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*Article*

# Identification of Critical Source Areas (CSAs) and Evaluation of Best Management Practices (BMPs) in Controlling Eutrophication in Dez River Basin

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**Abstract:** Best management practices (BMPs) are a way to control pollution in river basins. Prioritization of BMPs helps improve efficiency and effectiveness of pollution reduction, especially in critical source areas (CSAs) that produce the highest pollution loads. Recently, the Dez River, Khuzestan, Iran, has become highly eutrophic from overuse of fertilizers and pesticides. Dry and irrigated farming produce 77.34% and 6.3% of the total nitrogen (TN) load, and 83.56% and 4.3% of the total phosphorus (TP) load in this basin, respectively. Residential, pasture, and forest land uses account for 16.36% of the TN and 12.14% of the TP load cumulatively. In this study, the Soil and Water Assessment Tool (SWAT) was implemented to model the Dez River basin, and evaluate the applicability of several BMPs including point source elimination, filter strips, livestock grazing, and river channel management, in reducing the entry of pollution loads to the river. Sensitivity analysis and calibration/validation of the model was performed using the SUFI-2 algorithm in the SWAT Calibration Uncertainties Program (SWAT-CUP). CSAs were identified using individual (sediment, TN, TP) and combined indices, based on the amount of pollution produced. Among the BMPs implemented, filter strips were most effective in reducing TN loads (59%), and, increasing the $D_{50}$ of particles for river channel management was most effective in reducing TP loads (49%).

**Keywords:** Best Management Practices; Critical Source Areas; SWAT; SWAT-CUP; SUFI-2; Dez River Basin

## 1. Introduction

Water pollution is a major global problem, which requires the continuous assessment of water resources and revision of policies in water resources management. Due to water scarcity in Iran, the quality of water in these resources has become one of the major concerns of the country. This situation necessitates the development of managerial strategies to identify critical source areas (CSAs) that contribute the most to pollutant loading.

Pollution sources are mainly classified into two categories of point and non-point sources. Point sources refer to contaminants that are generated from a single identifiable source of pollution, such as discharge from wastewater treatment plants. On the other hand, non-point sources refer to contaminants that do not have a specific source, such as excess fertilizers, herbicides, and insecticides from agricultural land and residential areas. These contaminants are usually transferred to rivers or other receiving water bodies through runoff [1]. A high concentration of nutrients in water bodies, originating from various sources including agriculture, wastewater, stormwater, and fossil fuel combustion, leads to eutrophication and blooms of algae in marine habitats. By disrupting the normal ecosystem functions, algal blooms can cause many problems, which ultimately threaten the reliable supply of drinking water [2—5].

Controlling the entrance of non-point pollutants that mainly originate from agricultural activities requires specific best management practices (BMPs) [6,7]. Implementation of BMPs in watersheds has been recognized as an effective method to reduce the impairment of water quality. BMPs are categorized into structural or nonstructural practices, and both have been used extensively to control runoff, sediment, and nutrients in watersheds. The literature shows that among common BMPs, fertilizer reduction strategies, land use changes, and irrigation management practices provide appropriate results [8—11].

Among BMP evaluation models, the Soil and Water Assessment Tool (SWAT) has been widely used in water quality and hydrological studies. In 2006, [12] used the genetic algorithm (GA) and SWAT to study two small watersheds in Indiana in order to optimize the planned BMPs for controlling the maximum monthly sediment, as well as phosphorus and nitrogen loads. The authors found the optimized solution to be three times more cost-effective than the previously planned strategies. In 2012, [13] studied water quality in the Sacramento River basin in California, using SWAT. The authors proposed BMPs such as fertilization restrictions during wet seasons in order to improve the water quality of the basin. Furthermore, the SWAT model was successfully used by [14] for Orestimba Creek Watershed in California, and CSAs were identified in the watershed.

By determining the trade-off among economic and multiple environmental objectives, and in order to minimize diffuse surface water pollution at the catchment scale, a new methodology and an associated decision support tool were developed by Panagopoulos et al. (2012), which suggest the optimal location for placing BMPs.

Moreover, [3] implemented SWAT and Generalized Watershed Loading Function (GWLF) models to identify the CSAs of sediment and nutrients in the Saugahatchee Creek watershed in east central Alabama. The highest amounts of sediment, total nitrogen (TN) and total phosphorus (TP) loads were observed in sub-basins dominated by urban land use. In order to identify the CSAs that required targeting for the overall reduction of sediment, TN, and TP, the authors used a combined index. This study concluded that the choice of model would affect the identification of CSAs since slightly different CSAs were identified using either SWAT or GWLF.

Using SWAT, [15] showed that nutrient loads, coupled with population density and water quality requirements, could be used as multi-factors for identification of CSAs in the Xiangxi River basin in China. Based on the results, CSAs occupied 19.7% of the basin and accounted for 53% and 54% of TN and TP loads, respectively.

More recently, using SWAT and an optimization model, under constraints of site-specific water quality standards, [16] proposed an identification framework for priority management areas (PMA), based on the simulation-optimization approach with ideal load reduction. The proposed approach was used for the identification of PMAs from diffuse TP in the Lake Dianchi watershed in China. Based on the modeling results, the authors found that 85% of diffuse TP originated from 30% of the watershed area.

Using SWAT, [17] modeled the Miyun Reservoir watershed in China. Considering the tradeoffs between economic costs and water quality responses, the authors developed a Markov Chain-based multi-objective optimization program to explore optimal BMPs. The authors explored the potential effectiveness of BMPs under two scenarios: Scenario 1 considered that national grants were the source of funding for BMP implementation, and the target was to reach high water quality standards; scenario 2 assumed funding was provided by farmers and targeted water quality met the drinking water standards. The authors found substantial discrepancies between the two scenarios concerning the types and spatial configurations of BMPs and associated economic costs. These findings highlight

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the need to reconcile the concerns of the various stakeholders in order to arrive at a BMP plan that all parties will agree upon.

## 2. Materials and Methods

In recent years, the growth of algae as a sign of eutrophication in the Dez River in Khuzestan province in Iran has heavily increased. Due to the warm climate in this region, agricultural products are cultivated several times a year, and high levels of fertilizers and pesticides are used to produce high yields of crops, which pollutes water supplies. To cope with the existing conditions and in order to improve the trophic status of the river, BMPs must be implemented in the basin.

