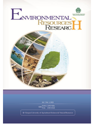

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An index based approach to identify and prioritize critical areas for reclamation using SWAT model

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Abstract

Erosion by water leads to considerable impacts on natural ecosystems and is accelerated in regions with high land use changes. In this study, through applying the K-means clustering approach on the output of SWAT model, the critical areas with respect to water erosion for Farsan Basin was prioritized for Best Management Practices (BMPs). Based on the results of SWAT model, three pollutant indicators were developed: i) contaminat Load per Unit Area Impact Index (LUAII), ii) contaminates Concentrating Impact Index (CII) and iii) the contaminat Load Impact Index (LII). The basin was divided into 26 sub-basins and according to the clustering results; the southern sub-basins which are situated on sloped areas (more than 25 degrees) were classified as high priority areas for management practice based on all indices. Sub-basins that are located in west, south west and south east have medium priority. These sub-basins are very sensitive to land use change including decreasing rangeland and increasing farming area. Among all sub-basins, those which are placed around two major streams are in stable condition because of low slope and low land use change. Finally, using the results of pollution indicators, we showed it was possible to reduce sediment and nutrient waste through implementing best management methods.

***Keywords*: Critical areas, SWAT Model, Farsan Watershed, Land Use, Pollution Indicators**

Introduction

Soil erosion is a major threat for sustainable natural resources management due to considerable environmental and socio-economic impacts (Young et al, 1986., Pimentel et al., 1993). Eutrophication and reducing the rate of dissolved oxygen in channels and reservoirs are major consequences of soil erosion in water resources in addition of direct impact of soil erosion like losing and depositing soil. In recent decades, phosphorus transportation trough the erosion process has received high consideration as it is one of the vital components of nourishment and livelihood (Ide et al., 2008).

Erosion control and soil protection is an important practice to reduce phosphorus load transportation and mitigate its consequences. Usually, soil protection and erosion control is costly and is executed at the catchment scale as part of watershed management projects (Torabi Haghighi et al., 2009a; Chen et al., 2016). Soil erosion is dependent on many factors like slope, rainfall intensity, and soil texture (Torabi Haghighi et al., 2009b) and consequently the rate of erosion is not uniformly distributed over the basin. To have an optimum condition, it is necessary to provide spatial prioritization in sub-catchment levels and make watershed management plans accordingly. Reduction of sediment transport and erosion needs a suitable method and proper execution plan (Patrick Laceby et al., 2015). To find the best method, we have to know different sources of sediment and their contributions (Chen et al., 2016). Preparing the vulnerability erosion map could help inform

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any soil protection plan (Fox et al., 2006). Since land use change is one of the main sources of variation in runoff, erosion and sediment transport (Gessesse et al., 2015), assessment of land use change can provide valuable information on sediment transport and soil erosion.

Soil and Water Assessment Tools (SWAT) is widely used for different purposes of water resources engineering. Some of well documented SWAT applications are simulation of sediments and erosion at the catchment scale (Ricci et al., 2018; Xu et al., 2009), identification of critical areas at the basin scale (Panagopoulos et al., 2011; Tripathi et al., 2003), and flow and water quality simulation (Ficklin et al., 2013). In addition, understanding the sources of erosion and how the pollutants (e.g. Nitrate and sulphate) move and distribute along the water body (Busteed et al., 2009; Pongpetch et al., 2015) and prioritizing the critical sub-basins for watershed management practices (Mishra et al., 2007; Ndomba et al., 2008; Pandey et al., 2009; Daggupati et al., 2009) are other well documented applications of SWAT. In recent years, outputs from the SWAT model have been used, to better manage watersheds and reduce costs and time, and implement the best management strategies (Tuppad and Srinivasan, 2008; Giri et al., 2012; Himanshua et al., 2019; Liu et al., 2019; Zare Garizi and Talebi, 2016; Uniyal et al., 2020).

In this paper, we combine SWAT model with k-means classification for identification and prioritization of the polluted areas based on the pollution indices. To show the developed approach, the Farsan Basin located in headwater of Karun River (the largest river in Iran) was selected as the case study. To model the basin, the Tannge Darkash-Varkash gauge was chosen as basin outlet, and sediment and flow data from this station were used for model calibration and verification. This research helps us to identify areas in need of management and in the future research, watershed management models will be proposed.

Materials and methods

Study area

The Farsan River basin (area 83035.5 ha) is a sub-basin of Karun River located in western part of Iran (Figure 1). The basin is located at high altitude between 1970 and 3610 msl with mean annual temperature of 12.5°C and mean annual rainfall of 416.7 mm. The monthly precipitation varies from 96 mm in April to 5 mm July.

Land use change data

Land use/land cover (LULC) maps were produced based on available Landsat TM 05.Jul.2011 and Landsat OLI/TIRS images y using maximum likelihood classification in ENVI 5.3. The land use change map shows changes from 2001 to 2017 (Figure 2). Overall, a 13.9% change was observed due to urban areas expansion and reduced rangeland areas (Figure 2).

Using maps including digital elevation, land use, soil and slope the main basin was divided into 26 sub-basins in ArcSWAT. The climatological daily data were taken from Shahrekord and Koohrang synoptic stations and flow and sediment data from Tannge Darkash-varkash gauge (Figure 3).

