Cost-effectiveness analysis of different watershed management scenarios developed by simulation–optimization model

Hamzeh Noor, Somayeh Fazli, Mohammad Rostami and Ali Bagherian Kalat

ABSTRACT

The effort to control sediment yield at watershed scale is an ongoing challenge that needs to take into account trade-offs between two conflicting objective functions, i.e. economic and hydrologic criteria. Therefore, researchers have coupled hydrologic and multi-objective optimization models to find Pareto-optimal solutions. However, very limited studies have been conducted to analyse the cost-effectiveness (C/E) of scenarios obtained in the Pareto-front optimal. This could provide new information leading to effective watershed management. Therefore, in the present study, the Soil and Water Assessment Tool (SWAT) was used to simulate sediment yield under different combinations of best management practices (BMPs) and was coupled with the Non-dominated Sorting Genetic Algorithm (NSGA-II). The model attends to providing the Pareto-optimal solutions by minimizing the costs of BMPs and maximizing sediment reduction. The results of the application of the cost-effective optimization model in Mehran watershed, Iran, showed that the solutions in the Pareto-optimal front reduce sediment yield between 2% and 40.5% from baseline at costs of between $6,500 and $72,100, respectively. Finally, comparison of four sediment reduction solutions (i.e. 10%, 20%, 30%, and 40%) showed that the total cost and C/E ratio of solutions increased as the sediment reduction criteria increased.

Key words | BMPs, integrated watershed management, NSGA-II, optimization algorithm, SWAT

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INTRODUCTION

Applications of best management practices (BMPs) recommend improving stormwater quality at watershed scale (Artita *et al.* 2013; Emami Skardi *et al.* 2015; Noor *et al.* 2016). BMPs are widely accepted as effective sediment control measures at a watershed, including structural and non-structural practices (Arabi *et al.* 2006).

Only a few critical areas in the watershed may contribute large amounts of sediment in the watershed. Therefore, targeting critical areas in the watershed for implementing BMPs has long been recognized as an effective way to control sediment yield. In other words, it is not possible to implement BMPs at every area in a watershed (Muleta & Nicklow 2002; Veith *et al.* 2003; Noor *et al.* 2016). Implementation and maintenance cost of BMPs is another important constraint in designing a watershed management program in a watershed (Panagopoulos *et al.* 2012; Artita *et al.* 2013; Herman *et al.* 2015). Therefore, for trade-off between two conflicting criteria (i.e. cost and sediment reduction), there is a need to be able to identify optimal locations for BMPs at watershed scale.

For a given watershed there can be many different ways of targeting BMPs that give cost-effective hydrologic goals. Finding such a solution through on-site evaluation of different watershed management plans in a watershed is neither economical nor practically feasible (Maringanti *et al.* 2011). Random selection and placement of BMPs in the watershed

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is another method. However, such a solution does not have a directional effect to find an optimal solution (Maringanti *et al.* 2011). This makes the selection and placement of BMPs at the watershed scale a multi-objective problem, which has a large number of possible solutions, especially for a large watershed with heterogeneous soil and land cover. In other words, watershed management problems are nonlinear with a large number of decision variables and possible solutions (Karamouz *et al.* 2010). Meta-heuristic methods such as genetic algorithms handle the problems of discontinuities and nonlinearities which exist in most watershed management (Emami Skardi *et al.* 2015).

Some previous studies (Muleta & Nicklow 2002; Gitau *et al.* 2004; Arabi *et al.* 2006; Karamouz *et al.* 2010; Maringanti *et al.* 2011; Panagopoulos *et al.* 2012; Artita *et al.* 2013; Yazdi *et al.* 2013; Emami Skardi *et al.* 2015; Wu *et al.* 2016) developed an optimization model for allocation of BMPs at watershed scale to maximize non-point-source pollution reduction and minimize the implementation cost of BMPs. Meanwhile, Gitau *et al.* (2004), Veith *et al.* (2004), Karamouz *et al.* (2010), and Kaini *et al.* (2012) did not address the issue of multi-objective optimization and did not provide the trade-off curve between competing objectives. Also, very limited studies analyse the cost and effectiveness of solutions obtained in the Pareto-front optimal. The cost-effectiveness (C/E) ratio analysis is the popular criterion for comparison of different watershed management scenarios. The results of C/E scenario analysis depend on watershed characteristics such as soil, land cover and topography and are site-specific.

