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Sediment Estimation of the Mosul Dam Lake Using SWAT and Dual ANN Models

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Keywords:
Dual ANN; Mosul Dam; Sediment Concentration; Sediment Load; SWAT.

Highlights:
- *SWAT model used to estimate the runoff and sediment in ungagged areas.*
- *A Dual ANN model was applied to estimate the sediment using precipitation data.*
- *The Ephemeral stream supplies the lake with high sediment during the storm.*

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Abstract: Managing sediment in river basins and waterways became a key point in water management. The continuous sediment deposition from the rivers and streams flowing to the reservoirs is today's problem. Entering sediment from the Sweedy, Crnold, and Alsalam valleys located at the right bank to the reservoir of Mosul Dam in the north of Iraq has been estimated using the ANN model. This study aims to estimate the sediment values using only available precipitation data. The challenges and difficulties in this study were that the catchments of these valleys were ungauged with very limited available data, so the ANN models were used with the assistance of the SWAT using three different models in three main steps. In the first step, the flow, concentration, and load of sediments were calculated using the SWAT model for a period (1994-2018) using the available meteorological data. Then, as a second step, based on the available rainfall data and the flow resulting from the SWAT model, the ANN model was used to obtain the flow discharge. In the last step, two separate ANN models were used to estimate the sediment concentration and sediment load entering the dam reservoir from the right-side bank. The coefficient of determination (R^2) and Nash Sutcliff Efficiency (NSE) were used to evaluate the models. Finally, the result showed the ability of ANN to use two successive models (Dual ANN) to estimate the sediment concentration and sediment load for the valleys, as mentioned earlier.

تقدير الرواسب لبحيرة سد الموصل باستخدام نموذجي اداة تقييم الماء والتربة والشبكة العصبية الاصطناعية المزدوجة

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الخلاصة
أصبحت إدارة الرواسب في أحواض الأنهار والمجاري المائية قضية مهمة لإدارة الموارد المائية. يعتبر الترسيب المستمر للرواسب من الأنهار والجداول المتدفقة إلى الخزانات السطحية مشكلة اليوم. تم تقدير دخول الرواسب من أودية السويدي وكرنولد والسلام الواقعة على الضفة اليمنى لبحيرة سد الموصل الواقع في شمال العراق باستخدام نموذج (ANN). تهدف هذه الدراسة إلى تقدير قيم الرواسب باستخدام بيانات الهطول المتوفرة فقط. كانت التحديات والصعوبات في هذه الدراسة هي أن الاحواض المائية لهذه الوديان تعتبر غير مقاسة، لذلك تم استخدام نماذج (ANN) بمساعدة نموذج (SWAT)، وذلك باستخدام ثلاثة نماذج مختلفة في ثلاث خطوات رئيسية. في الخطوة الأولى، تم حساب التصريف المائي الناتج من السيح السطحي وتراكيز والحمل الرسوبي باستخدام نموذج (SWAT) للفترة الزمنية (١٩٩٤-٢٠١٨) باستخدام بيانات الأرصاد الجوية المتوفرة. ثم، كخطوة ثانية، واستناداً إلى بيانات هطول الأمطار المتوفرة والتصريف الناتج عن نموذج (SWAT)، تم استخدام نموذج (ANN) للحصول على التصاريف المائية. في الخطوة الأخيرة، تم استخدام نموذجين منفصلين لـ (ANN) لتقدير تركيز الرواسب والحمل الرسوبي التي تدخل خزان السد من الضفة اليمنى. وتم استخدام المعامل (R^2) و (NSE) لتقييم نتائج النماذج المستخدمة. وأخيراً أظهرت الدراسة قدرة الشبكة العصبية الاصطناعية باستخدام نموذجين متتاليين (Dual ANN) على تقدير تركيز الرواسب والحمول الرسوبي للوديان المذكورة اعلاه.

الكلمات الدالة: الشبكة العصبية الاصطناعية، الحمل الرسوبي، تركيز الرسوبيات، سد الموصل، سوات.

1.INTRODUCTION

When precipitation falls, the process of separating the soil grains and trying to transport them due to the energy possessed by the surface runoff occurs, leading to soil erosion and dredging. On the other hand, when the speed of the surface runoff that carries the soil and grains entering the lakes decreases, the potential energy that carries the sediments also decreases, leading to sedimentation. The size of settable and sediment particles varies according to the system and nature of the water. One of the main difficulties of hydraulic structures is accumulating sediment transport upstream of the structure. Hence, it is important to estimate these deposits' amount and their negative impacts on these hydraulic structures to maintain their stability. There are many professional programs and software for estimating the productivity of sediments, such as The Soil and Water Assessment Tool (SWAT). The SWAT model is associated with the ArcMap software. This model is an incessant and physically circulated simulation model invented by the United States Department of Agriculture (USDA). The SWAT was used to calculate the total amount of sediments transferred to the study catchment area. Many other studies were conducted to estimate sediment using the SWAT model. Sanjay et al. [1] proposed that for sediment yield simulation from the basin, the SWAT was applied to a portion of the Satlug River basin, placed between Suni and Kasol in the Himalayan western region in Pakistan. Ezz-Aldeen et al. [2] used the SWAT model to measure the sediment yield for the study period (1988-2008) from seven valleys that arrived at the Mosul dam reservoir from the left side of Iraq. Alwan et al. [3] estimated the volume of the runoff for the Wadi Al-Naft watershed in the northeast of Diyala in Iraq by using the SWAT model for the period (2000-2014). Zende [4] applied the SWAT model to measure the sediment yield of the Kerala river basin located in the Peninsular India semi-arid region for the period (1998-2011). Mustafa et al. [5] utilized the SWAT model to measure sediment load-carrying from the main valleys at the Haditha dam reservoir left bank in Iraq. Khaleel et al. [6] estimated the sediment loads using the Bagnold method, applying the SWAT model for seven main valleys in the left bank of the Mosul dam reservoir during the period (1988-2016). Alwan et al. [7] used SWAT to predict the impact of land management and the land use, soil type, and soil texture maps to predict the sediment yield of the Wadi Al-Naft watershed in Iraq, Additionally, Hallouz et al. [8] used the SWAT model to simulate the sediment concentration for the period (2004-2009) in Wadi Haraz's basin in Algeria. Besides, Zhang et al. [9] used the SWAT model to simulate the sediment loads for the period of (2008-2016) in the Hun River Basin in Northeast China. Hadadin et al. [10] applied the SWAT Model to estimate the sediment yield in the Wadi Al-Arab dam in northern Jordan during the period (2003-2014). Artificial neural networks (ANN) or connection systems compute systems vaguely inspired by the biological neural networks that constitute animal brains. The neural network is not an algorithm but a framework for many machine learning algorithms to work together and process complex data inputs. Such systems learn to perform tasks by considering examples, generally without being programmed with any task-specific rules. Many similar studies have been conducted to estimate sediment using the ANN model. For example, Talebizadeh et al. [11] applied the SWAT model and ANN to simulate the sediment loads of the Kasilian watershed in northern Iran. Singh et al. [12]

used the SWAT model and ANN to compare the monthly sediment yield simulation results of the Nagwa watershed in Jharkhand state. Gharde et al. [13] used an artificial neural network ANN model to forecast the sediment yield of the Kal River in Maharashtra State in India. Bouzeria et al. [14] used the training algorithm in Multilayer Perceptron neural networks (MLP) to predict suspended sediment discharges in Mellah Wadi, which is the right bank affluent of Seybouse River, which joins with the outlet of the valley of Guelma in Algeria. Ghosh and Maiti [15] estimated the annual sediment yields of the Mayurakshi River Basin of Eastern India using the ANN and SWAT models. Romero et al. [16] applied the Artificial Neural Network Multilayer Perceptron model to predict the volumetric concentration at the deposition limit using 544 experimental data from the literature in Brazil. Sulaiman et al. [17] used the SWAT model to predict the amount of surface runoff for the period (2020-2030) of the catchment area of the Wadi Al-Masad in the Western Desert of Iraq. Most of the articles that used the SWAT model to predict the sediment and flow related in the valleys located on both sides of the Mosul Dam Lake used the observed sediment data of the Fayda Valley, such as [2, 6]; therefore, the calibration of SWAT in this study used the same values. The main objective of this study is to estimate the sediment load and sediment concentration. This objective was achieved by applying dual artificial neural network models using available meteorological data and a flow estimated by the SWAT model for three ungauged valleys, Sweedy, Crnold, and Alsalam, entering the Mosul dam reservoir. The reason for using two models of ANN in this study is the inability to use one model to get acceptable values using only the precipitation data as an input set, so the discharge data was added. The flow data was created firstly using the ANN-1 model and then entered with the precipitation data for Mosul city and Mosul Dam in the ANN-2 and ANN-3 models to estimate the sediment concentration and sediment load entering the dam reservoir from the right side bank by the three valleys.

