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Optimal Prioritization of Best Management Practices Through a Simulation-Optimization Model to Sediment Load Reduction

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ABSTRACT

Aims: Watershed management practices are as appropriate solutions to control nonpoint sources of pollution at the watershed scale. Nevertheless, the best way to allocate limited resources is a challenge for watershed management efforts. Therefore, to achieve the most suitable strategies, the manager requires using mathematical techniques to prioritize management practices. In this regard, in the present study, an optimization-based Decision Support Tool (DST) was used to assign the optimal combinations of management practices at the Taleghan Dam Watershed, Alborz Province, Iran.
Materials & Methods: To achieve the present research goals, the Soil and Water Assessment Tool (SWAT) was applied to determine the sediment yield at the outlet of the watershed under different combinations of management measures and was coupled with a genetic algorithm in MATLAB computer software, which provides as the optimization engine.
Findings: the optimization results in the Taleghan Dam Watershed showed that implementation costs for 10% and 20% sediment reduction in optimal solution were obtained 110300$ and 235500$, respectively. The cost-effectiveness ratio of scenarios 10% and 20% sediment reduction obtained about 11030 and 11770.5 (dollars for 1% sediment reduction), respectively. The results also showed that filter strips and seeding are the most cost-effective option for sediment load control. Conversely, the grade stabilization structure and detention pond are the least cost-effective option.
Conclusion: This tool is transferable to other watersheds and is one of the practical approaches to watershed management. The presented tool could provide better information on location, the BMPs area, and the effects of measures on NPS and flood reduction in the watershed. The developed DST can be easily used in any other watershed.

Keywords: Integrated watershed management, Hydrologic model, Optimization algorithm, Resources allocation.

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Introduction

In recent decades, population growth and land-use change have increased flood and erosion-prone areas and consequently sediment yield and pollutants. Suspended sediment as an important Nonpoint Pollution Source (NPS) is a widespread environmental problem that threatens human beings. In Iran, specifically, soil erosion is of significant concern as it affects 120Mha out of a total of 165 Mha [1,2].

Applications of Best Management Practices (BMPs) are recommended for improving storm-water quality and quantity at field or watershed scales [3]. BMPs are divided into two categories include structural or non-structural practices[4]. According to implementation location, some BMPs such as tillage management, terraces, and filters strip are placed at field or Hydrological Response Unit (HRU) levels, and some of them, such as grassed waterway and grade stabilization structures, are placed in the tributary or main river channel.

Implementing BMPs at every watershed area is not applicable because only a few sub-watersheds may produce large amounts of soil loss in the watershed [5-7]. So, the maximum efficiency would achieve when BMPs implemented in these critical sub-watersheds. An important constraint in designing a watershed management program in a watershed is the implementation and maintenance cost of BMPs [8]. Therefore, for a trade-off between the hydrological impacts of BMPs and economic benefits, there is a need to identify optimal locations for BMPs at the watershed scale to maximize their effectiveness while minimizing their cost [2].

Different ways of BMPs can be applied for a given watershed. Therefore, a comprehensive decision-making framework for watershed management is required. Such complex problems can be solved by integrating a distributed hydrologic model and a suitable optimization technique [9-11].

A GIS-based spatial hydrologic model such as the Soil and Water Assessment Tool (SWAT) model [12] has been widely used in designing BMPs to control problems of high streamflow and NPS load in the watershed scale [13,14]. On the other hand, optimization evolutionary Algorithm applications such as Genetic Algorithm (GA) coupled with SWAT could be considered to decrease the watershed flood and NPS load effect effectively and at least cost [2,15,16].

Generally, BMPs are divided into two types of implementation: river channel networks, such as detention pond and grade stabilization structures, and hillslopes at farm or HRU levels, such as filter strips and parallel terraces. Accordingly, some previous studies [5, 9, 10,15,17,18] determined the placement of BMPs at sub-watersheds and river channel networks in the cost-effective approach by linking optimization algorithms with watershed simulation models.

Some other studies [6,11,16,19,20,21] developed a simulation-optimization model in different conditions regarding allocating land-use and BMPs in the cost-effective approach at farm or HRU levels. This model was successfully applied to maximize the NPS reduction and minimize the cost of BMPs implementation. In these approaches, the dynamic linkage between SWAT and the optimization algorithm has been substituted by a BMP database that serves as the real-time NPS load estimator and cost data provider. At the same time, these tools did not explore for BMPs scenarios at the river channel.

In summary, the previously mentioned studies have included some of the BMPs types (structural vs. non-structural, and river vs. farm-HRU level), and before application of these methods in other watersheds, users should modify their code for the project.