Therefore, in this study a time continuous distributed hydrologic model (Soil and Water Assessment Tool, SWAT) was coupled with the Non-dominated Sorting Genetic Algorithm (NSGA-II) in the MATLAB computer program for the simultaneous selection and placement of BMPs at watershed scale. This tool was applied to the Mehran watershed, which directly drains into Taleghan Dam where watershed management measures are urgently required. Finally, the optimal solutions were analysed based on their costs and sediment reduction.

MATERIALS AND METHOD

Study area

The Mehran watershed with an area of 97 km^2 is located on the north side of the Taleghan watershed, West Tehran (capital of Iran) as shown in Figure 1. The Taleghan watershed is located in Sefidroud Basin. The mean elevation of the watershed is about 2,948 m above sea level (a.sl) and varies between 1,989 m a.sl. and 4,363 m a.sl. Also, the mean slope is about 42%.

Design and construction of Taleghan dam started in the last decade and water-storage in the dam started in 2006.

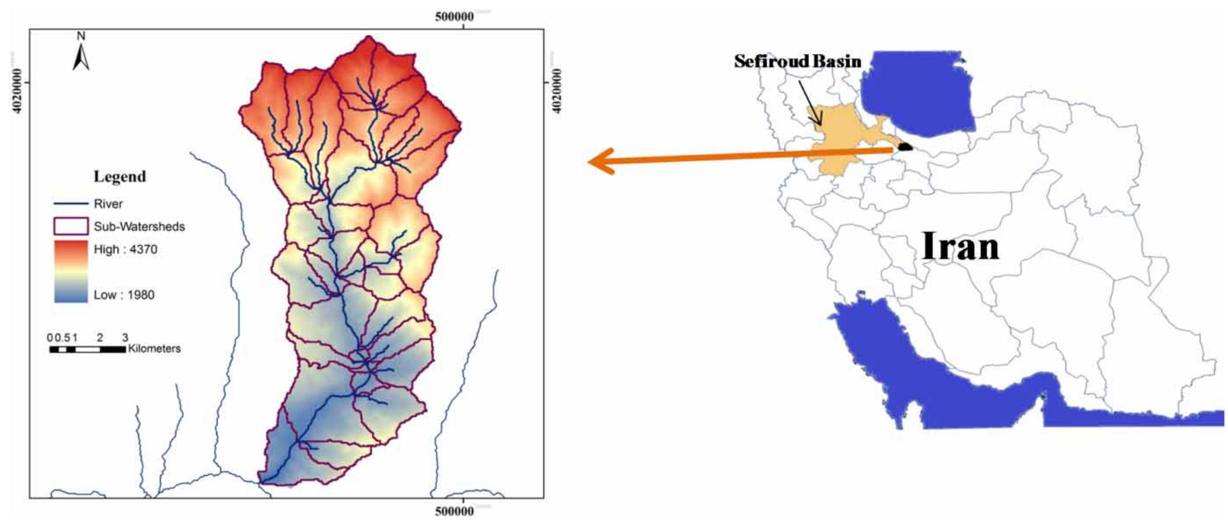

Figure 1 | Mehran SWAT watershed delineation with 37 sub-watersheds, stream networks and the DEM (digital elevation model).

The Mehran watershed has undergone rapid land-use change and water resource system development for agricultural, industrial, and domestic water supply (Noor *et al.* 2014b). These changes could have devastating impacts on both the water balance and water quality of the watershed. Therefore, in the Mehran watershed identification of critical source areas (CSAs) and then implementation of the BMPs in the critical areas of the watershed is necessary (Noor *et al.* 2014a).

