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Synergetic Integration of SWAT and Multi-Objective Optimization Algorithms for Evaluating Efficiencies of Agricultural Best Management Practices to Improve Water Quality

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Abstract: Nitrate is one of the most complicated forms of nitrogen found in aquatic surface systems, which results in the eutrophication of the water. During the last few decades, due to agriculture and animal husbandry activities, as well as urban development, a significant amount of pollutants have accumulated in the Jajrood river in northern Iran. In this research, we simulated nitrate load in a rural watershed to assess the outlet stream's qualitative status and evaluate the influence of best management practices (BMPs). To accomplish this, we prepared, processed, and integrated different datasets, including land-use land-cover (LULC) maps, physiographic layers, and hydrological and agricultural datasets. In the modeling section, the Soil and Water Assessment Tool (SWAT) was used to simulate nitrate load over 28 years (1991–2019). Additionally, the multi-objective optimization algorithm (MOPSO) was implemented to reduce the intended objective functions, including the number of best management practices and the nitrate concentration considering different scenarios. The calibration of the basin's discharge and nitrate indicated that the SWAT model performed well in simulating the catchment's streamflow (R^2 = 0.71) and nitrate (R^2 = 0.69). The recommended BMPs for reducing nutrient discharge from the basin are using vegetated filter strips on river banks and fertilizer reduction in agricultural activities. According to the results from this investigation, the integrated model demonstrates a strong ability to optimally determine the type, size, and location of BMPs in the watershed as long as the reduction criteria change. In a situation of water scarcity, the studies reported here could provide useful information for policymakers and planners to define water conservation policies and strategies.

Keywords: water nitrate pollution; SWAT; best management practices (BMPs); multi-objective optimization algorithm (MOPSO)

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1. Introduction

Rivers are the primary source of water for human activities [1,2]. Additionally, they provide a crucial ecosystem of services such as food production [3,4], carbon storage [5,6], flood protection [7,8], and the preparation of spaces for recreation and transportation [9]. In the last few decades, due to the increase in water pollution caused by point (e.g., sewage treatment plants and factories) and non-point (e.g., agricultural and animal feedlot runoff) pollutants, water quality has become an important global concern [10,11]. Additionally, water monitoring and management practices are more important than ever due to the current situation of climate change and the expected increase in the intensity and frequency of related events, including droughts [12–14], floods [15,16], landslides [17,18], soil erosion [19,20], and water scarcity [21,22].

Optimal water management and conservation strategies, including water quality monitoring and improvement, require adopting effective practices [23–25]. In this regard, the implementation of best management practices (BMPs) is the main component of hydrological pollution monitoring and management [26,27]. For this purpose, an integrated modeling framework can be employed as a simulation optimization model to find optimal solutions [28,29]. Structural or non-structural agricultural BMPs are usually employed to reduce nitrate in vulnerable areas of the watershed, such as vegetated filter strips [30,31], contour farming [32,33], nutrient management [34,35], cover crops [36,37], tile [26,38], no-tillage [39,40], irrigation management [41,42], and grade stabilization structures [43,44]. To identify the BMPs, investigate their efficiency, and find out the best combination of them, well-organized and real-time studies are necessary to simulate the results and provide a set of scientific recommendations.

A number of modeling and optimization approaches based on a variety of tools, data sets, and practices have been studied in this context. In the modeling part, the integration of watershed or river basin-scale models with optimization algorithms, such as the genetic algorithm [45], multi-objective Non-dominated Archiving Ant Colony Optimization (NA-ACO) algorithm [46], Bayesian Networks (BNs) [47], and Multi-Objective Particle Swarm Optimization (MOPSO) [48], is the main methodology. For example, Zhang et al. [49] compared five optimization algorithms, including genetic algorithms, a modified complex mixed method, particle swarm optimization, differential transformation, and an artificial defense system, and used the SWAT tool as a hydrological model. The results showed that the particle swarm optimization algorithm outperformed the other models and could be integrated efficiently into the SWAT model. Aalami et al. [50] utilized the SWAT and reservoir water quality simulation (CE-QUAL-W2) models coupled with a MOPSO algorithm and used the ensemble model for the simulation. In another study, Taghizade et al. [51] used a MOPSO multi-objective optimization algorithm and the Storm Water Management Model (SWMM) to minimize quantitative objective functions. In terms of BMPs, different practices based on various scenarios have been considered. For example, in the study by López-Ballesteros et al. [52], the effectiveness of agricultural and combined BMPs (contour planting, filter strips, reforestation, fertilizer application, and check dam restoration) was assessed for the reduction of sediment and nutrients in the Segura River basin, Spain. In another study by Himanshu et al. [53], using a hydrological model (SWAT) in the Marvel watershed in India, evaluated and recommended BMPs (contour farming and filter strips) to control watershed degradation. Another study by Liu et al. [54] developed a long-term BMP (vegetated filter strips) optimization method (LBMP-OM), which was tested in the Daning watershed, China, to recommend BMP maintenance and replacement strategies. Several datasets, viz., remotely sensed [55–57], hydro-meteorological [58,59], agricultural, and ones for other human activities such as urbanization [60,61] are used widely. An exhaustive review of the literature shows that identifying BMPs is a rather complex process, which requires real-time and precise information about the pollutant sources, activities, hydrologic process, and landscapes. Additionally, the resulting BMPs are specific to time and place and the different roles they played in different regions.

Iran is a country in a severe water crisis and is regularly facing water quality issues under the combined pressure of urbanization [62], agricultural activities [63], population growth [64,65], fuel spillages [11], deforestation [66,67], and much more. The Latian dam is one of the most critical and important water reservoirs in Iran, which supplies the main part of the total water needs of Tehran. The streamflow is transferred to the reservoir by various branch streams, especially to the Jajrood river. In recent decades, the nitrate concentration in the Jajrood river has enhanced substantially due to poor management strategies, the excessive use of fertilizers in agricultural production, urban development, and tourism activities [68]. Considering the importance of the region, some previous studies have been carried out on the Jajrood river and its watersheds to investigate the point and non-point pollutants and their effects on water quality. Additionally, previous studies reported that nitrate pollution is one of the leading causes of eutrophication in water reserves [69,70]. From previous studies, it is now clear that a significant amount of pollutants contaminate the Jajrood River, and management practices must be implemented immediately to prevent further water pollution. However, the evaluation of different management scenarios and the identification of BMPs are not well studied as of yet.

The literature review for this study demonstrated that the application of the SWAT to simulate the impacts of BMPs on water quality urgently requires the attention of researchers. Therefore, a semi-distributed hydrological model and the SWAT were integrated into the MOPSO algorithm to identify the optimal BMPs for the Jajrood watershed. The main objective of this study is to identify the most effective and practical management practices to prevent pollution and improve water quality using a strategic combination of the SWAT tool and the MOPSO algorithm. This study was conceived with the following objectives considering the Jajrood watershed as the study area:

1. Develop a hydrological model for the simulation of streamflow and nitrate loading;
2. Evaluate the effects of different combinations of BMPs on nitrogen load reduction;
3. Explore the optimal combinations of BMPs and the best set of decisions that can control the water quality of the Jajrood river.