2.MATERIAL AND METHODS

2.1.Area of Study

Mosul Dam is the largest dam in Iraq and the fourth largest dam in the Middle East. It was built during the 1980s and located at the Tigris River, approximately 60 km northwest of Mosul city, at 36° 37' 44"N latitude and 42° 49' 23"E longitude [18]. The water surface area of the dam is about 380 km². At the maximum operating level of 330 m above mean sea level, the storage capacity is about 11.11 billion m³. The live storage and the dead storage of the reservoir are 8.16×10^9 and 2.95×10^9 m³, respectively [18]. The dam height is about 113 meters, with a 3.4 km length and a crest width of 10 m. The earth-fill embankment type includes a clay core. The service spillway is located on the east side of the dam, controlled by five radial gates, and has a maximum release capacity of 12400 m³/sec at the maximum level. The inflow to the reservoir is basically from the River Tigris [19]. The area of study includes three tributary valleys, which are responsible for feeding the reservoir from the right side, located northwest of Mosul city, as shown in Fig. 1. The major valleys, i.e., Sweedy, Crnold, and Alsalam, have an area of 447.5, 75.27, and 45.26 km², respectively. They were chosen to estimate their effects on transporting sediments from erosion during precipitation and runoff to the Mosul Dam lake.

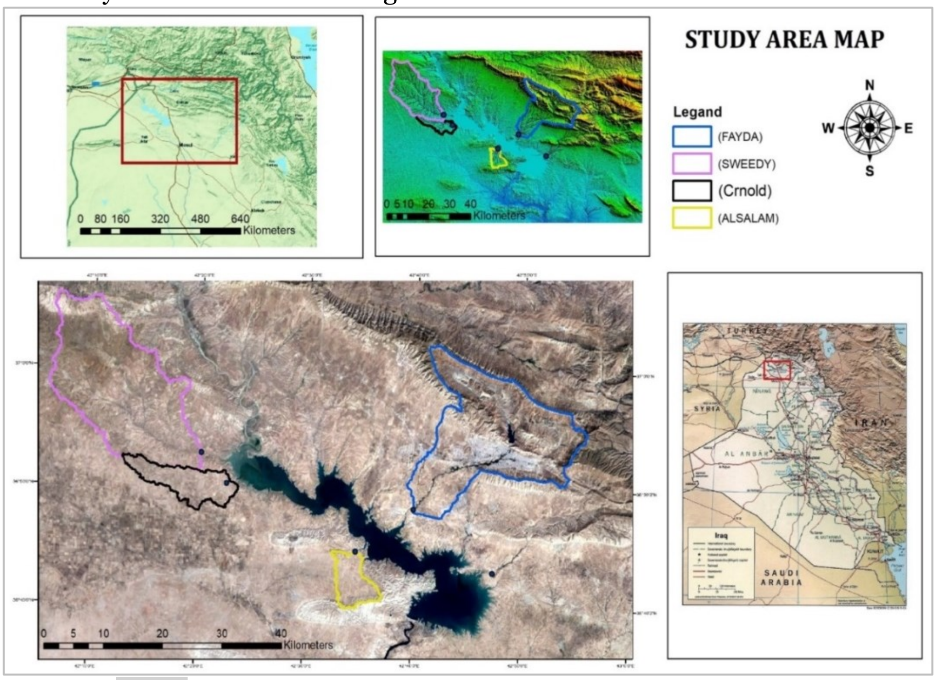

Fig. 1 Location of the Mosul Dam Reservoir and its Valleys.

2.2.Available Data

The daily climatic data like precipitation, relative humidity, wind speed, solar radiation, and temperature for the period (1994 - 2018) were adopted for meteorological stations near the study area, precisely Mosul and Mosul dam stations. The maps used were a Digital Elevation Model (DEM), a land use map, a soil type map comprising soil depth data, and a topography map. Figures 2 - 6 show the average monthly precipitation, temperature, relative humidity, solar radiation, and wind speed, respectively, for the water year, starting in October and finishing in September.

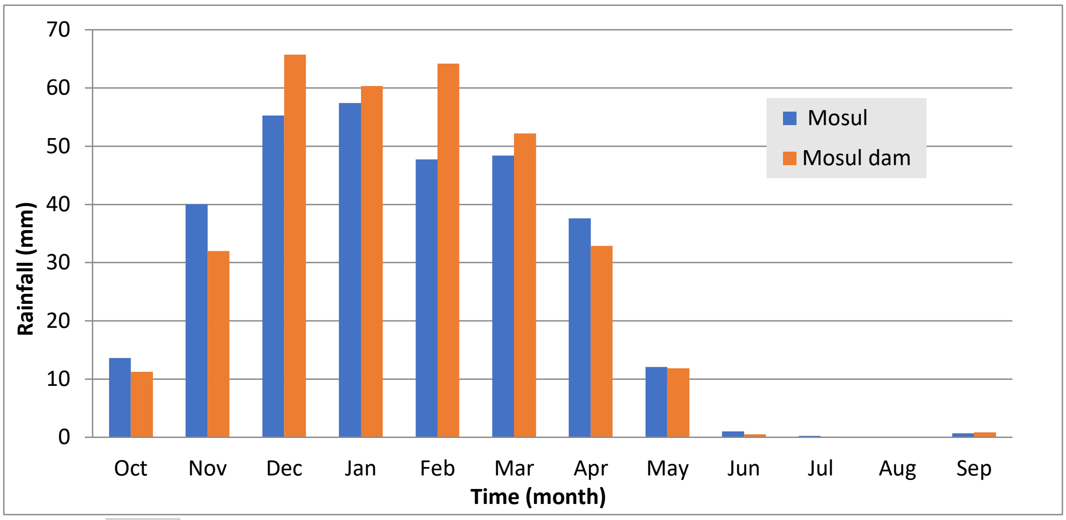

Fig. 2 Average Monthly Precipitation in Mosul and Mosul Dam Stations.

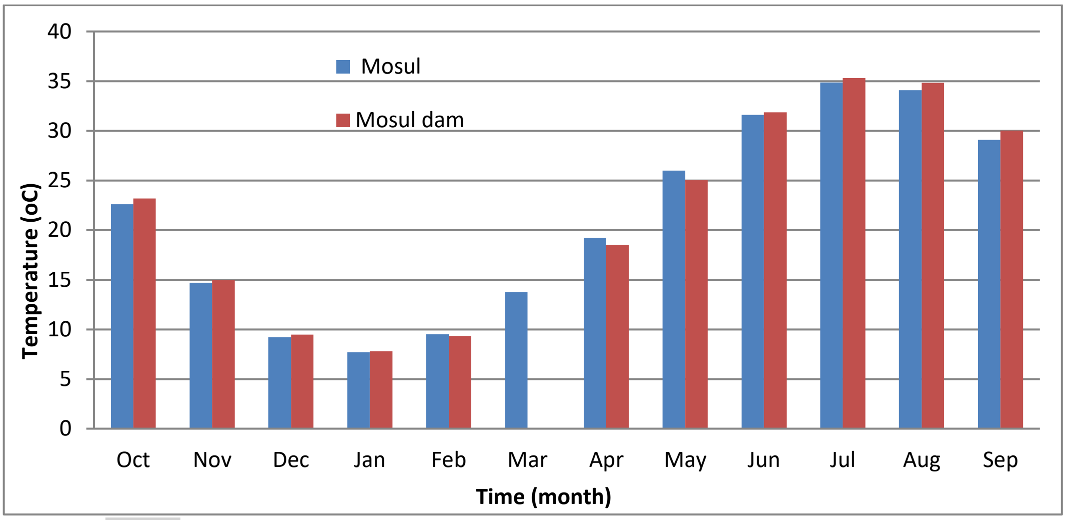

Fig. 3 Average Monthly Temperature at Mosul and Mosul Dam Stations.

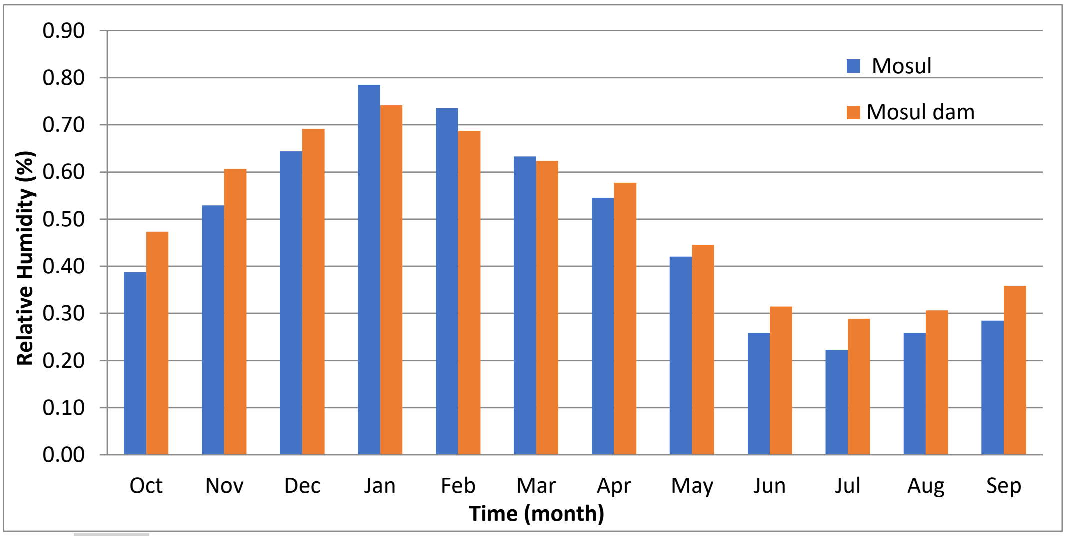

Fig. 4 Average Monthly Relative Humidity at Mosul and Mosul Dam Stations.