Pasture is the dominant land use within the study area. Approximately 90% of the land within the watershed is covered by low and high density pasture. Close to 10% of the total area is covered by orchid, agricultural and other land uses. The locations of the Mehran watershed in Sefidroud basin and Iran are shown in Figure 1.

Watershed simulation model

The SWAT ((Arnold *et al.* 1998), which was jointly developed by Texas A & M AgriLife Research and USDA Agricultural Research Service, is a semi-distributed hydrological model. In the SWAT model, sediment yield is predicted using the modified universal soil loss equation (Equation (1)), and sediment routed through the river is reached using a stream power equation (Arabi *et al.* 2007).

$$S_{ed} = 11.8\left(Q_{surf} \cdot q_{peak} \cdot Area_{hru}\right)^{0.56} \cdot \mathrm{K_{USLE}} \cdot \mathrm{C_{USLE}} \cdot \mathrm{P_{USLE}} \cdot \mathrm{LS_{USLE}} \cdot \mathrm{CFRG} \quad (1)$$

where S_{ed} is defined as sediment yield (tonnes/day), Q_{surf} is the surface runoff volume (mm/day), q_{peak} is the peak runoff rate (m^3/s), $Area_{hru}$ is the area of the hydrological response unit (HRU) (ha), $\mathrm{K_{USLE}}$ is the universal soil loss equation (USLE) soil erodibility factor (0.013 tonne m^2 hr/(m^3- tonne cm)), $\mathrm{C_{USLE}}$ is the USLE crop management factor or cover management factor, $\mathrm{P_{USLE}}$ is the USLE support practice factor, $\mathrm{LS_{USLE}}$ is the USLE topographic factor, and CFRG is the coarse fragment factor.

The Soil Conservation Service (SCS) curve number (CN) method is used in SWAT to predict the volume of surface runoff. The peak runoff rate is predicted using a modified rational method. Runoff volume and peak along with the sub-watershed area are used to calculate the runoff erosive energy factor.

Data sources

The basic datasets of both spatial and non-spatial data required to set up the model inputs were as follows:

- Rainfall and temperature (maximum and minimum) data from three climatology stations located inside the watershed from 2005 to 2010 were collected from Iranian water resources research, Tehran.
- A topographic map at a scale of 1:250,000 produced by the National Cartographic Center of Iran and a digital elevation model (DEM) with a 25 m × 25 m spatial resolution was generated from the topographic map (Figure 1).
- A land-use map for the year of 2008 was prepared by the Soil Conservation and Watershed Management Research Institute. The land-use map used in this study is shown in Figure 2.
- A 1:50,000 pedological soil texture map was obtained from the Faculty of Agriculture, University of Tehran as well as some textural soil profile descriptions for all the major soils (Figure 2).
- Irregular suspended sediments and daily stream flow data from 2005 to 2010 measured at Mehran hydrometric station were used for the calibration and validation of SWAT.

In this application process, the Mehran watershed was divided into 37 sub-watersheds (Figure 1) by the SWAT model. The total model running time was from 2005 to 2010: the first year (2005) was defined as the warmup period, the years of 2006–2008 were the parameter calibration period and the remaining years of 2008–2010 were the model validation period.

CALIBRATION OF SWAT MODEL

In this study, the Sequential Uncertainty Fitting version-2 (SUFI-2) method as an inverse optimization approach was used for the calibration and sensitive analysis of the SWAT model. Parameter uncertainty in SUFI-2 is accounted for by uncertainty in the driving variables and measured data, parameters and conceptual model and shows the degree of all uncertainty. The *p*-factor is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). The *r*-factor is another measure which quantifies