2. Materials and Methods

2.1. Study Area

This study was executed in the Jajrood watershed (approximately 710 km^2) of the upper Latian dam in Northeast Tehran, Iran. It is located between a longitude of 51°22′ and 51°55′ E and a latitude of 35°45′ and 36°50′ N (Figure 1). The Jajrood river originates in the Kholeno mountains at the height of the central Alborz mountain range at an elevation of 4375 m. The slope of the Jajrood river from the beginning to the Latian dam is 19.8%, its average slope is 20.2%, and the length of its main branch is 40 km [71,72]. Piezometric explorations prove that the Jajrood basin has some minor aquifers of the suspended type in the central and southern parts of the basin. In the lower southern regions, the aquifer is divided into basins separated by a clay layer [71].

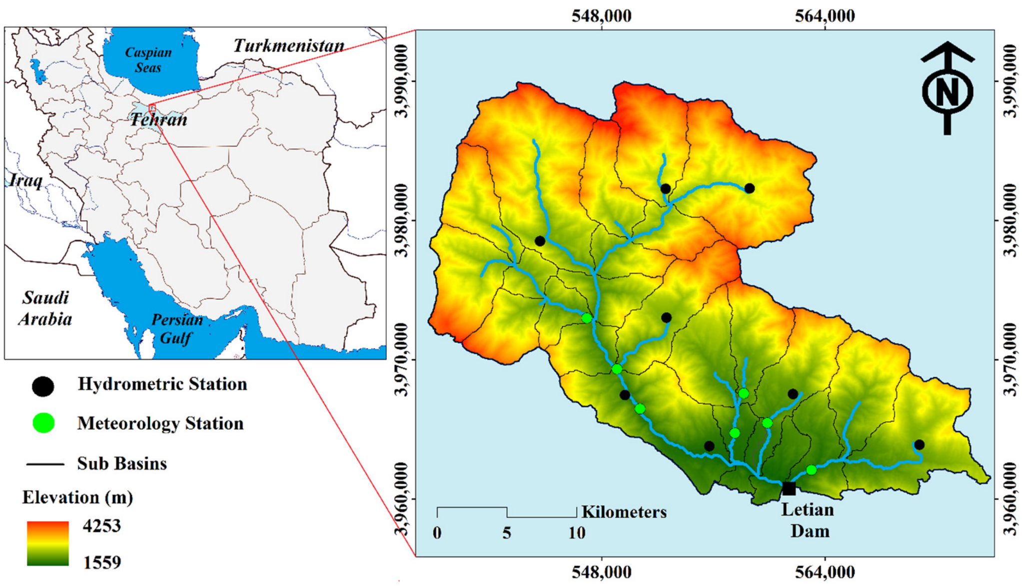

Figure 1. The geographical location of the Jajrood river watershed.

Meteorological observations from 1991 to 2019 (Firuzkuh Station: Lat. 35°50′ N; Long 52°50′ E; 1975.6 m a.s.l (Height above mean sea level)) characterized the mean annual precipitation and mean annual temperature to be around 650 mm and 15 °C, respectively [73,74]. This study area is shared by the three cities (Lavasan, Roodak, and Fasham) and 34 villages with a total population of around 52,000 (Iran Population and Housing Census 2016). According to the De Martonne climate classification, the climate of the study area is cold and semi-arid. The climograph of the studied area is shown in Figure 2. Climatology studies show that the air masses in the region are Mediterranean from the west and arctic from the north and northwest in the winter, and in the summer, tropical air flows from the Iranian desert and northwest currents flow from Central Europe. The study area's landscape is composed of a variety of LULC classes, including build-up areas, grasslands, rainfed and irrigated farmlands, and barren lands.

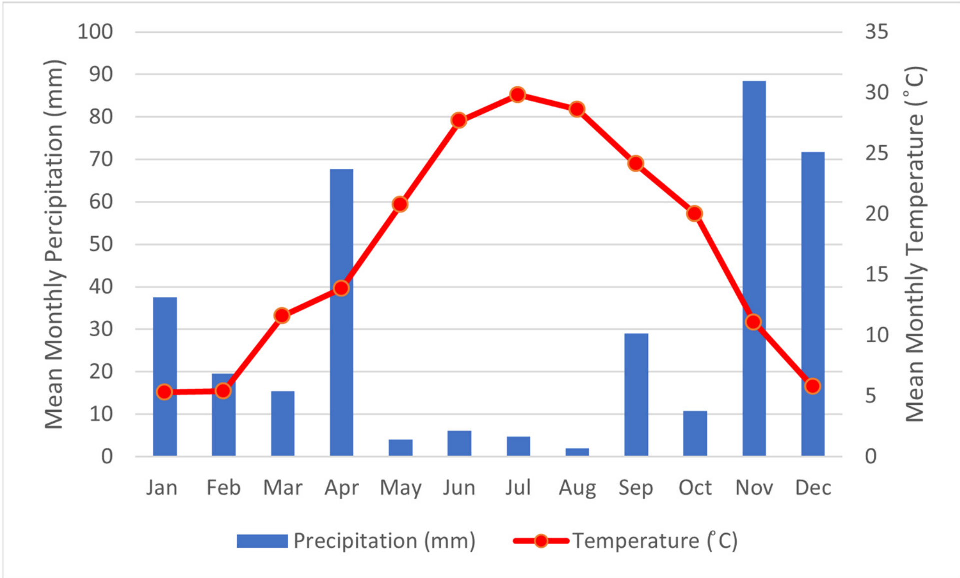

Figure 2. Climograph for the study area, based on data from Firuzkuh Station.

2.2. Research Methodology

The research methodology consisted of a number of tasks, including data collection and preprocessing, simulating the catchment's streamflow and nitrate load based on the SWAT model, model calibration and validation using SWAT-CUP, BMP application and evaluation, and BMP optimization (see Figure 3).