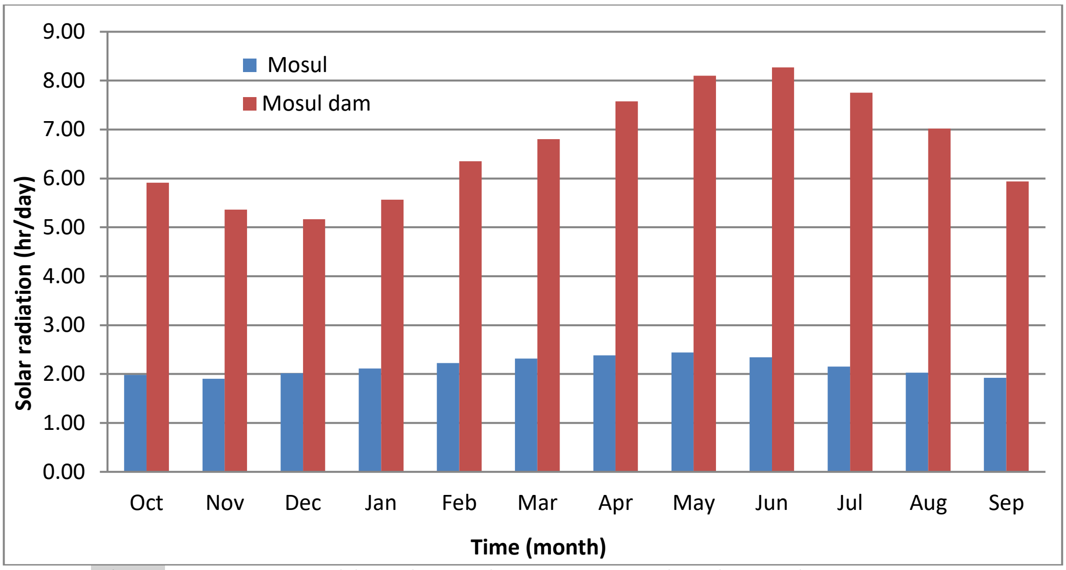

Fig. 5 Average Monthly Solar Radiation at Mosul and Mosul Dam Stations.

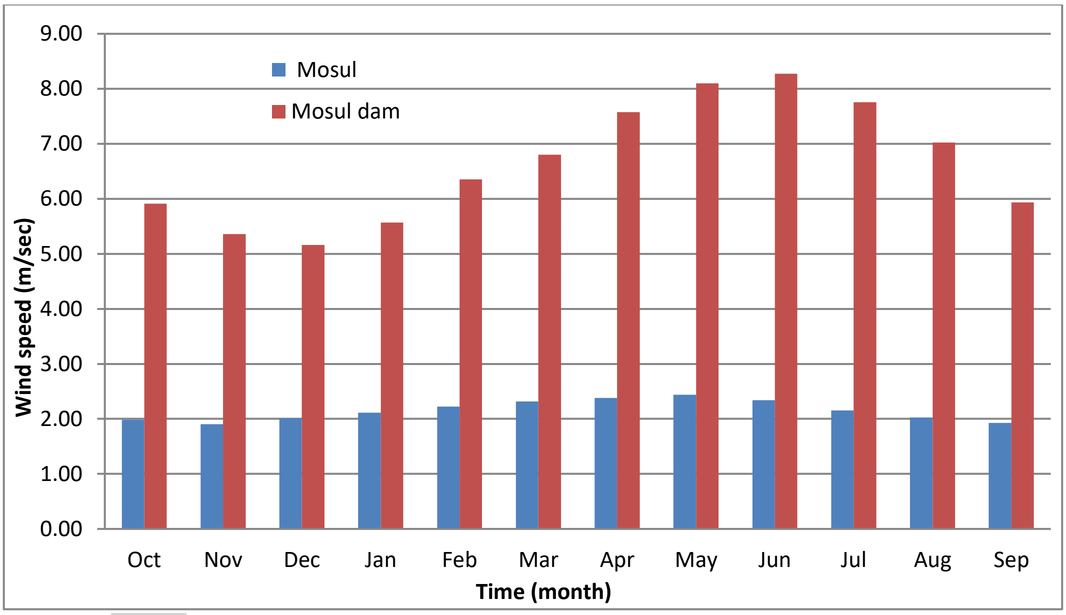

Fig. 6 Average Monthly Wind Speed at Mosul and Mosul Dam Stations.

3.APPLICATION OF THE MODELS

Two models were used in this research: Soil and Water Assessment Tool and Artificial Neural Networks.

3.1.SWAT Model

In the present study, the SWAT model is used to calculate sediment yield and surface runoff. The SWAT is generally applied to calculate the total amount of sediment transfer to the watershed. The SWAT model is based on two crucial methods for determining surface runoff. The first is the Green and Ampt (1911), Green-Ampt model, which finds the infiltration amount first; as a result, the residual precipitation will become the surface runoff. Much information is required regarding the soil of the study area for this method and measurements of precipitation depths against time, like hourly depth. This method also needs information about the precipitation falling intensity, which is unavailable with the meteorological stations of the study area. The second method is the Natural Resources Conservation Service (NRCS), the most widely used to estimate the surface runoff depth, as shown in Eqs. (1) - (3). This method has been developed to link the surface runoff from precipitation to the soil types. The NRCS equation is [20]:

$$R = \frac{(P-I_a)^2}{(P-I_a+S)} \quad (1)$$

$$I_a = 0.2 \times S \quad (2)$$

$$S = \frac{(25400 - 254 \times CN)}{(CN)} \quad (3)$$

where R is the surface runoff (mm), P is the precipitation depth (mm), I_a is the initial abstractions including the infiltration before the runoff, the interception, and the stored water in the soil (mm), S is the retention coefficient (mm), and CN is the value of the curve number, it is at a maximum value of 100 for water surfaces. The peak flow rate is measured by Eq. (4) with the modified rational method:

$$Q = C \times I \times A \quad (4)$$

where Q is the maximum rate of flow (m^3/sec), C is the runoff coefficient, I is precipitation intensity (m/sec), and A is the catchment area (m^2). In the channel component, sediment degradation or deposition can occur depending on the stream power, the channel side exposure, the erosive force of the stream at the bottom, bed sediment, and the composition of the channel bank. In sediment transport, two currencies of degradation and sedimentation are computed by the SWAT using the same channel dimensions for the whole population. These two components are the landscape and the channel. The SWAT uses a simplified Bagnold (1977) stream power equation to calculate the maximum amount of sediment that can be transported by the water that can be computed by Eq. (5) [21]:

$$conc_{sed} = C_{sp} \cdot v_{max}{}^{spexp} \quad (5)$$

where $Conc_{sed}$ is the maximum sediment concentration that can be transported by water (ton/m^3), C_{sp} is the coefficient defined by the user between (0.0001–0.01), *spexp* is the exponent factor parameter for channel sediment routing that varies between 1 and 2, and v_{max} is the maximum velocity (m/sec). The SWAT model estimates the process of soil erosion from the well as a result of rainfall using the MUSLE method. This method represents using the general soil loss equation developed by (Williams, 1995). The modified universal soil loss equation is shown in Eq. (6):

$$Sed = 11.8 \times \left(Q_{surf} \times Q_{peak} \times A_{hru}\right)^{0.56} \times K_{usle} \times C_{usle} \times P_{usle} \times LS_{usle} \times C_{FRG} \quad (6)$$

where Sed is the sediment load yield in a day (tons), Q_{surf} is the surface runoff volume (mm/ha), Q_{peak} is the peak surface runoff rate (m^3/sec), A_{hru} is an area of the hydrological representation unit (ha), K_{usle} is the USLE erodibility factor (tons/ha), C_{usle} is coefficient of vegetation and management, P_{usle} is the USLE practice factor, LS_{usle} is the topographic coefficient, and C_{FRG} is the coarse fragment factor.

3.2. ANN Model

Among the successive layers, multilayer perceptron exists as a feedforward neural network architecture, forming unidirectional connections. Figure 7 illustrates this fact. It depicts the structure of MLP-ANN, which possesses three primary layers: input, hidden, and output. The input dataset is the first layer, connected by a network called the weight with one hidden layer or more. The number of optimal hidden layers and neurons depends on the input-output dataset and could be determined during the training process [22].