In this study, a user-friendly Decision Support Tool (DST) was developed by

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linking SWAT and a GA in MATLAB computer program to simultaneously suggest BMPs type and location of implementation at three configurations of HRU, sub-watershed, and river network. The proposed tool suggests the optimal pattern (type and location) of BMPs, which minimize the implementation cost to meet users regarding reducing the sediment load. DST was tested in the Taleghan Dam Watershed, where watershed management measures were urgently required, for 10% and 20% reduction on sediment yields over the 2005–2010 period.

Material and Methods

Decision Support Tool (DST)

In this study, a cost-effective DST was developed. It was applied for the selection and placement of BMPs in order to achieve the watershed management goals. This method was comprised of four components:

1) A well-known BMPs set were collected based on the watershed management practices, including detention ponds, grade stabilization structures, filter strip, land-use management scenario, strip cropping, parallel terraces, and grassed waterway. The representative parameters for the BMPs were used according to Arabi et al. [19], and Tuppad et al. [22].

2) SWAT hydrologic model, which evaluated the watershed baseline and the hydrological effectiveness of the BMPs (for example, reduction of sediment yield),

3) Economic component, which used unit establishment cost for each BMP and then calculated the BMPs implementation cost, and

4) A single-objective optimization of GA, which served as the optimization engine for the choice and placement of BMPs to find a solution for the problem.

The proposed framework was developed in MATLAB computer program. Figure 1 describes the components and relationships in the study simulation–optimization model for BMP selection and placement.

This user-friendly and transferable methodology can be used in other

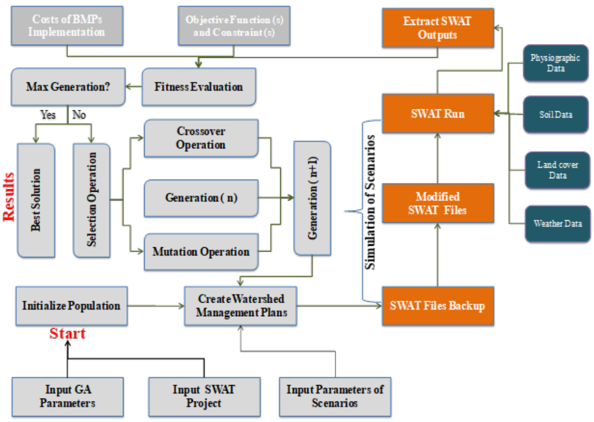

Figure 1) Flowchart of the proposed DST in MATLAB computer program including input data, hydrologic model, optimization algorithm, and their interactions

watersheds; users should only insert some information about watershed management plans (Figure 2). In addition, the developed DST is included popular structural and non-structural BMPs that users can select favorite BMPs for placing at different HRUs and river reaches.

In the developed DST, the procedure was simple and completely automated for creating watershed management plans, hydrological effectiveness of the BMPs, and selecting the best solution. The user only needs to copy the “TxtInOut” file in the SWAT project directory and paste it into the SWAT-GA directory path. The user then selects favorite BMPs, and SWAT parameter ID (par_n in Figure 2b) that need to incorporate each BMP into SWAT.

For example, when the model simulates filter strips, it needs to determine the width of filter strips. There are three options (10, 15, and 20m width) that the user can change for simulating (see par value in Figure 2b). Therefore, par-n (column 1 in Figure 2b) is selected, and par value (column 5 in Figure

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a

```
31    | NSUB   : Number of subbasins in the project setup
13    | OUTLET : Outlet subbasin number where the calibration is being performed
10    | IVARS  : Output variables of concern in the watershed (Choose from values below)
24    | NMONT  : Number of months in project
2     |NYEAR   : Number of years in project
3     |NBMP    : Number of BMPs
300   | MAXIT  : Maximum Iterations for GA
10    | NPOP   : Population Size in GA
0.7   | PC     : Crossover Percentage
0.4   | PM     : Mutation Percentage
0.02  | MU     : Mutation Rate
```

b

par_n	parname	Symbol	Units	parvalue
1	FILTERW	.mgt	m	10
2	FILTERW	.mgt	m	15
3	FILTERW	.mgt	m	20
4	CN_F	.mgt	-	-6
5	USLE_P	.mgt	-	0.10
6	USLE_P	.mgt	-	0.15
7	USLE_P	.mgt	-	0.20
8	CH_S2	.rte	-	5
9	CH_COV1	.rte	-	0.001
10	PND_FR	.pnd	-	10
11	PND_PSA	.pnd	-	10
12	PND_PVOL	.pnd	-	10
13	CN_F	.mgt	-	-3
14	USLE_P	.mgt	-	0.30
15	CH_COV1	.rte	%	-0.012
16	CH_COV2	.rte	%	-0.012

Figure 2) MATLAB file of developed DST and some input requirement

2b) is written by a user based on the desired BMPs simulated.