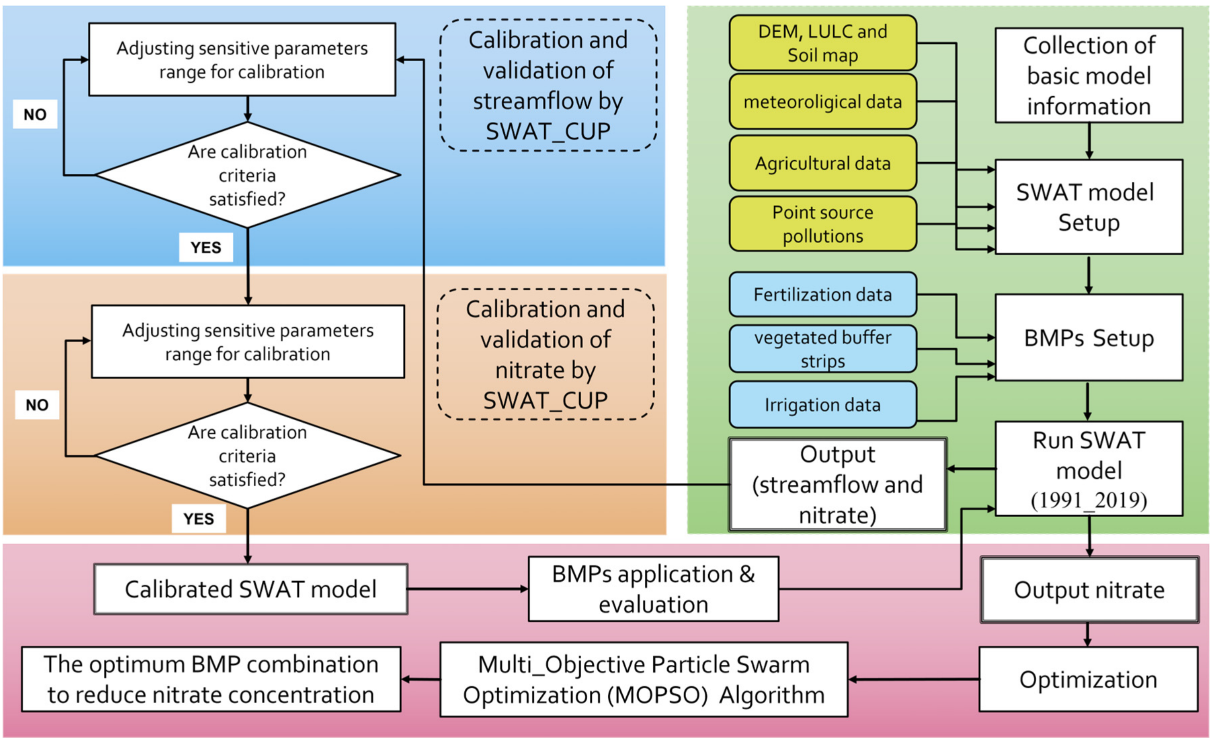

Figure 3. Schematic representation of the proposed methodology.

2.3. SWAT Model and Input Dataset

The soil and water assessment tool is a comprehensive, continuous, physically based, semi-distributed, and data-intensive model that estimates streamflow, sediments, and chemical pollutants on a daily time scale basis and simulates the effects of BMPs [75–78]. This model divides each watershed into sub-basins and hydrological response units (HRUs) based on the digital elevation model, LULC, and soil layers. HRUs are a part of the sub-basin with unique land use, management, and soil characteristics. In our research study area, 25 sub-basins and 823 HRUs were created.

In this study, the Shuttle Radar Topography Mission (SRTM 1 Arc-Second Global) elevation data with a resolution of 1 arc-second (30 m) was used to consider the elevation and slope information (see Figure 1). A soil map with a scale of 1:250,000 was procured from the Geological Survey and Mineral Exploration of Iran (Figure 3). For the LULC mapping, we used the capabilities of the Google Earth Engine (GEE) cloud computing platform and Sentinel-2 (S2) spectral and temporal metrics. Accurate and precise LULC mapping requires a sufficient number of training and validation samples that can be collected during in situ measurement or from very high-resolution (VHR) satellite images. Therefore, as a first step, we used VHR satellite imagery in Google Earth (GE) and visual inspection to collect a sufficient number of training and validation samples. Following that, to produce the LULC map, the GEE cloud computing platform was used to generate S2 image collections, and conduct preprocessing, feature extraction, classification, and accuracy assessment. To accomplish this, the S2 surface reflectance products ("COPERNICUS/S2_SR") between 1 April to 30 September (during the growing season) with a cloud cover of less than 30% were used (number of images = 27). Furthermore, in addition to spectral bands, we calculated vegetation indices, including SAVI (Soil Adjusted Vegetation Index), NDVI (Normalized Difference Vegetation Index), GNDVI (Green Normalized Difference Vegetation Index), and DVI (Difference Vegetation Index). Finally, using the spectral bands and vegetation indices, spectral and temporal metrics were generated based on statistic roles, including median, standard deviation, minimum, maximum, and 25th, 50th, and 75th percentiles [79,80]. For the LULC classification, we used the above-mentioned samples (70% of all samples) and the S2 spectral–temporal features (98 STMs) to train the random forest (RF) model. The accuracy assessment results (with 30% of samples) confirmed that further analysis could be conducted based on the produced LULC map (Table A3). The LULC and soil maps used are shown in Figure 4.

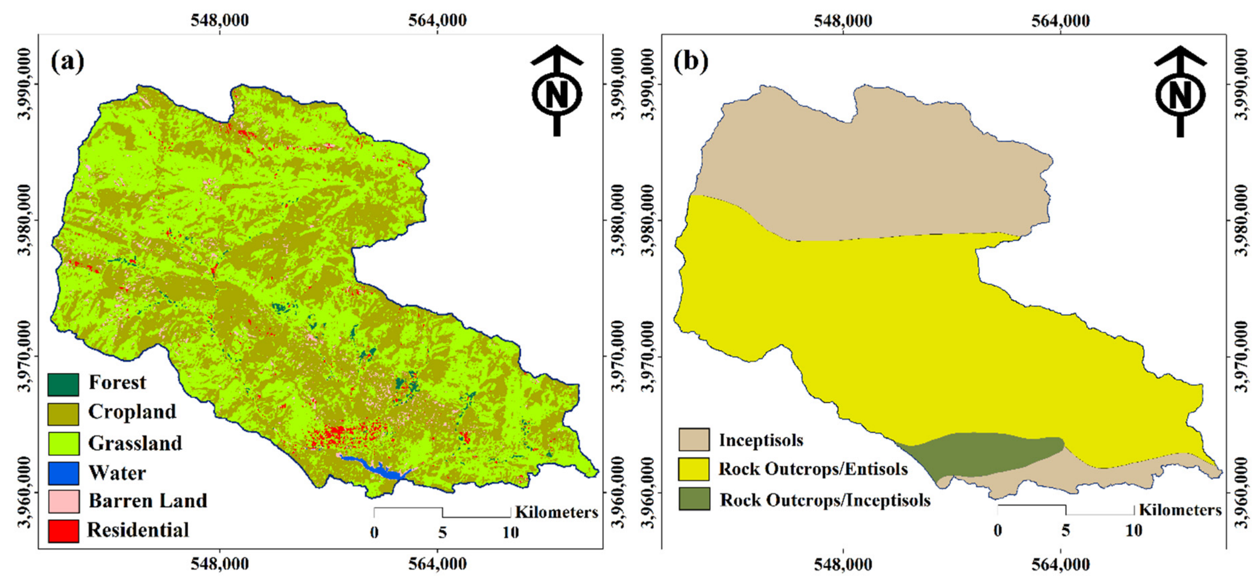

Figure 4. Layers used in SWAT model: (**a**) LULC map; (**b**) Soil map.