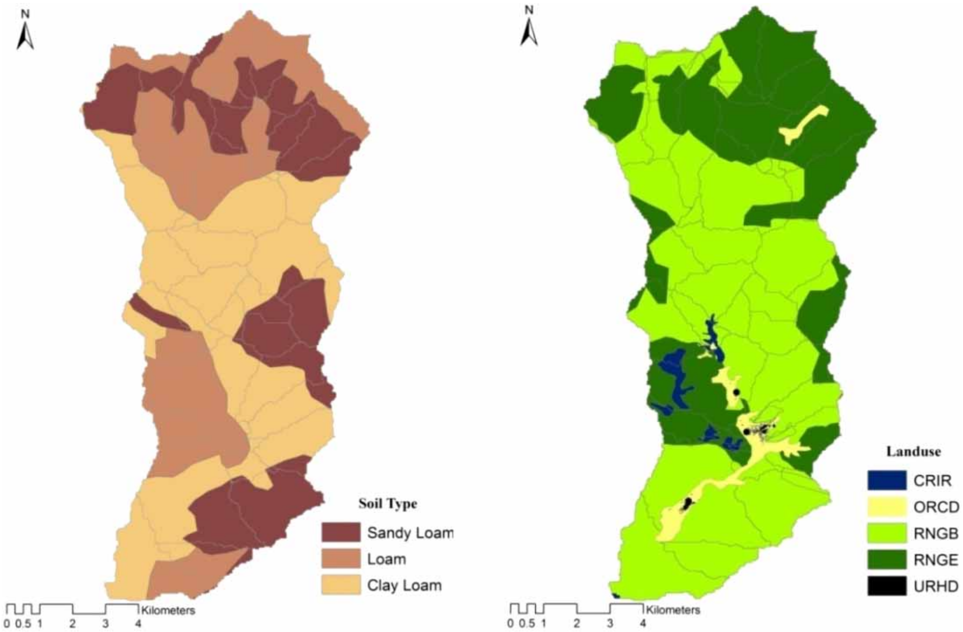

Figure 2 | SWAT land-use classification (right) and soil-type map (left) of the Mehran watershed.

the strength of a calibration–uncertainty analysis. The *r*-factor is the average thickness of the 95PPU band divided by the standard deviation of the measured data. SUFI-2 searches to bracket most of the measured data (*p*-factor approaching the maximum value of 1) with the smallest possible uncertainty band (*r*-factor approaching the minimum value of 0) (Akhavan *et al.* 2010). The coefficient of determination (R^2) and Nash–Sutcliffe efficiency (NS) were also used for performance evaluation of the SWAT model (Moriasi *et al.* 2007).

PROBLEM DEFINITION

The current problem can be stated as the selection and placement of BMPs at watershed scale. For this purpose, three structural and one non-structural BMPs were selected for placing in moderate and poor rangeland (filter strip, FS), abandoned dryland farming (parallel terrace, PT) and river network (detention pond, DP) to reduce sediment yield at the outlet of the Mehran watershed.

A FS is represented in the SWAT model by its width (FILTERW). The trapping efficiency for sediment or the $trap_{ef\_sed}$ parameter is calculated from Equation (2) (Arabi *et al.* 2007):

$$trap_{ef\_sed} = 0.367 \times \mathrm{FILTERW}^{0.2967} \tag{2}$$

A DP is a permanent pool located within sub-watersheds or HRUs. A DP receives inflow from a fraction of the sub-watershed or HRU area and reduces the sediment load (Arabi *et al.* 2007). In the Mehran watershed, the normal type of DP with zero permeability is used. The third selected BMP is PT. CN, $\mathrm{USLE_P}$ and average slope length or SLSUBBSN were modified for representation of parallel terraces in SWAT. For this purpose, the CN value was reduced by six units from its calibrated value (Arabi *et al.* 2007). SLSUBBSN was modified based on Equation (3):

$$\mathrm{SLSUBBSN} = (x \times S + y) \times 100S \tag{3}$$

where S = average slope of the field and x and y are dimensionless constants, x depending on the location of the watershed and the y value varying from 0.3 to 1.2 and depending on soil erodibility, cropping system and management, with lower values for more erodible soil.