Limitations in the direct measurement of physical parameters, such as streamflow and sediment, as well as nitrogen and phosphorus loads and concentrations, necessitate the implementation of computer models. Additionally, for cost-effective implementation of BMPs, identification of the CSAs that are generating most of the pollutants in a basin is crucial. This process is often done through watershed modeling.

In this regard, the SWAT model has been implemented in this study, to identify CSAs based on individual and combined pollution load indices, and to evaluate the applicability of BMPs in the Dez River basin. Moreover, The SUFI-2 (Sequential Uncertainty FItting, ver. 2) module of the SWAT-CUP software has been utilized for sensitivity analysis, calibration, and validation of the SWAT model. The following flowchart summarizes the main steps in this study (Figure 1).

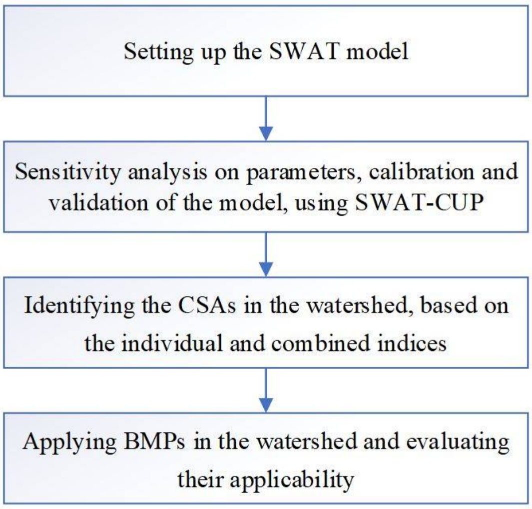


**Figure 1.** Flowchart of this study.

### *2.1. Study Area and Data*

The Dez River basin (556,008 ha) is located in the province of Khuzestan in Iran (Figure 2). Based on the meteorological records (1990-2014), the area receives an average precipitation of 376 mm/yr, and the average air temperature in the basin is 25.6 °C. Arable lands constitute 200,000 ha of the region, of which 150,000 ha can be irrigated, and 50,000 ha are cultivated under dryland farming [18]. The major agricultural products in the basin are wheat, sugar cane, and corn, which are cultivated two to three times a year.

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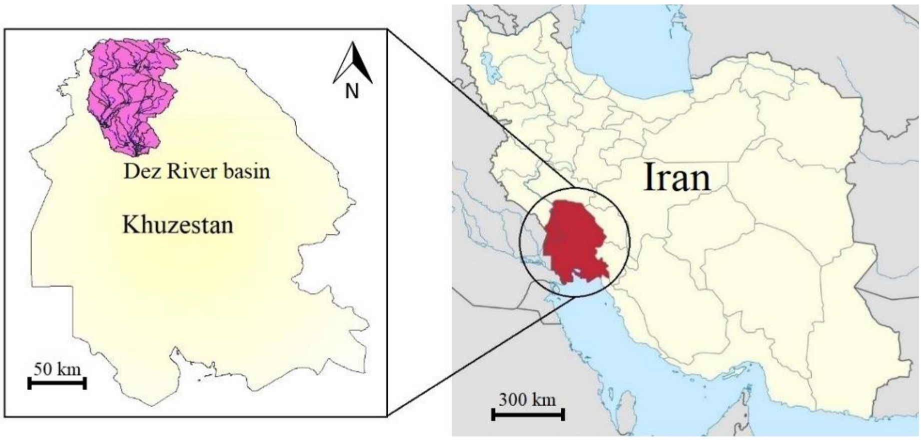


**Figure 2.** The geographic location of the Dez River basin.

Dry and irrigated farming produce 77.34% and 6.3% of the TN load, and 83.56% and 4.3% of the TP load in the basin, respectively. Moreover, residential, pasture, and forest land uses account for 16.36% of the TN and 12.14% of the TP load in the basin, cumulatively. Three cities of Dezful, Andimeshk, and Shush are located in this basin. Besides, many villages have been built in the vicinity of the Dez River, and their sewage drains directly into the river. To address these pollution sources, only the city of Dezful has a wastewater treatment plant, which treats 70% of the city's wastewater. Moreover, three factories in the basin significantly influence the water quality status of the river.

In this basin, streamflow data were available at the Dezful and Harmaleh hydrometric stations (Figure 3), while water quality data were only available at the Dezful station.

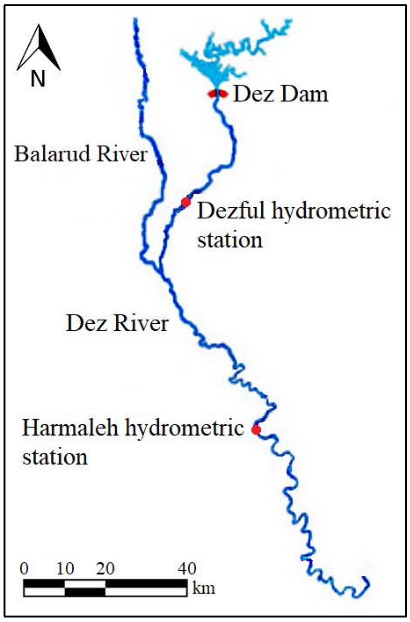


**Figure 3.** Hydrometric stations.

In order to set up the SWAT model of the Dez River basin, data presented in Table 1 were used.

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**Table 1.** SWAT model input data.

| Data | Source |
|---|---|
| Digital Elevation Model (DEM) - 2011 | United States Geological Survey (USGS) |
| Soil map - 2011 | FAO Soils Portal |
| Land use map - 2006 | Iran's Forests, Range and Watershed Management Organization |
| Meteorological data - (1991 to 2014) | I.R. of Iran Meteorogical Organization |
| Hydrometric and Sediment Data - (1991 to 2014) | Khuzestan Water and Power Authority |
| Data on water quality and sources of point source pollution - 2012 | Directorate General of Environmental Protection of Khuzestan Province |
| Management and agricultural data | Royan Consulting Engineers |

### *2.2. SWAT and SWAT-CUP*

SWAT is a conceptual, semi-distributive, and continuous river basin scale model [19]. SWAT requires input data such as topography, soil, and land use maps, as well as meteorological data (precipitation, temperature, wind speed, relative humidity, and solar radiation), inter-basin water transfer data, point source pollution data, and land management practices in order to simulate the physical processes within a watershed [20]. Based on the soil type, land use, and slope, SWAT divides the basin to hydrological response units (HRUs) and runs the simulations at the HRU level [21].

