, the volume of the pond is evaluated after determining its height. The hydrologic model uses the results and determines the loading TSS from the watershed. If the calculated loading TSS by the SWAT is more than the primary TSS loading, this design is not feasible and a penalty function is used. After penalizing the objective function (which was determined by the ACO before), the fitness of the answer is evaluated and ACO searches for a new answer again. This process is repeated for both cooperative and non-cooperative form (for each landowner individually and for both of then cooperatively).

The optimization algorithm of the problem is formulated as follow:

Minimize,

$$PONDC = \sum_i \sum_j PONDC_{ij} \tag{1}$$

Subject to,

$$TSS_{load} \leq TSS_{max}$$

$$A_i \leq A_{i\ max}$$

$$S_i \leq S_{i\ max}$$

Where $PONDC_{ij}$ is the cost of making pond number j in sub-basin i, A_i is the surface area of the pond in sub-basin number i which should be less than a maximum surface area A_{max}, S_i is the storage of the ponds which should be less than a determined maximum volume $S_{i\ max}$, TSS_{load} is the TSS loading from the basin and TSS_{max} is the maximum permitted TSS loading from the watershed that is agreed upon. The solution to this model provides the best strategy for individual players identifying their primary TSS loading with possible minimum cost.

In the second step, the land owners have the chance of making a coalition. In this stage, all possible coalitions (including grand coalition) are identified and the sub-basins are integrated into larger basins, accordingly. The optimization procedure will be employed to determine the minimum cost of pond constructing in the integrated system. In this situation different coalitions are formed to reduce the total TSS loading to the pre-specified level. In this step, players collaborate with each other to satisfy the environmental restriction set by the authorities in a cooperative form. Players try to minimize the total cost due to pond construction while reduce the loading rate of the TSS to the requested rate in a coalition. It is often expected to bear lower total cost as a result of coalition.

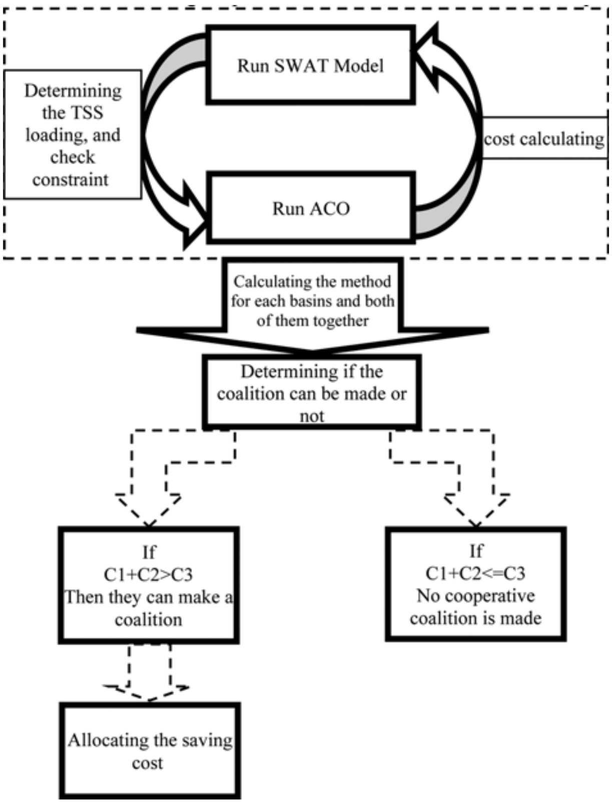

Fig. 1. A Schematic Plan of the Proposed Methodology where c1: is the Optimal Cost of the Player no. 1, c2: is the Optimal Cost of Player no. 2, and c3: is the Optimal Cost of Two Players in Cooperative Form

In the third step, if the cost of the pond construction of a determined coalition is less than those of the primary loading case, the Nash Bargaining Theory is applied to find equitable cost allocation. Fig. 1 presents a brief scheme of these steps.