In this study for selection and placement of BMPs at watershedscale, SWAT and NSGA-II were coupled in the MATLAB computer program. The proposed simulation–optimization model was comprised of three components:

(1) A time continuous distributed watershed model (SWAT).
(2) An economic component, which calculated the cost of their implementation based on unit establishment cost for each BMP. The total cost of BMP implementation was evaluated by establishment and maintenance costs. Establishment costs included the cost of BMP construction and maintenance cost is usually evaluated annually as a percentage of establishment cost (3% of the establishment cost). The establishment costs are assumed with respect to the current implementation costs in the region, which are mentioned in the contract documents.
(3) A multi-objective optimization algorithm (NSGA-II), which served as the optimization engine for the selection and placement of BMPs in the watershed in order to optimize and find solutions for the problem.

In the developed decision support tool (DST) the procedure for creating watershed management plans, hydrological effectiveness of the BMPs, and selecting the best solution was simple and completely automated as described below:

(1) Copy 'TxtInOut' file in the SWAT project directory and paste in the SWAT-NSGA directory path (MATLAB code).
(2) Select BMPs, and then, in the user-input file for each BMP (scenario) identify some information: (a) land-use code that the BMP will be placed in and (b) SWAT parameter ID that is needed to incorporate each BMP into SWAT.
(3) An editor for SWAT files is created in MATLAB for modifying SWAT .rte, .mgt, .sub, .pnd etc. files according to selected parameters in the previous section. After modifying the files, SWAT is run and after each run, the mean annual sediment is obtained, as well as the respective cost estimates for each BMP implementation. Finally, these solutions are applied by the optimization model to find the best solution, and create new watershed management plans.
(4) The model searches for the lowest-cost combination of BMPs in the watershed that have the greatest reduction of sediment at watershed scale.

RESULTS AND DISCUSSION

SWAT calibration and baseline scenario

The parameter ranges and calibrated values are presented in Table 1.

The *p*-factor, *r*-factor, R^2 and NS are calculated for performance evaluation of SWAT. In flow calibration, 59% of measured data were bracketed by the 95PPU, whereas for sediment calibration, 53% of measured data fell in the 95PPU band (Table 2).

Also, the SWAT simulated and measured data for flow and sediment are compared in Figure 3. As can be seen in Figure 3, the monthly observed and simulated flow have a good match. The NS coefficients for calibration and validation periods were 0.71 and 0.66, respectively. In the case of river flow calibration and validation, the graphical plot (Figure 3) shows that SWAT consistently underestimated the flow. This finding is in agreement with the findings of Akhavan *et al.* (2010) which showed SWAT consistently underestimated river flow in a region where snowmelt plays a key role in a flow similar to the Mehran watershed (Noor *et al.* 2016). 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 (Kaini *et al.* 2012). The NS coefficients 0.62 and 0.59 were obtained for sediment calibration and validation. In this case, Kaini *et al.* (2012) state that insufficient sediment load data and other uncertainties as in the case of flow calibration are expected to be the causes of lower performance of sediment calibration.

Moriasi *et al.* (2007) recommended threshold values of NS for model calibration. When NS is greater than 0.5 for river flow and 0.55 for sediment, calibration is considered satisfactory (Moriasi *et al.* 2007). The results obtained here showed NS coefficients equal to 0.71 and 0.66 for river flow calibration and validation, respectively, which are higher than the generally acceptable minimum NS value (0.5) for river flow calibration (Moriasi *et al.* 2007). NS coefficients obtained for sediment calibration and validation are 0.62 and 0.59, respectively, which are within the acceptable.

Table 1 | Calibrated parameters of SWAT model with their ranges and calibrated values