The meteorological parameters (daily precipitation, temperature, and relative humidity) from 8 different gauge stations were obtained from the Iran Meteorological Organization for a 28-year period (1991–2019). In addition, daily streamflow (1991–2019) and nitrate concentration (2014–2016) data were also collected at the Roodak gauging station of the Iran Water Resource Management Company. Additionally, management data (i.e., fertilizer application, irrigation, etc.) and point sources of pollution from towns, villages, and tourism populations were procured from the agriculture organization of Tehran province. The input of the management information in the model, including planting, irrigation, harvesting, tillage, fertilizer, and manure, is shown in Table 1. Additionally, the livestock which traditionally grazes in pastures, fallow lands, and forests were included. Assuming the weight and amount of waste produced, multiplying it by the number of livestock and taking into account the area of pastures and forests in the basin, which is equal to 61,108 hectares, the waste produced from each cow, sheep, and goat was calculated to be 1.54, 1.72 and 0.21 kg/day/ha, respectively.

Table 1. Management data and standard fertilizer application in the Jajrood river watershed.

Crop	Plant	Harvest	Tillage	Irrigation (mm)	Fertilizers (kg/ha)			
					Manure	K	P	N
Apple	21 March	22 September to 21 November	-	1006	25,000	170–230	150	200
Cherry	21 March	22 May to 21 August	-	1006	25,000	120	70	80
Apricot	16 March to 25 March	6 August	-	700–1000	25,000	180–200	50	80
Peach	16 March to 25 March	22 September	-	360	25,000	170–230	20–50	150–200
Spring wheat	7 October to 21 November	21 June to 21 July	Disk	264	15,000	100	100	200
Winter wheat	23 September to 21 November	5 June to 21 July	Disk	-	15,000	100	100	200
Spring barley	7 October to 21 November	21 May to 21 June	Disk	204	15,000	100	100	200
Winter barley	23 September to 21 November	5 June to 21 July	Disk	-	15,000	100	100	200
Alfalfa	3 April to 21 May	5 June to 6 December	Disk	967	25,000	500	100	100
Tomato	5 May to 21 June	22 August to 22 October	Disk	854	10,000	100	100	100
Cucumber	22 April to 5 June	22 June to 6 July	Disk	202	25,000	370–400	170–200	350–400
Potato	21 March to 21 April	22 June to 22 October	Disk	742–803	35,000	50–100	90–130	180–200

Sensitivity Analysis of Model Parameters, Calibration, and Validation

The sensitivity analysis of several parameters was performed to check their impact on the desired outputs of the model. This analysis was conducted with SWAT-CUP software (SWAT calibration and Uncertainty Procedures) and the SUFI-2 (Sequential Uncertainty Fitting version 2) algorithm. In the sensitivity analysis, t-stat and p-value are calculated for each parameter to show the sensitivity and importance of one parameter compared to other parameters. Based on this analysis, 10 parameters affecting flow rate (Table 2) and 5 parameters affecting nitrate (Table 3) were determined. These parameters are described in Tables A1 and A2.

Table 2. Streamflow-sensitive parameters in the study area.

Sensitive Parameter	Min Value	Max Value	Fitted Value	t-Stat	*p*-Value
CN2	25	90	65	1.436597	0.246872971
TLAPS	−10	10	9.5	21.64841	0
SNOCOVMX	0	500	305	−1.22826	0.632632198
SFTMP	−5	5	4.87	−0.39213	0.695139901
ALPHA_BF	−0.03	0.42	0.21	−2.12301	0.045010265
ESCO	0	1	0.33	−1.82773	0.064480029
TIMP	0	1	0.98	9.2514896	0.0014584
SURLAG	1	24	9	2.516264	0.004710358
GW_DELAY	0	500	169	16.4289	0
SLSUBBSN	10	150	21	−1.35082	0.025778202

Table 3. Nitrate-sensitive parameters in the study area.

Sensitive Parameter	Min Value	Max Value	Fitted Value	t-Stat	*p*-Value
ERORGN	0	5	1.2	8.0254612	0.00575489
NPERCO	0	1	0.15	−1.055649	0.01626484
RCN	0	15	2.5	15.6549056	0
BC3_BSN	0.02	0.04	0.038	−0.953108	0.25848901
BC2_BSN	0.2	2	1	−0.5219501	0.7619523

After selecting the sensitivity parameters, the initial stage is the calibration and validation of the streamflow. The model was calibrated and validated for eight hydrometric gauge stations in the Jajrood watershed with monthly observed streamflow data and plotted for the model's qualitative performance evaluation. Monthly streamflow data from these stations were calibrated using data from 1991 to 2011 and validated from 2012 to 2019. After calibrating the streamflow, the calibration and validation of nitrate were performed from 2014 to 2015 and 2015 to 2016, respectively.

The performance of the SWAT model was evaluated based on NSE (Nash–Sutcliffe efficiency) and R^2 statistical indices for streamflow and nitrate simulation [81–83]. One of the main drawbacks of R^2 is that it quantifies dispersion when considered alone [84]. The Nash–Sutcliffe coefficient has been utilized to evaluate the performance of hydrological models to eliminate these limitations related to using the correlation coefficient. These coefficients are defined as [85]:

$$R^2 = \left[\frac{\sum_{i=1}^{n} (Q_i - \overline{Q})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n} (Q_i - \overline{Q})^2} \sqrt{\sum_{i=1}^{n} (P_i - \overline{P})^2}} \right]^2 \tag{1}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q_i - P_i)}{\sum_{i=1}^{n} (Q_i - \overline{Q})} \tag{2}$$

where Q_i and P_i are observed and simulated data, respectively, and $\overline{Q}$ and $\overline{P}$ are observed and simulated means, respectively. The model performance is considered accurate for a range of NSE of >0.75 [86,87], while model performance is deemed acceptable for a range of 0.36 < NSE < 0.75 [85,88].

2.4. Evaluating the Performance of BMPs

Best management practices (BMPs) provide activities to reduce the pollution of surface and groundwater discharges from agricultural lands [89–91]. The current research focuses on the investigation of the experimental studies on the effects of BMP efficiency on hydrology and water quality, including the short-term efficiencies of BMPs [92,93], long-term performances of BMPs [94,95], the performance of BMPs over time taking into account maintenance activities [96], management innovations in quantitative and qualitative water issues [97,98], and existing BMP productivity data. According to the region's conditions, three management practices were applied in this study: fertilizer management, irrigation management, and vegetated filter strips.