SWAT Model calibration and validation

The calibration and validation were completed on flow simulation. In the first run of the model, the major error was seen in the over-estimation of flow and the recession limb of hydrograph did not match the observed data. Initial calibration was implemented considering the water balance of the basin. Then, using SWAT–CUP, the sensitivity analysis was applied and the most sensitive parameters were recognized, focusing on sensitive parameters to get a good match with the observed data (Figure 4a). The calibrated model was validated for the period 2011-2015. Nash–Sutcliffe coefficient (N_{SE}) and coefficient of determination (R^2) for the validation period confirmed the calibration process and also the SWAT model was found suitable for flow simulation in Farsan Basin (Table 2).

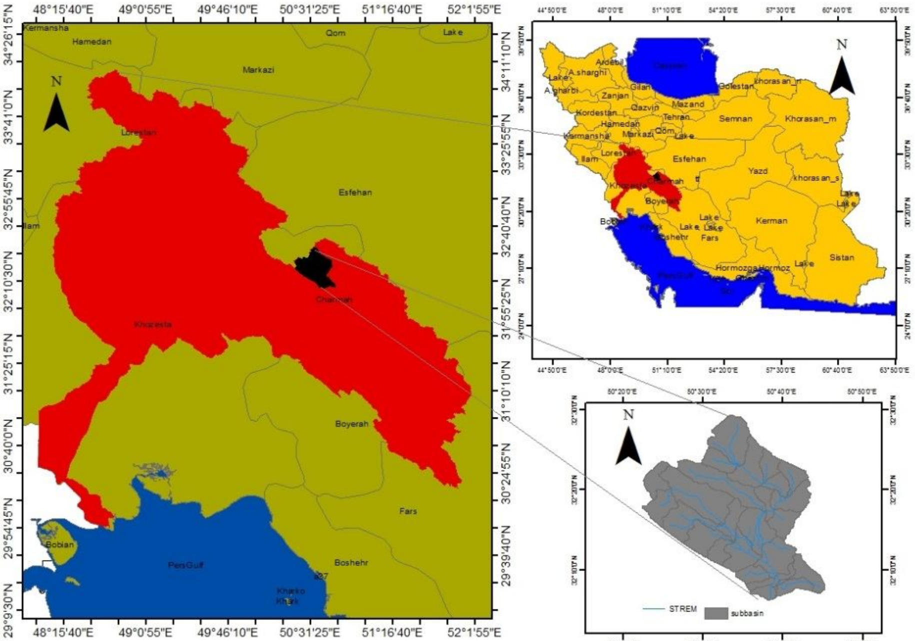

Figure 1. Study area location in Karun Basin of Iran

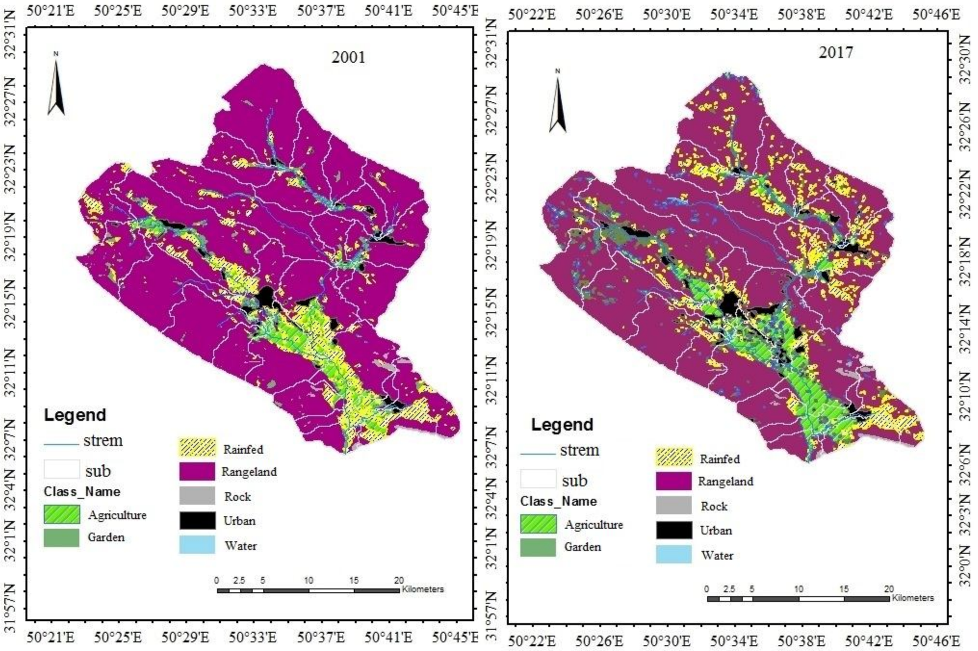

Figure 2. Land use map for the years 2001 and 2017

Sediment data from the Tange Darkaskash-Varkash gauge was used for SWAT model calibration. Sediment measurement caused the main uncertainty in calibration as the measurements had not been done at regular intervals. For some months, there were several records while for other months, no measurements were available. However, we used all available data. This is usual, as sediment measurement is costly and time consuming. Cases can be found where the SWAT model has been used without calibration (Niraula et al., 2012) or at best through other data such as discharge (Young et al, 1986; Ide et al, 2008; Ide et al., 2007;

Mihara et al., 2005). Niraula et al. identified and compared sediment, total phosphorus and nitrogen in two different catchments in Alabama with and without calibration in the SWAT model and the result was quite similar (Niraula et al., 2012). For Farsan Basin, we applied the SUFI-2 method in SWAT-CUP, recommended by Abbaspour (Abbaspour, 2013).