It should be noted that, in the developed DST, might be all BMPs applicable at a sub-watershed and or might be one or some BMPs not be applicable at a sub-watershed. In this program, users could also eliminate some sub-watershed (For example, sub-watershed which previously soil and water conservation programs have been done) to implement BMPs. In other words, the BMP stypes are predetermined for each BMP configuration unit at the sub-watershed scale. Since the aim of this study is to reduce only sediment yield depending on user opinion, so a single objective function method was used, which makes the algorithm easier and faster to implement. The Pareto curve considered in multi-objective function has not been needed in the single objective function method.

An editor of SWAT files was created in MATLAB for modifying SWAT .rte, .mgt, .sub, and .pnd files according to selected parameters in the previous section. Finally, these solutions are applied by the optimization model to find the best one and created new watershed management plans. The model searches for the most minor cost combination of BMPs in the watershed that meets hydrologic reduction criteria defined by the user (such as reducing NPS based on baseline condition) as a constraint.

Optimization Algorithm

Two decades ago, extensive growth in the development and application of genetic algorithms (GA) in particular had been seen to solve watershed management problems due to its ability to solve non-linear, nonconvex multimodal, and discrete problems [15]. Heuristic optimization methods such as GA provide near-optimal solutions by searching a global variable space; however, they do not ensure optimal global solutions [9]. Nevertheless, the main advantage of GA is to solve a discrete problem globally which is complicated by deterministic techniques. The deterministic techniques need continuous solution space and can converge to the local optimum point [10,15,23].

The following common elements characterize GA.

1) Generation of an initial population, each identified as a chromosome. Each chromosome (or individual) in the GA represents a particular watershed management scenario, with each variable being represented by a gene [6,16].

2) Computation of the objective function value related to each solution and subsequent ranking of individuals according to his metric and selecting the fittest solutions under specified selection rules. In the selection process, the fittest individuals are duplicated.

3) Selection, crossover, and mutation are the GA operations that generate new solutions.

4) The model will run for a user to define iterations or generations.

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To optimize the type and location of BMPs, some appropriate GA parameters were required. The genes were displayed by a "0 and 1" coding (or binary). In binary coding, 1 and 0 represent the implementation and no BMP, respectively [15]. The selection of individuals was performed by tournament and roulette wheel selection. For crossover performance, a random binary vector (0 and 1) was also created (uniform crossover). If the binary vector was 1, the algorithm combined the genes of the first parent [6].

Watershed Simulation Model

In the proposed framework, the SWAT model as a time continuous and semi-distributed hydrologic model was used. The model has been developed and used to predict the long-term effects of different management scenarios on daily, monthly, and annual streamflow [24,28]. SWAT uses a two-level classification phase. Preliminary identification of sub-watershed is carried out based on a topographic map, accompanied by further discretization using land-use and soil maps considerations. Areas with the same soil type and land-use form of an HRU, a fundamental computational unit assumed to be homogeneous in hydrologic response to land cover change [26].

The simulation of watershed hydrology can be divided into two main phases by SWAT, i.e., land and routing phases. The land phase controls the quality (amount of sediment and nutrient) and quantity of water to the main river networks in each sub-watershed. The routing phase considers the movement of water, sediments, and nutrient [26,27,29].

SWAT predicts surface runoff for daily rainfall by using the curve number (CN) method. Soil loss and sediment yield are predicted using a modified version of USLE (MUSLE). Surface runoff and sediment are then routed to the watershed outlet [26].

SWAT model requires measured daily, monthly statistical weather data, digital elevation model (DEM), soil and land-use maps to define the physical watershed [26]. This study used the Sequential Uncertainty Fitting version-2 (SUFI-2) procedure to calibrate the SWAT model. It is an inverse optimization approach that uses the Latin Hypercube Sampling (LHS) procedure and a global search algorithm to examine the behavior of objective functions. SUFI-2 has linked to SWAT in SWAT calibration and uncertainty procedures the calibration package (SWAT-CUP) [28].

Evaluation of SWAT model performance was carried out by coefficient of determination (R^2), Nash-Sutcliff Efficiency (NSE), p-factor, and r-factor [30]. The R^2 indicates of relationship strength between the measured and predicted data. The range of NSE values is between $-\infty$ to $+1$. Moriasi et al. [30] classified NSE for SWAT performance evaluation. NSE>0.75are considered ''very good,'' whereas values between 0.50 and 0.65 as ''satisfactory'' [28].

Case Study

The Taleghan Dam Watershed, with 800 km^2, is located east of the Sefidroud Basin, Alborz Province, Iran (Figure 3). The weighted mean of elevation is 2948 m a.s.l. and varies between 1989 and 4363 m a.s.l..

The design and construction of Taleghan Dam were started in the last decade, and water stored in the dam started in 2006. The Taleghan Dam Watershed has undergone rapid land-use change and water resource system development for the agricultural, industry, and domestic water supply [26]. These changes could have devastating impacts on both the water balance and water quality of the watershed. Therefore, identifying critical source areas and then implementing the BMPs in the critical areas of the watershed is necessary for the Taleghan Dam Watershed. The peak of river flow and sediment load occurs in spring due to high soil antecedent moisture and spring

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rainfall events [25,31,32].