Before running a model under different scenarios, it has to be calibrated. Moreover, before calibrating a model, sensitive parameters have to be identified. Sensitivity analysis is the process of determining the significance of the impact of one parameter or a combination of parameters on the output of a model. In SWAT-CUP, the sensitivities of parameters are measured by t-stat values and p-values. Parameters that show higher t-stat values and p-values closer to 0 are more sensitive, and the effect of varying the parameter will be more significant on the target variable [22].

Calibration means adjusting the model input parameters with the goal of achieving the best fit between observed and simulated values. In SWAT-CUP, the goodness of calibration is measured using p-factor (the fraction of data in the range of 95% prediction uncertainty (95ppu)) and r-factor (the average thickness of the 95ppu band, divided by the standard deviation of the observed data). The p-factor is a value between 0 to 1, and the r-factor has a range of 0 to ∞. When the p-factor = 1 and the r-factor = 0, the simulated model is precisely in accordance with observed data. p-factors greater than 0.7 and r-factors smaller than 1.5 show satisfactory calibration and validation results [23].

Another means for evaluation of the goodness of calibration and validation is the Nash-Sutcliffe (NS) criterion, presented in Equation (1) [24]:

$$NS = 1 - \frac{\sum_{i=1}^{n}(Q_m - Q_s)^2}{\sum_{i=1}^{n}(Q_m - Q_{avg})^2} \quad (1)$$

where Q is the variable, such as streamflow or sediment; the indices m, and s, represent the observed and simulated values; and $Q_{avg}$ is the mean of the measured variables.

The NS function has a range of -∞ to 1. NS = 1 corresponds to a perfect match of simulated values to the observed data. The values between 0 and 1 indicate that the simulated and observed values are

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close to each other, whereas values less than 0 show the simulated and observed values do not match well [25].

### 2.3. Identification of CSAs

CSAs are areas that produce the highest pollution loads in the basin, and are identified at the sub-basin level [26]. In order to identify the CSAs, sediment and nutrient yields from each sub-basin have to be analyzed based on loads per unit area (tons per hectare per year). Afterward, sub-basins will be ranked in descending order based on yields (the sub-basin with the highest yield will be ranked first). Moving from the highest ranking to the lowest, and based on the analysis of management practices and operational costs, sub-basins that contribute to 5 - 8% (based on the literature) of the sedimentary, TN, or TP loads in the basin will be considered as CSAs [3].

Combined indices can also be implemented to identify the sub-basins, which can be considered as CSAs. In this method, CSAs are defined by multi-factors. These factors include a weighted combination of TN, TP, and sediment loads [15]. The combined index can help identify the areas that are critical for multiple stressors, where implementation of BMPs will be more economical. This index is given by:

$$G_i = \sum (\omega_i G_{ij}) \tag{2}$$

$$NG_i = \frac{G_i - G_{\min}}{G_{\max} - G_{\min}} \tag{3}$$

where $G_i$ is the combined index for sub-basin i; $G_{ij}$ is an index for TN (j = 1); TP (j = 2); and sediment (j = 3). In Equation (3), $NG_i$ is the normalized evaluation variable for the sub-basin i; and $G_{min}$ and $G_{max}$ are the lowest and highest ranks for constituent i for the entire basin.

In managerial tasks where the priority of one variable is higher than the others, the variable can be weighted in Equation (2), using the coefficient ω. The weight is subjectively chosen and assigned to each $G_i$ based on their importance, where $\sum \omega_i = 1$ [3].

### 2.4. BMPs and Pollution Load Indices

In this study, in order to reduce pollution entry into the Dez River, the BMPs implemented are: point source pollution elimination (treating the wastewater from residential areas and the effluent of the factories); 5 and 10m filter strips in residential and agricultural lands; a 20% and 50% reduction in livestock grazing in the basin; and management of the main river channel.

Filter strips are small edge-of-field tracts of vegetated land that are used to reduce the contamination of surface water. This practice is primarily used with agricultural fields to control non-point source pollution. In this method, by reducing the velocity of the surface runoff and the deposition of particles, the pollutants are removed. In this study, 5m and 10m filter strips were used in areas with irrigated farming, and 5m filter strips were used in residential and dryland farming areas.

Livestock grazing, with the damage to plants and production of fertilizer, increases the amount of nutrient entry from rangelands to receiving water bodies through runoff. Managing the timing of livestock grazing, reducing the number of livestock, and preventing livestock grazing are among the most popular practices for livestock grazing management. In this study, 20% and 50% reduction in the number of livestock are used as BMPs.

Management of the river main channel is done by controlling erosion in the channel wall through mulching, controlling the amount of vegetation in the channel wall, using dense vegetation cover, and doubling the $D_{50}$ (the diameter of a particle that 50% of a sample's mass is smaller than, and 50% of a sample's mass is larger than) of the particles in the river bed and channel wall.

Individual and combined indices were used in this study to identify CSAs. Using individual indices, areas contributing the most to TN, TP, and sediment loads were identified individually. In the next step by using combined indices, CSAs for TN + TP, TN + TP + sediment, and TN + TP + 0.1 sediment were identified.

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## 3. Results

### 3.1. Sensitivity Analysis

In order to find the most effective parameters affecting the yields of runoff, sediment, TN, and TP, the sensitivity analysis was performed on each variable separately. In this regard, first, the sensitivity analysis was performed on runoff parameters. The results of the sensitivity analysis are presented in Table 2. In this study, nitrate and phosphate were calibrated/validated as proxies representing TN and TP, respectively.