2.4.1. Fertilizer Management

Proper nutrient management is essential to help maintain adequate nutrients for crops in the field and off the production line [31,99]. Farmers must choose the best management practices for their crops and land to maximize nutrient productivity and protect water quality [100,101]. Considering the existence of farms and orchards in the Jajrood watershed and the studies conducted, it is necessary to evaluate the effects of fertilization on river water quality. Nitrogen fertilizer was reduced by 25, 50, and 75% after applying fertilization management in the study area. Manure fertilizer was decreased by 50% in all these scenarios, and its effect was evaluated.

2.4.2. Vegetated Filter Strips

Vegetated filter strips are designed to reduce the size of downstream water and enhance the water quality of downstream water bodies [102]. A filter strip is a strip of dense vegetation that separates and filters runoff from upslope pollutant sources [103]. This filtration is conducted by reducing the speed of surface currents and, as a result, separating pollutants through settling particles [104]. Considering the high slope of the area and the reduction in nutrients under its influence, the widths of these filters were chosen to be 10 and 15 m.

2.4.3. Irrigation Management

By reducing irrigation, secondary water flows into rivers decrease. Due to the transfer of organic nitrogen and nitrate in the form of water solution and the reduction in dilution of agricultural runoff, it leads to an increase in nutrients. Irrigation management effectively controls the input flow to the reservoir or lake [105,106]. Additionally, irrigation management is the artificial application of water on land to help produce crops [107]. It was determined that increasing irrigation would not be possible due to water scarcity, so this study chose scenarios of 25 and 50% irrigation reduction.

2.5. Qualitative Optimization of the Model

After determining the type, size, and amount of BMPs suitable for the study area, the subsequent discussion pertained to which places are ideal for applying these BMPs in such a way that it has the most significant effect in reducing nutrients in the watershed's output. For this purpose, a MOPSO algorithm was implemented with quality objectives, viz.: (1) nitrate concentration; and (2) the number of applied BMPs in sub-basins. Particle swarm optimization (PSO) is a very efficient and effective method for solving complex multi-objective problems where conventional optimization tools do not work well. Each particle in the PSO optimization algorithm is like a bird in a flock, each with its own speed and position [108]. Particles move through the solution space to obtain the optimal global solution through self and social learning [109].

This algorithm selects suitable sub-basins and places for applying BMPs that significantly improve the quality of the basin's output. Due to the many decision variables and the nonlinearity and complexity of relationships between water quality parameters, a simulation–optimization approach can be a suitable tool to determine the optimal combination of BMPs in watersheds.

3. Results

3.1. Calibration and Validation Results for Streamflow and Nitrate

The model calibration and validation results for the streamflow simulation using monthly streamflow data from 1991–2019 and for nitrate simulation using the monthly nitrate data of 2014–2016 are depicted in Figures 5 and 6. Streamflow calibration and validation were applied for seven hydrometric gauge stations in the Jajrood watershed. The model performance illustrated calibration and validation are reasonable, and the simulated discharges are in good agreement with the observed discharges. Based on the results in the station scale, R^2 and NSE ranged from 0.42 to 0.88 and 0.36 to 0.80 for calibration and from 0.35 to 0.71 and 0.39 to 0.65 for validation, respectively (Table 4). Calibration and validation for nitrate were applied for Roodak Station. The model's performance was satisfactory, as the value of R^2 and NSE for calibration were 0.82 and 0.64, respectively, and for validation were 0.69 and 0.61, respectively.

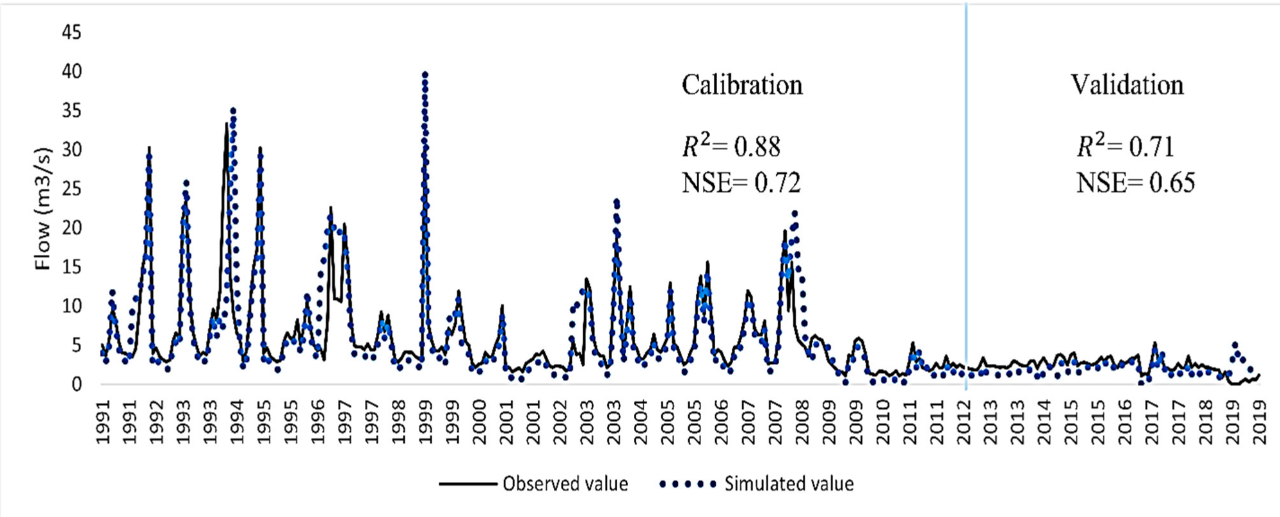

Figure 5. Monthly observed vs. simulated discharge during model calibration and validation for 1991–2019 at the Roodak gauge.