Low and moderate-density rangelands cover 90% of the Taleghan Dam Watershed area. Other land-uses (about 10% of the watershed) are under orchid, irrigated agriculture, and dryland farming. The analysis of the soil maps shows that the silt loam, loamy, and clay loam are the prominent soil textures in the watershed [33].

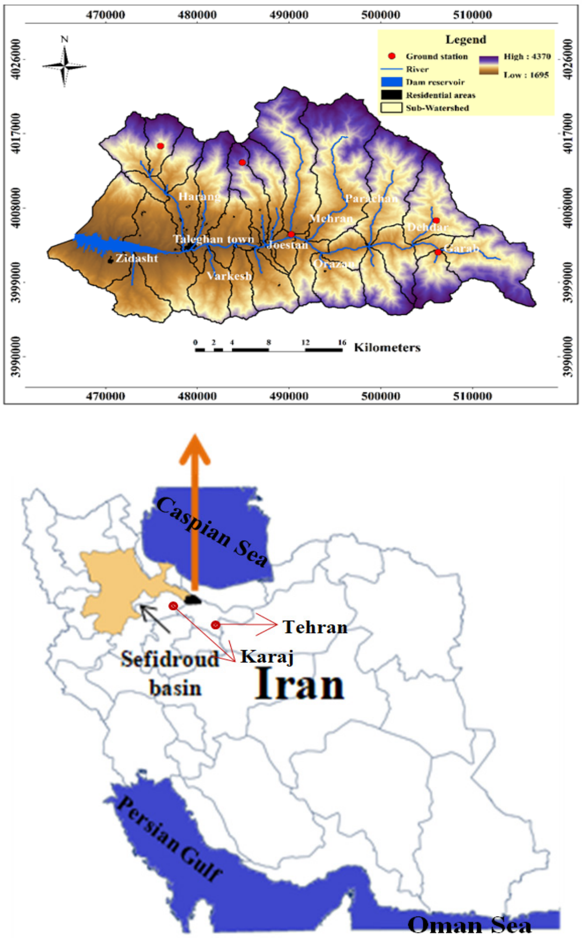

Figure 3) The delineation of the Taleghan Dam Watershed into SWAT with 31 sub-watersheds, gauging station, stream networks and the digital elevation model

Data Collection

SWAT model requires many data to be defined for the physical watershed:

The climate data include rainfall and temperature (max and min), were collected from 8meteorological stations located inside the study watershed from 2005 to 2010 through the Iran Water Resources Researches Company, Tehran.

- A 25× 25 m spatial resolution digital elevation model (DEM) was generated from the 1:25000 topography map (National Cartographic Center of Iran).
- Land-use and land cover maps for the year 2008 were prepared by Soil Conservation and Watershed Management Research Institute (SWMRI).
- A 1:50000 pedagogical soil map and textural soil profiles description for all soil types were obtained from the Faculty of Agriculture, University of Tehran.
- Daily streamflow and total suspended sediments (TSS) data from 2005 to 2010 measured at Galinak hydrometric station located in the Taleghan Dam Watershed outlet were used for the calibration and validation steps of SWAT.

Problem Definition

The current problem can be stated as the designs of BMPs (type and allocation) at the watershed scale that:

Minimize: total cost of BMPs

Subject to the following constraints:

(1) BMP implementation criteria constraints

(2) Land-use constraints

(3) Meets sediment reduction criteria

(4) Water balance in the watershed

Mathematically, this can be expressed as Eq. (1):

$$\text{Minimize } T_{Costs} = \sum_{i=1}^{m}\sum_{j=1}^{n} Cost_{BMP(x_{i,j})} \qquad (1)$$

Subject to:

$$SedL_{max} \leq SedL_{maxlim}$$

where TCostsis the total cost of BMPs implemented in a watershed. CostBMP (xi,j) is the cost of a j type of BMP implemented in area i. The total cost of execution of BMPs was evaluated by establishment and maintenance costs. Unit establishment costs were calculated based on the list price of watershed management practices in Iran (Plan and Budget Organization of Iran, 2016). Also,