**Table 2.** Sensitivity analysis on runoff, sediment, nitrate and phosphate parameters.

| Parameter | Definition | Calibrated Value | t-stat | p-value |
|---|---|---|---|---|
| | Parameters affecting streamflow | | | |
| ALPHA_BF.gw | Baseflow alpha factor (1/days) | 0.0037 | -10.35 | 0 |
| CH_K2.rte | Effective hydraulic conductivity in main channel alluvium (mm/hr) | 352.12 | 4.15 | 0 |
| OV_N.hru | Manning's "n" value for overland flow | 12.41 | 2.41 | 0.016 |
| SOL_AWC.sol | Available water capacity of the soil layer (mm $H_2O$/mm soil) | 0.214 | 1.83 | 0.067 |
| GW_REVAP.gw | Groundwater "revap" coefficient | 0.092 | -1.73 | 0.085 |
| CANMX.hru | Maximum canopy storage (mm $H_2O$) | 53.74 | -1.63 | 0.104 |
| CH_S2.rte | Average slope of main channel along the channel length (m/m) | 6.7 | 1.59 | 0.112 |
| GW_DELAY.gw | Ground water lag time | 108.7 | -1.48 | 0.14 |
| | Parameters affecting sediment load | | | |
| SPCON.bsn | The linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing | 0.00116 | -41.45 | 0 |
| SPEXP.bsn | Exponent parameter for calculating sediment reentrained in channel sediment routing | 1.015 | 6.73 | 0 |
| CH_ERODMO.rte | Erosion rate of the channel | 0.457 | 1.49 | 0.136 |
| ADJ_PKR.bsn | Peak rate adjustment factor for sediment routing in the sub-basin (tributary channels) | 0.907 | -0.67 | 0.5 |
| | Parameters affecting phosphate load | | | |
| ERORGP.hru | Phosphorus enrichment ratio for loading with sediment | 2.52 | -3.43 | 0 |
| ORGP_con.hru | Organic phosphorus concentration in runoff, after urban BMP is applied | 26.95 | 2.84 | 0.004 |
| PSP.bsn | Phosphorus availability index | 0.44 | 0.92 | 0.42 |
| SOLP_con.hru | Soluble phosphorus concentration in runoff, after urban BMP is applied | 0.231 | -0.33 | 0.73 |
| | Parameters affecting nitrate load | | | |
| SOLN_con.hru | Concentration of nitrogen soluble in runoff | 0.132 | -3.64 | 0 |
| NPERCO.bsn | Nitrate percolation coefficient | 0.172 | -2.05 | 0.172 |
| ERORGN.hru | Organic N enrichment ratio for loading with sediment | 2.81 | 0.119 | 0.9 |
| K_N.wwq | Michaelis-Menton half-saturation constant for nitrogen (mg N/L) | 0.174 | 0.058 | 0.953 |

The results showed that the parameters ALPHA_BF (baseflow alpha factor), CH_K2 (effective hydraulic conductivity in main channel alluvium), and OV_N (Manning's "n" value for overland flow) had the most significant impact on runoff yield.

In addition, other parameters with the highest sensitivity on sediment, phosphate, and nitrate yields were SPCON (linear parameter for calculating the maximum amount of sediment that can be re-entrained during channel sediment routing), ERORGP (phosphorus enrichment ratio for loading with sediment), and SOLN_con (concentration of soluble nitrogen in runoff).

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### *3.2. Calibration and Validation*

The calibration and validation of the model were performed in four steps. At first, the runoff was calibrated and validated based on the observed data at the Dezful and Harmaleh hydrometric stations. In the next step, nitrate and phosphate were calibrated and validated for the Dezful station. Objective functions of NS, $R^2$, p-factor, and r-factor were used to evaluate the goodness of fit between simulated and observed values. The results and time series of the simulated data and observational data are presented in Figures 4 to 8.