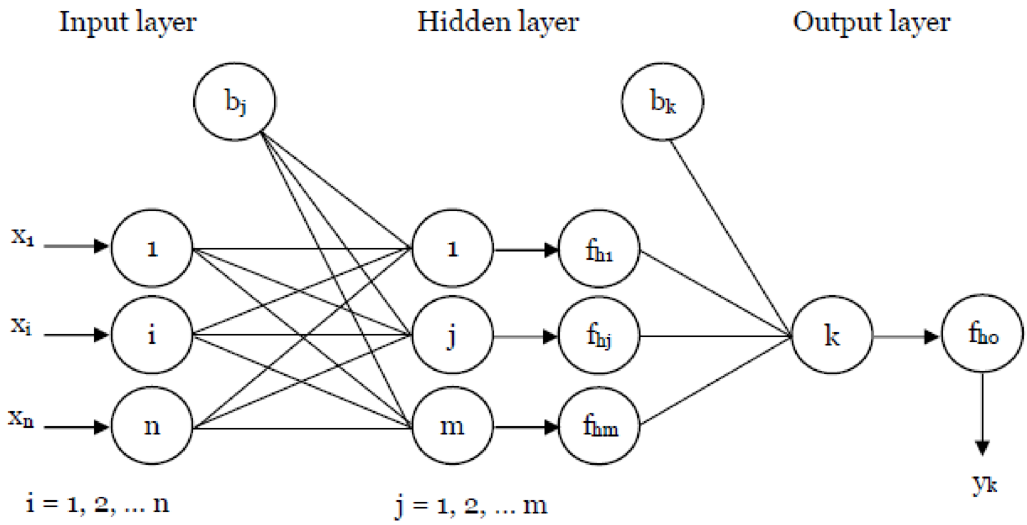

Fig. 7 Structure of the Multilayer Perceptron Network Function.

The output results were estimated by Eq. (7) [23]:

$$Y_k = f_o\left[\sum_{j=1}^{m}\left(w_{k,j} * f_h\left(\sum_{i=1}^{n}\left(w_{j,i} * x_i\right) + b_j\right)\right) + b_k\right] \quad (7)$$

where Y_k is the output variable; x_i is the input variable; $w_{j,i}$ is the weights of input-hidden and $w_{k,j}$ is the weight of hidden-output layers; b_j is the bias of the hidden layer and b_k is the bias of the output layer; *n, m, and k* are the number of input, hidden, and output variables, respectively; f_h is the activation function of the hidden layer; and f_o is the activation function of the output layer.

3.3. Building and Applying of the Dual ANN Models

The steps of building the models used in this research include three successive stages. The first stage is applying the SWAT model by entering all the metrological data, soil information, and maps necessary for the study area. The objective of this stage is to provide a required data set, such as the sedimentary concentration, sedimentary load, and discharges for a limited period, to build ANN models in the following stages. The second stage applies the ANN-1 model to obtain the discharges entering the dam reservoir, using the available rainfall for the specified period as input data. Lastly, the last stage is the application of the ANN-2 and ANN-3 models in which the precipitation of Mosul city, Mosul Dam. Also, the discharges resulting from the second step are used as input data, and then the sediment concentration and sediment load are obtained, respectively. The results of the last two steps were compared with the results of the SWAT model to obtain the best model of the Dual ANN. During the last two stages, all parameters of the ANN models have been determined. Figure 8 shows a flow chart of constructing the Dual ANN models. After constructing the Dual ANN models, these models were applied in two steps to estimate the sediment concentration and sediment load. The first step was applying the ANN-1 model and using the available rainfall data of Mosul City and Mosul Dam stations to obtain the discharges entering the dam reservoir. The second step was applying the ANN-2 and ANN-3 models, in which the previous data, as well as, the computed discharges resulting from the first step were used as input data. Then, the sediment concentration and sediment load were estimated.

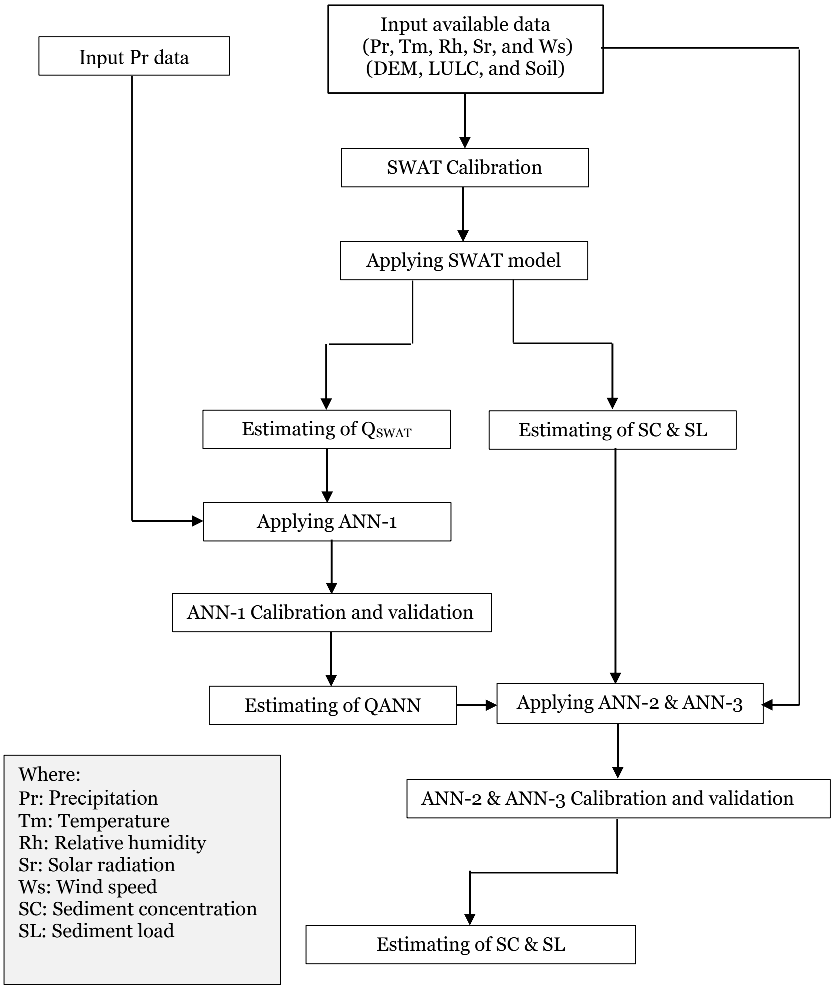

Fig. 8 Flow Chart of Estimating SC and SL Using the Dual ANN Model.

3.4.Statistical Methods for Models Evaluation

The model performance was evaluated using the coefficient of determination (R^2), as suggested to be used by Eq. (8) [24]:

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O-\bar{O}).(P-\bar{P})}{\sqrt{\sum_{i=1}^{n}(O-\bar{O})^2 . \sum_{i=1}^{n}(P-\bar{P})^2}} \right]^2 \quad \textbf{(8)}$$

where O is the observed data; P is the predicted data; n is the number of data; $\bar{O}$ is the average of observed data; and $\bar{P}$ is the average of predicted data. R^2 equals 1, corresponding to a perfect match of the modeled to the recorded values, while 0 indicates that the model predictions were accurate, as the average of the recorded data. Nash Sutcliff efficiency (NSE) comes under the category of normalized statistics, which helps determine the relative magnitude of the residual variance and measured data variance. When the value of NSE

= 1, it showed a perfect match of the model concerning the observed data. When NSE = 0, it showed that the model predictions are correct and cohere with the mean of the observed data, which could be calculated using the following equation.

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(O-P)^2}{\sum_{i=1}^{n}(O-\bar{O})^2}\right] \quad (9)$$

4.RESULTS AND DISCUSSION

The first step of the SWAT model was calibration. In this step, many measured values for the Fayda Valley, which lies on the opposite side of the lake, were used. These data are some observed runoff and sediment values used in the previous study from the close location. Manual calibration of the SWAT model was used by changing various parameters, such as manning roughness coefficient (n), effective hydraulic conductivity in the main channel (CH_K), hydraulic conductivity (SOL_K), curve number CN, linear factor parameter for channel sediment routing (Spcon), and exponent factor parameter for channel sediment routing (Spexp). Where each one was changed separately by fixing the other parameters' values. The SWAT results were evaluated using (R^2). The results of changing the (n, CH_K, and SOL_K) parameters showed the insignificant effect of each one on the surface runoff, while their effects were noticed slightly on the sediment values. Therefore, the associated change in their values was neglected in the calibration process. In the meantime, the CN was tested by continuously changing the initial value until the acceptable results of surface runoff were based on the results of the value of (R^2). The best results were obtained in the case of increasing CN value by 10%. Each parameter, i.e., Spcon and Spexp, was changed separately, while the other parameters were fixed. The results showed a significant effect on the sediment load values. The best results were at (Spcon = 0.0002 and Spexp = 1.7). After the calibration stage, the appropriate values of CN, Spcon and Spexp were selected in the software. Then, the software was run with these calibrated and optimized values to get the final results of the surface runoff and sedimentation values. The next step was to apply the SWAT model in the study area using available metrological data for 25 years (1994-2018), soil information, land use, soil, and DEM maps. The predicted results of the model were sediment load, sediment concentration, and flow discharge for the Sweedy, Crnold, and Alsalam valleys. Figures 9 - 11 demonstrate the annual flow, sediment concentration, and sediment load, respectively. They were calculated by applying the SWAT model for the aforementioned valleys. The results showed that the flow and sediment load entering the reservoir from Sweedy Valley is more than that from Crnold and Alsalam valleys. Table 1 shows the value of the curve number (CN) estimated by applying the SWAT model and other characteristics for the catchment area of the valleys.

Table 1 The Characteristics of Sweedy, Crnold, and Alsalam Valleys.