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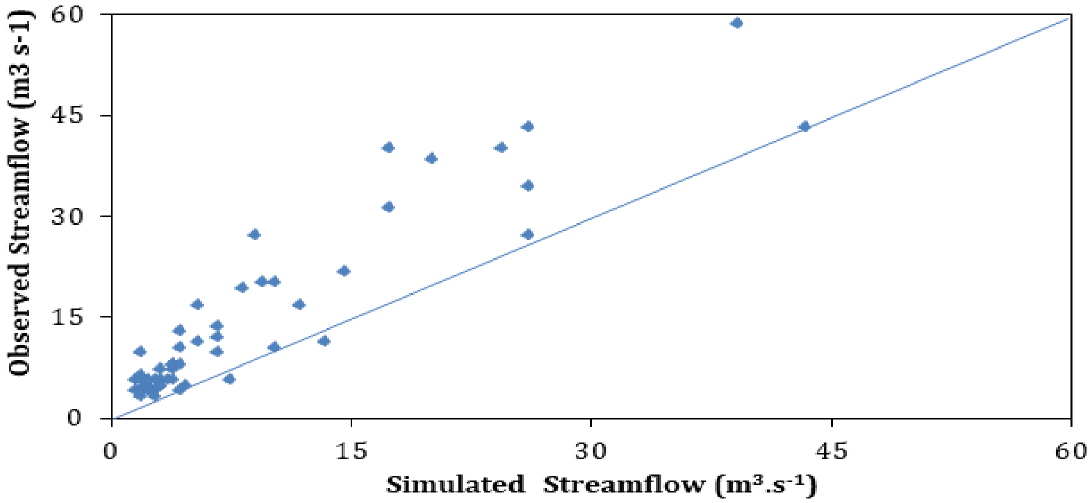

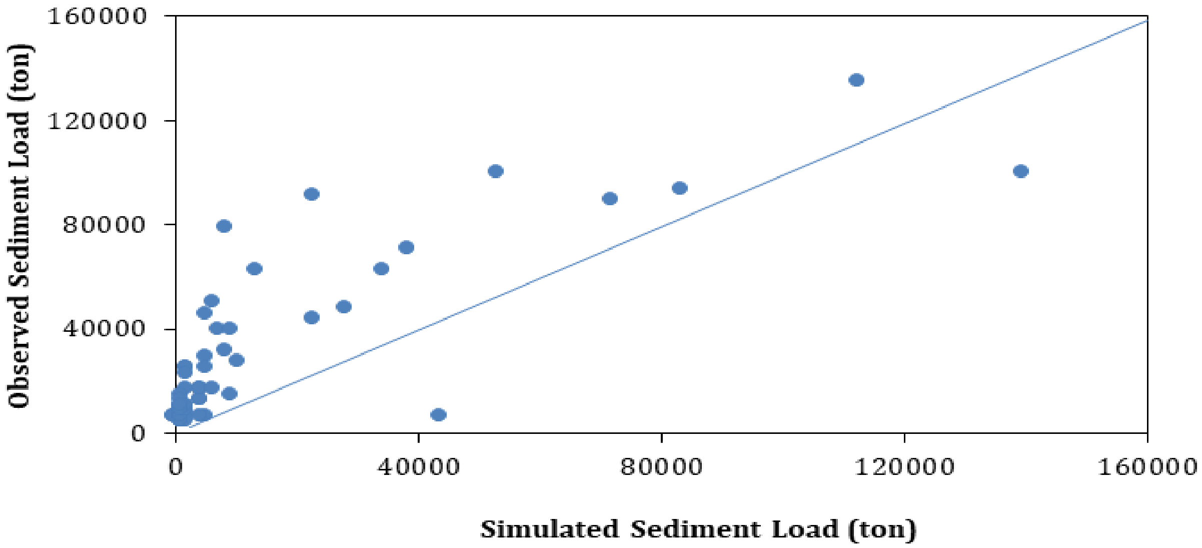

Figure 4) Correlation between the simulated and observed monthly streamflow in the Taleghan Dam Watershed

3% of the establishment cost is assumed for maintenance cost.$SedL_{max}$ and $SedL_{maxlim}$ indicate the maximum annual sediment load and user-defined maximum annual sediment load, respectively.

For this purpose, five structural and one non-structural BMPs were selected for placing in moderate and poor rangeland, dryland farming, and river network to reduce sediment yield in the Taleghan Dam Watershed. Table 1 shows the selected BMPs, SWAT parameters, and unit establishment costs for the Taleghan Dam Watershed.

Each chromosome has 133 gens or decision variables where 1 and 0 refer to implementation and no (implementation) BMP in a location. In this way, the possible number of solutions is 2^{133}.

For example, gen#80 represents placed Grade Stabilization Structure (GSS) in sub-watershed 18, and gen#105, which has moderate rangeland as the land-use in sub-watershed 30and, receives a filter strip.

After the definition of the model input, a DST was applied for a 10% and 20% reduction in the watershed sediment yield.