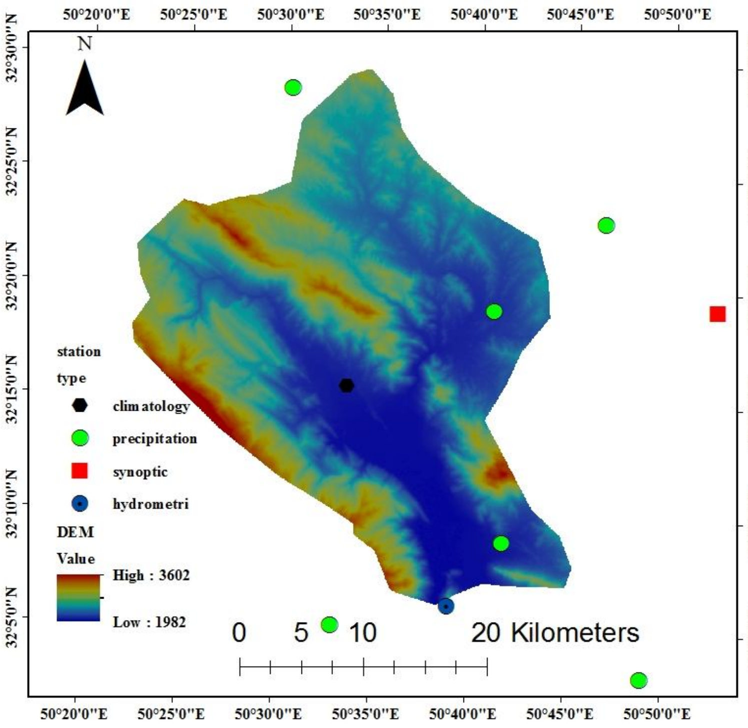

Figure 3. Locations of gauge and climate stations

The validation was executed based on the following guidelies from Abbaspour (2013) to define the optimum range of model's parameters in calibration process. Then, the SUFI-2 method was performed for optimum ranges, R factor and observed P for the period 2011-2015. The validation process was confirmed by the coefficient of determination (R^2, Eq. 1), Nash–Sutcliffe (Eq. 2) and weighted correlation coefficient bR^2.

$$R^2 = \frac{\left[\sum_{i=1}^{n}(Simulated_i - Simulated_{avg})(Measured_i - Measured_{avg})\right]^2}{\sum_{i=1}^{n}(Simulated_i - Simulated_{avg})^2 \sum_{i=1}^{n}(Measured_i - Measured_{avg})^2} \tag{1}$$

Where $Simulated_{\mathrm{avg}}$ and $Measured_{avg}$ are the mean of simulated and observed data. Coefficient of determination (R^2) varied between 0-1.

$$E_{NS} = 1 - \frac{\sum_{i=1}^{n}(Measured_i - Simulated_i)^2}{\sum_{i=1}^{n}\left[Measured_i - {}^{1}/_{n}\sum_{i=1}^{n} Measured_i\right]^2} \tag{2}$$

Nash–Sutcliffe vary between - ∞ to one. The optimum value of ENS is 1. If $0.75<E_{NS}<1$, $0.36<E_{NS}<0.75$ and $E_{NS}<0.36$, the model is evaluated as perfect, acceptable, and unsatisfactory respectively (Xu., et al. 2009, Nash & Sutcliffe, 1970). The bR^2 coefficient shows the difference between the observed and simulated data and their dynamic relationship and is calculated as follows.

$$bR^2 = \begin{cases} |b|R^2 & if \quad |b| \le 1 \\ |b|^{-1}R^2 & if \quad |b| > 1 \end{cases} \tag{3}$$