Characteristic	Unit	Valley		
		Sweedy	Crnold	Alsalam
Latitude Coordinates	Degree	36° 49' 58"	36° 48' 52"	36° 43' 53"
Longitude Coordinates	degree	41° 50' 12"	42° 29' 11"	42° 44' 2"
Catchment Area	km²	447.5	75.27	45.26
Main Stream Length	km	37.6	20.8	8.3
Maximum Daily Flow	m3/sec	194.6 (1996)	174.9 (1998)	102.5 (1998)
Average Slope	%	4.3	2	4
Curve Number	-	83	73	70

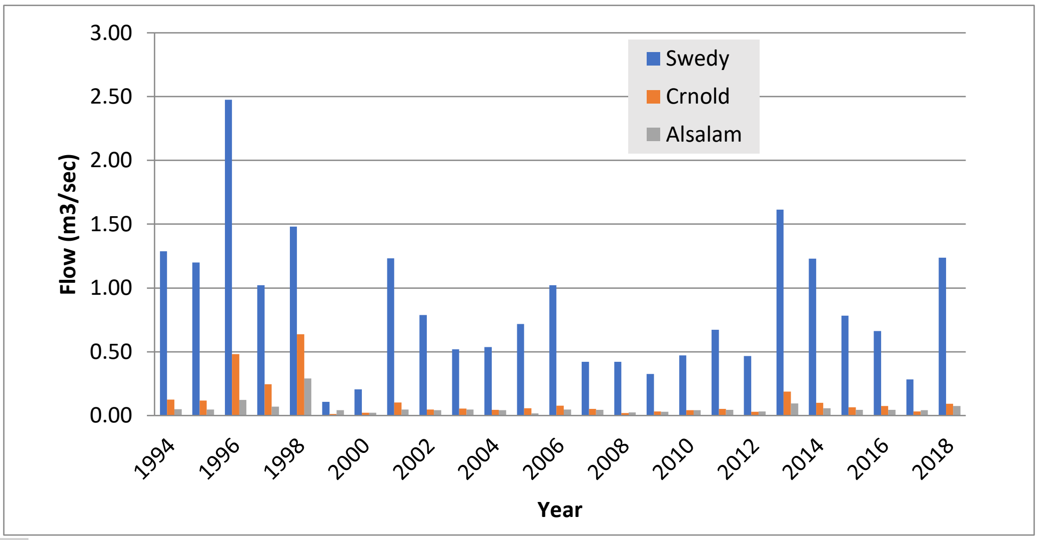

Fig. 9 The Average Annual Flow of the Sweedy, Crnold, and Alsalam Valleys by Using the SWAT Model for the Period (1994-2018).

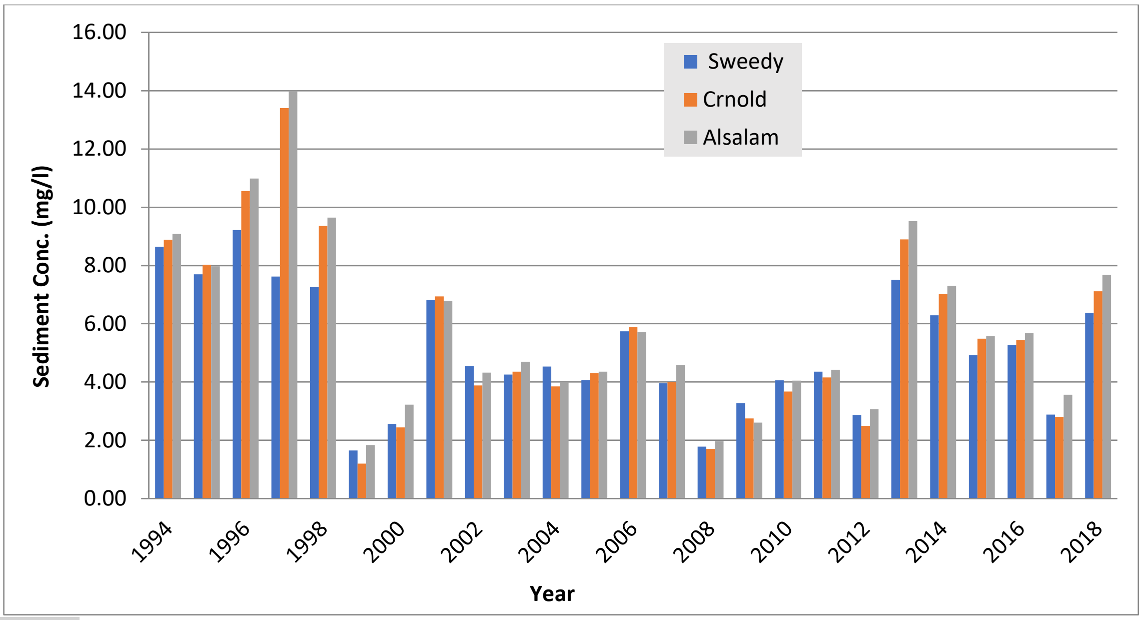

Fig. 10 The average Sediment Concentration of the Sweedy, Crnold, and Alsalam Valleys Using the SWAT Model for the Period (1994-2018).

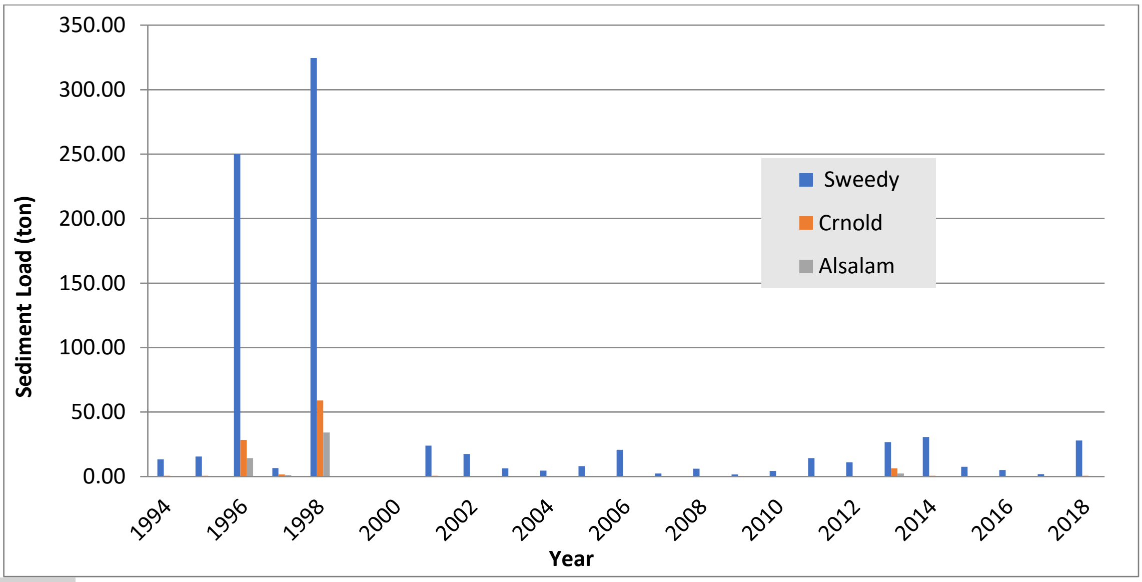

Fig. 11 The Annual Sediment Load of the Sweedy, Crnold, and Alsalam Valleys by Using the SWAT Model for the Period (1994-2018).

The second model in this study was the multilayer Perceptron Neural Network Model (ANN-1) for estimating main parameters, such as the weight and activation faction. The precipitation data was used as an input data set. Because of the unavailable recorded flow data, the discharge, which was found by the SWAT model, was used as an output data set. To calibrate and validate the used models, the available data for 25 years, for the period from (1994-2018), was divided into two sets. The first 22 years of the data were used for the calibration, and the other 3 years were used for the validation. The output of the ANN-1 model was compared with the output of the SWAT model. The results showed that the values of R^2 for Sweedy, Crnold, and Alsalam valleys were 0.82, 0.96, and 0.96, respectively, for the calibration stage. While, the results were 0.88, 0.72, and 0.78 for the validation stage, respectively, as shown in Table 2. The values of NSE for the calibration stage were 0.80, 0.81, and 0.92 and 0.87, 0.87, and 0.79 for the validation stage for the same valleys, respectively. The best discharge model in this study for the Sweedy Valley was MLP-ANN (2,2,1). The values in the parenthesis (2,2,1) were as follows: 2 is the number of input nodes (Mosul and Mosul dam precipitation); 2 is the number of hidden nodes (given best result); and 1 is the number of nodes for the output layer (discharge). Otherwise, Crnold and Alsalam Valleys were (2,2,1) and (2,1,1), respectively. Figures 12-14 demonstrate the average annual flow estimated by the ANN-1 models for Sweedy, Crnold, and Alsalam Valleys, respectively.