Results

SWAT Calibration and Baseline Scenario

The calibration process began with 30

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Table 1) BMP Type and unit establishment cost in the study area

Location	BMP Type	Parameter	SWAT input file	Unit	Unit establishment cost ($)
Poor Rangeland	Convert to moderate range by Seeding (Seeding)	Land-use parameters	.mgt	ha	60
Moderate Rangeland	Filter Strip (FS) (10 m)	FILTERW	.hru	m of filter	10
River Channel	Detention Pond (DP)	pnd_pvol	.pnd	m^3 pond volume	2
		Pnd_fr	.pnd		
		Pnd_psa	.pnd		
	Grade Stabilization Structure (GSS)	CH_S2	.rte	Structure	5000
Abandoned Dryland Farming	Parallel Terraces (PT) and Convert to orchard	SLSUBBSN	.hru	m length	25
		USLE_P	.mgt		
		CN2	.mgt		
		Land-use parameters	.mgt		

Table 2) Calibrated parameters of SWAT model with their ranges and calibrated values in the Taleghan Dam Watershed

parameter	Min – Max Value	Optimum value
Discharge calibration		
r-CN2.mgt	(0.08)-(-0.15)	-0.05
v-SMFMN.bsn	(2)-(6)	4.20
r-SOL-K.sol	(-20)-(20)	-0.12
v-SNOCOVMX.bsn	(200)-(300)	288.00
v-SNO50COV.bsn	(0.4)-(-0.6)	0.52
v-SMFMX.bsn	(3)-(7)	4.91
r-SOL-AWC.sol	(-0.2)-(-0.2)	-0.08
v-ALPHA-BF.gw	(0.03)-(-0.07)	0.056
v-GW-DELAY.gw	(5)-(15)	7.50
v-CH-N2.rte	(0.1)-(-0.2)	0.12
v-CH-K2.rte	(45)-(55)	0.51
v-SURLAG.bsn	(4)-(11)	7.51
Sediment calibration		
v-SPCON.bsn	(0.001)-(0.005)	0.003
v-SPEXP.bsn	(1.00)-(1.50)	1.10
v-CH_EROD.rte	(0.10)-(0.40)	0.21
v-CH_COV.rte	(0.20)-(0.70)	0.32
v-ADJ_PKR.bsn	(0.50)-(2.00)	1.13
v-PRF.bsn	(0.10)-(1.00)	0.31

parameters in the SUFI-2 algorithm, but only 18 parameters were found to be sensitive to discharge and sediment in the last iteration. Five hundred model runs were performed in each iteration. The parameter ranges and calibrated values are presented in Table 2.

Uncertainty in SUFI-2, calculated based on all sources of uncertainties by two factors, i.e., r- and p-factors. SUFI-2 searches to bracket most of the measured data (p-factor approaching the maximum value of 1) with the most petite possible uncertainty band (r-factor approaching the minimum value of zero) [28].

p-factor, r-factor, R^2, and NSE were calculated for the evaluation of SWAT model performance. In streamflow calibration, 59% of observed data fell in the 95PPU, whereas for sediment calibration, 53% of observed data were bracketed by the 95PPU band (Table 3).

Also, the SWAT predicted and observed data for streamflow and sediment are depicted in Figure4. Figure 4 clearly shows that the simulated monthly streamflow shows a good match with the observed monthly streamflow.

Solution of problem

Watershed management scenarios in the

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Table 3) Results of calibration and uncertainty analysis of SWAT in the Taleghan Dam Watershed

Criteria	Streamflow		Sediment	
	Calibration	Validation	Calibration	Validation
NS	0.80	0.77	0.64	0.61
R^2	0.85	0.82	0.66	0.61
r-factor	0.73	0.76	0.81	0.85
p-factor	0.67	0.64	0.56	0.52

Taleghan Dam Watershed include the random generation of combined measures (Table1). The simulation-based optimization model was run by an initial population equal to 80 chromosomes. Other GA parameters required to search the type and location of BMPs include crossover rate, mutation rate, and generations assigned 0.8, 0.05, and 100, respectively. The operation parameters used for the GA are selected based on a trial and error effort [6]. The developed DST was applied for 10% and 20% reduction on sediment yields at the watershed outlet. The type and location of BMPs for 10% and 20%sediment reduction scenarios are depicted in Figure 5.

Finally, the effects of optimal watershed management plans on streamflow were analyzed. Figure 6depicts monthly streamflow change due to BMPs implementation in the Taleghan Dam Watershed.

According to Figure 6, each alternative BMP design found with DST reduces the peak flow for significant rainfall events (in spring) but has no appreciable effects on baseflow (in summer). This type of watershed response is ideal since the maintenance of minimum streamflows is vital for water quality, water supply from the dam, and ecological function.

Discussion

NSE values for streamflow were 0.80 and 0.77 at calibration and validation stages, respectively. Figure 4 shows that SWAT consistently underestimated streamflow.