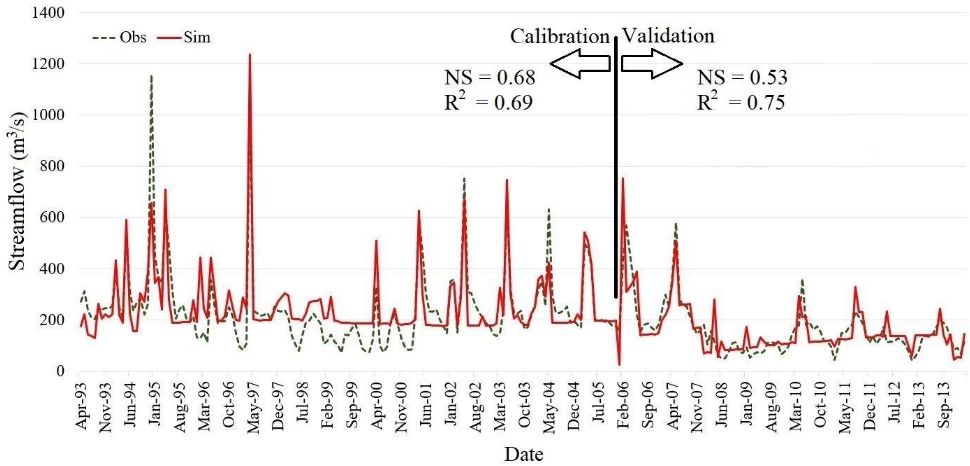


**Figure 4.** Calibration (1993-2005) and validation (2006-2014) of monthly streamflow in Dezful station.

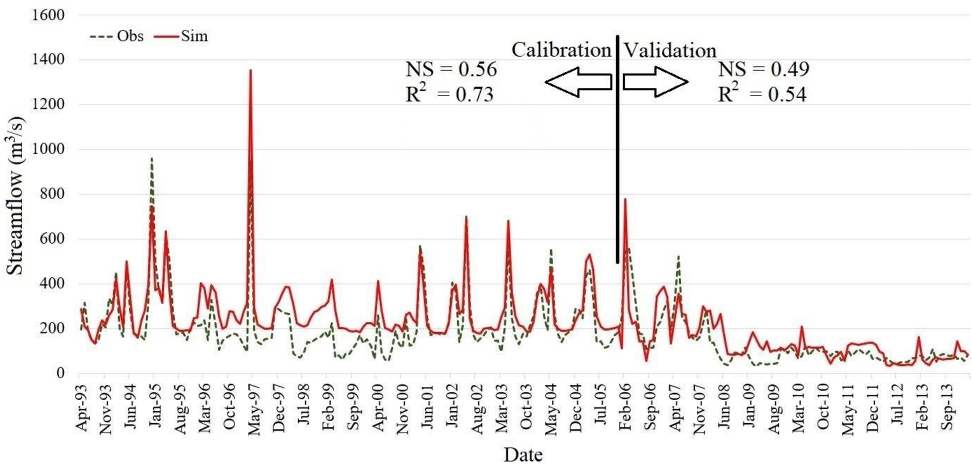


**Figure 5.** Calibration (1993-2005) and validation (2006-2014) of monthly streamflow in Harmaleh station.

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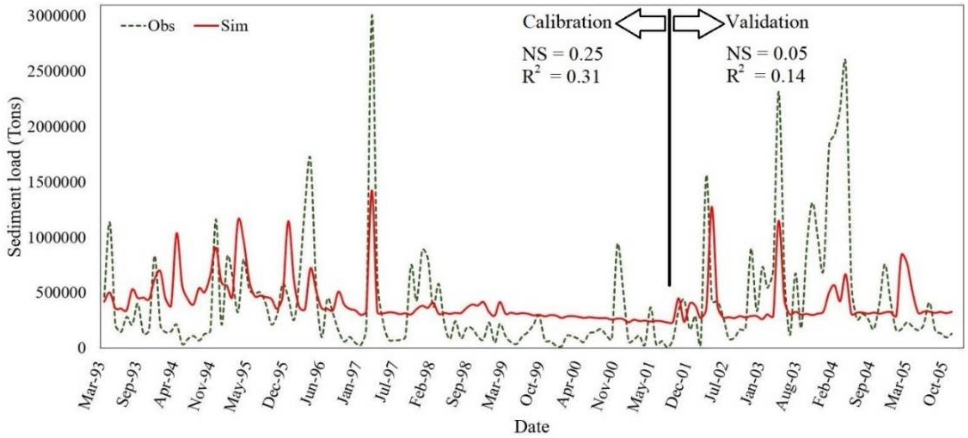


**Figure 6.** Calibration and validation of monthly sediment load in Dezful station (2012-2013).

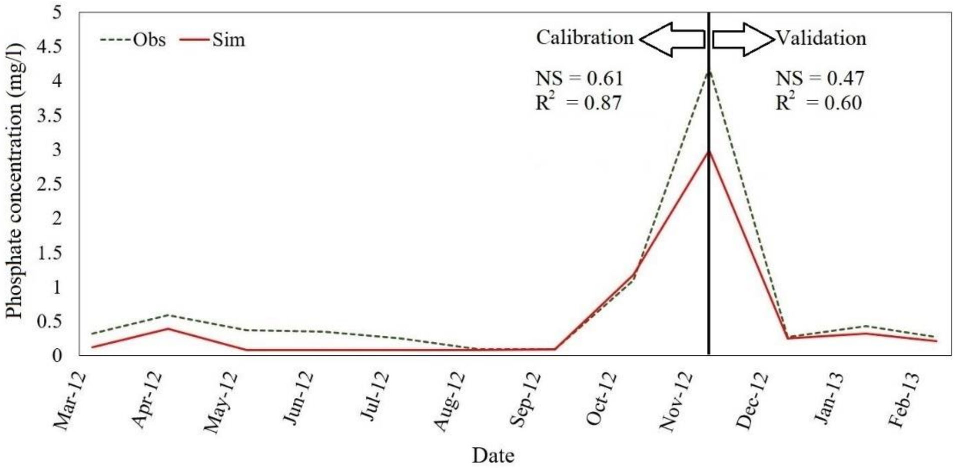


**Figure 7.** Calibration and validation of monthly phosphate concentration in Dezful station (2012-2013).

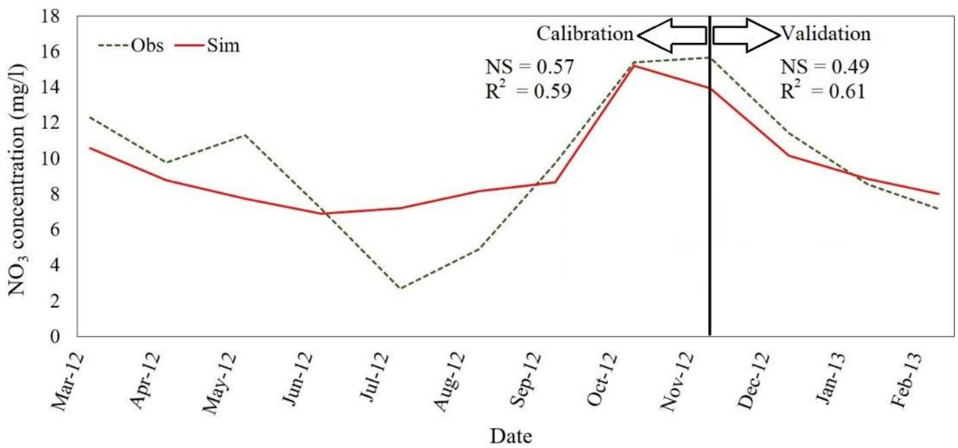


**Figure 8.** Calibration and validation of monthly nitrate concentration in Dezful station (2012-2013).

### *3.3. Identifying CSAs*

Figure 9 shows the delineated Dez River basin in SWAT.

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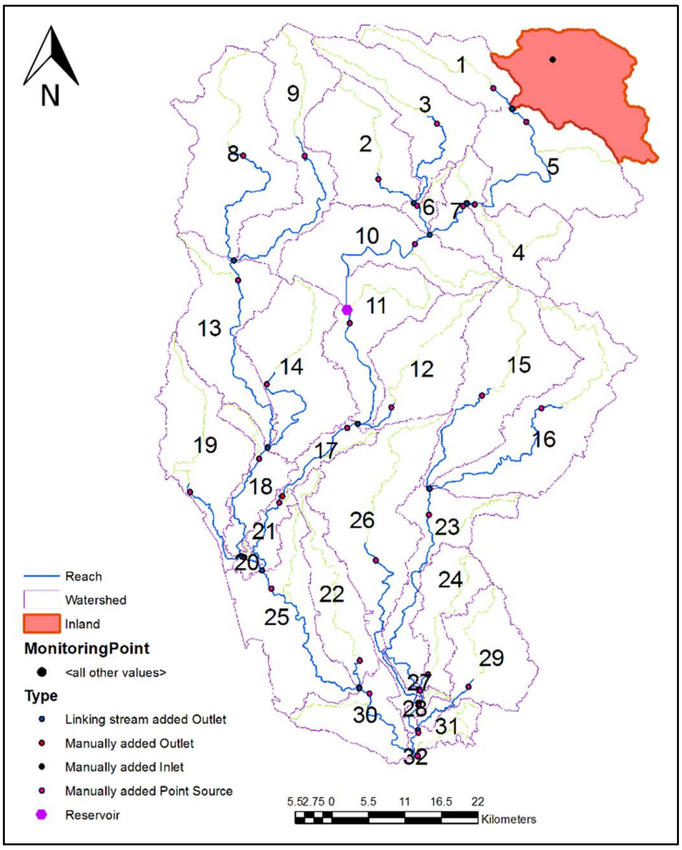


**Figure 9.** The delineated Dez River basin in SWAT.

Based on simulation results, the highest erosion rates occur in the upstream of the basin. Contrary to sediment load, TN and TP loads are higher downstream of the dam and in areas where agricultural activities and population densities are higher, as well as in areas where nomads are located, and livestock graze. TN and TP loads upstream of the basin, which is more mountainous and has less agricultural activity than the plains, are much less than in the downstream area. Sugar cane farms and a factory are located in sub-basin number 25. Therefore, in this sub-basin, the burden of pollution is higher than in other sub-basins. Figure 10 shows the results of each analysis using individual indices.