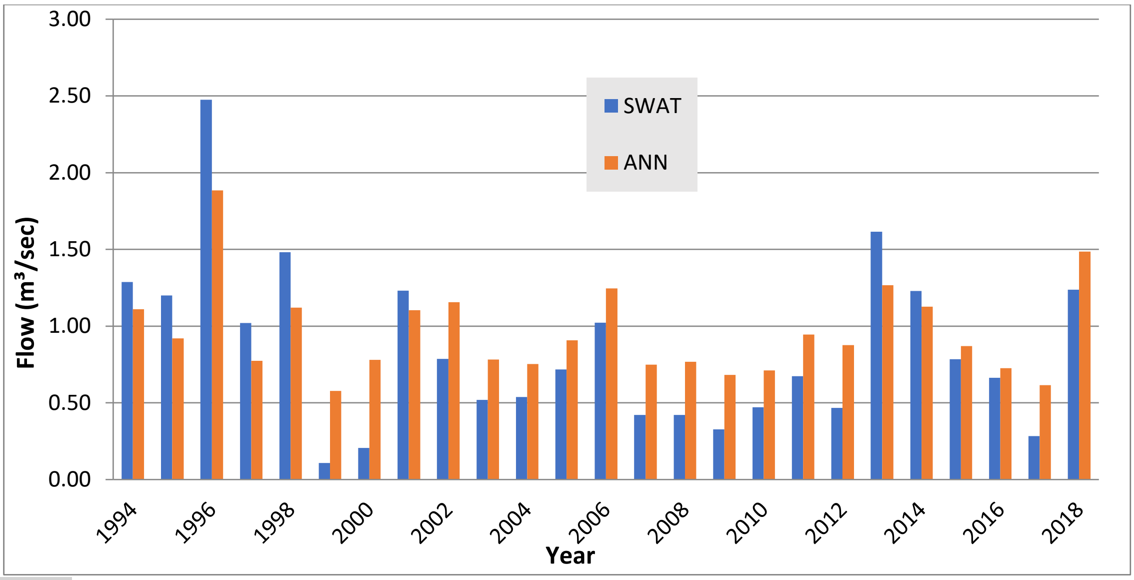

Fig. 12 The Average Annual Flow for Sweedy Valley Using the SWAT and ANN-1 Models for Period (1994-2018).

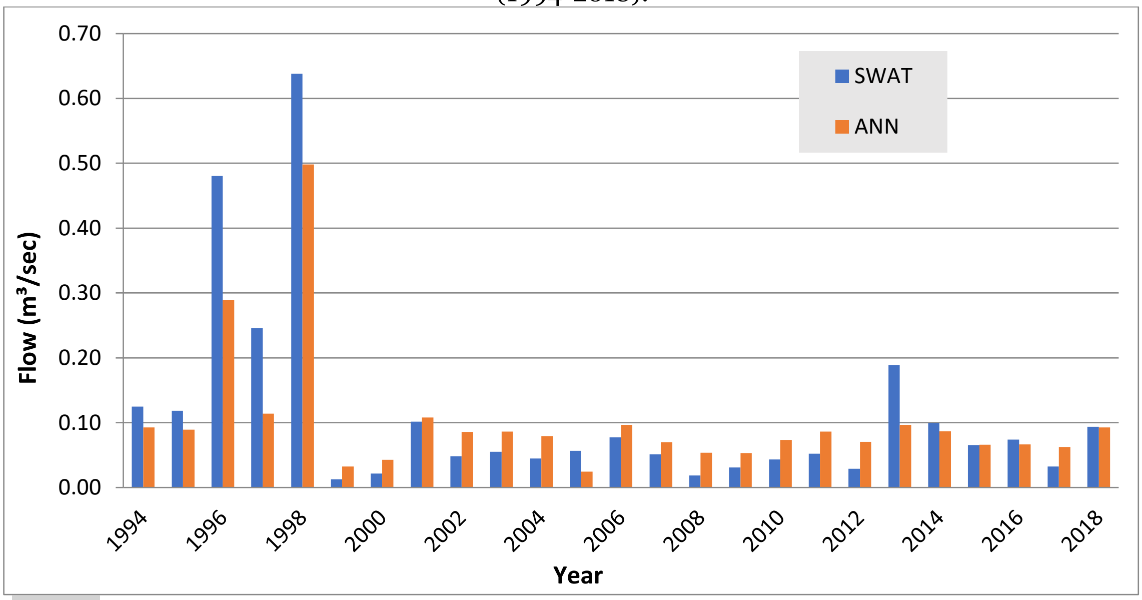

Fig. 13 The Average Annual Flow for Crnold Valley Using the SWAT and ANN-1 Models for the Period (1994-2018).

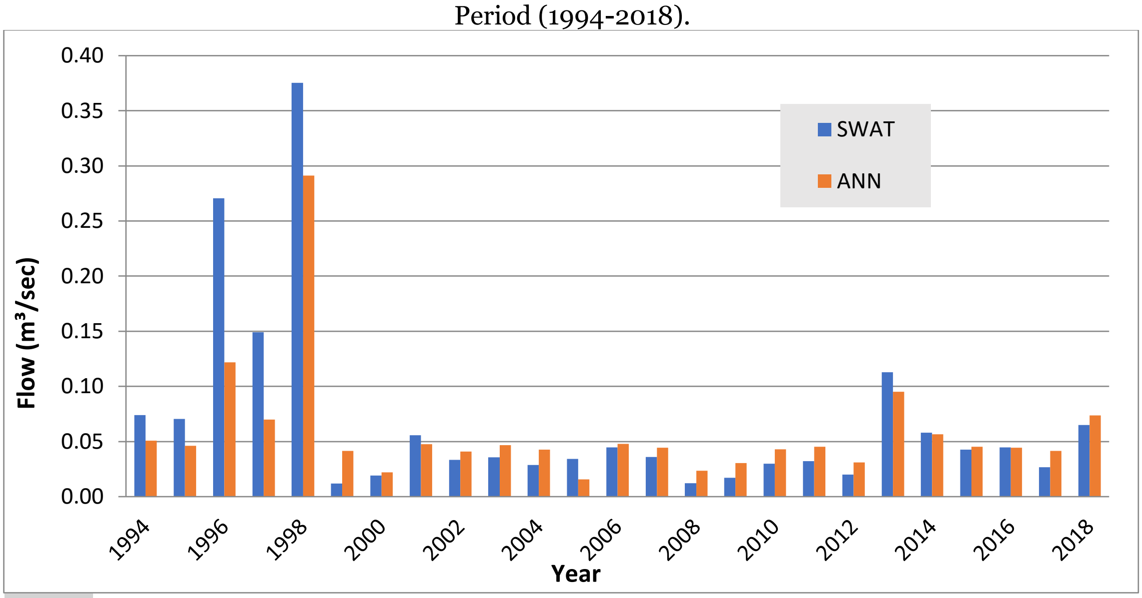

Fig. 14 The Average Annual Flow for Alsalam Valley Using the SWAT and ANN-1 Models for the Period (1994-2018).

The third model is the multilayer perceptron network models (ANN-2) and (ANN-3). These models were applied to estimate the sediment concentration and sediment load, respectively. The precipitation data and flow found by the ANN-1 model were used as the input data set, and the sediment concentration and sediment load found by the SWAT model were used as an output data set. The available data was also divided into two sets for calibration and validation. The output of the ANN-2 model was compared with the sediment concentration output of the SWAT model. The results showed that the values of R^2 were 0.87, 0.94, and 0.94 for the calibration and 0.86, 0.97, and 0.95 for the validation, as shown in Table 2. The values of NSE were 0.90, 0.95, and 0.92 for the calibration stage, and for the validation stage were 0.86, 0.96, and 0.95. Also, the output of the ANN-3 model was compared with the sediment load as the output of the SWAT model. The results showed that the values of R^2 were 0.92, 0.85, and 0.91 for the calibration stage and 0.98, 0.92, and 0.93 for the validation stage. While, the values of NSE were 0.93, 0.93, and 0.94 for the calibration stage and 0.97, 0.90, and 0.93 for the validation stage for the same valleys.

Table 2 Determination Coefficients (R^2) and Nash Sutcliff Efficiency (NSE) for ANN Models of the Valleys.

Model	Valley	Calibration		Validation	
		R^2	NSE	R^2	NSE
ANN-1	Sweedy	0.82	0.80	0.88	0.87
	Crnold	0.96	0.81	0.72	0.87
	Alsalam	0.96	0.92	0.78	0.79
ANN-2	Sweedy	0.87	0.90	0.86	0.86
	Crnold	0.94	0.95	0.97	0.96
	Alsalam	0.94	0.92	0.95	0.95
ANN-3	Sweedy	0.92	0.93	0.98	0.97
	Crnold	0.85	0.93	0.92	0.90
	Alsalam	0.91	0.94	0.93	0.93

The best model of sediment concentration for Sweedy Valley was MLP-ANN (3,4,1), where 3 is the number of input nodes (Mosul, Mosul dam precipitation, and flow), 4 is the number of hidden nodes, and 1 is the number of nodes for the output layer (sediment concentration). Otherwise, for the Crnold and Alsalam valleys were (3,3,1) and (3,3,1), respectively. While, the best models for sediment load for valleys were MLP-ANN (3,2,1), (3,5,1), and (3,3,1), respectively. Figures 15-17 show the average annual sediment concentration estimated by the ANN-2 and SWAT models for the Sweedy, Crnold, and Alsalam valleys, respectively. Figures 18-20 show the annual sediment load estimated by the ANN-3 and SWAT models for the Sweedy, Crnold, and Alsalam valleys, respectively.