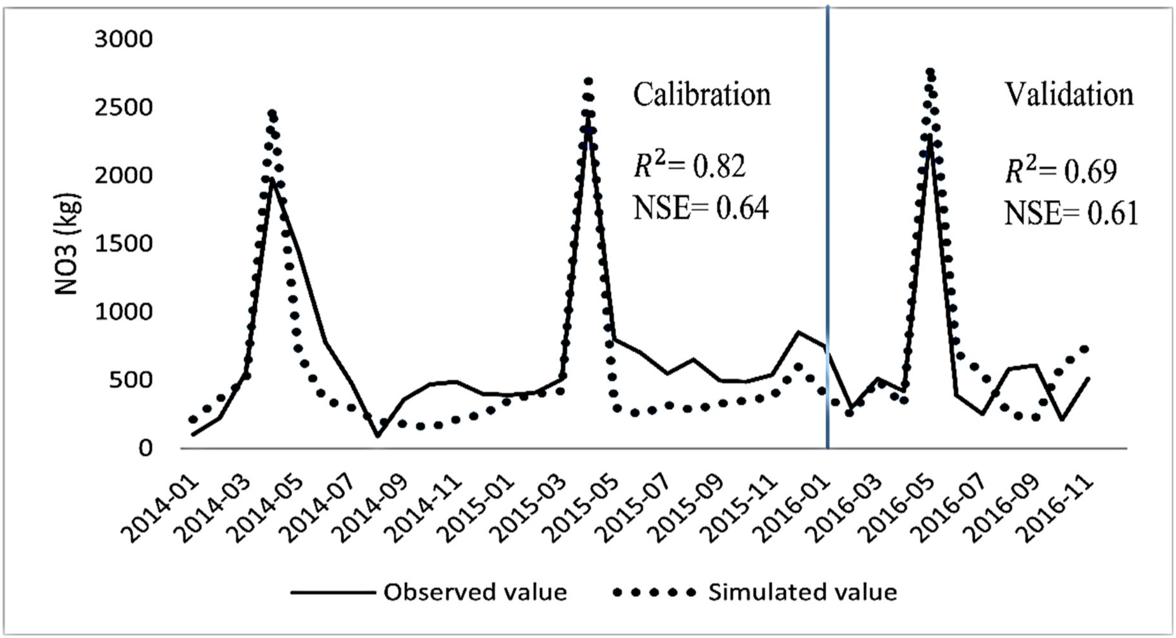

Figure 6. Monthly observed vs. simulated nitrate during model calibration and validation for 2014–2016 at the Roodak gauge.

Table 4. Calibration and validation results of all seven stations for streamflow.

S. No.	Gauge Station	Calibration		Validation	
		R^2	NSE	R^2	NSE
1	Kamar Khani	0.75	0.72	0.35	0.39
2	Roodak	0.88	0.72	0.71	0.65
3	Oushan	0.66	0.61	0.69	0.56
4	Najjar Kola	0.72	0.68	0.71	0.55
5	Naron	0.62	0.6	0.7	0.58
6	Ali Abad	0.8	0.8	0.69	0.54
7	Kond Sofla	0.42	0.36	0.5	0.46

3.2. Investigating the Effect of BMPs on the Water Quality

3.2.1. Fertilizer Management

In this study, we considered three different types of practices to reduce organic nitrogen and nitrate concentration. Based on the results of reducing 25%, 50%, and 75% of nitrogen fertilizer, nitrate concentration decreased by around 5.24%, 6.6%, and 9.42%, respectively, and organic nitrogen was reduced by 0.03%, 0.08%, and 0.11%, respectively (Table 5).

Table 5. Percentage reduction in organic nitrogen and nitrate concentrations at varying reductions of nitrogen fertilizer.

Type of Practice	NO3-Out (Nitrate Concentration) (%)	OrgN (Organic Nitrogen)(%)
25% reduction of nitrogen fertilizer	5.24	0.03
50% reduction of nitrogen fertilizer	6.6	0.08
75% reduction of nitrogen fertilizer	9.42	0.11

3.2.2. Vegetated Filter Strips

An analysis of modeling results indicated that a 10 m filter reduced nitrate concentration by 4.12% and organic nitrogen concentrations by 51.5%. Furthermore, a 15 m filter reduced nitrate concentration by 6.35 % and nitrogen concentration by 57.52% (Table 6).

Table 6. Percentage reduction in the concentration of organic nitrogen and nitrate in different widths.

Type of Practice	NO3-Out (Nitrate Concentration) (%)	OrgN (Organic Nitrogen) (%)
Width of 1 m	4.12	51.5
Width of 5 m	6.35	57.52

3.2.3. Irrigation Management

In this study, changing the method and amount of irrigation did not have much effect on the nitrate output. Therefore, we did not consider applying this management method (Table 7).

Table 7. Percentage reduction in the concentration of organic nitrogen and nitrate at varying reductions of irrigation.

Type of Practice	NO3-Out (Nitrate Concentration) (%)	OrgN (Organic Nitrogen) (%)
25% reduction of nitrogen fertilizer	1.05	0.01
50% reduction of nitrogen fertilizer	0.85	0.03

3.3. Results of Qualitative Optimization of the Model with the MOPSO Algorithm

In order to optimize the model, three scenarios were considered (Table 8). The first scenario assumed that optimal management practices do not exist (S1). The second scenario was based on vegetated filter strips (S2), and the third scenario dealt with the reduction in fertilization in each sub-basin (S3). Scenarios were applied to the model utilizing SUFI-2 of the SWAT_CUP model separately to the entire basin and then to each sub-basin. Then, the combination of scenarios was discussed so that both management methods were applied first, reaching a total of 97 iterations. These results were introduced and recognized as intervals to the optimization objective functions in the MOPSO algorithm in MATLAB.

Table 8. Proposed scenarios for application in sub-basins.

S1	S2	S3
No BMPs have been applied in the sub-basins	Application of vegetated filter strips with a width of 5 m in sub-basins and the land use of the orchard, irrigated, and pasture lands	Reduction of fertilizer by 50% in sub-basins and the land use of the orchard and irrigated lands

Furthermore, the optimization was carried out by introducing objective functions to the algorithm and specifying the number of variables to 25 and their change interval as well as the number of populations to 100 members, an archive of 50 members, and 60 repetitions. The results obtained from implementing the MOPSO optimization algorithm include an archive with 13 non-dominated members. It represents the algorithm's selected scenarios to minimize the objective functions, which determines the best modes in terms of the lowest output nitrate concentration and the number of BMPs in the sub-basins. These results are presented as a Pareto-front diagram, as shown in Figure 7, and the corresponding extracted information is provided in Table 9.

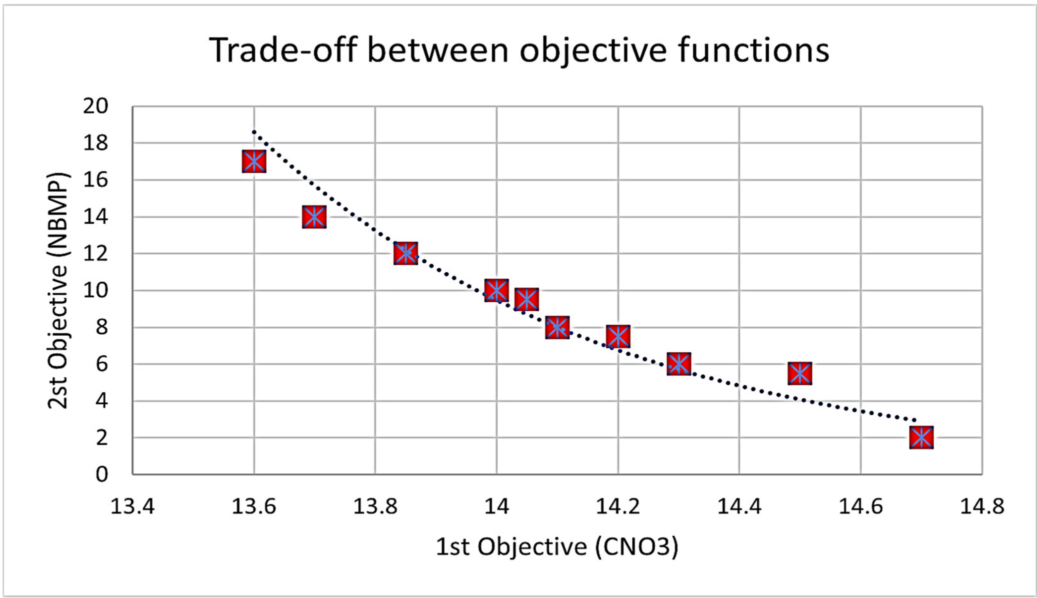

Figure 7. The trade-off between the objective functions represents the percent improvement in the water quality objective function on the Pareto front considering BMPs in the watershed.