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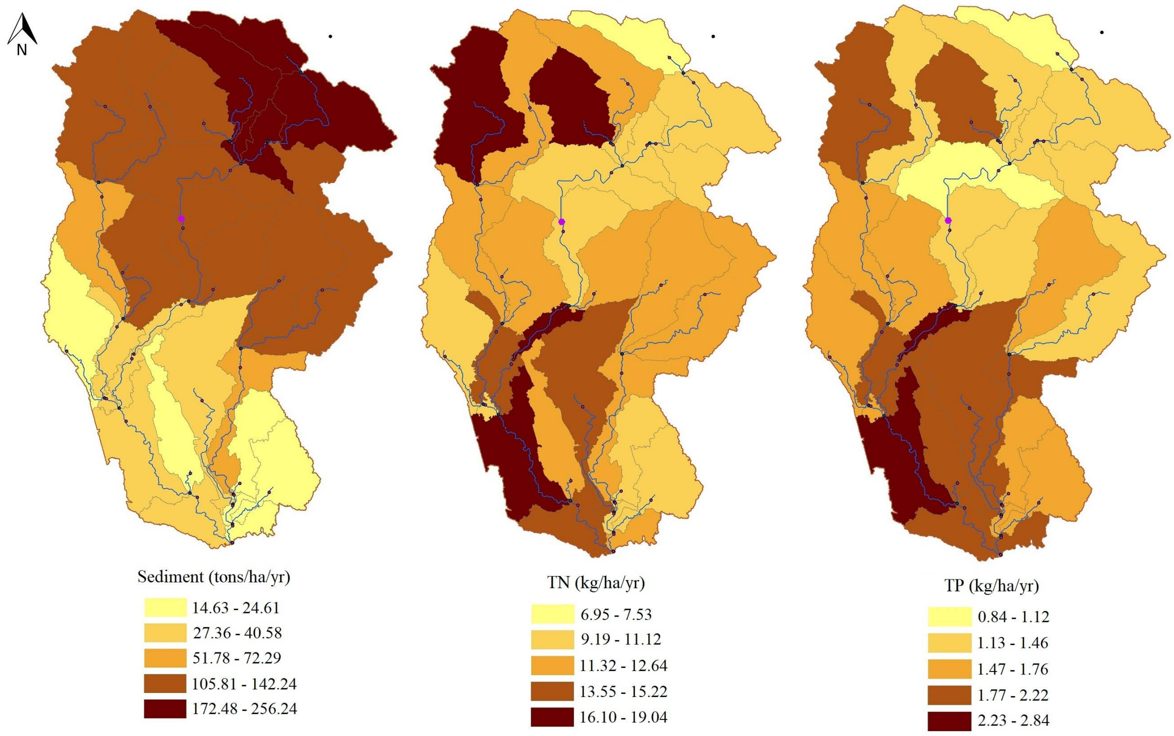


**Figure 10.** CSAs in the basin, identified using individual indices.

Using the combined indices, sub-basins 25 and 17 are identified as the most critical. These sub-basins are located downstream, where the sugar cane factory is located. Subsequently, sub-basins 2 and 8, representing livestock grazing and nomadic settlement sites, are ranked next. By examining the combined indices, it is observed that only introducing nutrient parameters does not provide proper identification of CSAs. By adding sediment to TN and TP, sub-basins 1, 3, 5, and 7 were identified as CSAs due to high sediment loads (because of steep slopes upstream of the river). After applying the 0.1 weight to the sediment, sub-basins 1, 2, 5, 8, and 25 were identified as CSAs. The results of this section are presented in Figure 11.

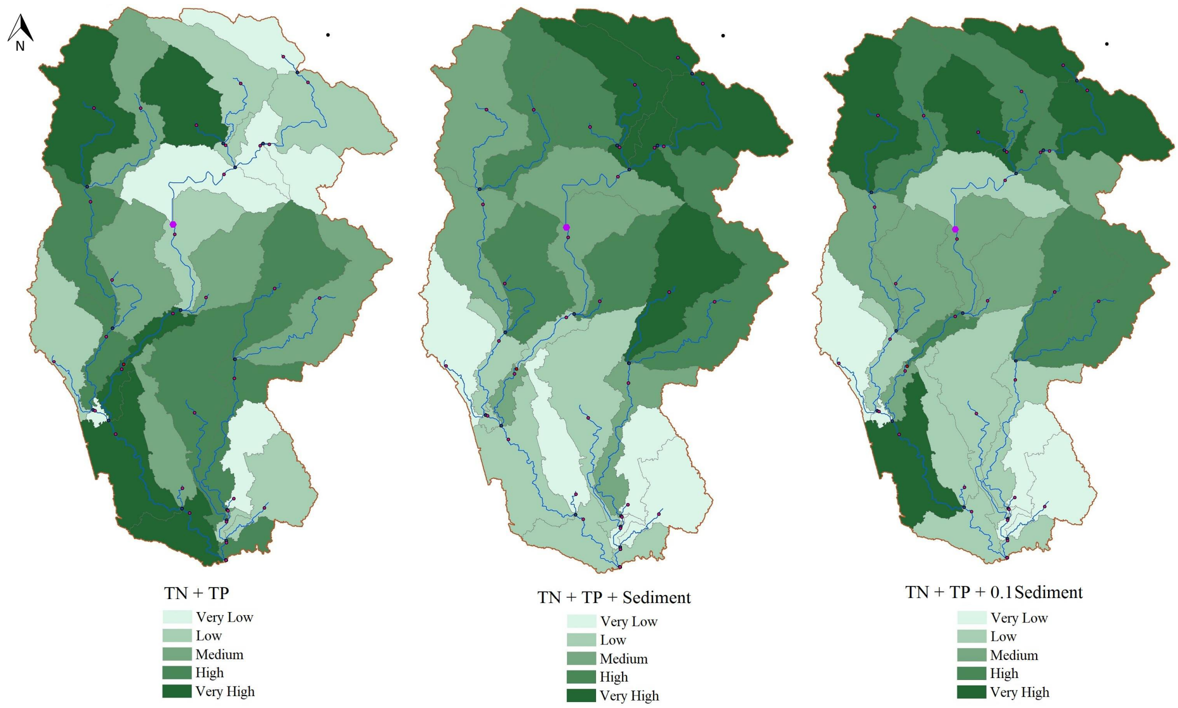


**Figure 11.** CSAs in the basin, identified using combined indices.

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### 3.4. Evaluation of the BMPs

After identifying the CSAs, BMPs were implemented in the model to evaluate their applicability in reducing pollution loads. The percentage of reduction of contaminants after utilizing BMPs is presented in Figure 12.