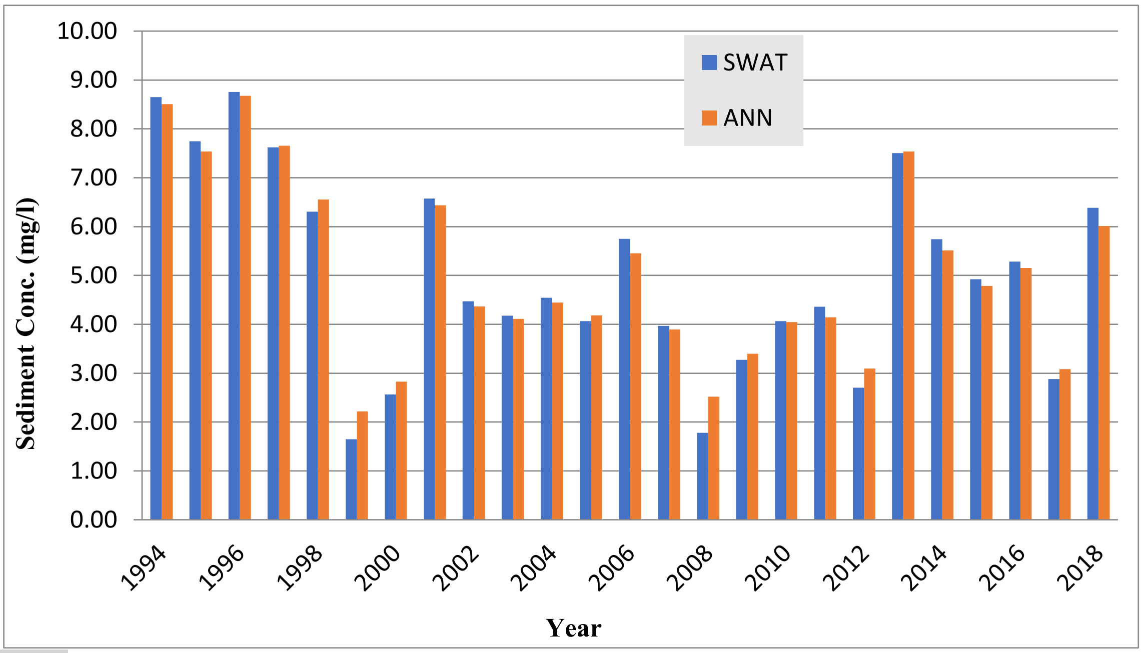

Fig. 15 The Average Annual Sediment Concentration for Sweedy Valley Using the SWAT and ANN-2 Models for the Period (1994-2018).

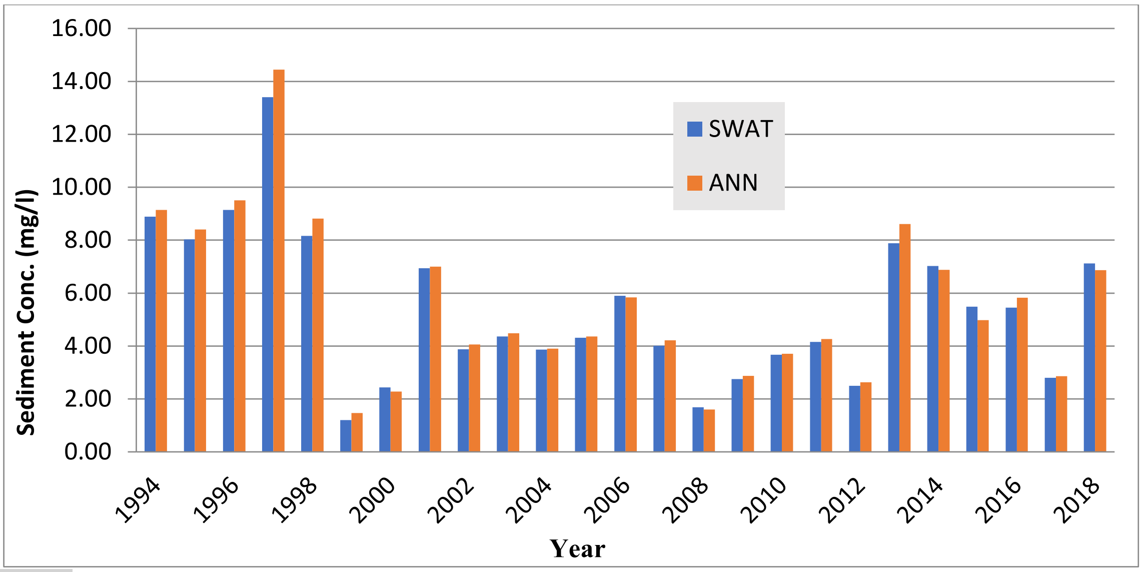

Fig. 16 The Average Annual Sediment Concentration for Crnold Valley Using the SWAT and ANN-2 Models for the Period (1994-2018).

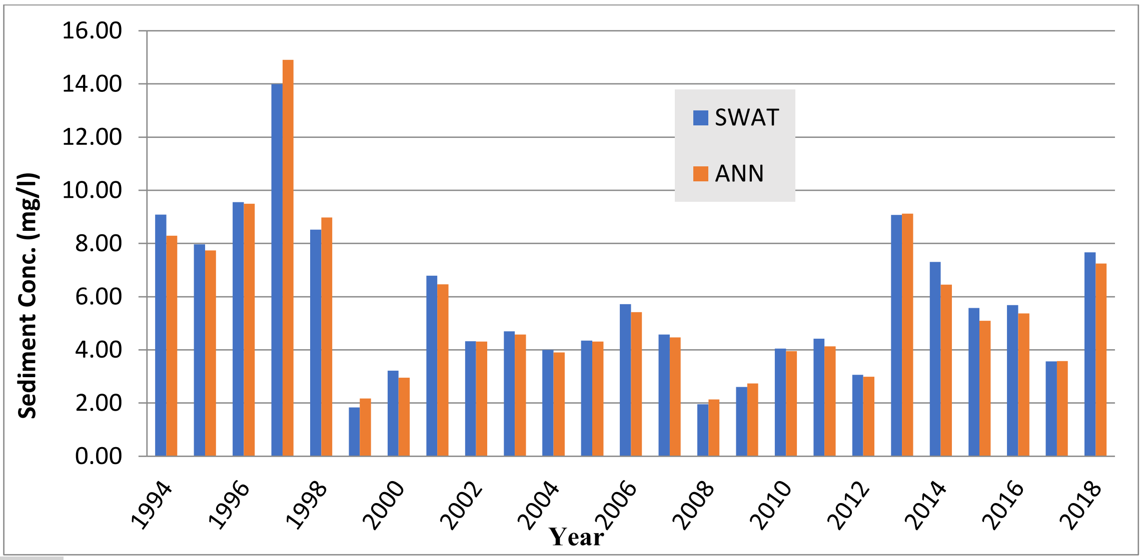

Fig. 17 The Average Annual Sediment Concentration for Alsalam Valley Using the SWAT and ANN-2 Models for the Period (1994-2018).

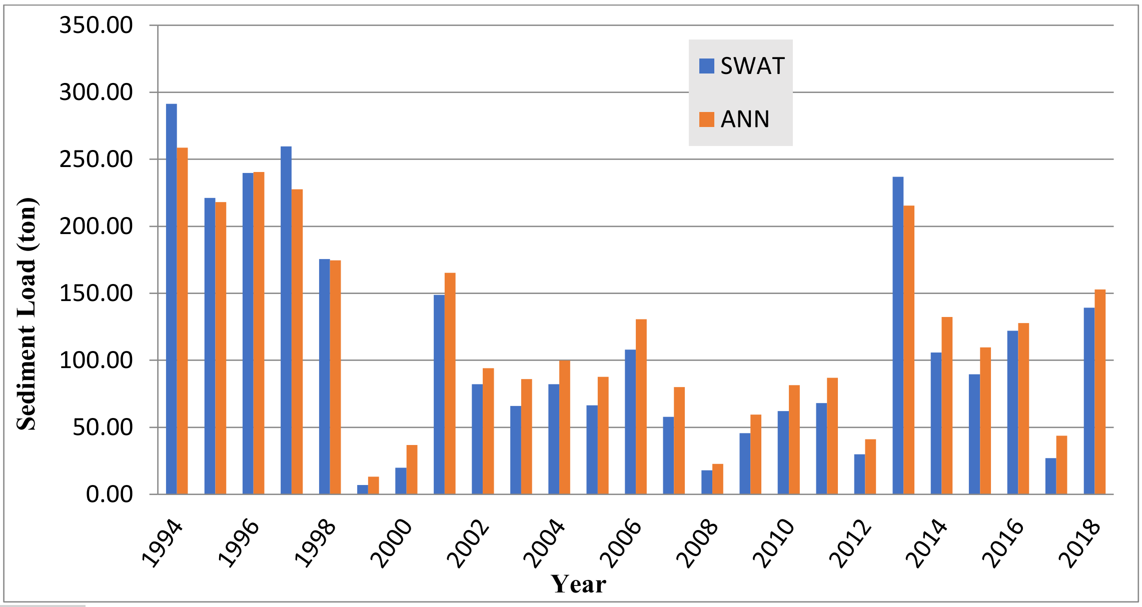

Fig. 18 The Annual Sediment Load for Sweedy Valley Using the SWAT and ANN-3 Models for the Period (1994-2018).