2.1 Hydrologic Simulation Model

The SWAT platform is used to develop a hydrologic simulation model. SWAT is a basin-scale, continuous time platform that operates on a daily time step and evaluates the impact of management practices on water, sediment and agricultural chemical yields in the basins (Arnold *et al*., 1998). The major elements of this platform are: weather, hydrology, erosion, soil temperature, plant growth, nutrients, pesticides, land management, channel and reservoir routing. SWAT requires specific information about climate, topography, soil properties, land use and management of a watershed for simulation (Neitsch *et al*., 2002).

SWAT uses Digitals Elevation Models to define the sub-basins in a watershed, it can also account for the spatial heterogeneity of climate, topography, land use and soil in sub-basins. Sub-basins are further sub-divided in to Hydrological Response Units (HRUs). These units consist of homogeneous land-use, management and soil characteristics. SWAT uses the Soil Conservation Service curve number and/or the green-Ampt infiltration for runoff estimation. Groundwater flow contribution to total stream flow is simulated by creating shallow aquifer storage. Water flow is routed through the channel network using variable storage routing method or the Muskingum River method. The sediment yield in SWAT is estimated with the Modified Universal Soil Loss Equation (MUSLE) developed by Williams and Berndt (1977).

2.2 Ant Colony Optimization (ACO) Algorithm

During last two decades application of soft computing and metaheuristic algorithms in various fields of water management have received considerable attention (Cheng *et al*., 2002; Xie *et al*., 2006). Ant Colony Optimization (ACO) as a metaheuristic algorithm is derived from the observation of social insect behavior and especially by the behavior of ant colonies in finding optimal path between the source of the food and their nest. According to the discrete nature of this optimization algorithm, one can achieve better solution than other algorithms in discrete nature problems. The initial ACO was proposed by Dorigo *et al.* (1996). Like other search-based algorithms, ACO has successfully been applied to a wide range of water resource management problems such as, optimizing water distribution networks (Simpson *et al*., 2001; Afshar and Marino, 2006), single and multi-objective optimization of reservoir operations (Jalali *et al.,* 2006a, b, and 2007), and continuous reservoir operation (Madadgar and Afshar, 2009). The decision policy of ant colony algorithm $P_{i,j}(t)$ is the probability that edge (i, j) will be the selected point in iteration t given by Eq. (2):

$$P_{i,j}(t) = \frac{[\tau_{i,j}(t)]^{\alpha}[\eta_{i,j}]^{\beta}}{\sum_{l:(i,l)\in\theta_i}[\tau_{i,l}(t)]^{\alpha}[\eta_{i,l}]^{\beta}} \tag{2}$$

In Eq. (2), $\tau_{i,j}(t)$ is the pheromone concentration associated with edge (i, j) at iteration t, $\eta_{i,j}$ is the desirability factor. To control the relative importance of the pheromone and the desirability in this optimizing method α and β are considered, respectively. Finally, θ_i is the set of edges available at decision point i.

Pheromone at each edge (i, j) may be updated using Eq. (3):

$$\tau_{i,j}(t+1) = \rho\tau_{i,j}(t) + \Delta\tau_{i,j}(t) \tag{3}$$

In Eq. (3), ρ is a coefficient representing pheromone persistence ($0<\rho<1$) and $\Delta\tau_{i,j}(t)$ is the pheromone addition for edge (i, j).

2.3 Nash Bargaining Theory

There could be several classifications of game theory, dividing a game into cooperative and non-cooperative form is the most common classification. A cooperative and non-cooperative form of the game is very important to understand the behavior of the players. Briefly speaking, a game in which players are allowed to cooperate to improve their payoffs is called cooperative game. On the contrary, a game in which players are not allowed to cooperate and/or their interests are fully opposed to cooperative actions is called non-cooperative game.