Table 9. The information extracted from MOPSO.

No.	Number of Applied BMPs	Output Nitrate Concentration (mg/L)	Subbasins Under the S2	Subbasins Under the S3
1	13	13.75	20/17/9	20/9/8/7/5/4/2
2	12	13.84	18/15/9/5	20/15/8/7/3/2
3	7	14.25	20/5/2	9/7/5/4
4	6	14.34	20/15/14/2/1	8/5/1
5	14	13.69	18/15/9/8/4/2	20/9/8/7/5/4/2
6	11	13.92	18/14/7/3/4/2	20/9/8/7/5/4/2
7	2	14.91	5	2
8	18	13.67	18/7	20/9
9	4	14.71	20/15/14/2/1	9/7/5/4
10	10	14.04	9/7/4/3/1	20/5
11	5	14.41	14/7/4/3	10/9/8/5
12	8	14.106	20/18/5	15/14/2/1
13	9	14.092	3/1	9/7/5/4

According to the results, subbasins 5, 8, 9, 10, 15, 17, 18, and 20 could be treated with vegetated filters and fertilizer reduction simultaneously, assuming 15.02 mg/L of the output nitrate. Additionally, the fertilizer reduction method could be applied in sub-basins 1, 2, 3, 4, 7, and 14 (Figure 8).

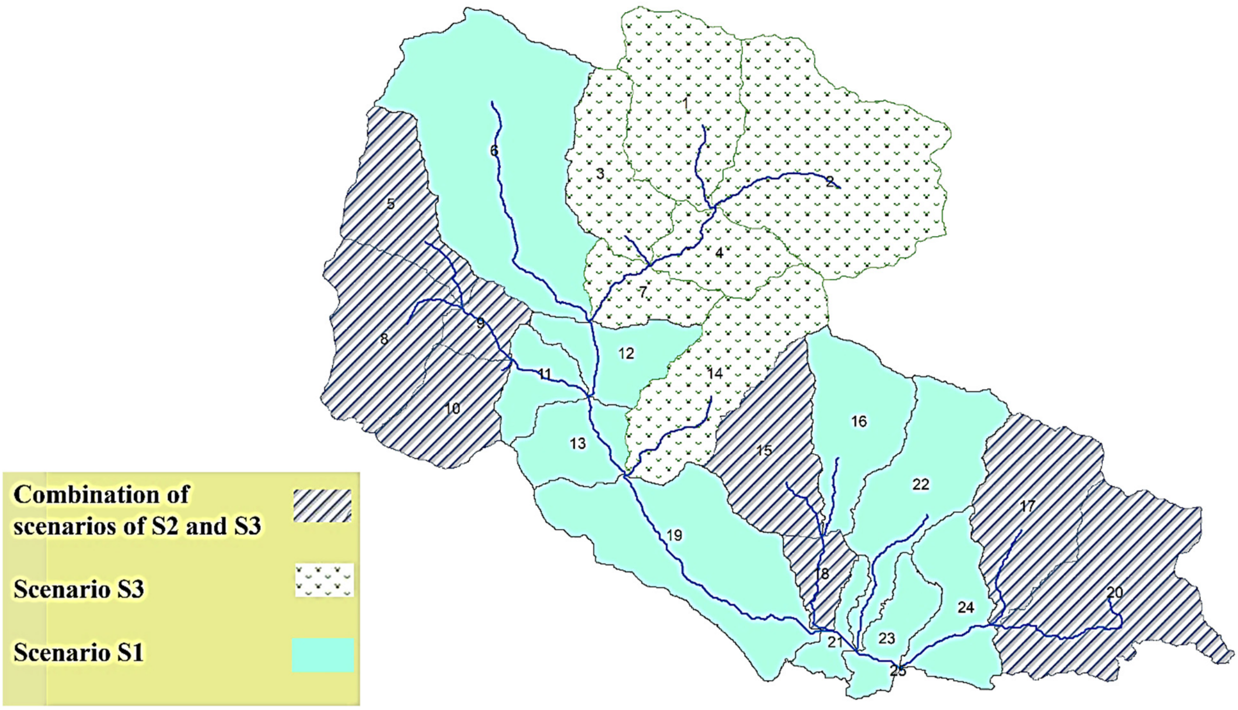

Figure 8. The types and locations of optimal BMPs.

4. Discussion

This study analyzed and compared simulated and measured streamflow at seven stations as well as simulated and measured water quality values at Roodak Station and found that simulated and observed values indicate a similar trend. Despite some overestimates, the fitting effect of the model is satisfactory, leading to further studies that can be conducted with this model. There is a comprehensive sensitivity analysis for streamflow, nitrate, and their respective best parameter values, as presented by Jamshidi et al. [110] in the study area. It was determined that the temperature lapse rate (TLAPS) and groundwater delay time (GW_DELAY) parameters had the most significant effect on the outflow of the basin compared to the other parameters. The flow rate was also influenced by the fraction of snow volume (SNOCOVMX), the initial SCS runoff curve number for moisture conditions (CN2), the snowfall temperature (SFTMP), the baseflow alpha factor (ALPHA_BF), the soil evaporation, the compensation coefficient (ESCO), the snow temperature lag factor (TIMP), the surface runoff lag coefficient (SURLAG), and the average slope length (SLSUBBSN). Due to its large area, pastureland use was chosen as the most sensitive land.

Furthermore, several parameters that affect nutrients are the organic nitrogen enrichment ratio (ERORGN), nitrogen percolation coefficient (NPERCO), the nitrogen concentration in rainfall (RCN), the rate constant for the hydrolysis of organic nitrogen to ammonia (BC3_BSN), and the rate constant for the biological oxidation of NO_2 to NO_3 (BC2_BSN), which was more sensitive than other parameters. According to Figure 6, the simulated monthly nitrate follows the trend of observed nitrate, but most of the simulated peaks differ from the observed ones. In this case, rainfall data is uncertain, which could lead to high simulated monthly nitrate levels. A seasonal variation in the concentration of simulated nitrate was also observed in response to changes in rainfall patterns and fertilizer applications. This result aligns with the findings of Cerro et al. [111] and Zheng et al. [112]. Based on the results of the model, the average annual nitrate load in the output of the basin for 2019 was about 1200 tons per year, and according to the calculations, the share of the agricultural sector was about 60% of the total nitrate load. This result highlights the importance of using BMPs to control water pollution in the basin.