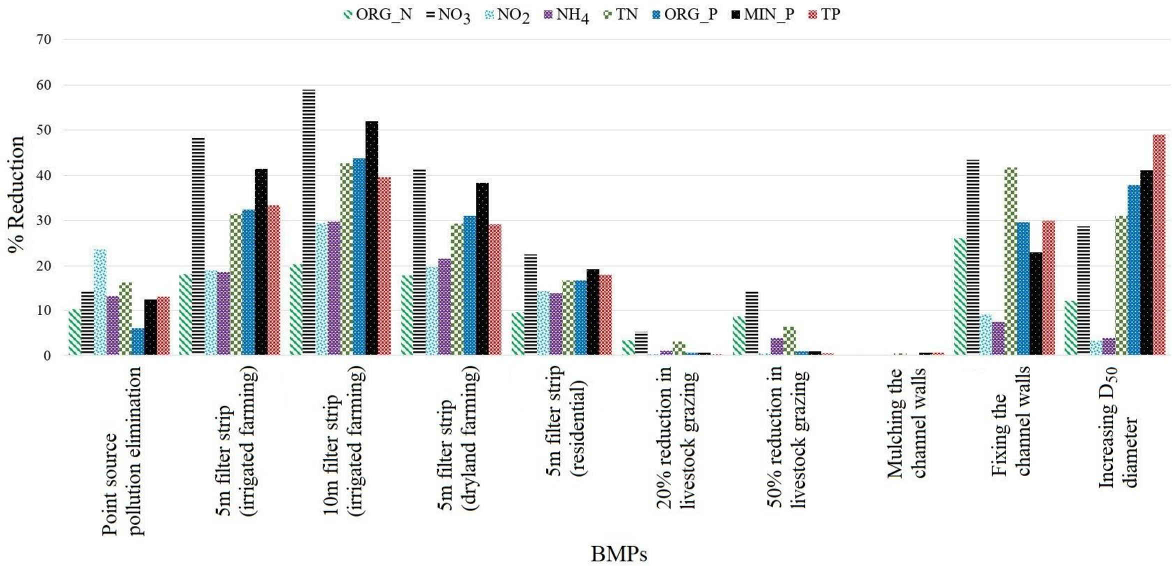


**Figure 12.** Reduction in pollution loads after utilizing BMPs.

Removing point source pollution by constructing a treatment plant reduced the nitrite and ammonia from domestic and industrial sewage in the river. The highest reduction in pollution load was achieved by implementing filter strips in agricultural areas. Under this BMP, the highest reduction in pollutants was observed for nitrate (almost 50%). Further, by increasing the length of the filter strips, the TN load was reduced more than the TP. 20% and 50% reduction in the number of livestock reduced the amount of organic nitrate and nitrogen, compared to the other nutrients. This BMP did not show a significant impact on the amount of phosphorus compounds.

River channel wall mulching had little impact on reducing the nutrients and only decreased the amount of sediment input into the river. Due to the tendency of phosphorus to stick to sediment particles, the only observed effect of this strategy was in reducing the phosphorus compounds in the river. The results also show that doubling the $D_{50}$ of particles in the riverbed and channel walls is a good way to deal with nutrient pollution.

## 4. Discussion

In this study, the Dez River basin in Iran was modeled using the SWAT model, and the sensitivity analysis and calibration/validation of the model were performed using the SUFI-2 algorithm of the SWAT-CUP software. After delineation of the basin, CSAs were identified based on the amount of pollution produced in each sub-basin, using individual and combined indices. Moreover, several BMPs, including source elimination, filter strips, livestock grazing management, and river channel management were implemented to evaluate their applicability in reducing the entry of pollutants to the river. The following are the main findings of this study:

- The model calibration results during dry, normal, and wet years indicated more confidence in the model results during wet years.
- A significant decrease in TN and TP loads were observed in areas with irrigated farming, where a 10m filter strip was used.
- Doubling the $D_{50}$ of particles showed the highest impact in reducing the TP load.
- Reducing the number of livestock was not effective in reducing phosphorus compounds.
- The mulching of the river channel walls did not have much impact on reducing pollution.

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- The combined indices for identifying CSAs without weighting variables are not desirable, and CSAs should be weighed according to the priority of the variables.

For future studies, considering climate change and its consequences, the researchers recommend evaluating the management practices by changing inputs such as precipitation, relative humidity, and solar radiation, and then reassessing the adequacy of these practices in future studies.