In a cooperative form of the game players participate in a coalition and try to maximize their total welfare of the game. In these games players make a coalition to gain more than what they would have if they act individually. Some kind of the bargaining problems can be classified as the cooperative form of the game. Bargaining problems are concerned to the situation in which two or more players need to choose one of the many outcomes of a common cooperation. They obtain these benefits through coordinating their strategies with other players. In a bargaining game, the main question is: How the surplus (which is the resulting benefits of the cooperation) should be divided among the players? In order to answer this question, different methods have been proposed such as the Shapely (1953) or Nucleolus (Straffin, 1993; Dinar *et al.,* 2007). One of the best effective methods in a bargaining problem is Nash bargaining theory. Nash (1950) proposed the Nash Bargaining solution for two-player cooperative games that the players maximize their benefits over the treat points. The treat points in this method are the outcomes of the non-cooperative form of the game for players. In addition, Nash showed that just one solution exists which can satisfy the following appealing properties. The mentioned properties are: symmetry; pareto optimality; invariance; independence from irrelevant or Independence of Irrelevant Alternatives (IIA).

1. **Symmetry:** A bargaining solution $f(X, d)$ satisfies symmetry if for all symmetric bargaining problems (X, d):

$$(x_1, x_2) \in f(X, d) \Leftrightarrow (x_2, x_1) \in f(X, d) \tag{4}$$

Where f is the utility function, d is the set of disagreement points, X is the set of the decisions, and x_1, x_2 are the payoffs of the players' number 1 and 2, respectively. It means that payoff of the players should only depend on players' utility function and should not discriminate between the personalities of the players

2. **Pareto Optimality:** $f(X, d)$ should be a Pareto optimal solution, any solution should be better than the disagreement outcome.
3. **Invariance:** A bargaining solution satisfies invariance if whenever (X', d') is obtained from the bargaining problem (X, d) by means of the transformations $x_i \rightarrow \alpha_i x_i + \beta_1$ for $i = 1, 2$ where $\alpha_i > 0$ and $\beta_i \in R$ we have that $f_i(x', d') = \alpha_i f_i(x, d) + \beta_i$, for $i = 1, 2$. In addition, we can show this formulation in matrix form as follows:

   $A = \begin{pmatrix} \alpha_1 & 0 \\ 0 & \alpha_1 \end{pmatrix}$, $b = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}$ and thus, transformation can be

   defined as $\Gamma_{Ab} \rightarrow Ax + b$
4. **Independence of Irrelevant Alternatives (IIA):** A bargaining solution f satisfies IIA if $f(S', d) = f(S, d) \cap S'$ whenever $S' \subseteq S$ and $f(S, d) \cap S' = \phi$

   It could be shown that if the set of d_i for $i = 1, \ldots, n$ be the set of the disagreement points of the players; S is the set of the decisions and the set of f_i for $i = 1, \ldots, n$ be the set of the payoff function for them, the Nash solution is the answer of the following optimization program,

$$\text{Max } (f_1 - d_1)(f_2 - d_2), \ldots, (f_n - d_n) \tag{5}$$

Subject to, $f_i \geq d_i$ $(i = 1, 2, \ldots, n)$

$$f = (f_1, \ldots, f_n) \in S$$

This objective function is called Nash Product Objective function. The answer for a two player game with asymmetric bargaining power is as follows. First, the unique answer of the following equation is the answer of non-symmetric Nash solution.

$$\begin{aligned} &\text{Max } (f_1 - d_1)^{w1}(f_2 - d_2)^{w2} \\ &\text{Subject to, } d_1 \leq f_1 \leq f_1^* \\ &f_2 = g(f_1) \\ &w_1 + w_2 = 1 \end{aligned} \tag{6}$$

In the represented equation w_1 and w_2 are considered as the bargaining power of the players, and, f_1^* is the maximum possible amount for f_1 based on the situation. If we consider the powers of the player equal, then it will be like Nash bargaining solution that we mentioned before (Eq. 5).