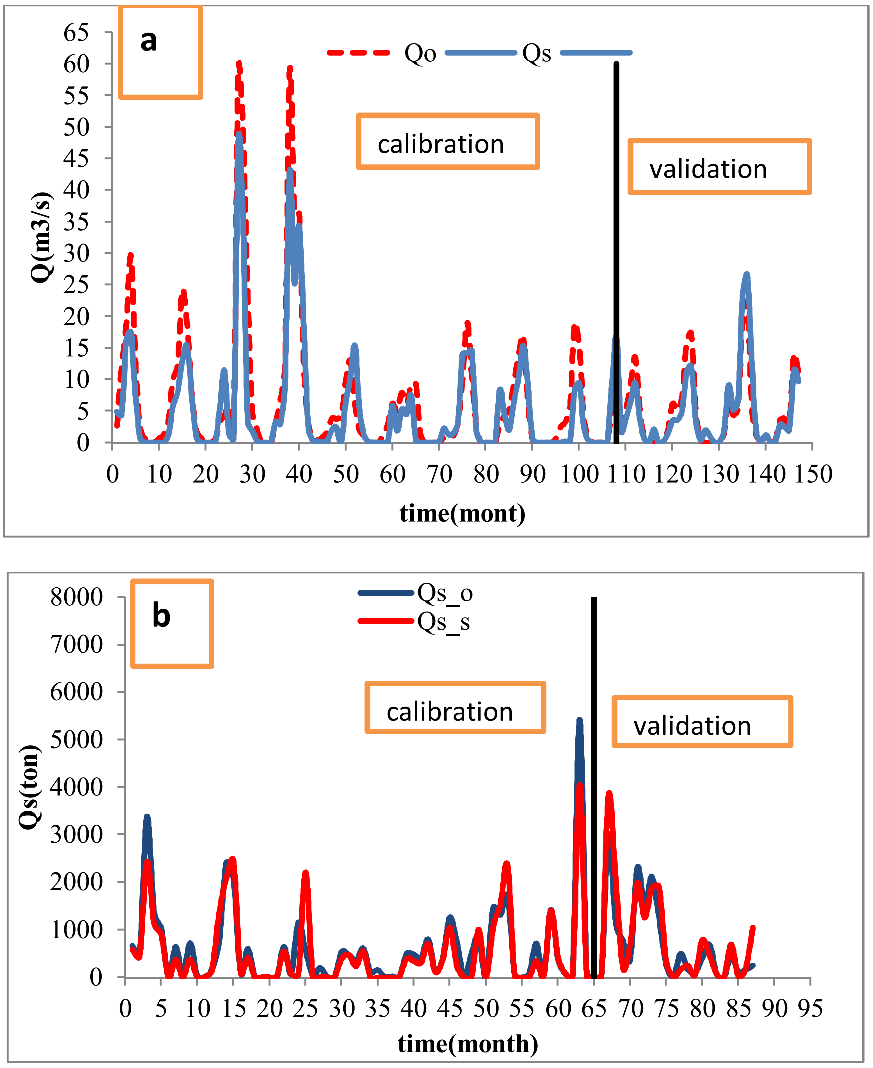

Figure 4. Calibration and validation process in SWAT modeling of a) discharge (l/2) and b) sediment concentration (1000 kg)

Table 1. Calibration and validation coefficients in SWAT model for flow and sediment based on different methods

Method	Flow		Sediment	
	Calibration	Validation	Calibration	Validation
Nash–Sutcliffe	0.67	0.82	0.7	0.53
Coefficient of determination	0.65	0.64	0.72	0.67
Weighted correlation coefficient	0.62	0.68	0.57	0.59

Identification and prioritization of the critical areas

To identify the critical areas and prioritizing sub-basins for watershed management, three indices were taken into account: the contaminate load per unit area impact index (LUAII), concentrating impact index (CII), and the contaminate load impact index (LII). These indices were calculated based on the result of validated SWAT model using the load of sediment, total phosphorus and total nitrogen as variables (Zare Gariz and Talebi, 2016).