According to the calibrated and fitted model, the model can be used to evaluate the effectiveness of BMPs in the studied watershed. By applying the management practices suggested in this study, conservation plans could be implemented more effectively to reduce pollution. As a result of the implementation of BMPs, nitrate concentrations in the watershed have decreased significantly. However, the irrigation management was slightly effective in reducing nutrients and did not have any significant impact on the nitrate and organic nitrogen concentration. The findings of this study agree with previous studies that reported irrigation reduction does not significantly reduce nitrogen loads, especially in soluble forms [113,114]. Implementation of the reduced nitrogen fertilizer scenarios increased the nitrate (NO_3-) losses (5.24% for a 25% fertilizer reduction, 6.6% for a 50% fertilizer reduction, and 9.42% for a 75% fertilizer reduction) but did not significantly affect organic nitrogen losses (0.03% for a 25% fertilizer reduction, 0.08% for a 50% fertilizer reduction, and 0.11% for a 75% fertilizer reduction). These results have been observed in studies conducted by Pandey et al. [115], Li et al. [116], and Craswell [117].

The vegetated filter strips BMP was effectively applied to reduce nutrient yields throughout the watershed. The implementation of the filter strip scenarios (1 m width and 5 m width) increased nitrate losses (4.12% and 6.35%) and organic nitrogen losses (51.5% and 57.52%). A filter strip with a 5 m width was selected due to its more remarkable and tangible effect on the reduction of nutrients in the watershed. This study confirms previous findings [78,118–120] regarding these BMP and nitrate output concentrations. Nevertheless, it is important to keep in mind that there are several factors that can affect the effectiveness of filter strips, including the slope, geography, size, and scope of the areas where they are situated.

Combined scenarios were assessed and optimized to determine which mitigation measure would reduce pollutants most significantly. Therefore, the BMP optimization process was used to select and place BMPs in sub-basins to manage and control water quality. It was achieved using the MOPSO multi-objective optimization algorithm, which minimized the objective functions, including the number of best management practices applied in the sub-basins and the nitrate concentration of each sub-basin. The fertilizer management (S2) and vegetated filter strips with fertilizer management (S2 and S3) scenarios were the most effective in minimizing the nitrate concentration level. Figure 7 shows the percent improvement in the water quality objective function on the Pareto front considering BMPs in the watershed.

In the sub-basins where the combination of two scenarios has been allocated, a significant area includes pastures, orchards, and irrigated agriculture. In areas where livestock grazing primarily occurs, using vegetated filter strips helps significantly reduce nitrate entering the stream. Nitrate fertilizer reduction in irrigated fields and orchards also leads to a decrease in nitrate concentration from the agricultural runoff into the river's mainstream. The simultaneous use of these two scenarios and their effect on nitrate reduction has been used in past studies [121–123]. One of the main limitations of implementing this method in the study area is farmers. Implementing effective BMPs identified in this research depends heavily on the farmers. Because the implementation of these BMPs includes BMP installation costs, it can be a financial problem for farmers.

5. Conclusions

Estimating the outlet nutrients of the Jajrood river watershed and evaluating BMPs to reduce the load of outgoing pollutants are the main goals of this research. In this study, through a combination of the MOPSO optimization algorithm and the SWAT model, the water quality in the Jajrood river watershed has been modeled. The hydrological and semi-distributed SWAT model was implemented to simulate the streamflow and water quality in the watershed. The calibration and validation of streamflow and nitrate were completed after sensitivity analysis. The calibration of the basin's discharge and nitrogen indicated that the SWAT model performed well in simulating the catchment's streamflow and nitrate.

Furthermore, the SWAT model was coupled with MOPSO algorithm to simulate and find the optimal combination of the BMPs in the watershed. Three scenarios were considered: (1) assumes that optimal management practices do not exist; (2) is based on vegetated filter strips; and (3) considers a reduction in fertilization in each sub-basin. The best-recommended management practices for reducing nutrient discharge from the basin are using vegetated filter strips on the riverbanks and decreasing fertilization in agricultural activities. The methodology and the results presented aim to facilitate decision-making for determining the type, size, and location of BMPs in the watershed as long as the reduction criteria change.

Applying these two items simultaneously in the whole basin will reduce the nitrate output from the basin by about 10%. Due to the constant slope of the watershed, this method is considered one of the effective solutions. For policymakers and management communities, our findings can offer a variety of ideas and updated information that will help them enhance current processes and develop new management practices.

As part of future and comprehensive research in the study area, it is suggested that the Latian dam and nutrients in the reservoir be modeled along with surface currents of the basin and that management strategies with structural performance be employed to control the nutrient concentration in the reservoir. Additionally, the high slope difference in the basin, the large volume of runoff, and the location of the Latian dam reservoir downstream cause a significant transfer of sediment downstream. Therefore, it is suggested for future research to estimate the amount of transferred sediment and examine the best management methods to reduce sediment. Additionally, in terms of economic analysis, it is recommended to calculate the cost-effectiveness of BMPs at the local scale and in watershed areas.

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Appendix A

Table A1. Description of sensitive parameters for stream flow in SWAT.

Parameter	Description
TLAPS	The temperature lapse rate
GW_DELAY	Groundwater delay time
SNOCOVMX	The fraction of snow volume
CN2	The initial SCS runoff curve number for moisture condition
ALPHA_BF	The baseflow alpha factor
SFTMP	The snowfall temperature
ESCO	The compensation coefficient
TIMP	The snow temperature lag factor
SURLAG	The surface runoff lag coefficient
SLSUBBSN	The average slope length

Table A2. Description of sensitive parameters for nitrate pollution in SWAT.

Parameter	Description
ERORGN	The organic nitrogen enrichment ratio
NPERCO	Nitrogen percolation coefficient
RCN	The nitrogen concentration in rainfall
BC3_BSN	The rate constant for the hydrolysis of organic nitrogen to ammonia
BC2_BSN	Rate constant for biological oxidation of NO_2 to NO_3

Table A3. Accuracy assessment results of LULC map used in SWAT model.

	FO [1]	RE [2]	CR [3]	GR [4]	WA [5]	BL [6]
FO	1000	0	2	1	0	0
RE	0	200	0	16	0	12
CR	10	4	3077	132	18	20
GR	0	0	130	2208	18	29
WA	2	0	5	12	528	5
BL	0	0	12	30	31	242
UA [7]	98.81	98.04	95.38	92.04	88.74	78.57
PA [8]	99.70	87.72	94.36	92.58	95.65	76.83
Kappa			91.06%			
OA [9]			93.11%			

[1] FO: forest, [2] RE: residential, [3] CR: cropland, [4] GR: grassland, [5] WA: water, [6] BL: barren land, [7] UA: user accuracy, [8] PA: producer accuracy, [9] OA: overall accuracy.

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