3. Models Set up and Application

3.1 Model Set up

As any other modeling scheme, the model's set up parameters must be determined before being implemented. The first set is the tuning parameters for ACO which is determined through extensive trial and error procedure. A combination of 50 and 150 iteration (i.e., 7500 function evaluations) resulted in satisfactory results. The number of function evaluation refers to the total number of SWAT call and run in the solution procedure. The other tunable parameters in the ACO model are: $\beta = 0$, $\alpha = 1$, $\rho = 0.9$. The most important SWAT calibration parameters are presented in Table 1. Since the case study is a hypothetical one and no real data is available, any combination of values for the parameters may equally be used.

In this study, two adjacent watersheds with a main outlet and common receiving water body (i.e., river reach) are considered

Table 1. Range of Values for 13 Calibration Parameters in SWAT

	Parameter	Minimum Value	Maximum Value
Discharge Calibration	CN2	-0.15	-0.25
	ESCO	0.75	0.90
	SOL-AWC	0.1	0.23
	ALPHA-BF	0.055	0.075
	GW-DELAY	12	15
	CH-K2	30	35
	ALPHA-BNK	0.55	0.65
	LAT-TTIME	10	12
Sediment Calibration	SPCON	0.0015	0.0030
	SPEXP	1.1	1.3
	CH-EROD	0.3	0.45
	CH-COV	0.6	0.8
	ADJ-PKR	1.3	1.7

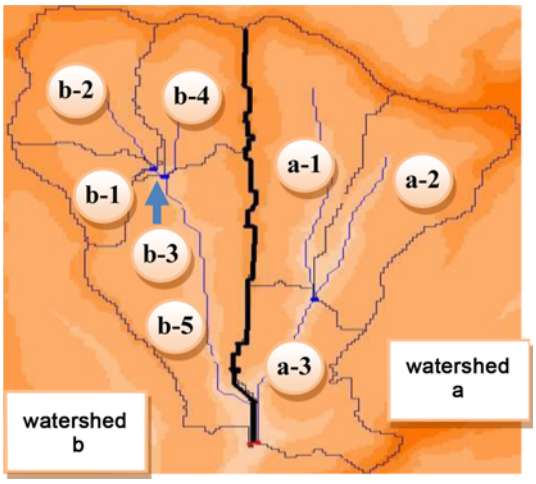

Fig. 2. Two Adjacent Watersheds Forming the Main Watershed

(Fig. 2). Each of the watersheds identified by *a* and *b* in Fig. 2 is assumed to be managed by a specific developer. Based on an integrated total maximum daily load study, it is assumed that each developer has to reduce his discharging TSS to a pre-determined rate in order to satisfy the environment restrictions. Without loss of generality in modeling scheme and the solution strategy it is assumed that the pre-specified rate of the TSS that should be reduced is 10% for each developer; however, this rate of sediment removal can be different. In addition, detention ponds are assumed to be the best way for reducing TSS from the watersheds. The decision variable in this problem is the height of the ponds to be constructed at different proposed sites. The ponds' locations are supposed to be fixed and shown by the fractions of the watershed area that drain to the ponds in each sub-basin. If a site is not to be selected for pond construction, its height and associated cost will turn out to be zero. The volume of the ponds can be calculated based on their heights and the geometrical relations between their width and length. Table 2 presents the possible heights of the ponds and the related widths and lengths as extracted from the geometrical and topographical information.

The area of the watersheds *a* and *b*are 71.96 and 73.98 km^2, respectively. Within watershed *a* and *b* there are three (a-1, a-2, and a-3) and five (b-1, b-2, b-3, b-4, and b-5) sub-basins, respectively. For each sub-basin various locations have been identified where ponds may potentially be constructed. Table 3 shows the predefined fixed fractions of the sub-basins area that drain into the ponds identified by their sub-basins titles; these locations are considered as the potential location for constructing

Table 2. Height and Related Width of the Ponds

Length of the ponds (m)	Width of the ponds (m)	Height of the ponds (m)
0.0	0.0	0.0
100.0	50.0	1.0
110.0	55.0	1.2
120.0	60.0	1.4
130.0	65.0	1.6
140.0	70.0	1.8
150.0	75.0	2.0
160.0	80.0	2.2
170.0	85.0	2.4
180.0	90.0	2.6
190.0	95.0	2.8
200.0	100.0	3.0

Note: For a higher TSS settling efficiency of , the length/width ratio of 2 is considered.