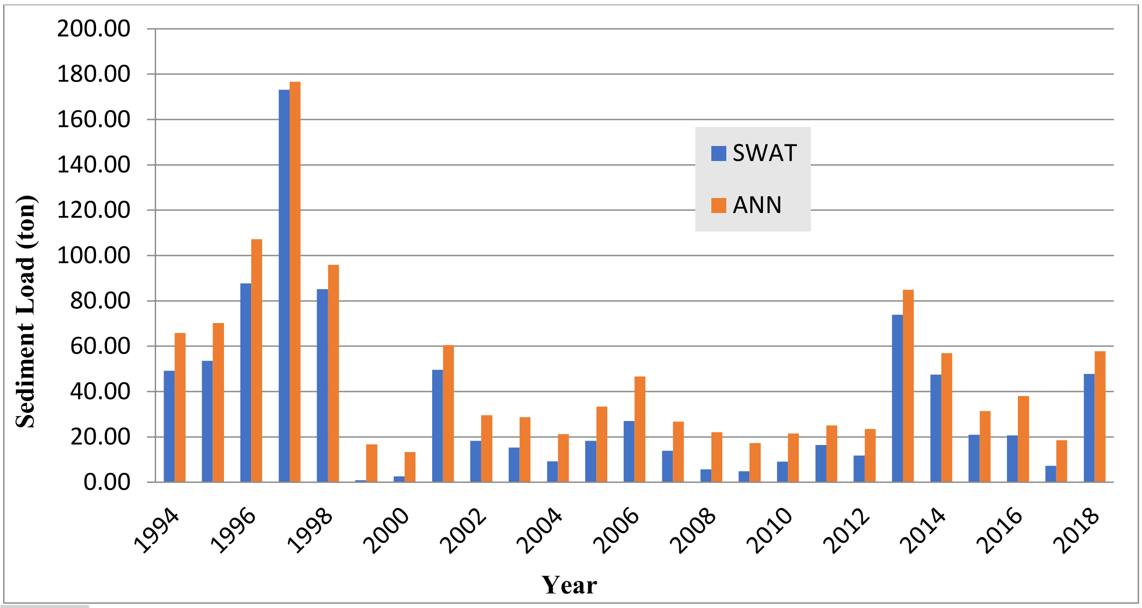

Fig. 19 The Annual Sediment Load for Crnold Valley Using the SWAT and ANN-3 Models for the Period (1994-2018).

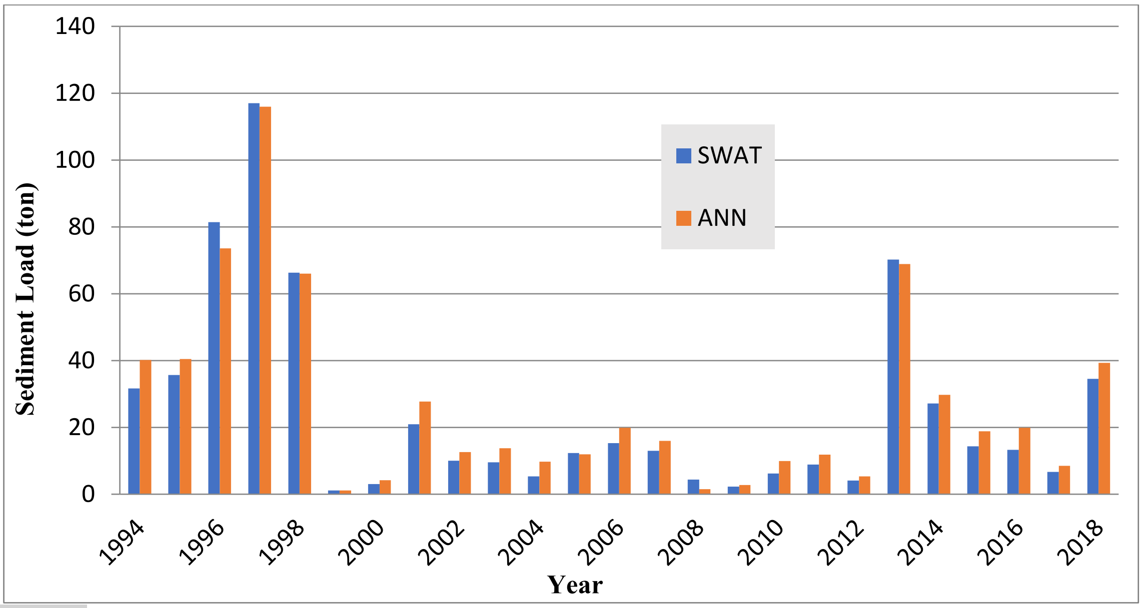

Fig. 20 The Annual Sediment Load for Alsalam Valley using the SWAT and ANN-3 Models for the Period (1994-2018).

For all types of Models, ANN-1, ANN-2, and ANN-3, the activation function type of the hidden layer was a hyperbolic tangent and identity for the output layer. The online type of training was selected, updating the synaptic weights after every training data record. While, maximum training epochs were computed automatically to avoid overtraining. The gradient descent method was selected to specify the optimization algorithm. The maximum annual surface runoff of Sweedy Valley occurred in 1996. While, for the Crnold and Alsalam valleys, the maximum surface runoff occurred in 1998. In the same way, the maximum annual sediments of Sweedy Valley occurred in 1996, While, for Crnold and Alsalam valleys, the maximum annual sediments occurred in 1997. The accumulated total loads of the sediments entering the reservoir of the dam during the period of the study were (111.4×103, 14.24×103 and 7.34×103 tons) for Sweedy, Crnold, and Alsalam valleys, respectively.

5.CONCLUSIONS

The key point in this research was the possibility of estimating the sediment concentration and sediment load entering Mosul Dam Lake from the Sweedy, Crnold, and Alsalam valleys using the ANN using available precipitation data, with the assistance of the SWAT model. Because the study area is ungauged and does not have recorded flow and sediment data, it only has precipitation data from nearby stations; therefore, the SWAT was used to obtain the required data for a limited period. These data were used in building the

ANN models to obtain sediment results for any possible period in the future using only the precipitation data. Therefore, the model ANN-1 was used first to find the catchment area discharge at the outlet for the aforementioned valleys. However, to estimate the sediment concentration and the sediment load of the catchment area, the ANN-2, and ANN-3 models were used. To estimate the sediment concentration, the Dual ANN models must be used. The ANN-1 model was applied first, followed by the ANN-2 model. While, for sediment load, the ANN-1 model and then the ANN-3 models were used. Finally, the Dual ANN model was effectively applied to measure the sediment load and sediment concentration entering the Mosul Dam Lake. In the SWAT calibration stage, the results showed that changing the Curve number (CN) significantly affected the values of runoff and sediment. The largest valley was the Sweedy, which provides sediments about 84% of the average total sediment loads for the entire study area. While, Crnold was about 11%, and Alsalam was 5% of the total sediment load. In general, the amount of precipitation, intensity, land use, land cover, soil texture, valley slope, and flow velocity may also play important roles in increasing runoff and leading to erosion and sediments. The study showed that a combination of the SWAT and ANN models could be used effectively and accurately to estimate the sediment concentration and the sediment load, especially in watersheds that particularly lack the necessary metrological data and only have precipitation data available.

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NOMENCLATURE

A	Catchment area, L^2
A_{hru}	Area of the hydrological representation unit, L^2
b_j	The bias of the hidden layer
b_k	The bias of the output layer
C	Runoff coefficient
C_{FRG}	The coarse fragment factor
C_{sp}	Sediment coefficient
C_{usle}	Coefficient of vegetation and management
CN	Curved number
$Conc_{sed}$	Maximum sediment concentration, M/L^3
C_{usle}	Coefficient of vegetation and management
f_h	The activation function of the hidden layer
f_o	The activation function of the output
I	Precipitation intensity, L/T
I_a	Initial abstraction, L
k	Number of neurons in the output layer
K_{usle}	The USLE erodibility factor, M/L^2
LS_{usle}	The topographic coefficient
M	Number of neurons in the hidden layer
N	Number of neurons in the input layer
Pr	Precipitation, L
P_{usle}	The USLE practice factor
O	Recorded flow, L^3/T
P	Forecasted flow, L^3/T
O'	Average of the observed flow, L^3/T
P'	Average of the forecasted flow, L^3/T
Q_{ANN}	Flow measured by SWAT model, L^3/T
Q_{SWAT}	Flow measured by SWAT model, L^3/T
Q_{surf}	Daily surface runoff or excess rainfall, L
Q_{peak}	Peak surface runoff rate, L^3/T
R	Daily rainfall depth, L
R^2	Determination Coefficient
R_h	Relative humidity, %
Sed	Daily sediment load yield, M
S	Retention parameter
S_r	Solar radiation, T
SC	Sediment concentration, M/L^3
SL	Sediment load, M
T_m	Temperature, ^{o}C
υ_{max}	Maximum velocity, L/T
W_s	Wind speed, L/T
$w_{j,i}$	Weights of input-hidden
$w_{k,j}$	Weights of hidden-output layers
x_i	The input variable
Y_k	The predicted value of the ANN model, L^3/T

Abbreviations

CH_K	Effective Hydraulic Conductivity in Main Channel
DEM	Digital Elevation Model map, L
LULC	Land use and land cover
MLP	Multi Activation Function
NSE	Nash Sutcliff efficiency
SOL_K	hydraulic conductivity
Spcon	Linear factor parameter for channel sediment routing
Spexp	Exponent factor parameter for channel sediment routing

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