Parameters	Description	Min–Max value	Optimum value
Discharge calibration			
r-CN2.mgt	SCS CN II	(0.1)–(−0.15)	−0.06
v-SMFMN.bsn	Snow melt rate in winter	(1)–(7)	3.80
r-SOL-K.sol	Saturated hydraulic conductivity	(−20)–(20)	−0.15
v-SNOCOVMX.bsn	Minimum snow water content that corresponds to 100% snow cover	(200)–(380)	320.00
v-SNO50COV.bsn	Fraction defined as the ratio of snow water at 50% areal snow	(0.4)–(0.7)	0.58
v-SMFMX.bsn	Snow melt rate in summer	(3)–(8)	5.12
r-SOL-AWC.sol	Plant available water	(−0.2)–(0.2)	−0.10
v-ALPHA-BF.gw	Base flow recession coefficient	(0.01)–(0.09)	0.062
v-GW-DELAY.gw	Ground-water delay parameter	(1)–(15)	5.50
v-CH-N2.rte	Manning's value for main channel	(0.1)–(0.2)	0.12
v-CH-K2.rte	Channel hydraulic conductivity	(35)–(55)	40.00
v-SURLAG.bsn	Surface lag time	(1)–(10)	6.51
Sediment calibration			
v-SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be re-entrained during channel sediment routing	(0.001)–(0.005)	0.003
v-SPEXP.bsn	Exponent re-entrainment parameter for channel sediment routing	(1.00)–(1.50)	1.15
v-CH_EROD.rte	Channel erodibility factor	(0.10)–(0.40)	0.24
v-CH_COV.rte	Channel cover factor	(0.20)–(0.70)	0.35
v-ADJ_PKR.bsn	Peak rate adjustment factor for sediment routing in the sub-watershed	(0.50)–(2.00)	1.02
v-PRF.bsn	Peak rate adjustment factor for sediment routing in the main channel	(0.10)–(1.00)	0.28

Note: v means the existing parameter value is to be replaced by the given value and r means the existing parameter value is multiplied by (1 + a given value).

Table 2 | Results of calibration and uncertainty analysis in SUFI-2

	Runoff		Sediment	
Criteria	**Calibration**	**Validation**	**Calibration**	**Validation**
NS	0.71	0.66	0.62	0.59
R^2	0.73	0.67	0.64	0.61
r-factor	0.81	0.85	0.92	0.95
p-factor	0.59	0.56	0.53	0.50

Application of DST

The simulation-based optimization model was run on an initial population equal to 50 individuals (chromosomes or solutions). Other NSGA-II parameters which are required to optimize the selection and placement of BMPs include crossover and mutation rate, and total number of generations are assigned 0.75, 0.04, and 500, respectively. The Pareto-front includes 50 points or watershed management plans (including type and location of BMPs at sub-watersheds) for the Mehran watershed. Costs of BMP implementation and sediment reduction for the optimal solutions in the Pareto front are shown in Figure 4.

In the first generation, NSGA-II assigns different BMPs randomly to any eligible sub-watershed and then SWAT simulates sediment yield at the watershed outlet. There are 50 chromosomes (solutions) in each iteration and the solutions are ranked based on the cost and sediment reduction; the lowest-cost and highest sediment-reduction solution is ranked highest. As can be clearly observed, sediment yield in the Mehran

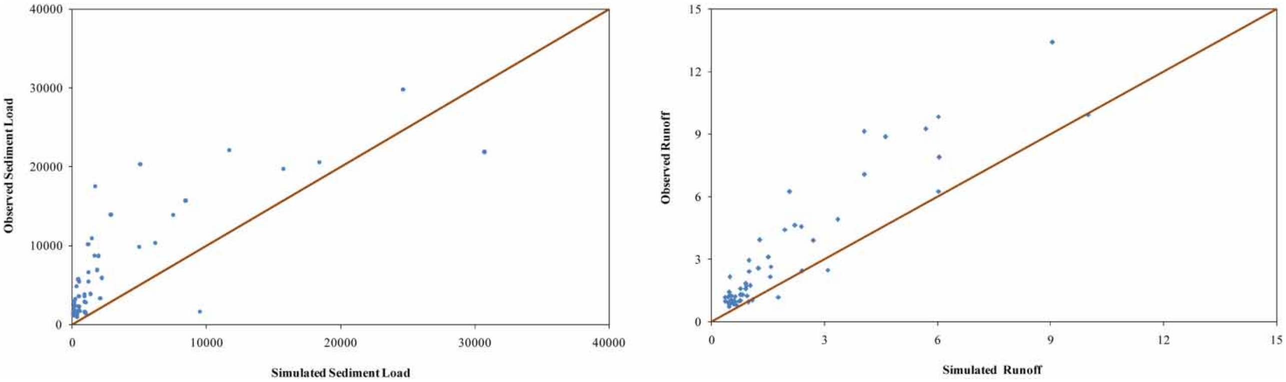

Figure 3 | Comparison between measured and SWAT simulated monthly runoff (right) and sediment yield (left).