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## References

1. Huang, J.; Lin, J.X.; Wang, J. The precipitation driven correlation based mapping method (PCM) for identifying the critical source areas of non-point source pollution. *J. of Hydrol.* **2005**, *524*, pp. 100–110, https://doi.org/10.1016/j.jhydrol.2015.02.011.
2. Natha, S.B.; Allan, J.D.; Dolan, D.M.; Han H.; Richards, R.P. Application of the Soil and Water Assessment Tool for six watersheds of Lake Erie: Model parameterization and calibration. *J. Great Lakes Res.* **2011**, *37(2),* pp. 263-271, https://doi.org/10.1016/j.jglr.2011.03.004.
3. Niraulaa, R.; Kalinb, L.; Srivastavac, P.; Anderson, C.J. Identifying critical source areas of non-point source pollution with SWAT and GWLF. *Ecol. Modell.* **2013**, *268*, pp. 123-133, https://doi.org/10.1016/j.ecolmodel.2013.08.007.
4. Panagopoulos, Y.; Makropoulos, C.; Mimikou, M. Decision support for diffuse pollution management. *Environ. Modell. Software* **2012**, *30*, pp. 57-70, https://doi.org/10.1016/j.envsoft.2011.11.006.
5. Nazari-Sharabian, M.; Ahmad, S.; Karakouzian, M. Climate change and eutrophication: a short review. *Eng. Tech. Appl. Sci. Res.* **2018**, *8(6),* pp. 3668-3672.
6. Chaplot, V.; Saleh, A.; Jaynes D.B.; Arnold, J.G. Predicting water, sediment, and NO3-N loads under scenarios of land-use and management practices in a flat watershed. *Water Air Soil Pollut*. **2014**, *154(1-4),* pp. 271-293, https://doi.org/10.1023/B:WATE.0000022973.60928.30.
7. Santhi, C.; Srinivasan, R.; Arnold J.G.; Williams, J.R. A modeling approach to evaluate the impacts of water quality management plans implemented in a watershed in Texas. *Environ. Model. Soft*. **2006**, *21(8),* pp. 1141-1157, https://doi.org/10.1016/j.envsoft.2005.05.013.
8. Pisinaras, V.; Petalas, C.; Gikas, G.D.; Gemitzi, A.; Tsihrintzis, V.A. Hydrological and water quality modeling in a medium-sized basin using the Soil and Water Assessment Tool (SWAT). *Desalination,* **2009**, *250(1),* pp. 274-286, https://doi.org/10.1016/j.desal.2009.09.044.
9. Bracmort, K.S.; Arabi, M.; Frankenberger, J.R.; Engel, B.A.; Arnold, J.G. Modeling long-term water quality impact of structural BMPs. *Trans. ASABE*, **2006**, *49(2),* pp. 367-374, https://doi.org/10.13031/2013.20411.
10. Santhi, C.; Arnold, J.G.; Williams, J.R.; Hauck, L.M.; Dugas, W.A. Application of a watershed model to evaluate management effects on point and nonpoint source pollution. *Trans. ASABE*, **2001**, *44(6),* pp. 1559-1570.
11. Bouraoui, F.; Benabdallah, S.; Jrad, A.; Bidoglio, G. Application of the SWAT model on the Medjerda River basin (Tunisia). *Phys. Chem. Earth*, **2005**, *30(8-10),* pp. 497-507, https://doi.org/10.1016/j.pce.2005.07.004.
12. Arabi, M.; Govindaraju, R. S.; Hantush, M. M. Cost-effective allocation of watershed management practices using a genetic algorithm. *Water Resour. Res.* **2006**, *42*, W10429, https://doi.org/10.1029/2006WR004931.
13. Ficklin, D.L.; Luo, Y.; Zhang, M. Watershed modelling of hydrology and water quality in the Sacramento River watershed, California. *Hydrol. Processes*, **2012**, *27*, pp. 236-250, https://doi.org/10.1002/hyp.9222.
14. Zhang, X.; Zhang, M. Modeling effectiveness of agricultural BMPs to reduce sediment load and organophosphate pesticides in surface runoff. *Sci. Total Environ.* **2012**, *409(10),* pp. 1949-1958, https://doi.org/10.1016/j.scitotenv.2011.02.012.

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15. Liu, R.; Xu, F.; Zhang, P.; Yu, W.; Men, C. Identifying non-point source critical source areas based on multi-factors at a basin scale with SWAT. *J. Hydrol.* **2016**, *533*, pp. 379-388, https://doi.org/10.1016/j.jhydrol.2015.12.024.
16. Dong, F.; Liu, Y.; Wu, Z.; Chen, Y.; Guo, H. Identification of watershed priority management areas under water quality constraints: A simulation-optimization approach with ideal load reduction. *J. Hydrol.* **2018**, *562*, pp. 577-588, https://doi.org/10.1016/j.jhydrol.2018.05.033.
17. Qiu, J.; Shen, Z.; Huang, M.; Zhang, X. Exploring effective best management practices in the Miyun reservoir watershed. *China. Ecol. Eng*. **2018**, *123*, pp. 30-42, https://doi.org/10.1016/j.ecoleng.2018.08.020.
18. Agricultural Comprehensive Plan of Khuzestan Province, 2006.
19. Arnold, J.G.; Srinivasan, R.; Muttiah, R.S.; Allen, P.M. Large area hydrologic modeling and assessment Part I: Model development. *J. Am. Water Resour.* **1999**, *34(1)*, pp. 37-89, https://doi.org/10.1111/j.1752-1688.1998.tb05961.x.
20. Kiniry, J.R.; Williams, J.R.; King, K.W. Soil and Water Assessment Tool Theoretical Documentation. Version 2009, Center for Agricultural & Rural Development Iowa, Iowa, USA, **2011**, p. 618.
21. Shang, X.; Wang, X.; Zhang, D.; Chen, W.; Chen, X.; Kong, H. An improved SWAT-based computational framework for identifying critical source areas for agricultural pollution at the lake basin scale. *Ecol. Modell.* **2012**, *226*, pp. 1-10, https://doi.org/10.1016/j.ecolmodel.2011.11.030.
22. Abbaspour, K.C.; Yang, J.; Maximov, I.; Siber, R.; Bogner, K.; Mieleitner, J.; Zobrist, J.; Srinivasan, R. Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. J. *Hydrol.* **2007**, *333(2-4)*, pp. 413-430, https://doi.org/10.1016/j.jhydrol.2006.09.014.
23. Alizadeh, A.; Izady, A.; Davary, K.; Ziaei, A.N.; Akhavan, S.; Hamidi, Z. Estimation of actual evapotranspiration at regional-annual scale using SWAT. *Iranian J. Irrig. Drain.* **2013**, *7*, pp. 243-258 (Persian).
24. Nash, J.E.; Sutcliffe, J.V. River flow forecasting through conceptual models 1. A discussion of principles. J. *Hydrol.* **1970**, *10(3)*, pp. 282-290, https://doi.org/10.1016/0022-1694(70)90255-6.
25. Moriasi, D.N.; Arnold, J.G.; Van Liew, M.W.; Bingner, R.L.; Harmel, R.D.; & Veith, T.L. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Trans. ASABE* **2007**, *50*, pp. 885-900, https://doi.org/10.13031/2013.23153.
26. Winchell, M.F.; Folle, S.; Meals, D. Using SWAT for sub-field identification of phosphorus critical source areas in a saturation excess runoff region. *Hydrol. Sci. J.* **2015**, *60*, pp. 844-862, https://doi.org/10.1080/02626667.2014.980262.