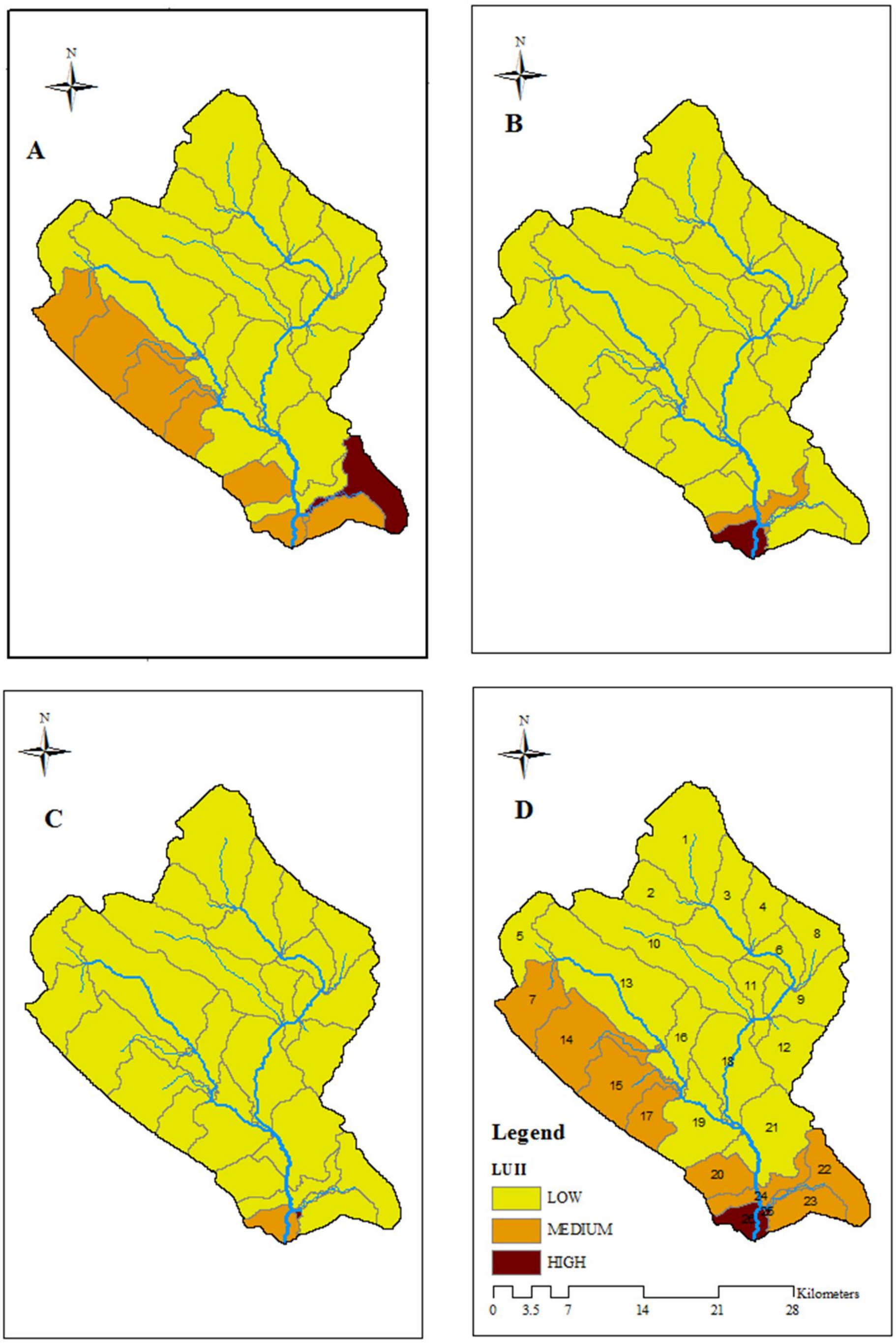

Figure 5. Prioritizing Farsan Sub-basins based on contaminant yield per unit area impact index (LUAII), a) sediment yield (LUAII$_1$), b) nitrogen yield (LUAII$_2$), c) phosphorus load (LUAII$_3$), d) and overall contaminant yield per unit area (LUAII)

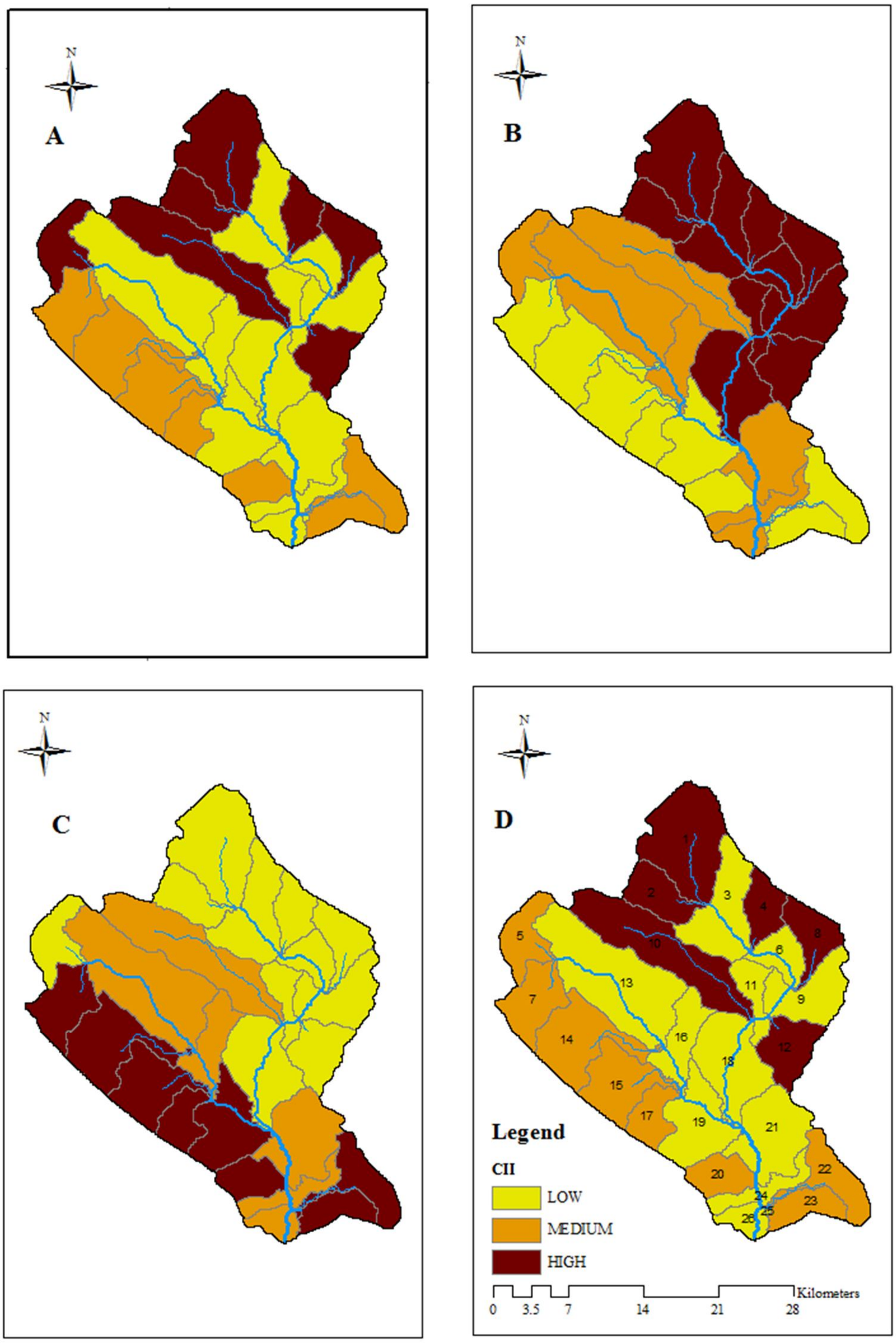

Figure 6. Prioritizing Farsan Sub-basins based on concentrating impact index (CII), a) sediment concentration (CII $_1$), b) Nitrogen concentration (CII $_2$), c) Phosphorus concentration (CII $_3$), and d) overall contaminant yield per unit area (CII)