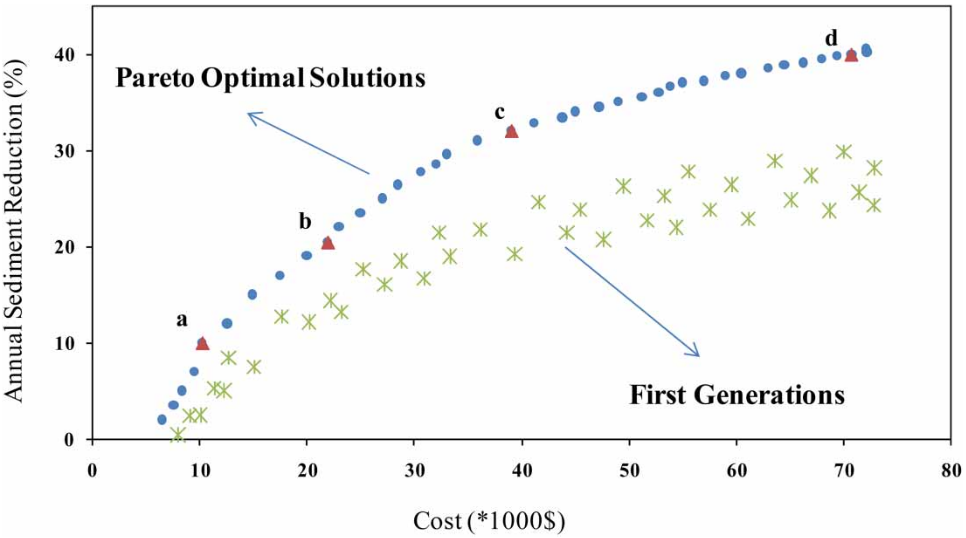

Figure 4 | Selected watershed management plans in Pareto-optimal solutions.

watershed was found to significantly decrease from the baseline starting even from the first generations (as most of the BMPs were included in the random initial population), which were actually effective in reducing sediment. But with similar costs, Pareto-front solutions in the first generation have lower sediment reduction solutions than Pareto-optimal solutions. In other words, according to sediment reduction, the developed watershed management scenarios in the first generation are more expensive. Therefore, DST progresses from a random BMP selection in the initial generation towards a more systematic BMP implementation while imposing improved objective functions. In this case, Artita *et al.* (2013) state that in the final generation, for a similar reduction of non-point-source pollution, the total number of BMPs is reduced significantly, and also only one or two BMPs are implemented in most of the sub-watersheds.

Each point in Figure 4 represents a watershed management plan with unique implementation cost and sediment reduction. Thus, the manager of the watershed can select a solution in the Pareto-front optimal for each investment cost or sediment reduction level.

DETECTION OF SOLUTIONS ON THE OPTIMAL TRADE-OFF FRONT

For effective watershed management and final decision-making, after obtaining many watershed management plans (solutions) with true Pareto-optimal solutions, it is important to reduce the large set of plans to a few representative plans. Therefore, we select four points in the

Pareto-front optimal solution for scenario analysis, which are shown in Figure 4. As can be seen in Figure 4, optimal solutions 'a', 'b', 'c' and 'd' reduce the sediment yield 10%, 20%, 30% and 40%, respectively, from the baseline scenario. It should be noted that all solutions in the Pareto front are nondominated solutions and are the best solutions.