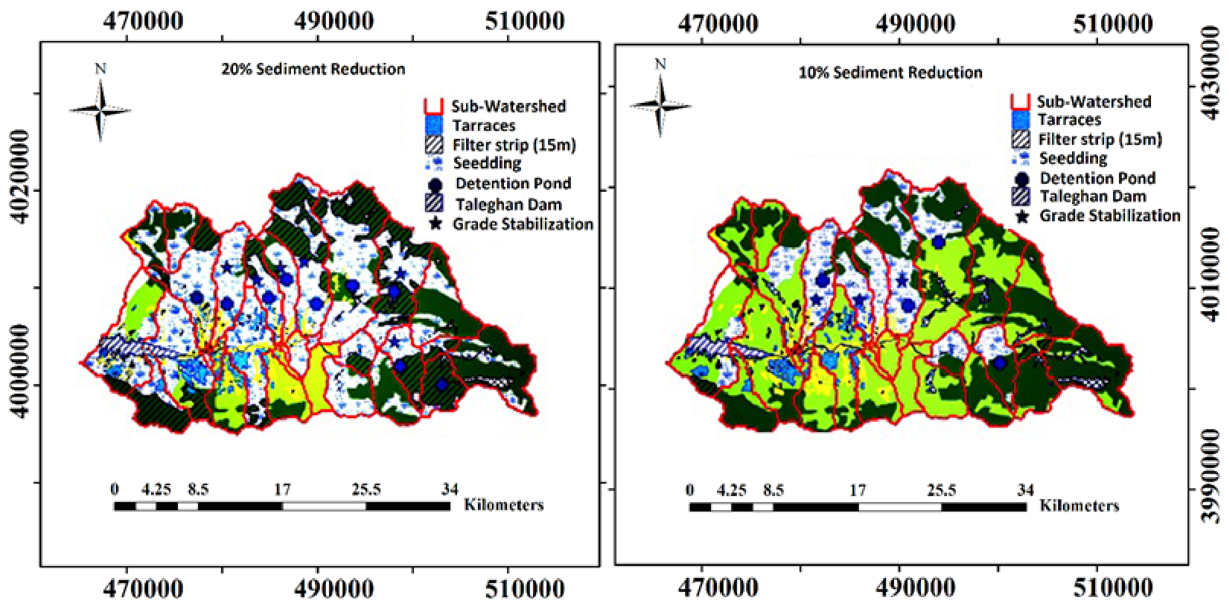

Figure 5) Optimal spatial allocations of BMPs for the 10 and 20% sediment reduction in the Taleghan Dam Watershed

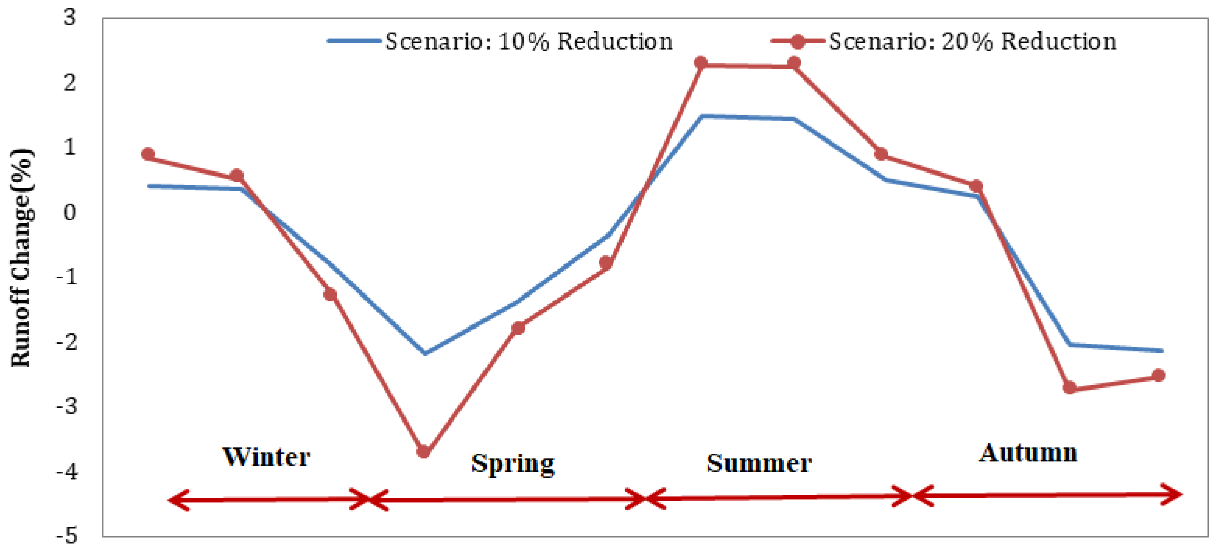

Figure 6) Effects of optimal design watershed-scale BMP configuration on mean monthly streamflow in the Taleghan Dam Watershed

This finding agrees with Akhavan et al. [34] findings that showed SWAT consistently underestimated streamflow in a region where snowmelt plays a crucial role in streamflow. Also, this could be due to one or more of the other uncertainties: errors in input data, errors in the observed data, or errors in the model itself [10,35,36]. NSE values of 0.64 and 0.61 were obtained for sediment calibration and validation, respectively. In this case, Kaini et al. [10] states that insufficient sediment load data and other uncertainties like streamflow calibration are expected to be the causes of the lower performance of sediment calibration.