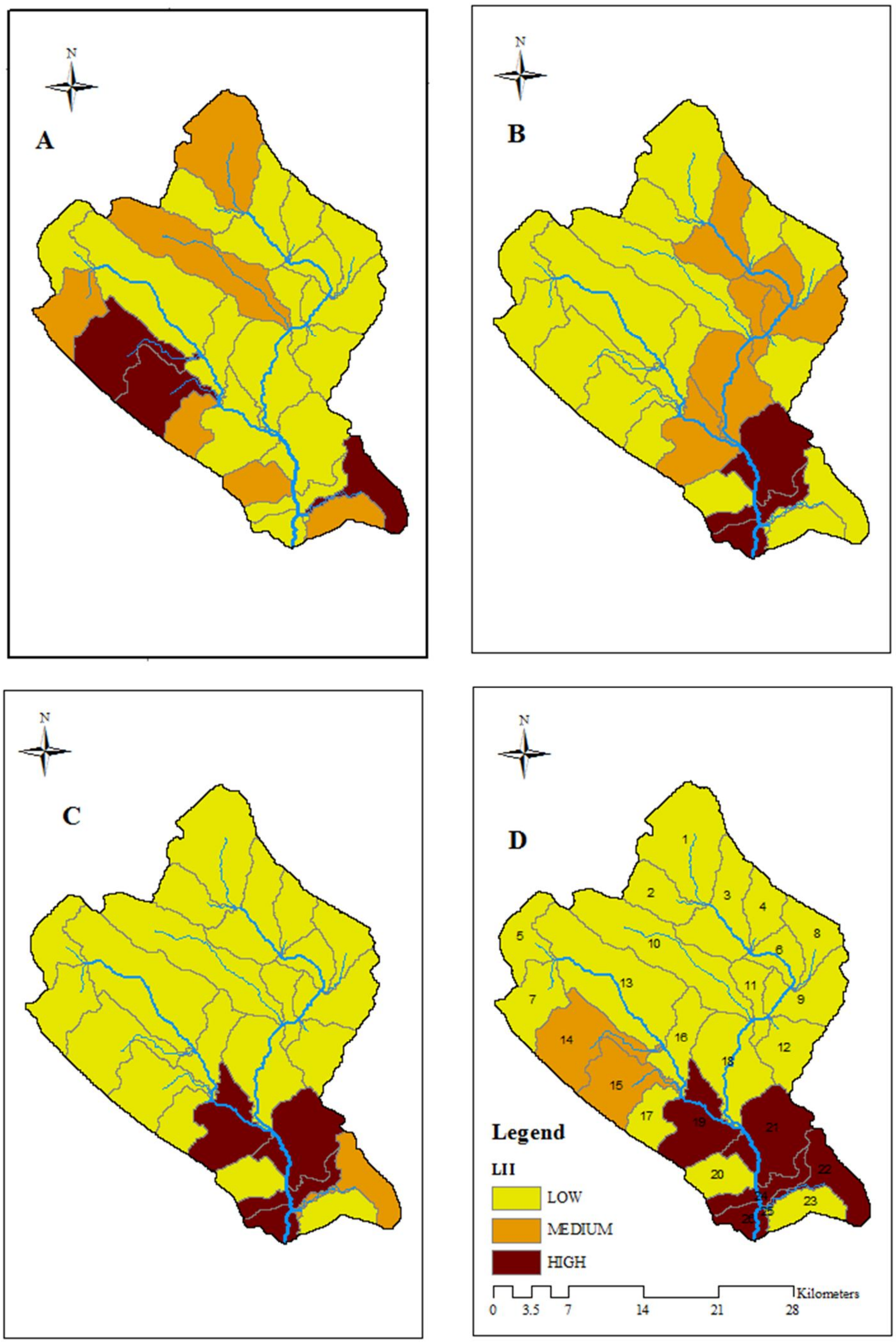

Figure 7. Prioritizing Farsan Sub-basins based on accumulated contaminant load impact index (LII), a) accumulated sediment load (LII_1), b) accumulated nitrogen load (LII_2), c) accumulated phosphorus load (LII_3), and d) overall accumulated contaminant load (LII)

- Contaminant load per unit area impact index (LUAII) was developed based on the potential of sediment yield (ton per hectare) and the potential of producing the nitrogen and phosphorus from the area of each sub-basin.

$$LUAII_1 = \frac{Sediment\ yield\ (ton)}{Area\ (ha)} \tag{4}$$

$$LUAII_2 = \frac{Nitrogen\ load\ (kg)}{Area\ (ha)} \tag{5}$$

$$LUAII_3 = \frac{\text{phosphorus}\ load\ (kg)}{Area\ (ha)} \tag{6}$$

- Concentrating impact index (CII) is the concentration of nitrogen or phosphorus (mg/lit) in the main stream of each sub-basin.
- Accumulated contaminant load impact index (LII), is the accumulated magnitude of sediments (ton), nitrogen (kg) and phosphorus in the main stream of each sub-basin which is generated in sub-basins or delivered from all upstream sub-basins. This index is a combination of concentration and discharge.