Table 3. Fraction Area of the Sub-basins that Drain to the Ponds

Sub-basin	a-1	a-2	a-3	b-1	b-2	b-3	b-4	b-5
Fraction area drain	0.1	0.5	0.3	0.1	0.5	0.5	0.2	0.1

the wet detention ponds. For both watersheds the projects' life is assumed to be 10 years with 4% of the construction cost as annual maintenance cost. Construction cost per cubic meter of pond volume are assumed as $25 and $70 for ponds in watershed *a* and *b*, respectively. Table 4 shows the characteristics of watershed *a* and *b*. Finally, the loading TSS from the two adjusted watersheds *a* and *b* are 6.591 and 5.229 ton/ha/year, which should be less than 5.9319 and 4.7061 ton/ha/year, respectively. The loading TSS from the main watershed is 3.909 ton/ha/year which exceeds the allowable value of 3.5181 ton/ha/year. Although the case example is hypothetical, the model structure and solution procedure is quite general and is not case dependent. In real world case examples may other alternatives be available to the decision makers with different cost which will results in different results and benefits to the players.

3.2 Results and Discussion

The first stage of the solution to the problem finds the best option for each individual to manage the environmental authority set standards, i.e., the primary optimum allocation of loads to the players in a non-cooperative environment. This means each individual must be aware of his own best option and minimum cost for satisfying the environmental restriction. To do so, a single objective version of the proposed methodology was applied for each watershed individually to find the associated

Table 4. The Characteristics of Watersheds *a* and *b*

Info / Watershed	Simulation Period	Maintenance Cost	Constructing Cost Per Cubic Meter	Decision Variable	Area (km^2)
Watershed *a*	2 years	4% of the constructing cost	$25	height	71.96
Watershed *b*	2 years	4% of the constructing cost	$70	height	73.89

Table 5. The Optimized Results for Watershed *a*

Sub-basin	Fraction of the sub-basin area that drains to the pond	Length (m)	Width (m)	Height (m)	Cost ($)
a-1	0.1	100	50	1.0	176,314
a-2	0.5	130	65	1.6	477,574
a-2	0.3	100	50	1.0	176,314
				Total cost	830,202

Table 6. The Optimized Results for Watershed *b*

Sub-basin	Fraction of the sub-basin area that drains to the pond	Length (m)	Width (m)	Height (m)	Cost ($)
b-1	0.1	100	50	1.0	493,680
b-2	0.5	130	65	1.6	1,337,209
b-3	0.5	0	0	0.0	0
b-4	0.2	110	55	1.2	717,309
b-5	0.1	0	0	0.0	0
				Total cost	2,54,8198

best option and minimum cost. Results of the model for basin *a* and *b* are presented in Tables 5 and 6, respectively. Table 6 shows that to limit the total TSS leaving the basin *a* at 5.9319 tons/ha/year, the total minimum cost is $830,203. The best option will be to construct three detention ponds on sub-basins a-1, a-2 and a-3 with length, width and height dimensions of (100,50,1), (130,65,1.6), and (100,50,1) units meters, to which 10,50, and 30 percent of the sub-basins drain, respectively. Results in Table 6 show that the optimal solution for basin *b*, with five sub-basins, is to build three ponds at a total cost of $2,548,198; to limit the total TSS leaving the basin at 4.7061 ton/ha/year. There are two sub-basins where the optimal management scheme indicates not to build ponds, b-3 and b-5 (Table 6). In summary, the total management cost for basin *a* ($830,203) and *b* ($2,548,198) adds up to $3,378,400.