Moriasi et al. [30] recommended threshold values of NSE for model calibration. Calibration processes are satisfactory when NSE is more significant than 0.50 for streamflow and 0.55 for sediment [30]. The results obtained here showed that NSE is equal to 0.80 and 0.77 for streamflow calibration and validation, respectively, higher than the generally accepted minimum NSE value (0.5) for river flow calibration [30]. NSE for sediment calibration and validation were 0.64 and 0.61, respectively, which are within the acceptable. Also, sediment calibration in the Taleghan Dam Watershed was higher than reported in previous studies [3,8,10,37,38].

The optimization results in the Taleghan Dam Watershed showed that implementation costs for 10% and 20% sediment reduction in optimal solution were obtained 110300$ and 235500$, respectively. The cost-effectiveness ratio of scenarios 10% and 20% sediment reduction obtained about 11030 and 11770.5 (dollars for 1% sediment reduction), respectively. The results indicate that the cost-effectiveness ratio is significantly lower in scenario '10% reduction' than scenario '20% reduction'. Comparison of selected scenarios showed that as the user-defined sediment reduction increased, the cost for a 1% reduction of sediment increased. This result agrees with a previous study [25] which state in minimum reduction scenario (in current study 10% reduction), GA can choose effective BMPs such as filter strip for implementation in most critical source areas. Therefore, BMPs combination with maximum efficiency or the less C/E ratio achieved. Nevertheless, in scenario

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20% reduction, the possible cheaper BMPs and most critical source areas were selected in the previous solution (10% reduction scenario), and GA has selected other BMPs (such as detention pond and grade stabilization structure) in the moderate critical area. Therefore, the cost-effectiveness ratio of the scenario increased. Therefore, according to Strauss et al. [34] ,the finding can be concluded that evaluation of critical source areas has demonstrated that effectiveness is much higher when BMPs are targeted at those areas.

In the first generation, GA was assigned different BMPs randomly to any site (HRU or reach of the river) and was predicted sediment yield from the watershed outlet. There are 80 solutions in each generation, and the solutions are ranked based on the cost; the least-cost solution is ranked highest. In this case, implementation costs for 10% and 20% reduction were obtained 1120100$ and 3251200$, respectively. Therefore, DST had a non-systematic implementation of BMP in the first generation but gradually progressed to a more systematic selection and placement of BMP while meeting the constraints.

The results show that filter strip and seeding (poor range management) is the most cost-effective option for sediment load reduction in all reduction cases as it has been used more than other options in the Taleghan Dam Watershed. Conversely, the grade stabilization structure and detention pond have been less used, and it can be stated that the grade stabilization structure and detention pond are the least cost-effective option in the Taleghan Dam Watershed. These findings agree with Karamouz et al. [15] and Kaini et al. [10] findings, which found that filter strip effectively reduces sediments. Also, according to Noor et al. [2] finding in the Taleghan Dam Watershed, the critical sediment source areas have high soil erosion and runoff. Therefore, these areas produce high runoff volume and exceptionally high sediment load.

Conclusion

In this paper, a Decision Support Tool (DST) was demonstrated to find the best combination of Best Management Practices (BMPs) to minimize their implementation costs and meet user define hydrological reduction criteria. In this tool, a single objective GA optimization model was coupled with the SWAT simulation model. BMPs considered in this DST were popular structural and non-structural BMPs include detention ponds, parallel terraces, grade stabilization structures, filter strips, land-use management scenario, strip cropping, and grassed waterway. The cost-effectiveness ratio of scenarios 10% and 20% sediment reduction obtained about 11030 and 11770.5 (dollars for 1% sediment reduction), respectively. The results indicate that the cost-effectiveness ratio is significantly lower in scenario '10% reduction' than scenario '20% reduction'. The results also show that filter strip and seeding (poor range management) are the most cost-effective sediment load reduction option in all reduction cases.

The proposed tool to the Taleghan Dam Watershed showed that the obtained optimum allocations could efficiently control sediment yield in the watershed. The presented tool could provide better information on where changes are required, how large the changes need to be, and how much the changes will reduce NPS and flood in the watershed. The developed DST can be easily used in any other watershed. The DST is a valuable model to find the optimal type and locations of BMPs in a watershed considering user define cost or hydrologic criteria. Finally, multi-objective optimization techniques such as Non-dominated Sorting

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Genetic Algorithm II (NSGA-II) include more BMPs in DST, such as tillage, to further improve this DST.

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