Table 2. Sub-basins ranking with respect to pollutant indices based on SWAT model outputs

LUAII (Kg/ha)						CII (mg/l)						LII (kg)					
SB	Se	SB	Ni	SB	Ph	SB	Se	SB	Ni	SB	Ph	SB	Se	SB	Ni	SB	Ph
13	1324	17	0.000	9	0.000	18	5.8	17	0.00	1	0.01	8	6276	10	0.03	7	0.02
3	2537	22	0.000	13	0.000	24	5.9	23	0.01	2	0.02	6	11106	15	0.04	1	0.04
18	3785	7	0.000	1	0.000	21	6.6	14	0.01	4	0.02	26	11641	1	0.07	2	0.09
9	4151	8	0.000	4	0.000	9	6.9	22	0.03	8	0.02	18	12706	2	0.32	16	0.12
16	6400	19	0.000	2	0.000	26	7.2	20	0.03	18	0.02	16	14203	14	0.62	4	0.14
19	6550	23	0.000	5	0.000	11	7.2	19	0.04	12	0.03	19	15886	20	0.76	13	0.23
6	7325	18	0.000	11	0.000	6	7.6	7	0.04	6	0.03	21	17014	22	0.79	17	0.36
21	8818	5	0.000	3	0.000	19	8.0	25	0.08	5	0.03	25	18277	5	0.81	8	0.42
11	10889	11	0.000	10	0.000	3	8.2	15	0.12	9	0.04	5	26476	4	0.86	5	0.45
8	17019	9	0.000	14	0.000	25	8.9	24	0.20	3	0.04	13	38676	17	1.09	23	0.46
12	17166	13	0.000	16	0.000	16	9.3	10	0.20	11	0.06	4	39385	25	1.17	20	0.59
10	23476	16	0.001	6	0.000	13	10.9	21	0.22	26	0.08	2	41173	12	1.19	9	0.95
5	24650	1	0.001	12	0.000	15	596.9	5	0.22	10	0.09	24	45679	16	1.55	10	1.90
24	24979	4	0.001	18	0.001	17	599.0	26	0.24	24	0.09	9	57353	8	2.43	12	2.07
1	29719	2	0.001	8	0.001	20	602.5	13	0.34	13	0.09	11	59753	13	3.46	18	2.22
4	29899	3	0.002	19	0.001	7	607.2	16	0.39	21	0.10	3	70561	7	4.20	6	2.53
2	29962	15	0.003	22	0.001	14	611.9	3	0.48	16	0.10	12	71594	23	7.23	14	3.01
26	63582	21	0.003	7	0.001	23	618.4	11	0.52	15	0.20	20	162270	3	8.25	3	3.51
7	75230	10	0.004	21	0.001	22	645.0	9	0.54	25	0.21	7	183372	19	10.18	15	3.93
14	76068	14	0.004	17	0.002	1	1136.9	1	0.56	7	0.22	10	204467	6	11.10	11	3.99
23	112021	6	0.006	20	0.003	4	1228.7	6	0.56	19	0.22	23	214144	9	13.71	22	8.82
17	118344	20	0.007	23	0.003	2	1245.3	12	0.56	23	0.28	17	228080	11	15.83	25	9.23
20	118661	12	0.010	15	0.004	5	1355.6	18	0.60	14	0.29	1	230707	18	20.47	24	12.85
15	120072	25	0.016	24	0.008	10	1361.2	2	0.61	22	0.32	14	352367	21	32.80	21	13.12
25	126794	24	0.022	26	0.015	8	1650.5	4	0.61	17	0.42	15	444026	24	34.67	19	16.37
22	179472	26	0.034	25	0.178	12	1749.5	8	0.66	20	0.48	22	487714	26	37.84	26	17.03

SB: Sub-Basin, Se: Sediment, Ni: Nitrate, Ph: Phosphor

Clustering sub-basins by K-mean

The k-means method is widely used for pattern recognition and classifying samples (Tokhmechi et al., 2009; Martelet et al., 2006; Song and Meng, 2010). The main purpose is to minimize the difference between the samples in each group and maximize similarity in the same group (Nugraha, 2011). The k-means clustering is also useful for the regions which lack data (Song and Meng, 2010).

In Farsan Basin, sub-basins were classified into three groups based on priorities for watershed management practices as low, medium and high, numbered 1, 2 and 3 respectively. Sub-basins were classified based on each index into one of those classes and received a point (from 1-3) accordingly. The sum of points from different indices for each sub-basin is represented as the final point. The highest point indicates the priority for watershed management and the sub-basin with the highest point is considered as critical area. Finally, based on the points and using the same algorithm, the sub-basins were categorized into three groups for further actions.