Table 7 shows the results for the grand coalition under an integrated water management scheme, in this case all the landowners cooperate to minimize the whole cost while achieving the sediment removal target. The total environmental cost decreased significantly, from $3,378,400 in the non-cooperative scheme to $1,758,880 in the fully cooperative grand coalition scheme, a total savings of $1,619,520. In this step a large basin was assumed with eight sub-basins and its minimum cost to reduce the total TSS to the pre-specified level at the outlet is determined. The optimal total cost and the suggested ponds with their design parameters are given in Table 7. Note that the grand coalition scheme recommends larger ponds in all the sub-basins of watershed *a* and no ponds in watershed *b*. In this case, to limit the total TSS leaving the basin at 3.5181 ton/ha/year, the total cost of system management is $1,758,880. Considering the total saving of $1,619,520, landowners may be encouraged to form the coalition and try to start a bargaining game.

Because economic savings can be obtained in the cooperative game, it can be assumed that the players have enough incentives

Table 7. The Results of the Cooperative form of the Game

Sub-basin	Fraction of the sub-basin area that drains to the pond	Length (m)	Width (m)	Height (m)	Cost ($)
b-1	0.1	0	0	0	0
b-2	0.5	0	0	0	0
b-3	0.5	0	0	0	0
b-4	0.2	0	0	0	0
a-1	0.1	100	50	1.0	176,314
a-2	0.5	170	85	2.4	1,226,675
b-5	0.1	0	0	0	0
a-3	0.3	120	60	1.4	35,891
				Total cost	1,758,880

Table 8. The Allocated Costs to Each Player After Applying Nash Solution

Bargaining power player		Allocated cost to	
Player 1 (w_1)	Player 2 (w_2)	Player 1 ($)	Player 2 ($)
0.0	1.0	830,203	928,677
0.1	0.9	668,251	1,090,629
0.2	0.8	506,299	1,252,581
0.3	0.7	344,347	1,414,533
0.4	0.6	182,394	1,576,486
0.5	0.5	20,442	1,738,438
0.6	0.4	-141,510	1,900,390
0.7	0.3	-303,462	2,062,342
0.8	0.2	-465,414	2,242,294
0.9	0.1	-627,366	2,386,246
1.0	0.0	-789,318	2,548,198

The positive numbers define paying and the negative numbers define gaining. w1 + w2 = 1

to participate in the coalition. In fact extra benefit or economic savings provides the basic incentives for the players. The rational players would find the cooperative activities more beneficial than the non-cooperative ones. The authors considered the saving cost as the profit that the players want to share between themselves to pay less than the non-cooperative form of the game. According to the Nash Bargaining formula, the related parameters are d1 = d2 = 0 as mentioned before; d1 and d2 are the disagreement points of the players where f1+f2 = $1,619,520. Depending on the players' bargaining power the allocated costs of the players are determined and demonstrated in Table 8.

4. Conclusions

The problem of non-point source pollution management in watershed scale is a complex and conflicting issue. Considering the wet pond alternative as the only solution available to the landowners in a BMP scheme, it was possible to determine the best location and size of the ponds for the minimum cost by coupling a watershed simulation model built in SWAT and an efficient optimizer using the ACO algorithm. These two components perform well and satisfactory in addressing the best solution while meeting at the same time the TSS load reduction to downstream. The Nash Bargaining theory was used to allocate the savings and to estimate the tradeoffs among players in the grand coalition cooperative game; this method proved to be applicable in this type of problems. Due to lack of available data on a real case basin, the proposed method was illustrated with a hypothetical case of study. A real-life application would strengthen the findings and provide stronger evidence and validation. A more comprehensive approach may address different options in a BMP system for pollution control strategy. The authors believe that the proposed approach is capable of considering those more options for decision makers with not much extra computational burdens.

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