Considering the first solution, indicated with 'a', this application management solution achieved a 10% sediment yield reduction from the baseline at a cost of approximately $10,240, providing a possibly acceptable compromise between conflicting objectives. Second and third selected watershed management plans (i.e. scenarios 'b' and 'c') selected and placed BMPs to reduce 20% and 30% of sediment yield from the baseline at a cost of $21,940 and $38,950 in the Mehran watershed, respectively. Solution 'd' had the best performance but also had more expenditure. This scenario reduced 40% sediment yield at watershed scale with a cost of about $70,747.

The C/E ratio of scenarios 'a', 'b', 'c' and 'd' obtained about 1,024, 1,070, 1,218 and 1,768 (dollars for 1% sediment reduction), respectively. The results clearly indicate that the cost-effectiveness ratio is much lower in scenario 'a' than in the other scenarios, especially scenario 'd'. In other words, the cost-effectiveness ratio of scenario 'a' is 57% less than scenario 'd'. Comparison of selected scenarios shows that the cost for 1% reduction of sediment increased as the sediment reduction criteria increased. To explain this result, it can be concluded sediment yield was significantly reduced from the baseline by all solutions, because most CSAs and BMPs effective in reducing sediment have been found. In the 10% reduction scenario, the optimization algorithm can select effective BMPs (such as FS) for placement in most CSAs. Therefore, a watershed management plan with maximum efficiency in reduction of sediment yield and the minimum cost- or least cost-effectiveness ratio was achieved. In the scenarios with 20% and 30% reduction, the possible cheaper BMPs and most CSAs were selected as in the previous solution (10% reduction scenario) and NSGA-II selected other BMPs (such as DP and PT) in moderate critical areas. Therefore, the cost-effectiveness ratio of the scenario increased. In the scenario with 40% reduction, NSGA-II selected available BMPs and placed at every subwatershed (CSAs, moderate critical and non-critical areas) in the Mehran watershed.

In the current study, among the considered BMPs, FS is the most preferred BMP in all reduction cases, whereas PT is the least preferred option. Parallel terraces are not considered at all in the cases of 10% and 20% criteria. FS is almost uniformly distributed throughout the entire watershed. It is remarkable to note that the parallel terraces are implemented only when the reduction criteria are increased. These results agree with the findings of Karamouz *et al.* (2010) and Kaini *et al.* (2012), who found that FS is very effective in reducing sediments and PT is the least preferred BMP. Also, based on the findings of Noor *et al.* (2016) in the Taleghan watershed, the critical sediment source areas have high soil erosion and runoff at their outlets. Therefore, those areas produce a high volume of runoff and particularly higher sediment load. It can therefore be concluded that evaluation of CSAs has demonstrated that effectiveness is much higher when BMPs are targeted at those areas (Strauss *et al.* 2007).

Finally, due to the difference between simulated and observed sediment yield (especially for the small values: Figure 3), the results of C/E ratio analysis may have uncertainty. However, it should be noted that, in the hydrological simulation study, the calibrated model represents all the physical processes of the watershed and can be assumed to simulate all the output data from the watershed. Also, in the current study the average of 5 years sediment yield was used for C/E ratio analysis, which includes all the small and big values. Finally, the goal of BMP implementation was 10%, 20%, 30% and 40% sediment reduction from the baseline (not based on the weight of sediment reduction), therefore, it is assumed that 10%, 20%, 30% and 40% reductions in simulated sediment equals, respectively, 10%, 20%, 30% and 40% reductions of observed sediment (regardless of the amount of sediment).

CONCLUSION

Studying all possible watershed management plans for the entire watershed to arrive at an optimal solution is tedious work. Therefore in this study, the NSGA-II optimization model was coupled with the SWAT hydrologic model. 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 sediment yield in the watershed. The developed DST can be a useful tool to implement user-defined criteria in a cost-effective manner by finding the optimal type and locations of BMPs in a watershed. Therefore, there are different options available to reach a desired watershed management goal. Finally, for selecting the final watershed management plan for the Mehran watershed, decision-makers and watershed managers can select one of the solutions in the Pareto-optimal front based on their decision criteria such as investment level, and environmental and social constraints.

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