Table 3. Prioritization of sub-basins based on the K-means method and the results of the SWAT model

Overall Score	LII	CII	LUII
13	13	3	1
16	16	6	2
5	5	9	3
3	2	11	4
6	4	18	5
9	8	13	6
11	12	16	8
18	7	21	9
2	17	24	10
4	20	26	11
8	23	19	12
12	1	25	13
7	10	5	16
17	3	7	18
20	6	14	19
23	9	15	21
1	11	17	7
10	18	20	14
25	25	23	15
14	14	22	17
15	15	1	20
19	22	2	23
21	19	4	22
24	21	8	24
22	24	12	26
26	26	10	25

Results and Discussions

Model performance for discharge and sediment yields

The result of the validation of sediment simulation shows more uncertainty in comparison with flow simulation. This is perhaps due to high uncertainty in soil map, the quality of in situ data, and uncertainty in model parameters such as characteristics of river channel which was not possible to be measured directly. In the SWAT model, sediment simulation is dependent on flow simulation as it is process-oriented and therefore runoff and erosion parameters interact at the basin scale. Consequently, the model is recommended for Spatio-temporal simultaneous analysis of sediment and runoff to optimize further watershed management plans. The results of three indices (LUAII, CII, and LII), considering the details on phosphorus, nitrogen, and sediments were calculated through SWAT and used for identification and prioritization of the critical areas in Farsan Basin using the k-means clustering approach (Table 3).

Identification and prioritization of the critical areas based on the indices

Based on the overall score of the three LUAII indices, only the basin outlet was placed in high priority class of watershed management practices and some other sub-basins were classified in the medium priority group (Figure 5d). These areas are mainly located on lands with 25% slope in the west and south and are recommended for watershed management. According to the potential for sediment production ($LUAII_1$), sub-basin #22 is placed in high priority for watershed management (Figure 5a) while in terms of nitrogen pollutant, the basin outlet has the highest priority (Figure 5b sub-basin #26). Based on $LUAII_1$, 25 % of the basin has potential for producing sediments in high sloped sub-basins in western and southern parts of the basin. About 3.3% of the basin is involved in nitrogen production (according to $LUAII_2$, this includes sub-basins #24, #25 and #26) which is due to land use change and increased irrigation and rain farming.

According to the concentrating impact index (CII), seven sub-basins in northern and eastern parts of the basin (#1, #2, #4, #8, #12, #10) were classified in the third high priority group (number 3 for CII, Figure 6d). This may be due to the location (except sub-basin #10), high slope, and change in land use from rangeland to dry farming, which includes soil plowing process. The results were similar to some other studies (Lindestrom et al., 2001; Van Oost et al., 2006; Zhang et al., 2004). Furthermore, the soil type in these sub-basins is classified in group C (according the soil map of the region) which includes considerable amount of silt with low permeability and high potential for erosion and dense sediment load. The nitrogen concentration in 10 sub-basins (#1, #2, #3, #3, #4, #6, #8, #9, #11, #12, #18) in eastern part of the basin puts these in group 3 of critical areas (high priority). The main reason for this is change in land use from dry farming to irrigated and increased application of nitrogen fertilizers. This is a common problem for the irrigated areas with slopes more than 15%. For example, in China, the land use change to farming in high slopes was recognized as the most critical and an illegal activity (Fu et al., 2004).

The high phosphorus concentration areas (with high priority), were mostly recognized in the western sub-basins and three downstream sub-basins (#7, #14, #15, #17, #19, #20, #22, #23 and #25), all related to the type of land use (gardens) and application of phosphate fertilizers. In the western basin, due to the high slope, in addition to the available dissolved phosphorus in water, the phosphorus can be seen in the sediment load as suspended load. The available phosphorus exerts environmental impacts like eutrophication in downstream and basin outlet (Blanco and Lal, 2008; Bowes et al., 2005; Noor et al., 2010). Overall, the results of load impact index (LII) indicate that the sub-basins in western and downstream of basin are classified as medium (#7, #14, #15, #17, #20, #22 and #24) to high priority (#25 and #26) for watershed management (Fig 7d). In terms of the phosphorous load, with the exception of sub-basins #26 and #25 which were classified in high and medium priority groups, the other basins are classified as low priority (Figure 7a). The nitrogen load has the same condition as phosphorus load and adds sub-basin # 24 to the medium priority class (Figure 7b). Based on the sediment load index ($LUII_3$), high slope sub-basins like #7, #14, #15 are classified as medium priority and only #22 is placed in the high priority class.

Conclusion

Hydrological modelling and sedimentation analysis of Farsan Watershed was performed using the SWAT model. The results showed that the model could very well simulate the runoff and sediment transport in Farsan Watershed. Prioritization of Sub-basins in the study area was completed based on the results of the SWAT model using three indices. The indices included contaminate load per unit area impact index (LUAII), contaminates concentrating impact index (CII), and the contaminate load impact index (LII). The results showed spatial distribution of critical areas because of different indices. The western sub-basins are mostly sensitive to LUAII, and the central basins are critical according to CII. In the central parts of the basin, the amounts of phosphorus and nitrogen are high with respect to the flow magnitude. Due to the transfer of large amounts of contaminates in downstream parts of the basin, the most sensitive sub-basins are located in downstream areas.

Acknowledgments
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